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Knowledge collaboration, firm productivity and innovation: A critical assessment

David B. Audretsch [a,e], Maksim Belitski [b,c,d,*]

[a] School of Public and Environmental Affairs, Indiana University Bloomington, 1315 E. 10th Avenue SPEA Bloomington, IN 47405, USA
[b] Henley Business School, University of Reading, Whiteknights campus, Reading RG6 6UD, UK
[c] ICD Business School, IGS-Groupe, Rue Alexandre Parodi, 12, Paris 75010, France
[d] College of Business, Loyola University New Orleans, 6363 St Charles Ave, New Orleans, USA
[e] Alpen-Adria University of Klagenfurt, Universitätsstraße 65/67, Klagenfurt, Austria

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ABSTRACT

We identify and measure the returns to regional, national and international knowledge collaboration for innovation in firms with different productivity levels. Drawing on the unbalanced panel of 17,859 innovative firms in the United Kingdom during 2002–2014, we find that the least productive firms are more likely to achieve higher returns from knowledge collaboration regionally, while the most productive firms that collaborate regionally limit their innovation. Knowledge collaboration with partners nationally increases innovation sales and propensity to innovate in both the least and most productive firms. High productivity firms have higher returns from knowledge collaboration with European and international partners, unlike the least productive firms. Firms that experience greater market risks are able to appropriate innovation outputs, invest in R&D and digital capabilities and are exporters have higher propensity to innovate and grow their innovation output. Firm productivity and geography of knowledge collaboration as two boundary conditions shaping firm's innovation.

1. Introduction

Firm innovation largely depends on the collaboration to new ideas and knowledge internally and with external partners (Baptista and Swan, 1998; Vega-Jurado et al., 2009; Soriano and Huarng, 2013; Audretsch et al., 2023) with scholars and firm managers calling for a better understanding of the frontiers and boundaries of knowledge collaboration for growth and productivity (Matsukawa et al., 2020; Belitski et al., 2021). Thus, unpacking the boundary conditions which bolster the relationship between investment in knowledge internally and creating social collaborative networks knowledge externally (Leyden et al., 2014) may be the ultimate and most desired objective for scholars and firm managers (Vedula and Kim, 2019; Kraus et al., 2021; Saura et al., 2023).

Prior research on open innovation and knowledge spillovers argues that the role that external knowledge plays in firm's ability and willingness to innovate depends on the internal capabilities of the firm (Chesbrough, 2003; Link et al., 2007; Cassiman and Valentini, 2016), availability of internal resources, (Barney, 2001) and firm productivity (Audretsch and Belitski, 2020b). By drawing on the extant literature, we argue that both internal and external knowledge is required to increase firm's ability to innovate (Vega-Jurado et al., 2009; Castrogiovanni et al., 2016) shown by an impressive empirical studies of the role of productivity in innovation and survival for the US (Vedula and Kim, 2019), German (Baumann and Kritikos, 2016) and the UK firms (Giovannetti and Piga, 2017). Productivity is essential for a firm to recognise, access and assimilate external knowledge, as well as adopt new technologies and commercialise them into the market (Los and Verspagen, 2000). The higher the productivity - the more innovation inputs available internally and externally will be transformed into innovation outputs.

However, the above argument although widespread, lacks sound empirical testing and prior research on the interplay between productivity, external knowledge sourcing and firm's innovation, and has produced mixed findings (Laursen and Salter, 2006, 2014; Cassiman and Veugelers, 2002, 2006; Audretsch and Belitski, 2022). Therefore, there is a paucity of knowledge regarding to what extent firm's innovation relies on a) the type of knowledge e.g. internal knowledge investment and external knowledge collaborations (Audretsch et al., 2020); b) geographical dimension of knowledge collaboration e.g. regionally,

* Corresponding author.
E-mail addresses: daudrets@indiana.edu (D.B. Audretsch), m.belitski@reading.ac.uk (M. Belitski).

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nationally or internationally (Boschma, 2005; Leyden and Link, 2015; Audretsch et al., 2021); and c) the level of firm's productivity which affects firm's ability to transfer knowledge inputs into knowledge outputs (Baumann and Kritikos, 2016). Therefore, this study objective is to theoretically debate and empirically examine the role of firm productivity in the relationship between various geographical dimensions of external knowledge collaboration and firm's innovation.

Whilst addressing the gap in the extant literature, this study makes two theoretical contributions. Firstly, it contributes to open innovation and knowledge spillover literature by examining how the geography of knowledge collaboration facilitates innovation activity in firms with different levels of productivity. We adopt an empirical approach which enables us to estimate and visualise the moderating effect of firm productivity in the relationship between knowledge collaboration with external partners for innovation outputs of a firm.

Secondly, it contributes to the resource-based view (RBV) literature by theorising how and under what circumstances firm productivity enables higher returns to knowledge collaboration regionally, nationally and internationally for firm innovation. In doing this, we are testing the strength of the relationship and the size of the impact linking knowledge collaboration, productivity and innovation outputs together into one model. Therefore, we are furthering prior research on open innovation under limited resources (Faems et al., 2005; Cassiman and Valentini, 2016; Guenther et al., 2023).

We use unbalanced panel data of 17,859 innovative firms in the United Kingdom, we created two samples of 29,805 and 21,704 firm-year observations respectively during the period of 2002–2014, related to availability of data on firm innovation behaviour. Our findings demonstrate that knowledge collaboration internationally, both in Europe and the rest of the world, has significantly facilitated innovation outputs for the most productive firms and has limited innovation outputs for the least productive firms. On the contrary, knowledge collaboration with regional partners increases innovation outputs in the least productive firms, and limits innovation in the most productive firms. We argue that efficient resource allocation and reduction of transaction, operational and managerial costs of knowledge collaboration internationally (Pitelis and Wahl, 1998; Kobarg et al., 2019) is unlikely to be achieved amongst the least productive firms, as they have a lack of resources and managerial capabilities (Helfat and Martin, 2015) required for productivity. Collaboration with external partners on innovation within national institutional boundaries facilitates innovation in firms (Audretsch et al., 2019) with different levels of productivity. The implications of this study are of particular interest to scholars and policymakers in the United Kingdom (UK) and other developing countries, where innovation policy aims to create favourable conditions for firm productivity growth and facilitate knowledge collaboration internationally.

The rest of the paper proceeds as follows. The next section provides an overview of the literature and develops research hypotheses. Section 3 describes the sample, data and empirical method. Results of the econometric analysis are discussed in section 4. Section five discusses the major results and implications for theory and practice. Section 6 concludes.

2. Theoretical framework

2.1. Theorising mechanisms and conditions for knowledge collaboration

The importance of knowledge collaboration for innovation is grounded in two primary conceptual frameworks. Firstly, the knowledge-based view (Grant, 1996) represents knowledge collaboration as the sourcing of external knowledge from different external partners, with the knowledge being different from the one possessed by a firm (Chesbrough, 2003; Chesbrough et al., 2006). Knowledge collaboration with external partners extends the knowledge base available internally, resulting in new knowledge recombination and innovation outputs (Antonelli et al., 2022: Audretsch and Belitski, 2023a). Secondly, according to the resource-based view (Penrose, 1959; Barney, 2001; Pitelis and Wahl, 1998; Foss, 2011), knowledge collaboration with external partners is a channel of access resources owned by external partners, such as customers, suppliers, competitors and more (Mowery et al., 1998; van Beers and Zand, 2014). The mechanism that underpins knowledge collaboration for a firm is being a part of a larger group, in a community, which is larger than the firm itself. This idea was first promoted by Hanifan (1916), who linked knowledge collaboration to how businesses and social communities were formed. He demonstrated that the accumulation of social capital as a result of interactions and collaboration may immediately satisfy individual and community social needs, substantially improve living conditions, as well as improve wellbeing in the whole community. Knowledge collaboration between a firm and external partner is inherently risky and uncertain activity associated with the process of knowledge sourcing, appropriation, development and commercialisation in the market (Belderbos et al., 2004). Hanifan (1916: 131) poses that "there must be an accumulation of community social capital" and for firms this means an outreach to different knowledge partners, across different geographical, social and cognitive proximities. For knowledge collaboration to produce news ideas, the managers involved need to become familiar with one another and their business practices, resources, challenges and innovation goals for all of the partners involved in the collaboration. Knowledge collaboration activity inevitably includes social intercourse (Granovetter, 1973), that is, when sufficient social capital has been accumulated over time, and then skilful leadership and collaboration can enable companies' resources to be used in knowledge creation and transfer for new products, services and processes.

