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Collaboration strategies and SME innovation performance

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ABSTRACT

There is a growing recognition that collaboration is a key source of new knowledge and innovation in small and medium-sized enterprises (SMEs). Bridging the gap in the open innovation in SMEs literature on returns to open innovation our study demonstrates that a type of partner and its geographical proximity predict innovation performance in SMEs. Controlling for selection bias and endogeneity and using the panel data on 9,213 SMEs in the United Kingdom (UK) during 2002–2014, we found that collaboration with suppliers and customers domestically and internationally, collaboration with universities domestically and competitors internationally facilitate innovation in SMEs. The results offer implications for policymakers, scholars, entrepreneurs and SME managers.

1. Introduction

Although the knowledge collaboration -innovation link has been thoroughly studied (e.g. Bathelt et al. 2004; Ribeiro-Soriano & Urbano, 2009; Leiponen & Helfat, 2010; Gesing et al. 2015), there is a paucity of research how small and medium-sized enterprises (SMEs) embrace open innovation (Teixeira, Santos & Brochado, 2008) and benefit from knowledge collaboration with different external partners such as enterprise group, suppliers, customers, consultants, competitors, universities, local and national governments (Audretsch & Belitski, 2020a). Innovation is seen as an increasingly complex and costly process that few SMEs have the resources to do on their own. Given the scarcity of resources available in SMEs, they are at a greater pressure what type of collaboration partner to choose (van Beers & Zand, 2014; Kobarg, Stumpf-Wollersheim & Welpe, 2019) and where these partners are located geographically (e.g. locally, nationally, internationally) (Boschma, 2005; Gallaud & Torre, 2005; Brunswicker & Vanhaverbeke 2015).

Extracting value from external knowledge collaborations for SMEs is challenging, because they have limited absorptive capacity and generally operate in narrow domains in the sense of distribution, research, target markets, or technologies. SMEs and entrepreneurs seek external R&D collaborations (Roper et al. 2017; Kraus et al. 2021) to exploit knowledge spillovers (Jaffe et al. 1993; Audretsch & Feldman, 1996) and facilitate inter-regional and international knowledge networks (Teixeira et al. 2008).

Despite this, prior studies have suggested that SMEs, compared to large firms, are more likely to source knowledge externally (Brunswicker & Vanhaverbeke 2015; Vahter et al 2014; Mas-Tur & Ribeiro Soriano, 2014; Ribeiro-Soriano, 2017), while the collaboration partner and the geography of SME collaboration remains largely unknown (Audretsch & Lehmann, 2006; Mas-Verdu, Ribeiro Soriano & Roig Dobon, 2010).

Drawing on this research gap in the SME innovation literature, this study poses the following research question: How does the relationship between knowledge collaboration with different external partners facilitate SME innovation nd how the relationship varies with the type of partner and its geographical proximity? To answer our research question, this study objective is to examine what role that geographical proximity and types of collaboration partners play in SME innovation, utilizing a dataset of 9,213 UK firms and 21,140 firm-year observations during 2002–2014.

Our results suggest that the localization of knowledge collaboration may take place across different external partners, however collaboration

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on innovation with customers, suppliers (Guenther et al. 2022) and universities (Audretsch, Belitski, Guerrero & Siegal, 2022b) in a close geographical proximity (Audretsch & Lehmann, 2006) and collaboration with competitors internationally (Ribeiro-Soriano, Roig-Tierno & Mas-Tur, 2016; Theodoraki & Catanzaro, 2022) has the strongest positive effect on SME innovation.

Our findings contribute to open innovation in SMEs and small business economics literature is two important ways. First, in contrast to absolute and benchmarked concepts of open innovation (Bogers et al. 2017), we distinguish SMEs innovation collaboration strategies as a unique input of SME innovation. We also consider how and why SMEs can achieve continuously higher innovation when collaborating with a specific type of external partner and within specific geographical proximity.

Second, we broaden scholarly understanding of the mechanisms of knowledge collaboration by demonstrating that not every type of collaboration partner will equally facilitate SME innovation, with collaborator type – enterprise group unit, supplier, customer, consultant, competitor, university, government as well as the geographical dimension of collaboration emerge as two boundary conditions of SME open innovation.

The remainder of this paper is organized as follows. The next section sets out the hypotheses. Section 3 introduces the data, sample and method. Section 4 outlines the results, while Section 5 presents the discussion. Section 6 concludes with limitations, policy implications and future research.

2. Theory

2.1. Firm size and knowledge collaboration

Open innovation in SMEs literature has examined the relationships between firm size and firm innovation (Brunswicker & Vanhaverbeke 2015; Vanhaverbeke & Cloodt, 2014; Vahter et al 2014) as well as the sources of knowledge for innovation and growth (Kraus et al. 2021). More precisely, firms of different sizes and different absorptive capacities, managerial skills and resources may benefit differently from external collaboration, including their ability to geographically outreach and cognitively engage with external partners (von Hippel, 2005; Balland et al. 2015). For a firm to be able to adopt, adapt, modify, and implement external knowledge as well as co-create with different types of collaborators, its absorptive capacity must constantly increase (Zahra & George, 2002; Flor et al. 2018). This implies that firms of different sizes have diverse experience, skills, technologies and innovative capabilities (Ribeiro-Soriano, 2017) to search and absorb external knowledge (Nieto & Santamaria, 2007).

While knowledge collaboration with different external partners facilitates innovation in both SMEs and large firms, the economic returns to knowledge collaboration are higher for SMEs as they not only rely on external knowledge, they also experiment and explore new business models, and require knowledge recombination (Audretsch & Belitski, 2022a, 2022b), especially at the early stage of firm growth (Audretsch, Belitski & Caiazza, 2021).

Why do SMEs collaborate? First, SMEs collaborate with external partners to develop their absorptive capacity through the mutual learning process (Frenz & Ietto-Gillies, 2009; Roper et al., 2017). Unlike larger firms with in-house resources for R&D and buying external knowledge and technology, SMEs cannot do so (Teixeira et al. 2008). Second, knowledge collaborations help SMEs to share innovation costs (Veugelers, 1997), shorten product development (Bogers et al. 2017). SMEs, which operate under higher resource constraints than large firms, aim to tap into their partners' external knowledge and expertise to reduce the cost of innovation through collaboration (Vahter et al 2014). Finally, SMEs collaborate externally as they aim to avoid unnecessary duplication of R&D in a technology domain (Audretsch & Belitski, 2020a).

Based on the above mentioned argumentation we hypothesize:

H1: The economic returns to knowledge collaboration for innovation are larger for small- and medium-sized firms than for large firms.

2.2. Regional proximity and innovation

Knowledge collaboration and co-creation of new knowledge may be easier in a close proximity (Boschma, 2005; Nooteboom et al. 2007; Lahiri, 2010). Spatial proximity may improve the flows of knowledge, generating knowledge spillovers. In the case of SMEs, one could expect that, despite the importance of knowledge collaboration with global partners, immediate colocation of SMEs with their collaboration partners may facilitate knowledge flows (Audretsch & Lehmann, 2006; Guenther et al. 2022).

Few studies have considered the role of local proximity in knowledge spillovers (Audretsch and Feldman, 1996; Audretsch & Belitski, 2013) as localized knowledge flows can play an important role in shaping the business models and understanding the culture and needs of local markets (Boschma, 2005; Balland et al. 2015).

It is now increasingly recognised that localized knowledge flows between firms facilitate investment decisions and knowledge spillovers (Audretsch & Belitski, 2021a). Access to local labor markets and finance, market demand, infrastructure, and cultural norms (Saxenian, 1994; Audretsch & Belitski, 2017) forms a conducive environment for knowledge transfer between firms, enhancing firm innovation.

Close geographical proximity where firms collaborate helps firms to reduce cognitive-cultural distance (D'Este et al. 2013; Balland et al. 2015), sharing ideas, culture, financial resources and knowledge. This exchange is often the result of regional trust between firms (Khlystova et al. 2022) and institutional closeness (Alvedalen and Boschma, 2017) as local proximity provides greater transparency of knowledge creation, transfer and implementation. In addition, local proximity in knowledge collaboration reduces doijng business costs, logistics and transportation costs, and most importantly transaction costs related to decision-making and negotiation (Audretsch & Belitski, 2020a). Hence the speed and the depth of knowledge transfer increases (Kobarg et al. 2019) with the geographical proximity Below we discuss the mechanisms how localization of knowledge may facilitate open innovation strategies in SMEs and increase economic returns to knowledge collaboration.

Firstly, we expect knowledge transfers with regional and national suppliers and customers to be more important for SMEs focused on local markets. This is because SMEs are likely to be more efficient at maintaining partnerships, supply chains with local partners than with more distant partners (Balland et al. 2015; De Massis et al. 2018). Knowledge from universities may become valuable only if applied to a specific regional context and supported by a specific localized advantages and technological specialisation (D'Este et al. 2013).

Secondly, localized formal and informal institutions (Audretsch et al. 2019, 2022a; Khlystova et al. 2022) determine the behavior of SMEs and play a key role in doing business. Thirdly, regional and national markets are used as a testing ground by SMEs for new products and services before scaling up internationally (Rugman & Verbeke, 2001; Lô & Theodoraki, 2020), with more opportunities for the transmission of "sticky knowledge" between firms located there in a area (Bathelt et al. 2004). Fourthly, it is easier to enforce contracts and resolve insolvency within national boundaries should there be any infringement of intellectual property (IP) rights and unauthorised leakage of knowledge to competitors (Audretsch & Belitski, 2020b).