Managerial perceptions about the favourability and efficiency of knowledge collaboration is based on the firm's needs, internal capability, and access to social networks between partners as a tool for linking micro and macro levels of knowledge collaboration (Audretsch et al., 2022, 2023a). Granovetter (1973) also argues that the degree of collaboration between individuals within a network varies directly with the strength of their tie to one another, and cognitive proximity (Balland et al., 2015). As a result, the extent of knowledge collaboration and transfer may depend on the ability of firms to create strong ties, and avoid weaker ones, to further exploit them in the collaboration process. By enhancing collaboration between partners, transaction and opportunity cost of knowledge collaboration will be reduced (Salge et al., 2013; Saura et al., 2023; Audretsch and Belitski, 2023b), as well as on every specific project in which the individuals collaborate on (Kobarg et al., 2019). Low productive firms with limited resources are more likely to be constrained by their ability to create social communities and establish strong ties for international collaboration, therefore facing high costs of knowledge search. Firms which are unable to overcome increasing transaction and operational costs of knowledge collaboration internationally, may need to re-allocate their resources and collaborate within local communities and focus on utilising their existing strong ties instead (Granovetter, 1973) with customers, local government and suppliers within close geographical proximity (Boschma, 2005). Firms that are able to allocate valuable resources and create networks internationally (Laursen and Salter, 2006) will be able to reduce transaction costs and facilitate innovation activity (Kobarg et al., 2019). Therefore, we argue that the degree to which transaction and opportunity costs of knowledge collaboration for innovation to be matched and dealt with depends on the extent of available resources (Penrose, 1959; Pitelis and Wahl, 1998), the nurturing of social capital and networks (Hanifan, 1916; Granovetter, 1973), firm productivity (Ili et al., 2010; Audretsch and Belitski, 2020b) and knowledge collaboration experience (Belitski, 2019; Audretsch et al., 2020; Al-Omoush et al., 2021).

2.2. Knowledge collaboration with regional partners and firm innovation

Competitive pressure and high risks related to knowledge collaboration under limited resources and an increased market competition, may result in the reduction of the ability of firm's to internationalise (Balland et al., 2015), choosing collaboration opportunities within close geographical proximity instead (Laursen et al., 2011; Guenther et al., 2023). In local markets, social capital and ties between collaboration partners are likely to be stronger and persistent, where operational, market and transaction costs can be reduced without an immediate effect on the intensity of knowledge collaboration. Also, it is helpful to note that knowledge collaboration and spillovers between firms and institutional context increase with the geographical proximity (Audretsch and Feldman, 1996), and can be beneficial for low productivity firms (Laursen et al., 2011). Interestingly, as the collaboration with regional partners increases, so do knowledge spillovers and knowledge stock, the collaboration with regional partners will further increase (Cantwell and Mudambi, 2011).

Laursen and Salter (2006) and more recently Kobarg et al. (2019) and Belitski et al. (2023) introduce the concept of knowledge breadth and depth, which could be useful in understanding why knowledge collaboration locally will demand less resources and is therefore likely to be chosen by low-productive firms. The breadth and depth of the external knowledge search increases while transitioning from regional to global knowledge collaboration, as the number of external knowledge partners increases, along with the diversity of knowledge which requires more complex knowledge interactions, specialised competences and skills. With an increase in the number and range of collaboration partners, the depth and breadth of knowledge collaboration may become a burden on low-productivity firms. As a result, this may significantly reduce their innovation outcomes and isolate them out of international markets.

Resources and high productivity are needed to face and withstand global economic shocks and market competition, which low-productive firms will not have (Syverson, 2011) and they will be selected into regional collaboration (resource-based view) (Teece, 1986; Balland et al., 2015). On the contrary, highly productive firms will be able to deal with knowledge breadth and depth internationally, by engaging increased resources available to them. High productive firms will increase their opportunity costs and will reduce their innovation outputs if collaborating with regional partners, as resources available to a firm will be under-used and not fully engaged (Knudsen and Mortensen, 2011; Nieto and Santamaría, 2007). When highly productive firms choose regional collaboration, they will be "locked" into regional knowledge, with little knowledge breadth and depth, and will be forced to internalise within a region. This will limit their innovation outputs. We therefore hypothesise:

H1a: Regional knowledge collaboration increases innovation output for the least productive firms.

H1b: Regional knowledge collaboration limits innovation output for the most productive firms.

2.3. Knowledge collaboration with national partners and firm innovation

An important insight is that firms are likely to go beyond the region to explore the benefits of knowledge diversity and depth across regions in a country. Certain types of knowledge collaboration, such as collaboration with external partners from other regions in a country, yield diverse and more specialised knowledge than the knowledge that regional collaboration can provide (Cantwell and Mudambi, 2011; Audretsch et al., 2023). We argue that knowledge collaboration nationally within the country's institutional boundaries, is likely to boost innovation activity in firms with different productivity levels due to the following reasons. Firstly, specific regions in the country and types of partners may be more conducive to innovation and may have skills and competences, technologies, and access to markets which regional partners will not have. Secondly, innovative activity emanating from knowledge collaboration between firms and their external partners nationally is richer and more diverse vis-à-vis regional knowledge collaboration. Thirdly, formal national regulation is easier to understand and enforce (Audretsch et al., 2019) when collaborating within national boundaries, particularly for some types of collaborators such as competitors. For example, coopetition (Mariani and Belitski, 2022) is particularly sensitive, for both highly productive and the least productive firms, requiring a certain level of trust as well as transparency and responsibility in coopetition. In particular collaboration within the same institutional jurisdiction (country or state) allows for knowledge that is co-created to be appropriated by both parties. Also, intellectual property rights can be quickly enforced in collaboration and in case of disputes (Nooteboom et al., 2007). Collaborating internationally, and in countries where intellectual property rights are weak or bilateral agreements do not exist, may increase the risk of copying and reverse engineering, (Cassiman and Veuglers, 2002) potentially limiting knowledge collaboration (Audretsch and Belitski, 2023a). Fourthly, migrating from regional to national knowledge sourcing will increase the breadth and the depth of knowledge collaboration (Kobarg et al., 2019), which relates to a firm's ability to outreach to a greater variety of knowledge partners independently, influenced by their level of productivity. For example, national innovation and entrepreneurship support programmes such as Small Business Innovation Research (SBIR) in the United States, directly supports the levelling-up in innovation activity across firms with different productivity levels and resources (Audretsch, 2003; Audretsch, Link and van Hasselt, 2019). Over time, the Small Business Innovation Research (SBIR) program has stimulated technological innovation and knowledge transfer and has been used mainly by small businesses to meet federal research and development needs (Link et al., 2022; Link and van Hasselt, 2023).

Fifthly, national markets have a degree of familiarity with products and services produced by either high or low productive firms, where every firm may be able to connect to a specific market and customer (Colombelli and Quatraro, 2018). In addition, national customers are used in regards to the testing of new products and services before scaling up internationally (Rugman and Verbeke, 2017). Sixthly, competition is less intense in national markets, compared to European and international markets, allowing firms with lower economies of scale and lower productivity to survive and adapt their products to the national market. They can enjoy a certain level of customer loyalty (e.g. Made in Germany or Made in Britain) (Audretsch and Lehmann, 2016) and government protection, such as tariffs and non-tariff import regulations (Rugman and Verbeke, 2017). Seventhly, national partners within the industry have technical standards, and national regulation offers more customised services, and so can supply firms with ready-made solutions that can be quickly incorporated into their production processes which lower the research and development (R&D) investment costs for low-productive firms (Antonelli and Colombelli, 2015). This enables them to compete with high-productivity firms in the national market. Finally, innovative firms located in developed countries, such as the UK, may access global knowledge locally within the Greater London area as well as other industrial clusters for multinational companies within the UK (Iammarino and McCann, 2006). We therefore hypothesise:

H2: Knowledge collaboration nationally increases innovation output for the most and least productive firms.

2.4. Knowledge collaboration with global partners and firm innovation

As we acknowledge the increase in heterogeneity of knowledge transactions whilst migrating from regional, to national, to international knowledge collaboration (Belderbos et al., 2004; Tödtling et al., 2009), and with the increase in the diversity of collaboration partners (Laursen and Salter, 2006; van Beers and Zand, 2014; Driffield et al., 2014), knowledge collaboration will demand more resources, higher absorptive capacity (Lane et al., 2006) and productivity (Audretsch and Belitski, 2020b). Searching is a costly process with "the expected cost of searching increasing as the size of the search region increases" (Leyden and Link, 2015: 477). In a competitive international environment that has a variety of formal and informal institutional contexts (Khlystova et al., 2022), only firms with high resource availability and productivity will be able to benefit from international knowledge collaboration. This is due to the following reasons. Firstly, the diversity of knowledge when operating within global networks enriches a firm's resources (resource-based view) (Ascani et al., 2020) and allows for a larger pool of knowledge and skills, which in turn strengthens the competitive advantages of a firm (Ketchen et al., 2007). Secondly, in international knowledge collaborations, firms often practice foreign direct investment (FDI) as a method to enter into foreign markets and engage in knowledge collaboration when local advantage cannot easily be exploited. Many multinational firms with foreign subsidiaries see knowledge collaboration with local partners internationally as a positive knowledge externality or 'knowledge spillover' (Narula, 2004; Driffield et al., 2014).