Finally, prior research on knowledge spillovers has found that knowledge emanating from R&D and human interactions activity spills over to generate innovative activity for other firms, but also that such knowledge spillovers are spatially localized within close geographic proximity to the knowledge source, ableit a supplier, customer or university (Jaffe et al. 1993; Acs et al. 1992). The spatially bounded nature of knowledge transfer was attributed to the importance of localization of tacit knowledge, as compared to explicit knowledge (Jaffe et al. 1993).

Based on the above-mentioned discussion we hypothesize:

H2: The economic returns to knowledge collaboration for innovation in SMEs are positively moderated by the regional proximity of collaboration partners, such that the more proximate the partner, the higher the returns to knowledge collaboration for innovation.

2.3. Type of collaboration partner and innovation

In knowledge collaboration, SMEs aim to obtain operational knowledge from suppliers to enhance existing skills and leverage the complementarities of existing products and technologies (Mueller et al. 2013; Kobarg et al. 2019). SMEs aims to obtain market-oriented knowledge from customers to better position a product in the market and retain or gain a competitive advantage (Teece, 1992; Belitski & Rejeb, 2022). In collaboration with universities SME aims to create new products and services drawing on knowledge transfer from research labs and exercise new skills and competencies, which we often observe in university-industry partnerships (D'Este et al. 2013) and in technology transfer offices.

Regional proximity is likely to be more important for university collaboration where transfer of tacit knowledge tkes place. We first explain the role of university collaboration for SME innovation then we move to the role of customers and suppliers. Collaboration with universities would aim to resolve regional challenges and facilitate regional economic development as a result of combining and applying new knowledge (Audretsch et al., 2022b). However, the technological distances between products realised by SMEs and developed at university could be large, geographical collocation and the opportunity to exchange tacit knowledge "on the ground" may bridge the technological gap and facilitate innovation in SMEs driven by university research (Link et al., 2019). Examples of such collaboration includes the collaboration between the Valencian Youth Institute and the University of Valencia between 3477 new firms founded and the university faculty on advice and support in areas related to the Aid Programme between 2000 and 2005 (Simón-Moya et al. 2016). Other collaborations include the Strength in Places Program on collaborative projects led by consortiums of university, local authorities and SMEs that include research organizations and businesses that facilitate local collaborations for regional innovation (UKRI, 2022). Other regional innovation programmes include "Business Ideas and Innovation" and "The Ideas 2 Innovation programme" in Wales (Innovation programme, 2022), which aim at collaboration between universities and Entrepreneurship who want to turn a Business idea into an innovative product or service. The programme has been created to help individuals develop and commercialize their Business idea and to provide funding, mentoring, advice, and a space to work. In Sweden VINNOVA programme aims at open innovation and discovering new ways for innovation that makes a difference between universities and SMEs (Vinnova programme, 2022).

Unlike regionally focused collaboration with universities, knowledge collaboration with both local and international customers and suppliers is important.

Firstly, knowledge collaboration with value chain partners such as suppliers and customers is useful in product development, independently whether product is for the domestic or international market. Customers can participate face-to-face, but also using digital tools (Digitally Driven, 2021) in testing and customising new products for market demands, and hence will help SMEs to fine-tune knowledge and create product for domestic and international customers (Un & Asakawa, 2015).

Secondly, collaboration with customers and suppliers compared to collaboration with competitors for example, can only increase innovation effort, while collaboration with other partners such as advisors, consultants and competitors may reduce innovation effort (Ribeiro-Soriano et al. 2016) due to an increased risk of product imitation by direct competitors and by competitors through advisors (Brunswicker & Vanhaverbeke 2015; Veer, Lorenz, & Blind, 2016; Castrogiovanni et al. 2016).

Thirdly, knowledge collaboration with customers and suppliers brings tested external knowledge and may complement SMEs internal investment in R&D or local collaborations with universities and government to co-create and develop new product, which also may take longer. The benefits from collaboration with suppliers and customers are short-term, while collaboration with universities is more long term, as knowledge from customers and suppliers can be implemented in a SME's production lines and marketing strategy quickly. The university-SMEs collaboration where investment in joint R&D takes longer time and SMEs may require lengthy authorization and investment in absorptive capacity (Flor et al. 2018) to start collaborating with university scientists, particularly with universities located abroad (Gulati & Singh, 1998).

Fourthly, SMEs often need more market knowledge and qualified personnel to produce R&D, while domestic and international customers can facilitate in product development as information is codified and not tacit, which means it can be easily shared (e.g. feedback, advice, comments, posts).

Fifthly, collaboration with suppliers domestically and internationally offers tried and tested knowledge related to input which can be integrated into existing routines and components (van Beers & Zand, 2014). The complimentarily of knowledge being in the same industry originating locally or internationally allows firms to adapt and apply knowledge faster to create new products, and in particular in knowledge industries (Soriano & Huarng, 2013).

Finally, collaboration with suppliers and customers domestically and internationally allows for understanding what customer needs and what components and materials are available domestically and internationally to adapt to those needs and create new products (von Hippel, 2005). This special relationship with suppliers and customers, enables for SME managers to synchronize their knowledge if they co-develop new products for domestic or international markets (Bathelt et al. 2004). We hypothesize:

H3: The economic returns to knowledge collaboration for innovation in SMEs are positively moderated by the type of collaboration partner and geographical proximity, such that collaborations with partners in the value chain (customers and suppliers) domestically and internationally, and collaboration with universities domestically result in higher innovation outputs, than collaborations with other types of partners.

3. Methods

3.1. Data

We test our hypotheses using three datasets (Business Registry, BSD), Business Enterprise Research and Development survey (BERD) and the UK Innovation Survey (UKIS), and six cross-sectional surveys with 9,213 firms. In consolidating our data set we performed the following steps.

First, we collected and matched six consecutive UKIS waves: UKIS 4 2002–04, UKIS 5 2004-06, UKIS 6 2006-08, UKIS 7 2008-10, UKIS 8 2010-12 and UKIS 9 2012-14. Each wave was conducted every second year by the Office of National Statistics (ONS) in the UK. Second, we used BSD and BERD data for the years 2002, 2004, 2006, 2008, 2010 and 2012. The data were matched to a correspondent UKIS survey wave for the initial year of the UKIS period. Firm age and ownership, employment, industry, and firm size were matched from BSD. The UKIS includes direct measures of innovation inputs and outputs, influencing barriers to innovation, measurements on human capital, partner types, training activity, partner locations, collaboration networks, and other information related to our hypotheses.

Table 1
Descriptive Statistics.

Label		Description	Mean	Std. Dev.
Product innovation (share new product revenue, %)		Dependent variable: share of firm's total turnover from goods and services, new to the market (%)	3.706	11.991
Binary variable = 1 if firm co-operates on innovation within a region	Enterprise group	With any of other businesses within enterprise group, 0 otherwise	0.048	0.214
	Suppliers	With any suppliers of equipment, materials, services, 0 otherwise	0.059	0.235
	Customers	With any clients or customers, 0 otherwise	0.073	0.261
	Competitors	With competitors or businesses in industry, 0 otherwise	0.032	0.175
	Consultants	With consultants, commercial labs or private R&D institutes, 0 otherwise	0.036	0.185
	Universities	With universities or high educational institutions, 0 otherwise	0.038	0.192
	Government	With any of other businesses within enterprise group, 0 otherwise	0.024	0.153
Binary variable = 1 if firm co-operates on innovation within national market	Enterprise group	With any of other businesses within enterprise group, 0 otherwise	0.055	0.228
	Suppliers	With any suppliers of equipment, materials, services, 0 otherwise	0.099	0.298
	Customers	With any clients or customers, 0 otherwise	0.111	0.314
	Competitors	With competitors or businesses in industry, 0 otherwise	0.050	0.218
	Consultants	With consultants, commercial labs or private R&D institutes, 0 otherwise	0.056	0.230
	Universities	With universities or high educational institutions, 0 otherwise	0.041	0.199
	Government	With any of other businesses within enterprise group, 0 otherwise	0.038	0.192
Binary variable = 1 if firm co-operates on innovation within European countries	Enterprise group	With any of other businesses within enterprise group, 0 otherwise	0.033	0.179
	Suppliers	With any suppliers of equipment, materials, services, 0 otherwise	0.043	0.203
	Customers	With any clients or customers, 0 otherwise	0.045	0.207
	Competitors	With competitors or businesses in industry, 0 otherwise	0.018	0.133
	Consultants	With consultants, commercial labs or private R&D institutes, 0 otherwise	0.014	0.116
	Universities	With universities or high educational institutions, 0 otherwise	0.009	0.094
	Government	With any of other businesses within enterprise group, 0 otherwise	0.007	0.081
Binary variable = 1 if firm co-operates on innovation within other world countries	Enterprise group	With any of other businesses within enterprise group, 0 otherwise	0.032	0.176
	Suppliers	With any suppliers of equipment, materials, services, 0 otherwise	0.032	0.177
	Customers	With any clients or customers, 0 otherwise	0.040	0.197
	Competitors	With competitors or businesses in industry, 0 otherwise	0.015	0.121
	Consultants	With consultants, commercial labs or private R&D institutes, 0 otherwise	0.011	0.106
	Universities	With universities or high educational institutions, 0 otherwise	0.008	0.089
	Government	With any of other businesses within enterprise group, 0 otherwise	0.006	0.076
	SMEs	Binary variable = 1 if full time employees < 250, zero otherwise	0.725	0.403
Control Variables	Foreign firm	Binary variable = 1 if a firm has headquarters abroad, zero otherwise	0.435	0.496
	Age of firm	Age of a firm (years since the establishment)	18.666	10.036
	Scientists	The proportion of employees that hold a degree or higher qualification in science and engineering at BA / BSc, MA / PhD, PGCE levels	6.313	15.930
	R&D intensity	R&D expenditure to sales ratio	0.010	0.046
Variables used as instruments at the first stage regression				
Suppliers collaboration industry (UKIS)		Mean of collaboration with regional, national and international suppliers at industry level for each year. Industry level is defined as two-digit SIC 2007.	0.246	0.157
Customers collaboration industry (UKIS)		Mean of collaboration with regional, national and international customers at industry level for each year. Industry level is defined as two-digit SIC 2007.	0.288	0.227
University collaboration industry (UKIS)		Mean of collaboration with regional, national and international universities at industry level for each year. Industry level is defined as two-digit SIC 2007.	0.089	0.115
Variables used as dependent variables in Appendix A Table A2 for testing the likelihood of collaboration				
Collaboration regional		Binary variable = 1 if a firm collaborates at	0.136	0.343

(continued on next page)

Table 1 (*continued*)

Label	Description	Mean	Std. Dev.
	least with one type of partners (or more up to 7 types) in a region, zero otherwise		
Collaboration national	Binary variable = 1 if a firm collaborates at least with one type of partners (or more up to 7 types) in a country, zero otherwise	0.179	0.383
Collaboration Europe	Binary variable = 1 if a firm collaborates at least with one type of partners (or more up to 7 types) in Europe, zero otherwise	0.083	0.276
Collaboration international	Binary variable = 1 if a firm collaborates at least with one type of partners (or more up to 7 types) internationally, zero otherwise	0.073	0.260
Collaboration suppliers	Binary variable = 1 if a firm collaborates with a supplier at least in one or more geographical regions, zero otherwise	0.166	0.372
Collaboration customers	Binary variable = 1 if a firm collaborates with a customer at least in one or more geographical regions, zero otherwise	0.181	0.385
Collaboration universities	Binary variable = 1 if a firm collaborates with a university at least in one or more geographical regions, zero otherwise	0.074	0.263

Source: Department for Business, Innovation and Skills, Office for National Statistics, Northern Ireland. Department of Enterprise, Trade and Investment. (2018). *UK Innovation Survey, 1994–2016: Secure Access*. [data collection]. *6th Edition.* UK Data Service. SN: 6699, https://doi.org/10.5255/UKDA-SN-6699–6 hereinafter named UKIS – UK Innovation Survey (2002–2014).
Office for National Statistics. (2017). Business Structure Database, 1997–2017: Secure Access. [data collection]. 9th Edition. UK Data Service. SN: 6697, https://doi.org/10.5255/UKDA-SN-6697–9, hereinafter named BSD - Business Register (2002–2014).

The final sample has 21,140 firm-year observations with 9,213 firms, including 849 firms that were observed over the entire period and 5420 firms observed only once during 2002–2014. To be included in a sample, all questions related to the variables of interest needed to be completed with no missing values (Table 1). The correlation matrix between the variables used in the study is in Table A1 (Appendix A).

Table 2 illustrates the sample distribution by industry, region in the UK, and firm size for 2002–2014 (six waves of UKIS) and provides information on the number of observations. Our sample embraces a wide spectrum of industries with most of the businesses coming from high-tech manufacturing (19.25%), construction (10.50%), wholesale and retail trade (16.19%), real estate and business activities (12.63%). Most underrepresented sectors are mining and quarrying (0.79%), electricity (0.79%), education (0.38%), and financial intermediation (3.27%). The distribution of firms across industries between population and estimation samples remains stable over 2002–2014. This is important, as it enables us to generalize estimation results on a bigger sample. Firms are equally represented across the UK regions, with most firms come from the Southeast (11.11%), London (9.36%) and the Northwest of England

Table 2
Industrial / Regional and Firm size distribution in the sample.

Industry distribution	Firms	Share, %
1 - Mining & Quarrying	166	0.79
2 - Manufacturing basic	1,282	6.06
3 - High-tech manufacturing	4,106	19.42
4 - Electricity, gas and water supply	167	0.79
5 - Construction	2,220	10.50
6 - Wholesale, retail trade	3,422	16.19
7 - Transport, storage	1,151	5.44
8 - Hotels & restaurants	1,150	5.44
9 - ICT	1,437	6.80
10 - Financial intermediation	692	3.27
11 - Real estate and other business activity	2,669	12.63
12 - Public admin, defence	2,133	10.09
13 – Education	80	0.38
16 - Other community, social activity	465	2.20
Total	**21,140**	**100.00**
Regional distribution		
North East	1,147	5.43
North West	1,984	9.39
Yorkshire and The Humber	1,750	8.28
East Midlands	1,704	8.06
West Midlands	1,861	8.80
Eastern	1,912	9.04
London	1,981	9.37
South East	2,348	11.11
South West	1,796	8.50
Wales	1,350	6.39
Scotland	1,671	7.90
Northern Ireland	1,636	7.74
Total	**21,140**	**100.00**
Firm size distribution		
small firms	11,588	54.82
medium	5,680	26.87
large	3,872	18.32
Total	**21,140**	**100.00**

Number of obs. 21,140.
Source: BSD - Business Register (2002–2014) and UKIS - UK Innovation Survey (2002–2014).

(9.39%). West Midlands and Eastern England follow with approx. 8% each in a final sample. At the same time, Wales and North-East of England are least represented in a sample with less than 6.39% and less than 5.43% of firm representation. As in the case with the industry distribution, the relative proportions of firms across the UK regions remain stable across both population and estimated samples over 2002–2014. The final part of Table 2 illustrates the distribution of firms by firm size (small, medium, and large firms).

3.2. Dependent variable.

We use product innovation as a measure of innovative output (Frenz & Ietto-Gillies, 2009; van Beers & Zand, 2014; Audretsch & Belitski, 2020b). Our dependent variable represents the share of new-to-market product sales which were new to a firm over the last 3 years. The new product share varies from 0 to hundred, with 3.7 percent on average and 11.99 standard deviation (see Table 1). The definition of product innovation, although capturing both goods and services, is applicable to both manufacturing and service sectors.

3.3. Independent variables

We followed Gesing et al (2015) we included several binary variables for each of the seven collaboration partners - Enterprise Group (alliance), collaboration for innovation with Suppliers, Customers, Competitors, Consultants and mentors, Universities and Government – and in four geographical dimensions (region, country, Europe, and world). We then constructed 28 partner-region indicator variables to account for a firm's collaborative landscape. In the data, vertical cooperation with the value chain is most common type. On average, 9% of firms in the sample collaborate with suppliers nationally, while 11 % of firms collaborate with customers nationally. On average, 4% collaborate with customers and suppliers in Europe and internationally. Collaboration with competitors is negligible (3% collaborate locally, 5% nationally, and 1% internationally) and expected. Collaboration with consultants, a form of horizontal cooperation, appears to be more important nationally (5.6%), than regionally (3.2%), while collaboration with overseas consultants is less than 1.5%.

Finally, we created a binary variable, "SMEs" indicating whether a firm has more or less than 250 full-time employees.

3.4. Control variables

In line with Greve et al. (2003), firms' in-house R&D intensity measured as the ratio of R&D in-house to total sales (averaged over 3 years), both over the last 3 years, is used as a proxy for the absorptive capacity of a firm (Zahra & George, 2002). In-house R&D intensity is also used as a control variable for human capital, following Hall (2011) in its relationship to innovation performance in various specifications. An average internal R&D intensity ratio is 0.01 with 0.04 standard deviation which means that on average, at least one percent of sales is invested in creative work expenses.

We use a share of employees that hold a degree or higher qualification (e.g. BA/BSc, MA/PhD, PGCE) in science or engineering subjects to further control for absorptive capacity (Cohen & Levinthal, 1989). An average proportion of scientists in a firm is 6 percent, with a minimum of 1 and a maximum 85 percent from all full-time employees. Foreign is a binary variable taking a value 1 if the firm is foreign-owned, e.g., a headquarter is not in the UK, and zero otherwise. Interestingly up to 43 percent of firms in our sample are foreign-owned. We cannot control whether a company is foreign owned for fiscal or other reasons (e.g., companies relocating the to minimize taxes in Ireland or The Netherlands). We control for firm age, known to increase enterprise ability to draw knowledge from their collaborators and use it for R&D and innovation activity. Start-ups are often viewed as a vehicle to transfer university research and obtain government grants to transfer research and new product development into marketable innovation, especially in science-based sectors (Hall, 2011). By creating new knowledge, various collaboration partners may even foster further start-up activity and spin-offs. Existing research suggests that start-ups are more likely to commercialize knowledge from government and universities as well as within the enterprise group for further innovation. Working within the boundaries of your enterprise group might imply pursuing synergies (e.g., improving existing products) and cost reduction (Faems et al. 2005).

Age in years since the establishment is used to control for firm's business circle. Finally, we use the innovation survey year (2002–2004 as a reference year), 11 region fixed effects (North-East of England as a reference category), membership in an enterprise group (alliance) and 2-digit sector controls as control variables (mining and agriculture as reference category).

Our control variables, such as R&D expenditure and share of employees with university degrees can be biased to certain types of SMEs and sectors.

Table 3
Random effects Probit estimates. Dependent variable: Binary variable innovation active.

Two-step Heckman approach	Innovation active (D = 1)		
	Coef.	SE	
Log of firm age	−0.103	0.013	***
Log of employment	0.041	0.011	***
R&D intensity	0.038	0.009	***
Constant	4.435	0.290	***
sigma u	0.832	0.033	
Rho	0.409	0.019	
Year, region and industry controls	Yes		
Observations	63,518		
Sectoral and regional dummies	Yes		
Wald chi2	401.22		

Number of obs. 63,518 observations available for the variables used in Heckman selection equation.
Source: BSD - Business Register (2002–2014) and UKIS - UK Innovation Survey (2002–2014).