Thirdly, internationally applied and tested knowledge serves as a powerful conduit of innovation activity should this knowledge be complemented by the firm's internal capabilities, technology and productivity (Roper and Hewitt-Dundas, 2015; van Beers and Zand, 2014). Therefore, the breadth and intensity of knowledge collaboration with international partners is conditional on the level of financial and human resources available to a firm (Barney, 2001; Narula, 2004) and firm productivity (Vedula and Kim, 2019).

Fourthly, greater collaboration with global knowledge partners has the potential to mitigate internalisation issues resulting from learning complex external knowledge and international regulation caveats (Lane et al., 2006), reducing transaction and adjustment costs for partners (Audretsch and Belitski, 2020a). In this regard, a firm's productivity plays an important role by learning from international collaboration at the micro and macro levels (Hanifan, 1916) and in-depth knowledge interactions (Kobarg et al., 2019).

Fifthly, knowledge collaboration with global partners requires high productivity and resources to facilitate knowledge spillover and move technologies across borders to create new and existing products (Audretsch and Belitski, 2022).

Low productive firms will isolate themselves out of international knowledge collaboration because a lack of resources and capabilities will result in higher operational, coordination and transaction costs compared to high productive firms. Those low productive firms that attempt to increase their diversity of knowledge spillover will be unable to match their capabilities to international market demands and supply, therefore increasing the cost of knowledge collaboration. Finally, knowledge collaboration with foreign partners in general constitutes less control over protection and access to knowledge dissemination overseas, and firms which lack resources to monitor, control and engage with external partners internationally, will be at a higher risk of unintended knowledge spillovers (Cassiman and Veuglers, 2006) and property rights enforcement (Nooteboom et al., 2007; Audretsch et al., 2019). This will limit returns to knowledge collaboration internationally. We hypothesise:

H3a: Global knowledge collaboration increases innovation output for the most productive firms.

H3b: Global knowledge collaboration limits innovation output for the least productive firms.

Fig. 1 summarises three research hypotheses developed in this section. It highlights the relationship between external knowledge collaboration, productivity and innovation output. The horizontal axis of Fig. 1 represents the level of a firm's productivity, whereas the vertical axis shows the level of knowledge localization and collaboration. The expected effects of external knowledge sourcing on innovation depend on the position relative to two axes.

Fig. 2 diagrammatically represents our theoretical argument in sections 2.2.-2.4. The horizontal axis represents the geographical dimension of collaboration from knowledge collaboration regionally, nationally and internationally. The vertical axis represents the degree of innovation output. The relationship between knowledge partner's location in collaboration and innovation output is described by two lines, one for the most, and one for the least productive firms. Point A is an intersection point, where both low and high productivity firms should be able to achieve the same innovation output in the national market. The slope of the relationship between knowledge collaboration geography and firm innovation is negative for low productive firms, and positive for the most productive firms.

3. Data and method

3.1. Sample

To test our hypotheses, we used six pooled cross-sectional datasets from the Business Structure database known as the Business Register and the UK Innovation Survey (UKIS) from the period 2002–2014. We also used annual business survey data to analyse the total factor productivity (TFP) calculation as part of the robustness check. Although the two datasets were pooled together and constructed from two different sources, they are matchable. Firstly, 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 United Kingdom (UK) was included in this study on behalf of the Department of Business Innovation and Skills (BIS). Secondly, we matched the Business Structure Database (BSD) data for years 2002, 2004, 2006, 2008, 2010 and 2012 to see the correspondence to CIS survey waves with the data from BSD which was taken for the initial year of the UKIS period. The BSD is a version of the Inter-Departmental Business Register intended for research use, and takes full account of

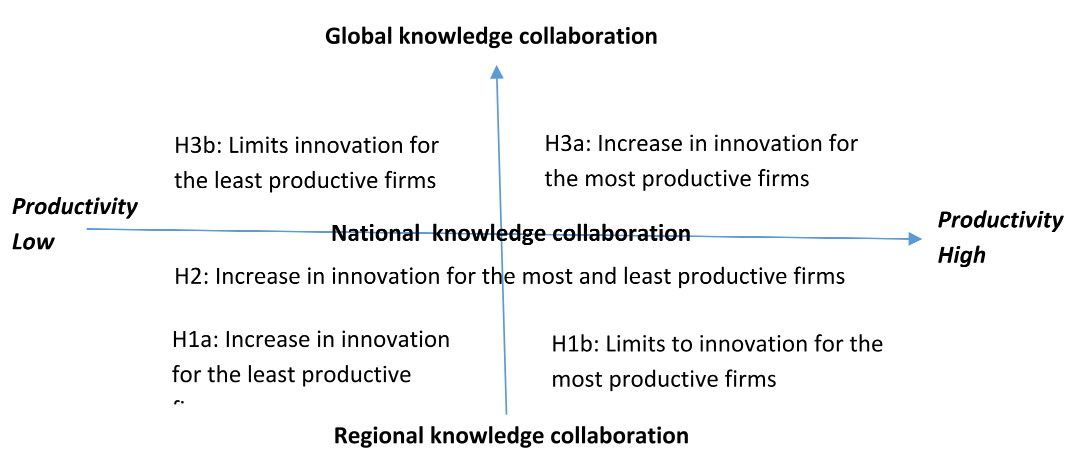

Fig. 1. Conceptual model of the hypothesized relationship. Source: Authors.

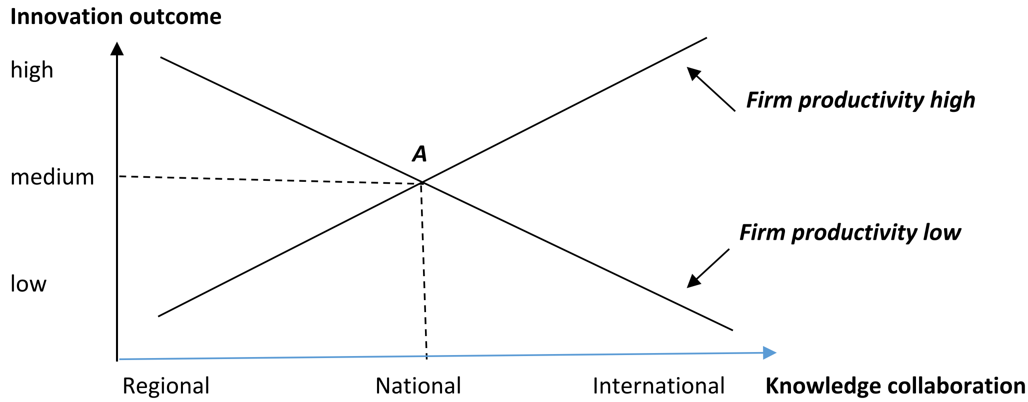

Fig. 2. Visualisation of the innovation- knowledge collaboration and productivity nexus, Source: Authors.

changes in firm legal status, ownership (foreign or national firm), alliance information (whether the firm belongs to a larger enterprise network), exports, turnover, employment, industry at the 5-digit level and firm location by postcode. The BSD is the key sampling frame for UK business statistics and is maintained and developed by the Business Registers Unit (BRU) within the ONS.

Given the availability of data in the UK Innovation survey and BSD, we analysed them and created two samples. The first sample includes innovation sales and has 21,702 firm-year observations. Innovative sales illustrate the commercial success of the innovation (innovative sales) [0,100] measured as sales share of products which are new to the market in total sales. Innovative sales do not measure technological innovation but are more biased towards commercialization of innovation (Laursen and Salter, 2006). The second sample includes the identifier of product (service) innovation as a dependent variable and has 29,805 firm-year observations. The number of firms in both samples was 17,859, and both samples were used to test our research hypotheses. Furthermore, regression analysis for each sample was split into subsamples and presented by the level of firm productivity in percentiles: 0–10 %, 20–30 %, 40–50 %, 60–70 %, 70–80 % and 90–100 %. We have excluded regressions on some intermediary percentiles in our analysis. Most of the firms in sample one (innovation sales), and sample two (product innovation) come from high-tech manufacturing (15.1 % and 19.44 % accordingly), constriction (9.9 % and 10.2 % accordingly), wholesale and retail trade (16.8 % and 16.0 % respectively), real estate and business activities (14.4 % and 12.3 % respectively), and public services (including healthcare and defence) (11.1 % and 10.1 % respectively). Only few firms samples one and two come from mining and quarrying sector (<1%), utility electricity (<1%) and education (1 %) (see Appendix A1).

Most firms in sample one (innovation sales), and sample two (product innovation), come from the South-east of England (10.91 % and 10.88 %), London (9.51 % and 9.72 % accordingly), the North-west (9.20 % and 9.08 % accordingly) and East England (8.97 % and 9.09 % accordingly). Wales (<6%), Scotland (<9%) and Northern Ireland (<8%) are least represented in both samples. The industrial and geographical composition of firms does not change across multiple samples, which illustrates that both samples are representative (see Appendix A2).

3.2. Variables

3.2.1. Dependent variable

We use two dependent variables to test our research hypotheses. Our first dependent variable is innovation sales measured as a percentage of new-to-market product and service sales in total sales (Audretsch et al., 2023; Santamaria et al., 2009), and including the UK businesses (Audretsch and Belitski, 2021a). Our second dependent variable is a binary one, and equals one if a firm has introduced new products and services to the market, or zero otherwise (Audretsch and Belitski, 2020b; Kobarg et al., 2019).

3.2.2. Explanatory variables

Our four explanatory variables measure knowledge collaboration m_i across four geographical dimensions. These are measured as 'one' if a firm reports knowledge collaboration regionally, nationally, within Europe and internationally (the rest of the world), or otherwise as 'zero' as used in prior research (Audretsch et al., 2021, 2022). In this study, regional knowledge collaboration is considered as the sourcing of knowledge for innovation with a regional partner located within a 100 mile area. National knowledge collaboration takes place within the UK geographical boundaries, which includes Wales, Scotland and Northern Ireland. Collaboration with European partners includes European Economic Area and European Union firms, and collaboration with partners internationally includes all other countries outside of the UK, European Union, and European Economic Area.

We use labour productivity as a moderator and explanatory variable. A firm's labour productivity is measured as a difference between firm sales per employee, and the industry average sales per employee (by 3 digit SIC). Industry average labour productivity is calculated using the entire BSD sample of all firms in the UK, which reports on both listed and non-listed UK firms every year during the period of analysis.

This approach is appealing for several reasons. Industry competitors are most likely to face similar conditions and experience common shocks to performance (Zeng, Ribeiro-Soriano and Ren, 2021). By comparing a firm's performance to the performances of its 3-digit SIC industry peers, it is likely to be the closest approximation of potential joint product and competitors, experience of common industry and time shocks, and therefore maintain a strong baseline of comparability.

3.2.3. Control variables

Several control variables were included. Firstly, knowledge spillover is calculated as a sum of scores (0 to 3) of how important innovation activities was participation in the conferences, trade fairs; professional and industry associations; reading technical, industry or service standards; reading scientific journals, trade/technical publications (rescaled between zero and one) drawing on the methodology of Cassiman and Veugelers (2002). While knowledge collaboration with external partners across four geographical dimensions enters into the regression as binary variables, knowledge spillover enters as a continuous variable. This is common practice in social science studies when studying open innovation (Faems et al., 2005; Cassiman and Veugelers, 2006; Audretsch et al., 2021, 2022).

Firm size is included and calculated as a logarithm of employment. We suggest that small sized firms are more flexible and innovative than larger firms (Santamaria et al., 2009). We also included a control variable for the number of enterprise units as a proxy for the firm's group size. We carried out a study to control firm age, calculated as the logarithm of the number of years since firm establishment. We included control variables as to represent a sector such as high-tech manufacturing and medium-tech manufacturing where a firm is located in order to control for a firm's knowledge intensity (Nooteboom et al., 2007). Also, we introduced other control variables for the export activity as a binary variable which equals one if firms export their products and services, or zero otherwise (Rugman and Verbeke, 2017). In addition, drawing on Cantwell and Mudambi (2011) we measured a control for foreign ownership and added a binary variable which equals one if a firm has their headquarters in a foreign country, zero if otherwise. To control for the role of risk, uncertainty, and technological development as constraints to innovation we included two variables. First, a variable "risk" if a firm has experienced constraining innovation activities such as excessive perceived economic risks from zero (no risk) to 3 –high risks. Second, a variable "technology" if a firm has experienced constraining innovation activities such as lack of information on technology from zero – not experienced to 3 –high level of shortage of technology information (Nooteboom et al., 2007). Furthermore, we used a binary variable survival if a firm survived until the last year in a sample. The human capital of a firm (Eisenhardt and Martin, 2000) was measured as the share of employees with university degrees in STEM in total full-time employment. We controlled for absorptive capacity using R&D intensity - the amount of expenditure for internal Research and Development (000 s) to total sales and digital intensity - the amount invested in purchasing advanced machinery, equipment and software to total sales (Zahra and George, 2002). Finally, we included eleven binary variables which represent the macro-region where a firm is located with the Northeast region as a reference category. Each model included controls for one year of the survey and two digit industry SIC 2007 controls as fixed effects. All variables are illustrated and explained in Table 1. Correlations between the variables demonstrated no multicollinearity issues between the variables.

3.3. Method

First stage estimation

Addressing firm's heterogeneity in knowledge collaborations is important. We know that certain types of firms (large firms with resources, internationalized, high-growth firms, etc.) tend to innovate and use open innovation more than others, and they are also the best performing firms. Furthermore, we know that there are unobserved specific characteristics fixed over time that can explain why some firms collaborate with external partners and others do not. These factors are likely to correlate with independent variables (knowledge collaboration) and are a source of endogeneity. Given a substantial cross-sectional component in both samples, instrumented regression should be applied, and knowledge collaboration variables need to be predicted. The first stage estimation concerns the decision to engage in external knowledge collaboration. Firms which answered no to knowledge collaboration, could have still undertaken a collaboration effort with external partners nationally or internationally, which is non-zero. We instrument m_i using two exclusion restrictions (exogenous variables) assuming that ϱ_1 (legal protection in the industry) and ϱ_2 (industry average level of knowledge collaboration within each geographical dimension), that do not appear in (2) and are uncorrelated with the error u_i. In the reduced form each equation is estimated in Appendix A3 as:

$$m_i = \pi_0 + \beta_i x_i + \pi_1 \varrho_1 + \pi_2 \varrho_2 + v_i \tag{1}$$

where $E(v_i) = 0$, $cov(\varrho_1, v_i) = 0$, $cov(\varrho_2, v_i) = 0$. The identification requires that $\pi_1 \neq 0$ and $\pi_2 \neq 0$ or both (Wooldridge, 2009: 523).

Using panel data element, and due to the nature of the dependent variables from the UKIS, we estimate (1) with four multivariate probit models to predict the level of knowledge collaboration ($\widehat{m_i}$). Appendix A3 includes the results of (1) estimation and post-estimation test (chi2) of a joint significance of chosen instruments. Appendix A3 (specifications 1–4), illustrates the evidence for the first condition being satisfied with the coefficients of the chosen instruments and significant and positively associated with endogenous variable m_i. Firms located in the industry with a higher level of collaboration with regional partners (β = 4.28, p < 0.001), higher level of collaboration with national partners (β = 3.22, p < 0.001), and higher level of collaboration with European partners (β = 3.24, p < 0.001), and the rest of the world (β = 3.77, p < 0.001) are more likely to decide on knowledge collaboration with external partners. Firms located with higher levels of industry protection by patents, as measured by industry level ability of patents to protect innovation (from zero to 3), will accordingly collaborate less regionally (β = -0.44, p < 0.001) and more internationally in Europe (β = 0.68, p < 0.001) as well as internationally in other countries (β = 0.55, p < 0.001).