3.5. Empirical model

We start by describing the collaboration patterns for SMEs (Table A1). The importance of this first step of analysis is to demonstrate the collaboration partner choice patterns of SMEs, while the second step is to examine the economic returns to innovation collaboration, when collaboration effectively happens. It is likely that there may be significant differences between whom SMEs collaborate with and who is the most beneficial partner for SMEs to collaborate.

We used logistic regression and reported odd ratios with the binary dependent variables y_{it} [0,1] representing the partner type (suppliers, customers and universities) and geography of collaboration (regional, national, Europe and international). Our independent variables x_{it} represent firm-specific characteristics illustrated in Table 1. We found that the likelihood of innovation collaboration for SMEs with external stakeholders regionally ($\beta = 0.83$, $p < 0.01$), nationally ($\beta = 0.73$, $p < 0.01$), within Europe ($\beta = 0.55$, $p < 0.01$) and internationally ($\beta = 0.53$, $p < 0.01$) was lower than the likelihood of collaboration for large firms (specifications 1–4, Table A2). For example, SMEs are twice less likely to collaborate with European and international partners compared to large firms. We also found that SMEs were less likely to collaborate with suppliers ($\beta = 0.75$, $p < 0.01$), customers ($\beta = 0.77$, $p < 0.01$) and universities ($\beta = 0.61$, $p < 0.01$) than collaborate large firms. Interestingly, SMEs are a third less likely to collaborate with external partners than larger firms (specifications 5–7, Table A2).

Once we measured that SMEs are more limited in collaboration with external partners, we moved to estimating the economic returns to collaboration with different external partners and across various geographical dimensions.

We used random effects Tobit model (Model 1) (given the existing panel element) with the dependent variable y_{it} left-censored between [0,100] (Wooldridge, 2009) independent variables x_{it} to test our research hypotheses. Our dependent variable product innovation is left -censored as there is a considerable number of firms in our data which do not produce and commercialize innovation. The following econometric model has been estimated.

$$Y_{it} = \beta_0 + \beta_1 x_{it} + \beta_2 z_{it} + \varepsilon_{it} \quad (1)$$

where I is a firm, t is time. The dependent variable y_{it} illustrates product innovation. The explanatory variables and interaction terms are represented by x_{it}, while other control variables representing firm-specific characteristics exogenous to innovation are z_{it}, Finally, ε_{it} is an error term which consists of:

$$\varepsilon_{it} = \mu_i + \nu_{it} \quad (2)$$

where $\mu_{i\bullet}$ denotes the random effect controlling for unobserved heterogeneity and ν_{it} is the error term.

There is a panel element of a sample of 849 firms which appear more than once in a sample (persistent innovators). The multicollinearity test examined the variance inflation factors for all variables, finding each being<10 (Wooldridge, 2009). In addition, the Pearson correlation coefficients were examined with all of them being statistically significant in a full sample at 5% significance level and < 0.70 to address multicollinearity concerns. We analysed all the variables' histograms and found the errors are identically and independently distributed with constant variance. Option "xttobit" in Stata 15 fits random-effects Tobit

Table 4
Random-effects Tobit estimation of product innovation. Dependent variable: product innovation.

Dependent variable:	Product innovation											
Geographical Diversity:	UK - Regional			UK National			European Countries			World		
Model:	Random-effects Tobit			Random-effects Tobit			Random-effects Tobit			Random-effects Tobit		
Variables	Coef.	S.E.	P>|z|	Coef.	S.E.	P>|z|	Coef.	S.E.	P>|z|	Coef.	S.E.	P>|z|
Enterprise group	7.16	1.23	0.00	3.52	1.11	0.00	4.90	1.38	0.00	6.81	1.42	0.00
Suppliers	5.10	1.20	0.00	7.84	0.97	0.00	10.28	1.24	0.00	9.10	1.40	0.00
Customers	6.40	1.11	0.00	11.81	0.93	0.00	8.92	1.24	0.00	8.00	1.32	0.00
Competitors	−1.73	1.62	0.29	0.03	1.18	0.98	1.61	1.76	0.36	3.73	1.95	0.06
Consultants	5.30	1.43	0.00	0.65	1.17	0.58	2.68	2.06	0.19	−1.53	2.39	0.52
University	5.57	1.35	0.00	2.40	1.33	0.07	−1.72	2.54	0.50	−10.39	3.13	0.00
Government	1.33	1.75	0.45	1.48	1.37	0.28	2.19	2.83	0.44	4.54	3.40	0.18
Foreign	1.86	0.61	0.00	0.33	0.68	0.63	0.37	0.68	0.58	0.51	0.69	0.46
Age	−7.03	2.03	0.00	−7.29	2.40	0.00	−7.49	2.45	0.00	−7.98	2.15	0.00
Age squared	0.31	0.12	0.00	0.38	0.13	0.00	0.34	0.09	0.00	0.28	0.09	0.00
SMEs	3.47	1.46	0.02	2.85	1.45	0.05	2.26	1.45	0.12	2.17	1.45	0.14
Scientists	0.35	0.02	0.00	0.32	0.02	0.00	0.33	0.02	0.00	0.33	0.02	0.00
R&D intensity	92.58	4.90	0.00	88.40	4.89	0.00	90.05	4.92	0.00	89.88	4.95	0.00
Inverse Mills ratio	89.68	4.50	0.00	86.40	7.33	0.00	93.05	8.98	0.00	92.22	11.87	0.00
constant	−37.22	3.75	0.00	−36.94	3.78	0.00	−36.39	3.77	0.00	−36.63	3.78	0.00
Year, region controls	YES			YES			YES			YES		
sigma_e	24.26	0.47	0.00	24.35	0.47	0.00	24.51	0.48	0.00	24.44	0.48	0.00
rho	0.333	0.023		0.316	0.023		0.317	0.024		0.325	0.024	
Industry control	YES			YES			YES			YES		
Number of obs.	21,140			21,140			21,140			21,140		
Log likelihood	−31342			−31177			−31368			−31409		
Wald chi2	3577			3790			3595			3529		
Prob > chi2	0.00			0.00			0.00			0.00		
Left-censored	16,780			16,780			16,780			16,780		
Uncensored	5323			5323			5323			5323		

Note: standard errors are robust for heteroscedasticity in parenthesis. Reference category for firm size = large firm (250 + FTEs); Reference category for firm ownership status: public corporation. Reference category for sector: mining. Reference category for wave: 2005. Reference category for region: Northern Ireland. Industry (2 digit SIC) and year fixed effects are suppressed to save space. Estimation method: Tobit. Significance level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$″ unless other stated.
Source: BSD - Business Register (2002–2014) and UKIS - UK Innovation Survey (2002–2014).

models for panel data where the outcome variable is censored for the entire sample.

One crucial aspect is that not all firms report product innovation: out of 89,518 observations in the initially received responses from the UK Innovation survey only 33,750 questionnaires report zero or positive innovation, otherwise missing. Having cleaned the data for missing values and included explanatory and control variables in the model (1) the final sample comprises 21,140 observations. Therefore, when estimating equation (1), it was necessary to control for a sample selection bias by carrying out a two-stage Heckman approach (1979). In the first stage of the analysis (selection equation), a probit selection model was estimated when we regressed the observed product innovation (binary variable taking value one if innovation is reported, zero otherwise) on firm characteristics which could explain why a firm will (not) report innovation. This selection step consisted of identifying, through a probit regression on the total number of observations and identifying those that innovate or not. Inverse mills ratio was calculated based on predicted values of product innovation (see Table 3).

$$\text{Selection equation (first stage)}: \Pr(D = 1|z_{it}) = \Phi(\alpha' z) \tag{3}$$

where D indicates that the firm reports the outcome of innovation (D = 1 if innovation = > 0and D = 0 otherwise), where innovation is the variable where product innovation is non-missing and a response is given, α is a vector of unknown parameters, and Φ is the cumulative distribution function of the standard normal distribution. Finally, z is a vector containing the explanatory variables that affect the decision to report or not innovation output from selection equation (3). We follow the generalised Heckman approach as developed by Green (2003) to compute two inverse Mill's ratios (λ_{it}) (Table 3). The selection bias was corrected by including this Mill's ratio when equation (1) was estimated in the second stage:

$$y_{it} = \beta_0 + \beta_1 x_{it} + \beta_2 z_{it} + \lambda_{it} + \varepsilon_{it} \tag{4}$$

4. Results

4.1. Main hypothesis.

Tobit estimation was used to estimate (4). In all Tobit regressions, the standard likelihood ratio test indicates that the panel estimation is preferable over the pooled cross-sectional version. To observe the differences and control for industry, region, and time fixed effects, we use two estimation samples in Tables 4 and 5. We start by estimating equation (4) using IV Tobit. The results are reported in Table 4 and illustrate the direct effect of collaboration on a firm's product innovation (share of new to market product sales).

We find that SMEs compared to larger firms have higher innovation performance (Teixeira et al. 2008; Audretsch et al. 2021). This finding holds across all specifications. The regression coefficient is positive and significant for SMEs and varies between 2017 ($\beta = 2.17$, $p < 0.01$) (specification 4, Table 4) to 3.47 ($\beta = 3.47$, $p < 0.01$) (specification 1, Table 4). The effect disappears once we control for European and international partners (Table 4, specifications 3 and 4).