Second stage estimation

Instrumental estimation "purges" m_i of its correlation with u_i. Tables 2-4 reports the second-stage IV Tobit (Logit) estimation with $\widehat{m_i}$ and x_i as explanatory variables. We estimate the innovation production function using a random-effects Tobit and logit models with a dependent variable y_i (innovative sales and product innovation binary variable), and four predicted variables of knowledge collaboration m_i from the first stage (regionally, nationally, in Europe and the rest of the world):

$$y_{it} = \beta_0 + \beta_i \widehat{m_{it}} + \vartheta_i x_{it} + \lambda_t + \tau_s + \psi_j + u_{it} \tag{2}$$

We are interested in β_i which is the elasticity of innovation output to knowledge collaboration $\widehat{m_{it}}$ and ϑ_i is the elasticity of innovation output to exogenous control variables x_{it} not correlated with u_{it}. Variable m_{it} is a vector of knowledge collaboration variables predicted in the first stage (1) (see Appendix A3); u_{it} is an error term;$\lambda_t and \tau_s$ are time and industry fixed effects, ψ_j represents regional fixed effects where a firm is located (Wooldridge, 2009).

4. Results

Firstly, we discuss the results of estimation (2) using the IV Tobit quartile regression (Table 2). Secondly, we discuss the results of estimation (2) using the likelihood of product innovation (Table 3).

4.1. Knowledge collaboration and innovation output

Table 2 illustrates the marginal effect of the independent variables on an increase in innovation sales, whilst keeping everything else constant. Robust standard errors are estimated for those coefficients. Regressions (1–6) in Table 2 include the direct effect of knowledge collaboration regionally, nationally and internationally for firm innovation at different levels of productivity (with 10–20 percentile interval). This is the reason why the total number of observations for all quartiles do not add up to the total number of observations in our sample one and two.

The overall predictive power of the estimated innovation in Table 2 is strong, with the Chi squares varying from 487 to 819. Our results support H1a, which states that regional knowledge collaboration increases innovation output for the least productive firms. In economic terms we find that regional knowledge collaboration increases innovation sales between 7.39 and 11.2 percentage points ($\beta_1 = 7.39$—11.2, p < 0.01) (Table 2, specifications 1–4) for the least productive firms (10th −70th percentiles). Interestingly, the positive effect disappears after the 70th percentile, which means that the most productive firms are unable to benefit from regional knowledge collaboration for innovation output, which supports H1b. Our findings extend to prior research on collaboration between firms and local partners, where firms with above-average R&D intensity were less prone to collaborate with (high-quality) local universities compared with firms with below-average R&D intensity, who chose local collaboration (Laursen et al., 2011).

Table 1
Description and summary statistics.

Variables	Description	Innovative sales sample = 21,702 obs.		Product innovation sample = 29,805 obs.		Product innovation sample for TFP = 2,475 obs.	
		Mean	St. dev	Mean	St. dev	Mean	St. dev
Productivity (all firms)	Difference between firm's laboor productivity and average laboor productivity (sales per employee) by 3 digit SIC industry using a full sample of firms from the Business registry by each year. Based on productivity variable percentile subsamples were created.	−0.47	83.19	−0.35	90.99		
Productivity (TFP)	Total factor productivity calculated using Annual business survey data on output, capital investment and material expenditure with two years lagged of the UK Innovation survey. The indicator is available for the period of 2008–2014 which was matched to the initial year period 2008–2010, 2010–2012 and 2012–2014 innovation survey data					3.05	1.39
Innovation sales	% of firm's total turnover from goods and services, that were new to the market (%)	4.18	12.70				
Product innovator	Binary variable = 1 if firm reports positive firm's turnover from goods and services that were new to the market or new to the firm, zero otherwise	0.41	0.49	0.36	0.48	0.43	0.49
Age	Age of a firm (years since the establishment), in logs	17.95	9.78	18.25	9.76	21.65	10.75
Firm size	Number of full time employees, in logarithms	4.03	1.49	4.07	1.51	5.31	1.61
High-tech manufacturing	Binary variable equal one if SIC2007 (2 digit): 21, 26, 30, 31 zero otherwise	0.01	0.06	0.01	0.07	0.01	0.09
Med-tech manufacturing	Binary variable equal one if SIC2007 (2 digit): 20, 22–25, 27–29, 32, zero otherwise	0.06	0.24	0.06	0.25	0.08	0.27
Risk	Firm has experienced constraining innovation activities such as excessive perceived economic risks (zero – not experienced, 3 – high)	1.18	1.13	1.15	1.14	1.35	1.12
Technology	Firm has experienced constraining innovation activities such as lack of information on technology(zero – not experienced, 3 – high)	0.77	0.83	0.75	0.83	0.86	0.81
Scientist	The proportion of employees that hold a degree or higher qualification in science and engineering at BA / BSc, MA / PhD, PGCE levels	7.12	16.89	7.18	17.00	7.05	15.81
Exporter	Binary variable = 1 if a firm sells its products in foreign markets, zero otherwise	0.38	0.49	0.37	0.48	0.40	0.49
Survival	Binary variable = 1 if a firm survived as an independent unit or as a part of a group until year 2017, zero otherwise	0.58	0.49	0.59	0.49	0.50	0.50
HHI	Herfindahl Index calculated using concentration in sales by 2 SIC digit industry as measure of market concentration.	0.04	0.05	0.04	0.06	0.06	0.09
Foreign	Binary variable = 1 if a firm has headquarters abroad, zero otherwise	0.45	0.50	0.42	0.49	0.54	0.49
Subsidiaries	Number of firm's foreign subsidiaries, in logarithms	1.00	0.93	1.02	0.94	1.49	1.22
Knowledge spillover	Sum of scores (0 to 3) of how important innovation activities was participation in the conferences, trade fairs; professional and industry associations; reading technical, industry or service standards; reading scientific journals, trade/technical publications (rescaled between zero and one) (Cassiman and Veugelers,2002).	0.30	0.28	0.29	0.28	0.28	0.30
Collaboration regional	Binary variable = 1 if firm co-operates on innovation regionally within enterprise group, suppliers; clients or customers; competitors; consultants, commercial labs, private R&D institutes; universities; government and public research institutes, zero otherwise	0.14	0.35	0.15	0.35	0.23	0.42
Collaboration national	Binary variable = 1 if firm co-operates on innovation nationally within enterprise group, suppliers; clients or customers; competitors; consultants, commercial labs, private R&D institutes; universities; government and public research institutes, zero otherwise	0.19	0.39	0.19	0.40	0.38	0.48
Collaboration international – Europe	Binary variable = 1 if firm co-operates on innovation in European countries (outside UK) within enterprise group, suppliers; clients or customers; competitors; consultants, commercial labs, private R&D institutes; universities; government and public research institutes, zero otherwise	0.15	0.28	0.16	0.30	0.30	0.41
Collaboration international – rest of the world	Binary variable = 1 if firm co-operates on innovation in countries outside the UK and Europe (rest of the world) within enterprise group, suppliers; clients or customers; competitors; consultants, commercial labs, private R&D institutes; universities; government and public research institutes, zero otherwise	0.12	0.32	0.12	0.32	0.25	0.43
R&D intensity	The amount of expenditure for internal Research and Development (000 s), to total sales (000 s pound sterling)	0.01	0.05	0.01	0.05	0.02	0.06
Digital intensity	The amount of expenditure for purchasing advanced machinery, equipment and software (000 s) to total sales (000 s pound sterling)	0.01	0.04	0.01	0.04	0.01	0.03
Appropriability	Sum of scores of the effectiveness of the following methods for protecting new products and processes: secrecy, complexity of goods and services, lead time advantages, patenting, design, copyright, trademarks, lead, complexity, secrecy (rescaled between zero and one).	0.09	0.15	0.07	0.21	0.04	0.09
Variables used as instruments in the first stage regression							
Collaboration regional industry	Mean of cooperation with regional partners at industry level for each year. Industry level is defined as two-digit SIC 2007.	0.11	0.06	0.12	0.06		
Collaboration national industry	Mean of cooperation with national (UK) partners at industry level for each year. Industry level is defined as two-digit SIC 2007.	0.14	0.10	0.16	0.11		
Collaboration Europe industry	Mean of cooperation with European partners at industry level for each year. Industry level is defined as two-digit SIC 2007.	0.10	0.08	0.10	0.09		
Collaboration rest of the world industry	Mean of cooperation with international (rest of the world) partners at industry level for each year. Industry level is defined as two-digit SIC 2007.	0.08	0.07	0.08	0.08		
Protection industry	How effective were patents as a method for maintaining or increasing the competitiveness of product and process innovations: patents (zero – not applicable to 3 – high protection)?.	0.35	0.82	0.30	0.75		

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.
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.
Further citation: UK Innovation Survey, 1994–2016; Business Structure Database, 1997–2017; Annual Business Survey, 2008–2014.

Table 2
Results of IV Tobit estimation by quartiles. Dependent variable: Innovation sales as % of all sales of new to market products (0–100) (N = 21,702 obs.).

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Percentile of productivity	10 %	30 %	50 %	70 %	80 %	100 %
Age	−0.50*	−0.14*	−0.28	−0.56	−0.83	−0.47
	(0.27)	(0.07)	(0.50)	(0.40)	(0.43)	(0.52)
Age squared	0.01**	0.02**	0.02	0.01	0.01	0.01
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Firm size	−2.02*(1.00)	−0.78**	−0.12**(0.05)	−0.80*	−0.93**	−0.59
		(0.34)		(0.42)	(0.40)	(0.54)
High-tech manufacturing	−15.98(15.00)	−1.97(9.82)	−6.123(17.00)	2.069(16.00)	−12.05(24.00)	8.50(14.00)
Med-tech manufacturing	0.37(8.30)	−6.04(4.30)	5.077(3.70)	0.02(3.30)	0.95(3.20)	−4.29(5.60)
Risk	−2.31(1.70)	4.01**(1.20)	1.87(1.30)	2.13*(1.00)	1.89(1.10)	3.41*(1.40)
Technology	−1.41(2.00)	0.21(1.40)	−0.72(1.40)	2.49*(1.10)	2.04(1.30)	0.37(1.60)
Scientist	0.30***	0.08	0.04	0.09*	0.17**	0.01
	(0.08)	(0.05)	(0.05)	(0.04)	(0.04)	(0.07)
Exporter	12.94***(3.02)	5.81*(2.32)	7.49**(2.43)	6.70***(1.94)	7.23***(2.04)	9.69***(2.57)
Survival	−2.13(3.10)	5.68*(2.20)	−1.37(2.30)	1.60(1.75)	1.75(1.84)	1.85(2.34)
Herfindahl Index	−28.46(17.00)	9.471(21.00)	−15.37(23.00)	−8.510(21.00)	33.02*(16.00)	26.11**(13.10)
Foreign	−5.75(3.80)	0.08(2.50)	1.23(2.50)	−4.09*(2.00)	−0.81(2.25)	−4.43(3.13)
Foreign subsidiaries	1.05(2.00)	2.65(1.80)	0.35(1.60)	1.00**(0.20)	0.87**(0.20)	1.13***(0.30)
Knowledge spillover	7.22(5.70)	8.02(4.30)	12.18**(4.60)	3.81*(2.10)	9.23*(3.70)	10.56*(4.80)
Collaboration regional predicted $\widehat{\beta_1}$ (H1/H3)	**11.25****	**5.51***	**6.04***	**7.39****	**3.82**	**4.45**
	(3.70)	**(2.55)**	**(3.00)**	**(2.35)**	**(2.42)**	**(3.10)**
Collaboration national predicted $\widehat{\beta_2}$ (H2)	**9.36***	**12.00*****	**12.42*****	**10.72*****	**13.03*****	**8.41****
	(3.70)	**(2.80)**	**(3.10)**	**(2.60)**	**(2.60)**	**(3.20)**
Collaboration international predicted – Europe $\widehat{\beta_3}$ (H1/H3)	**5.42**	**5.43**	**4.54**	**5.37****	**6.46****	**6.13****
	(3.02)	**(4.20)**	**(2.92)**	**(2.02)**	**(2.90)**	**(2.80)**
Collaboration international predicted – rest of the world $\widehat{\beta_4}$ (H1/H3)	**−5.12**	**4.58**	**3.94**	**0.37**	**0.56**	**1.84****
	(4.30)	**(3.10)**	**(3.50)**	**(2.80)**	**(2.80)**	**(0.80)**
R&D intensity	81.75***(21)	38.00**(14)	94.55***(19)	45.39**(17)	48.76**(19)	29.66(25)
Software	44.86*(22.00)	−0.829(18.00)	43.55*(21.00)	32.56(18.00)	21.26(19.00)	20.62(28.00)
Appropriability	45.95***	49.19***(8.43)	40.18***(7.62)	41.26***(5.62)	38.37***(5.82)	46.01***(7.40)
	(11.00)					
Constant	-23.72**	−44.35***	−55.21***	−52.48***	−29.37***	−47.84***
	(12.00)	(10.00)	(13.00)	(13.00)	(7.90)	(11.00)
Variance of error term	720.84**	613.84**(48.00)	708.94**(59.00)	508.71**(38.00)	562.41**	704.51**(60.00)
	(67.00)				(41.00)	
Industry, year and city-region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1133	1801	1972	2270	2201	1557
Chi2	603.58	819.50	672.93	768.44	784.12	487.88
Left-censored	861	1411	1610	1832	1751	1218
Log-likelihood	−1477.63	−2094.88	−2041.35	−2376.68	−2449.71	−1891.86
Pseudo R2	0.16	0.16	0.14	0.13	0.13	0.11

Note: reference category for legal status is Company (limited liability company), industry (mining), city-region (Newcastle). Instead of industry dummies in this estimation employment (in logs is used).
Robust standard errors are in parenthesis. The coefficients of the tobit and logit regressions are the marginal effect of the independent variable on the probability of knowledge spillover, knowledge collaboration, ceteris paribus. For dummy variables, it is the effect of a discrete change from 0 to 1.
Significance level: * $p < 0.05$; ** $p < 0.01$, *** $p < 0.001$.
Source: UK Innovation Survey, 1994–2016; Business Structure Database, 1997–2017; Annual Business Survey, 2008–2014.

Our results support H2, which states that national knowledge collaboration increases innovation output for the most and least productive firms. In economic terms, we find that national knowledge collaboration, increases innovation sales by 9.36 percentage points ($\beta_2 = 9.36$, $p < 0.01$) (Table 2, specification 1) for the least productive firms (10th percentile), as well as by 13.03 percentage points ($\beta_2 = 13.03$, $p < 0.01$) (Table 2, specification 5) for the most productive firms in 80th percentile and by 8.41 percentage points ($\beta_2 = 8.41$, $p < 0.01$) (Table 2, specification 6) in 100th percentile. The positive effect persists for the least and most productive firms when collaborating with partners nationally, adding to prior research on the role of national institutions on firm innovation in the UK (Audretsch and Belitski, 2021a).

Knowledge collaboration internationally with European partners increases innovation outputs in the most productive firms (70-100th percentile) between 5.37 and 6.46 percentage points ($\beta_3 = 5.37$–6.46, $p < 0.01$) (Table 2, specifications 4–6). International knowledge collaboration with the rest of the world increases innovation output by 1.84 percentage points($\beta_4 = 1.84$, $p < 0.01$) (Table 2, specification 6) for the most productive firms (100th percentile). Collaboration with international partners is associated with higher adjustment and transaction costs (Kobarg et al., 2019), to maintain collaborations across different institutional and cultural contexts (Boschma, 2005; Balland et al., 2015). These findings support our H3a as an increase in innovation when collaborating internationally is achievable and sustainable for the most productive firms. The coefficients of knowledge collaboration with partners in European countries and the rest of the world for the firms below 70th percentile, are insignificant in productivity. This means that firms with lower levels of productivity (<70th percentile) are unable to benefit from international knowledge collaborations therefore supporting H3b.

As we differentiate international knowledge sourcing across European partners and partners in the rest of the world, we found that returns to knowledge collaboration for Europe start at the lower levels of productivity, in the 70th percentile, whilst most productive firms can

Table 3
Results of IV logit estimation for propensity to innovate at different level of productivity. Dependent variable: Binary variable product innovation (N overall = 29,805 obs.).