Applied to all firms in the sample, there are greater benefits for firms that collaborate with suppliers ($\beta = 5.10$–10.28, $p < 0.01$) and customers ($\beta = 6.40$–11.81, $p < 0.01$) both domestically and internationally. Collaboration with universities within the region ($\beta = 5.57$, $p < 0.01$) and within the UK ($\beta = 2.40$, $p < 0.01$) is positive and significant, while collaboration with universities internationally reduces product innovation. Product innovation was also found to be significantly affected by collaboration within the enterprise group both domestically and internationally (specifications 1–4, Table 4).

There is no direct relationship between collaboration with competitors and government on innovation output, while collaboration with

Table 5
Random-effects Tobit estimation of product innovation. Dependent variable: product innovation.

Dependent variable:	Product innovation											
Geographical Diversity:	UK - Regional			UK National			European Countries			World		
Model:	Tobit regression			Tobit regression			Tobit regression			Tobit regression		
Variables	Coef.	S.E.	P>|z|	Coef.	S.E.	P>|z|	Coef.	S.E.	P>|z|	Coef.	S.E.	P>|z|
Enterprise group	7.03	1.55	0.00	2.60	1.26	0.04	4.15	1.48	0.01	6.37	1.60	0.00
Suppliers	2.22	1.40	0.11	6.63	1.20	0.00	8.21	1.38	0.00	4.81	1.66	0.00
Customers	4.24	1.35	0.00	9.86	1.13	0.00	7.64	1.47	0.00	7.62	1.49	0.00
Competitors	2.25	1.96	0.25	−1.75	1.41	0.21	2.32	2.02	0.25	5.35	2.25	0.02
Consultants	4.78	1.73	0.01	0.60	1.44	0.67	1.64	2.46	0.50	−4.84	2.75	0.08
University	4.29	1.63	0.01	2.92	1.67	0.08	−1.95	3.14	0.53	−8.50	3.77	0.02
Government	1.69	2.06	0.41	1.22	1.70	0.47	0.36	3.07	0.91	2.47	4.07	0.54
Foreign	1.82	0.73	0.01	0.89	0.73	0.22	0.90	0.73	0.22	1.25	0.74	0.09
Age	−6.68	2.22	0.00	−6.29	2.01	0.00	−6.90	2.02	0.00	−6.54	1.67	0.00
Age squared	0.23	0.05	0.00	0.28	0.03	0.00	0.33	0.03	0.00	0.22	0.03	0.00
SMEs	3.36	1.73	0.05	2.35	0.73	0.01	2.24	1.69	0.19	2.15	1.71	0.31
SMEs × Suppliers (H1-H3)	3.26	1.63	0.04	2.76	0.63	0.04	2.08	0.61	0.04	1.96	0.62	0.01
SMEs × Customers (H1-H3)	4.75	1.66	0.00	3.86	1.69	0.02	4.30	1.63	0.01	4.09	1.66	0.01
SMEs × University (H1-H3)	2.66	0.65	0.01	1.52	0.66	0.04	2.24	1.63	0.17	2.05	1.65	0.21
SMEs × Consultant (H1-H3)	−2.72	1.40	0.23	−2.22	1.42	0.18	−3.15	1.99	0.21	−2.99	1.98	0.19
SMEs × Competitor (H1-H3)	1.48	1.42	0.53	0.66	0.40	0.17	0.55	0.15	0.40	0.47	0.11	0.00
SMEs × Government (H1-H3)	1.34	1.06	0.40	1.32	1.20	0.37	1.36	2.07	0.51	1.27	1.07	0.44
Scientists	0.31	0.02	0.00	0.28	0.02	0.00	0.29	0.02	0.00	0.29	0.02	0.00
R&D intensity	74.46	8.51	0.00	69.91	8.66	0.00	71.05	8.55	0.00	71.73	8.86	0.00
Inverse Mills ratio	84.68	5.50	0.00	82.40	6.23	0.00	87.45	6.22	0.00	88.12	7.81	0.00
Constant	−33.05	3.61	0.00	−32.06	3.61	0.00	−31.18	3.58	0.00	−31.20	3.59	0.00
Year and region controls	YES			YES			YES			YES		
Sigma e	26.79	0.66		26.67	0.66		26.74	0.65		26.90	0.66	
Industry control	YES			YES			YES			YES		
Number of obs.	21,140			21,140			21,140			21,140		
Log likelihood	−7871			−7836			−7872			−7888		
Wald chi2												
Prob > chi2	0.00			0.00			0.00			0.00		
Left-censored	16,780			16,780			16,780			16,780		

Note: standard errors are robust for heteroscedasticity in parenthesis. Reference category for firm size = large firm (250 + FTEs); Reference category for firm ownership status: public corporation. Reference category for sector: mining. Reference category for wave: 2005. Reference category for region: Northern Ireland. Industry (2 digit SIC) and year fixed effects are suppressed to save space. Estimation method: Tobit. Significance level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$″ unless other stated. Source ONS: BSD dataset BSD (2002–2014); UKIS – UK Innovation Survey (2002–2014); **Number of observations 21,140.**

consultants within the region increases firm innovation ($\beta = 5.30$, $p < 0.01$) (specification 1, Table 4).

Investment in knowledge in a form of R&D intensity facilitates firm innovation ($\beta = 89$–92, $p < 0.01$). Other interesting results include the positive effect of share of workers with university degree on firm innovation ($\beta = 0.32$–0.35, $p < 0.01$) and a U-shaped relationship between firm age and innovation output. The Inverse Mills ratio was added in the estimation to control for selection bias (Heckman, 1979) and is positive and statistically significant. This demonstrates that firms which are more likely to report innovation were also more likely to commercialize innovation in the market. The significance of the Mills ratio serves as an indicator for the importance of selection bias correction in the sample.

Table 5 illustrates the returns to knowledge collaboration across different partner types and for SMEs testing our research hypothesis.

The results from Table 5 support H1 which stated that the economic returns to knowledge collaboration for innovation are larger for SMEs. However, the relationship is highly heterogeneous and depends on the type of collaboration partners and partner's geographical location (specifications 1–4, Table 5).

Our H2 which states that the economic returns to knowledge collaboration for innovation in SMEs are positively moderated by the regional proximity of collaboration partners, such that the more proximate the partner, the higher the returns to knowledge collaboration for innovation is supported only for collaboration with universities. The interaction coefficient between SMEs and collaboration with universities is positive and significant regionally ($\beta = 3.36 + 2.66$, $p < 0.01$) and in the UK ($\beta = 2.35 + 1.52$, $p < 0.05$), supporting H2 (D'Este et al. 2013), while the interaction coefficient is not significant for collaboration of SMEs with universities internationally.

The interaction coefficients of SMEs with the decision on collaborating with customers and suppliers are positive and statistically significant across all four geographical dimensions (specifications 1–4, Table 5) which does not support H2, but supports H3. Knowledge collaboration with government and consultants is not associated with innovation performance in SMEs as interaction coefficients are not significant (specifications 1–4, Table 5). The direct collaboration with competitors internationally is significant supporting prior research on innovative firms sees competitors as a useful source of information on technology and markets, when firms do not compete directly (Mariani & Belitski, 2022).

Table 5 results overwhelmingly support H3 which states that knowledge collaborations with partners in the value chain (customers and suppliers) domestically and internationally, and collaboration with universities domestically result in higher innovation outputs in SMEs. Collaboration with customers and suppliers becomes very important when SMEs have an ability to combine the locally embedded sticky knowledge in novel ways with international diversity and high-quality of knowledge (Scott, 1998).

Table 5 illustrates the cumulative benefits of SMEs collaborating with suppliers are positive and significant regionally ($\beta = 3.36 + 3.26$, $p < 0.01$), nationally ($\beta = 2.35 + 2.76$, $p < 0.01$), in Europe ($\beta = 0 + 2.08$, $p < 0.01$) and internationally ($\beta = 0 + 1.96$, $p < 0.01$) (specifications 1–4, Table 5). The cumulative benefits of SMEs collaborating with customers regionally are ($\beta = 3.36 + 4.75$, $p < 0.01$), nationally ($\beta = 2.35 + 3.86$, $p < 0.01$), in Europe ($\beta = 0 + 4.30$, $p < 0.01$) and the world ($\beta = 0 + 4.09$, $p < 0.01$) are positive and significant (specifications 1–4,

Table 6
IV Tobit estimation of product innovation (second stage) with predicted values of university, customer, and supplier collaborations. Dependent variable: product innovation.

Dependent variable:	Product innovation											
Geographical Diversity:	UK - Regional			UK National			European Countries			Other Countries		
Model:	Tobit regression			Tobit regression			Tobit regression			Tobit regression		
Variables	Coef.	S.E.	P>|z|	Coef.	S.E.	P>|z|	Coef.	S.E.	P>|z|	Coef.	S.E.	P>|z|
Enterprise group	3.71	0.91	***	2.64	0.91	***	1.10	1.10		1.81	1.10	
Suppliers ($\widehat{x_{it}}$)	2.64	1.92		4.12	0.70	***	7.62	2.20	***	7.21	2.10	***
Customers ($\widehat{x_{it}}$)	0.73	0.23	***	4.51	1.79	**	0.02	0.20		4.19	1.26	***
Competitors	1.22	1.21		0.40	0.90		3.12	1.44	***	2.30	1.60	
Consultants	0.91	1.12		−0.20	0.90		−1.22	1.62		0.12	2.06	
University ($\widehat{x_{it}}$)	1.05	0.45	**	0.78	0.36	**	−4.81	3.11		−12.50	4.50	*
Government	0.93	1.23		−1.10	1.11		4.64	2.50	***	1.53	2.70	
Foreign	1.34	0.43	***	2.34	0.40	***	2.03	1.90		2.54	1.10	**
Age	−8.33	2.13	***	−8.09	2.55	***	−8.90	3.75	***	−8.98	2.35	***
Age squared	0.33	0.09	***	0.32	0.11	***	0.45	0.11	***	0.48	0.14	***
SMEs	7.26	3.21	***	5.45	1.73	***	6.14	2.39	***	6.25	2.23	***
SMEs × Suppliers ($\widehat{x_{it}}$) (H1-H3)	2.39	1.01	***	4.81	1.53	***	2.34	1.21	**	0.56	0.32	
SMEs × Customers ($\widehat{x_{it}}$) (H1-H3)	5.63	2.81	***	5.64	2.20	***	6.04	2.80	***	1.42	0.65	**
SMEs × University ($\widehat{x_{it}}$) (H1-H3)	1.05	0.45	**	0.78	0.36	**	3.24	2.53		1.05	1.65	
SMEs × Consultant (H1-H3)	−2.12	1.70		−2.21	1.40		−2.15	0.92		−1.01	0.68	
SMEs × Competitor (H1-H3)	1.38	1.51		0.66	0.50		0.51	0.43		0.29	0.10	***
SMEs × Government (H1-H3)	1.93	1.23		1.20	1.21		3.14	3.50	***	2.13	1.99	
Scientists	0.21	0.02	***	0.22	0.02	***	0.23	0.02	***	0.21	0.02	
R&D intensity	30.46	11.51	***	32.11	12.66	***	30.15	12.25	***	29.23	9.11	***
Constant	−23.05	3.22	***	−22.11	4.61	***	−19.28	2.11	***	−21.10	4.19	***
Year and region controls	YES			YES			YES			YES		
Sigma e	16.29	0.23		12.27	0.62		16.24	1.11		16.20	0.78	
Industry control	YES			YES			YES			YES		
Number of obs.	21,140			21,140			21,140			21,140		
Log likelihood	−4570.4			−4533.2			−4561.8			−4568.3		
Wald chi2												
Prob > chi2	0.00			0.00			0.00			0.00		
Left-censored	16,780			16,780			16,780			16,780		

Note: standard errors are robust for heteroscedasticity in parenthesis. Reference category for firm size = large firm (250 + FTEs); Reference category for firm ownership status: public corporation. Reference category for sector: mining. Reference category for wave: 2005. Reference category for region: Northern Ireland. Industry (2 digit SIC) and year fixed effects are suppressed to save space. Estimation method: Tobit. Significance level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$″ unless other stated. Source ONS: BSD dataset BSD (2002–2014); UKIS – UK Innovation Survey (2002–2014); **Number of observations 21,140.**

Table 5). Interestingly, collaboration with international customers adds more to innovation output in SMEs than collaboration with international suppliers, while this difference disappears when they are geographically close. The interaction coefficient between SMEs and collaboration with universities is positive and significant regionally and within the UK which means domestic collaboration with universities has a greater effect on SME innovation supporting H3 (specifications 1–2, Table 5). Collaboration with competitors internationally increases SME innovation (β = 0.47, $p < 0.01$) (specification 4, Table 5).

4.2. *Correcting for endogeneity*

4.2.1. *First stage estimation*

As argued in the theoretical background section, the collaboration partner choice is not random. Therefore, we apply the following correction method to test the robustness of our results. In the first stage we instrument φ_i with two exclusion restrictions (exogenous variables) assuming that we have three exogenous instruments that affect collaboration with suppliers, customers and universities regionally, nationally and internationally, but do not affect the degree of firm innovation. These instruments are industry level of collaboration with suppliers (ϱ_1), customers (ϱ_2) and universities (ϱ_3) across different geographical proximities, at 2-digit sector. Each instrument is exogenous, i.e. it is uncorrelated with the error u_i but affects the decision on firms to collaborate first via a peer-pressure mechanism directly (signalling) and indirectly via market making mechanisms and changing the industry competitive advantage. In the reduced form of equation φ_i is estimated as:

$$\varphi_i = \pi_0 + \beta_i x_i + \pi_1 \varrho_1 + \pi_2 \varrho_2 + \pi_3 \varrho_3 + v_i \tag{5}$$

where $E(v_i) = 0$, $cov(\varrho_1, v_i) = 0$, $cov(\varrho_2, v_i) = 0$. For this IV not to be perfectly correlated with ϱ_1 we need $\pi_2 and \pi_3 \neq 0$ and not to be perfectly correlated with ϱ_2 and ϱ_3 we need $\pi_1 \neq 0$. The identification requires that $\pi_1 \neq 0$, $\pi_2 \neq 0$ and $\pi_3 \neq 0$ or both (Wooldridge, 2009: 523).

We used four multivariate probit models to predict the fact of collaboration with supplier across four geographical dimensions ($\widehat{\varphi_i}$), as well as four models for customers and four models for universities. In addition to $\varrho_1, \varrho_2, \varrho_3$ which are exclusion restrictions, other explanatory exogenous variables x_i are included as well as a set of time and legal status fixed effects. Regional dummies were not used, because our dependent variable φ_i in model (5) has regional and national collaboration aspect with suppliers, customers and universities, which is a linear combination of city-region dummies. The results of the first stage IV estimation across four geographical dimensions are reported in Table A3 (Appendix A), including the post-estimation test (chi2) of a joint significance of chosen instruments (F-test which is always >8). We also performed the The Sargan-Hansen test of overidentifying restrictions. The joint null hypothesis is that the instruments are valid instruments cannot be rejected for all equations in Table A3. This means that the instruments are uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation. Table A2 (specifications 1–4 for supplier collaboration across 4 regions) illustrates the evidence for the first condition being satisfied. The coefficients of the chosen instruments and significant and positively associated with endogenous variable φ_i and knowledge spillover, ceteris paribus. Table A2 illustrates the evidence for the first condition being satisfied the likelihood of collaboration with customers (spec. 5–8) and with universities (spec. 9–12). Firms located in the industry with a higher level of collaboration with suppliers will also have higher likelihood of collaboration with suppliers regionally ($\beta = 0.04$, $p < 0.01$), nationally ($\beta = 0.17$, $p < 0.01$), in Europe ($\beta = 0.17$, $p < 0.01$) and internationally ($\beta = 0.09$, $p < 0.01$).

Firms located in the industry with a higher level of collaboration with customers will have higher likelihood of collaboration with customers regionally ($\beta = 0.02$, $p < 0.05$), nationally ($\beta = 0.19$, $p < 0.01$), in Europe ($\beta = 0.13$, $p < 0.001$) and internationally ($\beta = 0.12$, $p < 0.001$). Finally, firms located in the industry with a higher level of collaborating universities will collaborate to a greater extent with universities regionally ($\beta = 0.16$, $p < 0.001$), nationally ($\beta = 0.28$, $p < 0.001$), in Europe ($\beta = 0.11$, $p < 0.001$) and internationally ($\beta = 0.08$, $p < 0.001$).

4.2.2. Second stage estimation

Once we have predicted values for each of three collaboration partner and across four proximities, we estimate (4) using the two-stage least squares described in Wooldridge (2009) and applied to Tobit:

$$y_{it} = \beta_0 + \beta_1 \widehat{x_{it}} + \beta_2 z_{it} + \varepsilon_{it} \tag{6}$$

Our two-stage procedure involves using equation (5) where we obtain the predicted values of collaborations with suppliers, customers, and universities $\widehat{x_{it}}$. The second stage of the Tobit regression (6) is when $\widehat{x_{it}}$ is used instead of x_i, correcting for potential endogeneity in the relationship between x_i and y_i. Because we predicted values of collaborations $\widehat{x_{it}}$ in place of x_{it}, the IV tobit which serves as a robustness check for (4). Table 6 presents the result of IV Tobit estimation (second stage).

The two-stage model (Table 6) supports our findings in Tables 4 and 5. First, we found that SMEs have on average between 5.45 and 7.26 percentage points higher innovation sales compared to larger firms ($\beta = 5.45$–7.26, $p < 0.01$) (specification 1–4, Table 6). We also found that knowledge collaboration with suppliers, customers has a positive effect on SMEs innovation as the interaction coefficients of SMEs with suppliers, customers are positive and significant both domestically and internationally, unlike collaboration with other partners supporting H3 (specification 1–4, Table 6). Collaboration with customers and suppliers both domestically and internationally adds more to product innovation in SMEs than in large firms supporting H3Collaboration with regional and national universities facilitates innovation to a greater extent in SMEs than large firms supporting H3 and partly supporting H2 (specification 1–2, Table 6). This finding demonstrates the importance of regional proximity in tacit knowledge transfer between SMEs and university (Audretsch et al., 2022b). Collaboration with consultants and local and national governmenrts has no effect on SME innovation, supporting our prior results in Tables 4-5 and our H3.

4.3. Post-hoc analysis

Additional robustness checks were performed. Firstly, we treated our dependent variable in the product innovation model with 21,140 obs. As non-censored and used generalized least squares (GLS) estimation with robust standard errors correcting for heteroskedasticity of the error term. The results were robust and statistical significance was at the same level, including the signs of the coefficients of all variables of interest. Secondly, we weighted the stratified sample of 21,140 obs. Accordingly by industry, firm size and UK region with weights provided in the data. The qualitative results on the direction of impact, sign, and statistical significance of the coefficient of interest related to our main hypothesis remain the same.

5. Discussion

This paper asks an important question: how does the relationship between knowledge collaboration and innovation in SMEs vary with the type of collaboration partner and its geographical proximity? Our results help us to better understand the role of these two factors in impeding and facilitating SMEs knowledge collaboration strategies for innovation furthering open innovation literature in SMEs.