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Percentile of productivity	10 %	30 %	50 %	70 %	80 %	100 %
Age	−0.21***	−0.11**	−0.01	−0.02	−0.03	−0.05
	(0.05)	(0.05	(0.02)	(0.02)	(0.02)	(0.03)
Age squared	0.01***	0.01**	−0.01	−0.01	0.01	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm size	−0.16*	−0.14*	−0.03*	−0.01*	−0.02*	0.04
	(0.08)	(0.06)	(0.01)	(0.00)	(0.00)	(0.05)
High-tech manufacturing	−0.53(3.11)	1.14	−0.52(1.11)	1.54(1.32)	1.44(1.32)	1.27(1.44)
		(0.97)				
Med-tech manufacturing	−3.32(1.9)	0.20	0.22	0.04	0.07	0.02
		(0.24)	(0.21)	(0.23)	(0.21)	(0.34)
Risk	0.63***	0.30***	0.20**	0.22**	0.25***	0.22**
	(0.16)	(0.07)	(0.07)	(0.06)	(0.07)	(0.08)
Technology	−0.36	−0.06	0.02	0.03	0.12	−0.01
	(0.19)	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)
Scientist	0.01	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Exporter	−0.52	0.45**	0.75***	0.53***	0.66***	0.63***
	(0.33)	(0.14)	(0.13)	(0.13)	(0.12)	(0.14)
Survival	0.27	0.02	0.01	0.13	−0.02	0.21
	(0.27)	(0.13)	(0.13)	(0.12)	(0.12)	(0.14)
Herfindahl Index	1.98(1.82)	0.77(1.10)	−0.82(1.30)	−2.00(1.20)	0.38*(0.17)	3.27**(1.20)
Foreign	0.16	0.07	−0.01	0.10	0.18	−0.11
	(0.35)	(0.16)	(0.14)	(0.14)	(0.14)	(0.17)
Subsidiaries	0.43*	−0.07	−0.06	−0.05	−0.06	0.05
	(0.19)	(0.11)	(0.03)	(0.03)	(0.07)	(0.07)
Knowledge spillover	**3.40*** **	**1.29*** **	**1.17*** **	**1.28*** **	**0.91*** **	**1.33*** **
	(0.56)	**(0.26)**	**(0.26)**	**(0.24)**	**(0.23)**	**(0.29)**
Collaboration regional predicted $\widehat{\beta_1}$ (H1/H3)	**0.22**	**0.36***	**0.57*** *	**0.39***	**0.60*** **	**0.29**
	(0.4)	**(0.17)**	**(0.18)**	**(0.17)**	**(0.17)**	**(0.2)**
Collaboration national predicted $\widehat{\beta_2}$ (H2)	**1.39*** *	**1.09*** **	**0.97*** **	**1.28*** **	**1.37*** **	**0.87*** **
	(0.44)	**(0.17)**	**(0.18)**	**(0.18)**	**(0.17)**	**(0.19)**
Collaboration international predicted – Europe $\widehat{\beta_3}$ (H1/H3)	**0.96**	**0.52**	**0.56**	**0.98*** *	**0.95*** *	**1.07*** *
	(0.60)	**(0.43)**	**(0.40)**	**(0.43)**	**(0.39)**	**(0.52)**
Collaboration international predicted – rest of the world $\widehat{\beta_4}$ (H1/H3)	**0.63**	**0.22**	**0.24**	**0.20**	**0.31*** *	**0.57*** *
	(0.67)	**(0.23)**	**(0.23)**	**(0.23)**	**(0.15)**	**(0.22)**
R&D intensity	25.72***(7.80)	6.90**(3.20)	5.76**(2.10)	3.40**(1.52)	1.02(0.70)	3.31(2.00)
Software	3.03(2.40)	3.55**(1.20)	3.95**(1.20)	5.21***(1.50)	2.84*(1.20)	1.92(1.80)
Appropriability	−0.12(1.20)	2.51***	1.74***	2.99***	2.75***	3.19***
		(0.57)	(0.48)	(0.43)	(0.4)	(0.49)
Industry, year and city-region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−16.85(85.24)	−2.91**	−4.24**	−1.79**	−1.85**	−2.76**
		(0.68)	(0.84)	(0.60)	(0.52)	(0.58)
Number of observations	1133	1801	1972	2270	2201	1557
Chi-square	248.32	845.10	781.36	937.47	923.61	700.29
Log-likelihood	−254.27	−943.70	−997.89	−1136.0	−1132.4	−831.27
Pseudo R2	0.32	0.30	0.28	0.29	0.28	0.29

Note: reference category for legal status is Company (limited liability company), industry (mining), city-region (Newcastle). Instead of industry dummies in this estimation employment (in logs is used).
Robust standard errors are in parenthesis. The coefficients of the tobit and logit regressions are the marginal effect of the independent variable on the probability of Incoming spillover, knowledge collaboration, ceteris paribus. For dummy variables, it is the effect of a discrete change from 0 to 1.
Significance level: * $p < 0.05$; ** $p < 0.01$, *** $p < 0.001$.
Source: UK Innovation Survey, 1994–2016; Business Structure Database, 1997–2017; Annual Business Survey, 2008–2014.

benefit from knowledge collaboration with partners outside of Europe. Our findings demonstrate that institutional and economic distance (in addition to physical distance) for knowledge collaboration, enables greater returns to knowledge collaboration at the lower levels of productivity.

The most productive firms receive higher returns from collaborating with European and international partners, whilst the least productive firms can benefit more from local knowledge collaboration. We argue that low productivity firms should avoid international knowledge collaboration, unless their level of productivity and internal capabilities are enhanced (Barney, 2001). On the contrary, highly productive firms should avoid regionalization in their knowledge collaboration.

4.2. *Other determinants of innovation output*

In this subsection, we discuss other determinants of innovation using Table 2. The marginal effects are positive and significant for knowledge spillover ($\beta = 3.8–12.8$, $p < 0.01$) (specifications 1–6, Table 2), and the value of the coefficient increases as a firm becomes more productive. Interestingly, the returns to knowledge spillovers can be compared with the results for knowledge collaboration nationally, while different origins of knowledge, both knowledge spillovers and collaboration nationally benefit least and most productive firms. In line with the knowledge spillover of innovation theory (Audretsch and Belitski, 2022), we found that an increase in labour productivity has an increasing moderation effect of knowledge spillovers on firm innovation. We controlled for firm age and size and found that the relationship between firm age and innovation output is U-shaped for firms with low

Table 4
Results of IV Logit estimation for propensity to innovate at different level of Total factor productivity. Dependent variable: Binary variable product innovation (N overall = 2,475 obs.).

Specification	(1)	(2)	(3)	(4)	(5)
Percentile of Total factor productivity	20 %	40 %	60 %	80 %	100 %
Age	−0.01*	−0.05*	−0.01	0.04	−0.02
	(0.00)	(0.02)	(0.03)	(0.04)	(0.03)
Age squared	0.01**	0.01*	−0.01	0.01	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm size	0.09	−0.22*	−0.29**	−0.11*	0.02
	(0.11)	(0.10)	(0.12)	(0.05)	(0.11)
High-tech manufacturing	−0.50	0.89	1.71	1.39	1.63
	(2.10)	(1.50)	(1.10)	(1.30)	(1.50)
Med-tech manufacturing	1.54	−0.13	−0.57	0.16	−0.14
	(1.20)	(0.15)	(0.40)	(0.37)	(0.48)
Risk	0.32**	0.27**	0.22**	0.24**	0.20
	(0.15)	(0.13)	(0.11)	(0.09)	(0.14)
Technology	−0.38	−0.16	0.39*	−0.11	0.02
	(0.20)	(0.18)	(0.18)	(0.18)	(0.20)
Scientist	−0.01	0.01	0.01	0.01	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Exporter	0.43	0.80**	0.41	0.33	0.61**
	(0.34)	(0.30)	(0.30)	(0.30)	(0.29)
Survival	−0.04	−0.18	0.38	0.28	−0.08
	(0.27)	(0.27)	(0.27)	(0.29)	(0.29)
Herfindahl Index	2.10	0.98	0.15(1.3)	0.78*	1.16**
	(1.3)	(1.6)		(0.30)	(0.45)
Foreign	−0.16	−1.07**	−0.43	0.02	−0.73
	(0.35)	(0.34)	(0.25)	(0.15)	(0.35)
Subsidiaries	−0.40*	−0.12	0.25	−0.04	−0.07
	(0.21)	(0.14)	(0.14)	(0.14)	(0.17)
Knowledge spillover	**2.01*** **	**2.32*** **	**1.77*** **	**2.72*** **	**2.47*** **
	(0.58)	**(0.56)**	**(0.53)**	**(0.53)**	**(0.54)**
Collaboration regional predicted $\widehat{\beta_1}$ (H1/H3)	**0.48**	**0.47**	**0.37**	**0.56**	**0.28**
	(0.32)	**(0.29)**	**(0.29)**	**(0.32)**	**(0.32)**
Collaboration national predicted $\widehat{\beta_2}$ (H2)	**1.52** **	**1.10*** **	**1.36*** **	**0.36** **	**1.21*** **
	(0.34)	**(0.29)**	**(0.28)**	**(0.13)**	**(0.31)**
Collaboration international predicted – Europe $\widehat{\beta_3}$ (H1/H3)	**0.31**	**0.57**	**0.63** **	**0.76** **	**0.59*** **
	(0.19)	**(0.35)**	**(0.30)**	**(0.30)**	**(0.20)**
Collaboration international predicted – rest of the world $\widehat{\beta_4}$ (H1/H3)	**0.01**	**0.07**	**0.51**	**0.97** **	**0.15** **
	(0.13)	**(0.34)**	**(0.32)**	**(0.34)**	**(0.06)**
R&D intensity	3.55	2.63	0.25	7.40*	2.62**
	(2.70)	(1.90)	(3.10)	(3.82)	(1.01)
Software	3.80	1.74	12.05***	3.24**	1.38
	(2.10)	(1.20)	(4.20)	(2.00)	(1.00)
Appropriability	7.85**	7.75***	3.84**	8.46***	13.12***
	(2.20)	(2.70)	(1.80)	(2.50)	(3.40)
Industry, year and city-region fixed effects	Yes	Yes	Yes	Yes	Yes
Constant	−16.85	−2.91**	−4.24**	−1.79**	−1.85**
	(35.93)	(0.68)	(0.84)	(0.60)	(0.52)
Number of observations	457	477	530	515	495
Chi-square	233.92	204.10	271.06	248.47	268.04
Log-likelihood	−194.72	−222.70	−225.89	−230.05	−208.29
Pseudo R2	0.37	0.31	0.37	0.35	0.39