First, compared to large firms, our study supports prior research of van de Vrande et al. (2009) and Vahter et al. (2014), that SMEs benefit more from collaboration with external partners, by adding the geographical dimension and partner typology to the extant literature. We argue this is feasible due to two key factors. First, differences in return to collaboration arise because of how SMEs and large firms report innovation. More specifically, the share of new-to-market products introduced by SMEs is likely to be higher compared to incumbents, which has already tested their business model and have a wide spectrum of mature products and services. Second, SMEs have limited resources, and their extent of investment in R&D is smaller than that of large firms. SMEs rely on knowledge available from external partners and knowledge spillovers to gather operational and market knowledge to use it as innovation inputs.

Third, our findings suggest that SMEs are likely to exploit collaboration with a variety of partners and across different geographies, supporting Mueller et al. (2013) and Kobarg et al. (2019) in identifying which types of collaboration partners are more strategic for product innovation. Interestingly, this study finds that the highest economic return from knowledge collaboration come from customers and suppliers internationally and domestically, and collaboration from universities in a region and the UK. This finding adds new knowledge to the geographical distribution of innovation described in prior research (Gallaud & Torre, 2005; Flor et al. 2018), extending the conversation on the joint effect of geographical proximity but also knowledge partner for SME's innovation. This study furthers Doloreux (2004) and Teixeira et al. (2008) and more recently Audretsch and Belitski (2022a) in understanding that localized effects of knowledge spillover of innovation, including the role of variety of collaboration partners and the breadth of collaboration (Kobarg et al. 2019) Our findings suggest that the reason behind this SME open innovation strategy– is the nature of the knowledge embedded in each specific type of knowledge partner – university versus industrial knowledge (Audretsch et al. 2004; Audretsch, 2014;) and firm size (Audretsch et al. 2021). Knowledge from the university is more complex and cannot be easily transferred to partners. It requires additional testing and often personal communication as the knowledge is tacit (Audretsch, 2014; Audretsch & Belitski, 2022b). Knowledge from suppliers and customers can be transferred within close and distant geographical proximities as SMEs are more familiar with the needs of customers and supply chain partners (van Beers & Zand, 2014; Audretsch, Belitski & Rejeb, 2023).

Third, prior research considered the depth and the breadth of collaboration (Kobarg et al. 2019), while this study considered each type of knowledge collaboration partners separately and emphasizes that the returns from collaboration depend upon a specific partner type (enterprise group unit, customer, supplier, university, consultant, competitor, government).

In doing so, we argue that the discussion on the "optimum geographical proximity" needs to be further informed by a partner type for SMEs (Boschma, 2005; Balland et al. 2015). The returns to collaboration may differ with the geographical proximity and depends it depends on the type of knowledge available domestically or internationally and the mechanisms it can be transferred (Belitski & Büyükbalci, 2021). For example, common work experience, including face-to-face interactions, may be most important for university knowledge and co-creation of knowledge with customers (Doloreux, 2004), which may also depend on the availability of resources for SMEs (Guenther et al., 2022). As a result, geographical proximity appears most important when co-creating new knowledge with universities, suppliers and customers. Collaborations with universities have become particularly common with SMEs when innovating new products and transferring knowledge, as SMEs access novel knowledge regionally, avoiding a creation of expensive R&D collaboration networks internationally (Audretsch et al. 2004).

Collaboration with local universities enhances innovation by reducing the time between research and a product's commercial market launch. Collaboration with competitors is often perceived by innovative firms as uncertain and risky, due to potential leakage of sensitive knowledge, unwanted outgoing spillover, and misappropriation of value created through R&D partnerships (Audretsch & Belitski, 2023).

Finally, our study sheds light on the role of local buzz and global knowledge pipelines, including face to face collaborations with local milieu for innovation (Bathelt et al. 2004) and temporary proximity to global customers (Gallaud & Torre, 2005; Torre, 2008).

The temporal proximity for SMEs could be realized via regular meetings with partners, congresses, conferences, trade fairs and exhibitions (Torre, 2008), including using digital tools (Digitally Driven, 2021; Audretsch & Belitski, 2021b) and through the exchange of information via Microsoft teams and Zoom. Our findings also extent prior empirical studies on SMEs' innovation and networking by Britton (2003) and Doloreux (2004), who illustrated show that an SME's innovation networks do not follow regional patterns and internationalization of collaboration is important for some SMEs. As regional geography undoubtedly matters (Audretsch & Belitski, 2021a), SMEs still rely on international sources of knowledge (Doloreux, 2004) that may help to develop new market niches locally and develop more diversified and cost-effective supply chains, outreach market knowledge and combine it with local and foreign customers.

6. Conclusions

Prior research on open innovation and small business is constrained by the assumption that SMEs are responsible for pushing the boundaries of open innovation (Chesbrough, 2003, 2006; Bogers et al. 2017) domestically and internationally (Zander et al. 2015; Theodoraki & Catanzaro, 2022). The resources for SMEs remain limited (De Massis et al. 2018), which also limits investment in internal knowledge, leaving localized and international collaboration with a variety of external partners an attractive source of innovation.

SMEs are persistent in collaboration and knowledge co-creation within local communities (Guenther et al. 2022), and they exercise in-depth engagement in collaboration with local suppliers, customers and university (Audretsch et al. 2023). This localization of knowledge inputs enables SMEs to develop localized networks and access knowledge at a lower cost and more quickly (Audretsch et al. 2021).

We respectfully reflect on the prior research on innovation in SMEs (Mas-Tur & Ribeiro Soriano, 2014; Ribeiro-Soriano, 2017) and argue that the conventional approach to innovation and collaboration strategies in SMEs is a crude oversimplification of a highly complex, unpredictable, and fast-changing reality. Furthermore, we argue that the geographical dimension of knowledge collaboration and partner type can further unpack conditions that impede and facilitate open innovation strategies in SMEs.

Given the high transaction and financial costs associated with international collaboration and limited resources (Ribeiro-Soriano, 2017; De Massis et al. 2018), SMEs may obtain greater returns on their investment in external collaborations and knowledge transfer in regional markets (Mas-Verdu, Ribeiro Soriano & Roig Dobon, 2010), compared to international collaborations, which is both costlier and more uncertain.Knowledge collaboration internationally will help them to overcome the liability of localization as localized collaboration may lead to a 'lock-in effect' of knowledge (Lahiri, 2010; Balland et al. 2015).

6.1. Policy implications

Our findings offer policy implications that would be difficult to establish without considering the partner type and geographical component of the collaboration strategy of SMEs. Scholarly ability to explain SME's innovation has been limited given that innovation inputs appear difficult to predict and plan, meaning that SMEs which collaborate with a different type of partner exhibit significant returns to collaboration with suppliers, customers, and universities. It is, therefore, necessary to study SME innovation using robust data on the type of partner and its location – locally, nationally, or(and) internationally. Yet, with such relevant data, industrial and regional factors can be detected to identify what enables regional collaboration to have the highest returns with one partner type but not another? As such, policies which include collaboration with universities, local government, and SMEs (Simón-Moya et al. 2016), such as "The Ideas 2 Innovation programme" in Wales (Innovation programme, 2022) and Vinnova programme on collaboration between universities and SMEs (Vinnova programme, 2022) are unlikely to foster a meaningful surge in SME innovation. While striving to understand the phenomenon, we intentionally abstain from making normative claims indicating what SMEs should do. Ideally, these choices should be guided with aspects beyond the desire to be *large* and instead be directed at fulfilling a desire to *create sustainable value* for stakeholders beyond shareholders. With environmental and social concerns in mind, policy makers may wish to avoid 'blindly' fostering SMEs to go international and facilitate digitalization of SMEs operations (Digitally Driven, 2021).

Foremost, policies targeted at younger firms are likely to be especially fruitful if they are directed at fostering collaboration within the supply chain and customers, i.e., market-demand pull policies. Policies targeted at SMEs collaborating with universities appear better aimed at regional employment and local market problems. Further government support may include the protection of intellectual property, in particular if SMEs aim to build international partnerships. Second, as the benefits of openness to external collaborations differ between SMEs and large firms, tit is of particular interest for future scholars whether the size-related differences in the effects of external collaboration with various partners can be only explained by differences in geographical proximity or partner type. These differences may also be explained by market experience, firm location, industry characteristics, and other firms' innovation-related characteristics, such as skill intensity, knowledge spillovers, and managerial experience.

6.2. Limitations and future research

There are three limitations of this study. First, the data is longitudinal but unbalanced, with more than 60% of firms in our sample observed only once. We could not take full advantage of the panel structure and perform dynamic panel estimation. Future studies should liaise with statistical offices and agencies on identifying forms, which enables a better match of data and adds a longitudinal perspective to the analysis.

Secondly, the underlying logic of the paper is that the type of collaboration partner and the geography of collaborations affect SME innovation. Yet, the relationship can also go in the opposite direction as more innovative firms may - for instance – may decide to expand their collaboration networks and combine various types of collaboration partners. More innovative firms may find the international context much richer in knowledge for fruitful collaborations and knowledge sourcing for local markets and partners than local markets (Rugman & Verbeke, 2001). If this is the case, the geography of collaborations may be endogenous to firm's innovative output, however, this depends on the firm and industry's idiosyncratic characteristics. In this study we aimed to overcome this limitation by predicting the propensity to collaborate across different geographical locations of partners and use predicted values in the innovation regression. In doing so, we vow that a set of firm

Table A1
Correlation matrix.

Variables…		1	2	3	4	5	6	7	8	9	10	11	12
1	Product innovation	1											
2	Collaboration regional	0.21*	1										
3	Collaboration national	0.20*	0.14*	1									
4	Collaboration Europe	0.30*	0.22*	0.39*	1								
5	Collaboration international	0.22*	0.21*	0.34*	0.57*	1							
6	Collaboration suppliers	0.18*	0.20*	0.26*	0.43*	0.58*	1						
7	Collaboration customers	0.28*	0.24*	0.15*	0.24*	0.18*	0.16*	1					
8	Collaboration universities	0.10*	0.05*	0.10*	0.11*	0.08*	0.06*	0.20*	1				
9	SMEs	0.15*	0.13*	0.14*	0.17*	0.12*	0.11*	0.22*	0.12*	1			
10	Foreign firm	0.10*	0.09*	0.09*	0.11*	0.06*	0.06*	0.15*	0.07*	0.32*	1		
11	Age of firm	0.09*	0.07*	0.09*	0.10*	0.07*	0.06*	0.14*	0.07*	0.36*	0.36*	1	
12	Scientists	0.13*	0.36*	0.10*	0.21*	0.22*	0.26*	0.16*	0.41*	0.12*	0.08*	0.07*	1
13	R&D intensity	0.04*	0.06*	0.09*	0.06*	0.09*	0.07*	0.01	0.01	−0.07*	−0.08*	−0.04*	−0.03*

Note: * significant at 5% significance level. Source ONS: matched Business Register (2002–2014) and UK Innovation Survey (2002–2014). Number of observations 21,140.

Table A2
The likelihood of collaboration of SMEs and non-SMEs across different partner types and economic geographies. Dependent variables: binary variable for regional, national and international collaborations, collaboration with suppliers, customers and universities. Method: logistic estimation with odd ratios.

Dependent variable	Geography of collaboration = 1, zero otherwise				Type of collaborator = 1, zero otherwise		
Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Collaboration type	region	nation	Europe	world	Supplier	Customer	University
Age	0.98*	0.97	0.96	0.98	0.95	0.99	1.03
	(0.00)	(0.00)	(0.00)	(0.02)	(0.03)	(0.03)	(0.03)
Age squared	1.01	1.01	1.02	1.03	1.00	1.00	1.01
	(0.03)	(0.03)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)
SMEs	0.82***	0.73***	0.55***	0.53***	0.75***	0.77***	0.61***
	(0.04)	(0.05)	(0.07)	(0.03)	(0.02)	(0.05)	(0.08)
R&D intensity	10.16***	37.11***	27.78***	40.01***	6.79***	23.09**	32.02**
	(3.06)	(16.01)	(10.06)	(16.00)	(1.09)	(9.01)	(11.00)
Scientists	1.00***	1.01***	1.01***	1.01***	1.02***	1.03**	1.02**
	(0.03)	(0.03)	(0.02)	(0.00)	(0.00)	(0.02)	(0.06)
Foreign	0.99	1.25***	1.46***	1.44***	1.18***	1.07***	1.17
	(0.04)	(0.04)	(0.08)	(0.02)	(0.04)	(0.04)	(0.06)
Inverse Mills ratio	1.22	0.52**	0.72	0.98	0.61	0.61**	0.31
	(0.21)	(0.08)	(0.17)	(0.23)	(0.41)	(0.09)	(0.43)
Year and region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.08***	0.08***	0.02***	0.001***	0.001***	0.001***	0.001***
	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Number of observations	21.140	21.140	21.140	21.140	21.140	21.140	21.140
R2	0.08	0.17	0.25	0.28	0.18	0.23	0.30
Chi-square	2083	4106	3273	3047	513	655	674
Log-likelihood	−12411	−13263	−7323	−6501	−1263	−1856	−409

Note: Geography of collaboration = 1 if firm collaborates at least with one type or more partners in a region (e.g. customers, universities, government, consultant, enterprise group, competitors, universities). Type of collaborator = 1 if firm collaborates with supplier/customer/university at least in one or more regions. Reference category for legal status is Company (limited liability company). industry (mining), region (North East of England); Robust standard errors are in parenthesis. Significance level: * $p < 0.05$; ** $p < 0.01$, *** $p < 0.001$. Source: BSD - Business Register (2002–2014) and UKIS - UK Innovation Survey (2002–2014).

and industry characteristics should be carefully thought in predicting the propensity to collaborate, which may depend on factors beyond the firm size and age, but related to its strategy, availability of resources and behavior, and collaboration strategies in the industry, where the firm is located. We acknowledge that geographical proximity may serve as a filter for SME's collaboration strategies and that firms that may not have reported the collaboration could still experience a certain collaboration effort and intent to knowledge sourcing from external partners. Applying the two-step procedure in predicting such effort and then using it to explain SME innovation outputs could be a way forward in unpacking the role of geography and firm industry characteristics play in SMEs collaboration strategies.

Finally, SME innovation is also influenced by regional factors beyond the location of main collaboration partners, and related to market demand for SMEs products and services and supplies, siuch as regional popuulation where SME is located, the level of economic development, availability of human capital including high-skilled and technical workers, access to funding, including venture, debt and alternative funding and other regional charcateristics such as regional industry structure. These elements are often referred to as innovation ecosystyems and may either impede or further facilitate knwledge colaboration domestically ajnd internationally and affect the access to resources and speed of innovation which could be an important direction for future research.

CRediT authorship contribution statement

David B. Audretsch: Conceptualization, Investigation, Supervision. **Maksim Belitski:** Conceptualization, Data curation, Investigation, Methodology, Resources, Software, Validation. **Rosa Caiazza:** Investigation, Project administration, Validation. **Phillip Phan:** Conceptualization, Investigation, Methodology.

Table A3
Results of the first stage IV regression used for predicting values of collaboration across four geographical dimensions. Dependent variables: collaboration with suppliers; collaboration with customers and collaboration with universities.

Dependent variable	collaboration with suppliers				collaboration with customers				collaboration with universities			
Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Geography of collaboration	**region**	**nation**	**Europe**	**world**	**region**	**nation**	**Europe**	**world**	**region**	**nation**	**Europe**	**world**
collaboration with suppliers in industry	0.04** (0.015)	0.17*** (0.019)	0.17*** (0.015)	0.09*** (0.012)								
collaboration with customers in industry					0.02* (0.013)	0.19*** (0.015)	0.13*** (0.012)	0.12*** (0.011)				
collaboration with universities in industry									0.16*** (0.019)	0.28*** (0.022)	0.11*** (0.015)	0.08*** (0.014)
Age	−0.01 (0.00)	−0.01 (0.00)	−0.01 (0.00)	−0.01 (0.00)	−0.01 (0.00)	0.01 (0.00)	0.01*** (0.00)	0.01* (0.00)	0.01* (0.00)	0.01* (0.00)	0.01* (0.00)	0.01* (0.00)
Age squared	−0.01 (0.00)	−0.01 (0.00)	−0.01 (0.00)	−0.01 (0.00)	−0.01 (0.00)	−0.01 (0.00)	−0.01** (0.00)	−0.01 (0.00)	−0.01 (0.00)	−0.01 (0.00)	−0.01 (0.00)	−0.01 (0.00)
Employment (SMEs)	−0.01 (0.01)	−0.02*** (0.01)	−0.03*** (0.01)	−0.02*** (0.01)	−0.01 (0.00)	−0.02*** (0.00)	−0.02*** (0.00)	−0.02*** (0.01)	−0.01** (0.00)	−0.03*** (0.00)	−0.01** (0.00)	−0.01*** (0.00)
SMEs	0.01** (0.00)	0.01 (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01* (0.00)	0.01 (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01* (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01** (0.00)
Scientist	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
R&D intensity	0.07 (0.042	0.23*** (0.05)	0.15** (0.04)	0.26*** (0.04)	0.13** (0.04)	0.12* (0.06)	0.27*** (0.05)	0.42*** (0.05)	0.28*** (0.04)	0.40*** (0.05)	0.21*** (0.03)	0.23*** (0.03)
Foreign (M)	−0.03*** (0.00)	−0.11*** (0.00)	−0.09*** (0.00)	−0.06*** (0.00)	−0.02** (0.00)	−0.17*** (0.00)	−0.11*** (0.00)	−0.09*** (0.00)	−0.03*** (0.00)	−0.05*** (0.00)	−0.01 (0.00)	0.01 (0.00)
Subsidiaries	−0.01 (0.00)	0.01*** (0.00)	−0.01 (0.00)	−0.01 (0.00)	−0.01 (0.00)	−0.01 (0.00)	−0.01** (0.00)	−0.01** (0.00)	−0.02 (0.00)	0.01 (0.00)	0.01* (0.00)	0.01 (0.00)
Industry controls (2 digit SIC)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-regions controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1133	1972	1832	1218	1133	1972	1832	1218	1133	1972	1832	1218
Constant	0.08*** (0.00)	0.17*** (0.01)	0.12*** (0.01)	0.09*** (0.01)	0.08*** (0.01)	0.22*** (0.01)	0.12*** (0.01)	0.10*** (0.01)	0.05*** (0.01)	0.07*** (0.01)	0.01 (0.01)	−0.01 (0.01)
R2	0.02	0.07	0.07	0.06	0.03	0.13	0.11	0.13	0.04	0.11	0.06	0.05
F-stats first stage	34.84	139.18	88.19	65.39	53.30	239.12	121.30	113.71	42.20	92.30	19.97	16.67
Sargan test of overidentifying restrictions (p-values)	0.24	0.22	0.31	0.21	0.23	0.32	0.18	0.12	0.23	0.22	0.35	0.17

Number of observations- total sample: 21, 140. Note: reference category for legal status is Company (limited liability company). industry (mining), region (North East of England). Robust standard errors are in parenthesis. Significance level: * $p < 0.05$; ** $p < 0.01$, *** $p < 0.001$. Source: BSD and UKIS (2002–2014).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix A

See Table A1, Table A2, Table A3.

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