Note: reference category for legal status is Company (limited liability company), industry (mining), city-region (Newcastle). Instead of industry dummies in this estimation employment (in logs is used).
Robust standard errors are in parenthesis. The coefficients of the tobit and logit regressions are the marginal effect of the independent variable on the probability of knowledge spillover, knowledge collaboration, ceteris paribus. For dummy variables, it is the effect of a discrete change from 0 to 1.Significance level: * p < 0.05; ** p < 0.01, *** p < 0.001.
Source: UK Innovation Survey, 2008–2014; Business Structure Database, 2008–2014; Annual Business Survey, 2008–2014.

productivity levels, while the relationship disappears after the 30th productivity percentile. Firm size is negatively associated with innovation output for firms with different levels of productivity, with the coefficient being insignificant for the most productive firms. This is a very interesting finding, as the most productive firms benefit from innovation independently on the firm size. The cost of technology and foreign ownership of a firm are not associated with innovation sales. A decrease in market competition, measured by the Herfindahl index (sales) benefits most productive firms which increase their innovation outputs (see specifications 5–6, Table 2).

There is no difference in innovation sales for firms located in high and medium-tech manufacturing firms at different levels of productivity. Although the results seem surprising, all industries are becoming technologically and digitally savvy. As well as this, product innovation does take time, which provides an essential competitive advantage to other firms in non-manufacturing industries to transform their knowledge inputs into innovation quicker.

Firms that reported excessive perceived economic risks have higher innovation output ($\beta = 2.13$–4.01, $p < 0.01$) (specifications 1–6, Table 2). Viewed from the innovation perspective this result is not so surprising. All innovators deal with higher uncertainty and risk to create new products, hence higher perception of risk and exposure to uncertainty is associated with innovative output (specifications 1 and 2, Table 2).

In economic terms, an increase in one percentage points of employees with a university degree, increases innovation sales by 0.30 percentage points ($\beta = 0.30$, $p < 0.001$) (specification 1, Table 2) for the least productive firms and by 0.17 percentage points ($\beta = 0.17$, $p < 0.001$) (specification 5, Table 2) for the most productive firms. Firms that export to Europe and the rest of the world have on average 5.81–12.94 % higher innovation sales (specifications 1–6, Table 2). Interestingly, the effect remains positive and significant for firms with low, medium and high levels of productivity, while the effect is stronger for the least productive firms (specifications 1 and 2, Table 2).

Firms with foreign subsidiaries on average have 1.00–1.13 percentage points higher innovation sales ($\beta = 1.00$–1.13, $p < 0.001$) (specifications 4–6, Table 2). The coefficient increases with firm productivity.

Firms with higher absorptive capacity measured by R&D intensity have on average higher innovation levels, whilst the effect decreases for the most productive firms ($\beta = 48.76$, $p < 0.01$) (specifications 5–6, Table 2) compared to the least productive firms ($\beta = 81.75$, $p < 0.001$) (specification 1, Table 2). Finally, the least productive firms benefit more than most productive firms from investment in software and advanced technology for innovation output ($\beta = 43.55$–44.86, $p < 0.001$) (specifications 1–3, Table 2).

4.3. *Knowledge collaboration and the propensity to innovate*

Table 3 (specifications 1–6) provides a robustness check of our previous estimation in Table 2. We estimated equation (2) with the binary dependent variable - new products and services introduced to the market. The coefficients of Table 3 cannot be interpreted directly, because we estimate logit regression with product innovation as a binary variable.

We confirmed that the least productive firms which collaborate with regional partners are more likely to innovate ($\beta_1 = 0.36$—0.60, $p < 0.01$), supporting H1a. Whereas the effect disappears after the 80th percentile (Table 3, regression 6). Most productive firms above the 80th percentile do not benefit from regional knowledge collaboration, supporting H1b. We argue that limitations related to the internalization effect of knowledge (Boschma, 2005), and low productivity, limit a firm's innovation output (Audretsch and Belitski, 2023b). In addition, we support H2 as both low and high productive firms benefit from collaboration with knowledge partners within national institutional boundaries. In economic terms, this means that national knowledge collaboration increases propensity to innovate between 0.87 and 1.39 ($\beta_2 = 0.87$–1.39, $p < 0.01$) (Table 3, specifications 1–6).

We found that the most productive firms (70th-100th percentile) that collaborate with European partners on innovation were more likely to innovate new products and services ($\beta_3 = 0.98$–1.07, $p < 0.01$) (specifications 4–6, Table 3) alongside knowledge collaboration with international partners in the rest of the world ($\beta_4 = 0.31$–0.57, $p < 0.01$) (specifications 5–6, Table 3), supporting H3a. Regressions 1–4 (Table 3) demonstrate that knowledge collaboration with partners in Europe and the rest of the world does not increase propensity to innovate for firms with low levels of productivity, which supports H3b.

4.4. Robustness check

In previous analysis (Tables 2 and 3), sales per employee was used to measure labour productivity in our analysis. This is a crude measure, specifically for capital intensive firms. These firms have few employees and thus seem highly productive, even when they are not. As part of a robustness check, we used total factor productivity as a measure of productivity and estimated (2) with the results provided in Table 4. Our dependent variable is a binary variable and equals one if a firm introduces new products and services, and zero otherwise. The data for this estimation was matched to the Innovation Survey from the Annual Business Survey and included four variables: total turnover, full time employment, value of total capital investment acquisitions and total purchases of goods, energy, materials and services. We apply log-transformation to all variables regress output (Y) on capital inputs and labour inputs following the procedure described in Van Beveren (2012). Also, we save the residual and take the exponential to calculate the total factor productivity (TFP). As there is a significant heterogeneity in TFP across sectors we have calculated the difference between the TFP of a firm, and an average TFP of a sector by 3-digit industry SIC 2007. The data from the Annual business survey is available between 2008 and 2014. Table 1 also describes the summary statistics for the reduced sample for which TFP is available and Fig. 3 produces the distribution of firms TFP in a sample of firms for which TFP data is available (2475 observations).

We follow the approach used in previous section (IV logit) to estimate (2) using TFP as an explanatory variable and a boundary condition in the relationship between knowledge collaboration and firm innovation. We split the sample of 2475 firm-year observations by the level of productivity on 20th, 40th, 60th, 80th and 100th percentile. Table 4 tests H1-H3 for the propensity of firms to innovate under different TFP levels during 2008–2014.

In this estimation, we do not find support for H1a which states that regional knowledge collaboration increases innovation output for the least productive firms, neither do we support H1b which states that regional knowledge collaboration limits innovation output for the most productive firms (specifications 1–5, Table 4). The coefficients of regional knowledge collaboration remain positive, but insignificant. Our H2a is supported as we found that firms with low and high-levels of productivity benefit from knowledge collaboration with external partners nationally. There is a slight reduction in the size of the coefficient for firms with high TFP (after 80th percentile) (specifications 1–5, Table 4), which may hint on diminishing marginal returns for knowledge collaboration for the most productive firms, furthering the discussion in Audretsch and Belitski (2022) on the role of internal R&D investment for external knowledge sourcing via spillovers, which was found to exhibit diminishing marginal return with an increase in knowledge spillover. Finally, our H3a is supported as we found that knowledge collaboration with European partners increases innovation output for the most productive firms starting from the 60th percentile between 0.59 and 0.76 ($\beta_3 = 0.59$–0.76, $p < 0.01$) and for knowledge collaboration internationally between 0.15 and 0.97 ($\beta_4 = 0.15$–0.97, $p < 0.01$) (specifications3-5, Table 4). H3b states that international knowledge collaboration limits innovation output for the least productive firms and is supported, extending our knowledge on the challenges of small firms collaboration internationally (Narula, 2004).

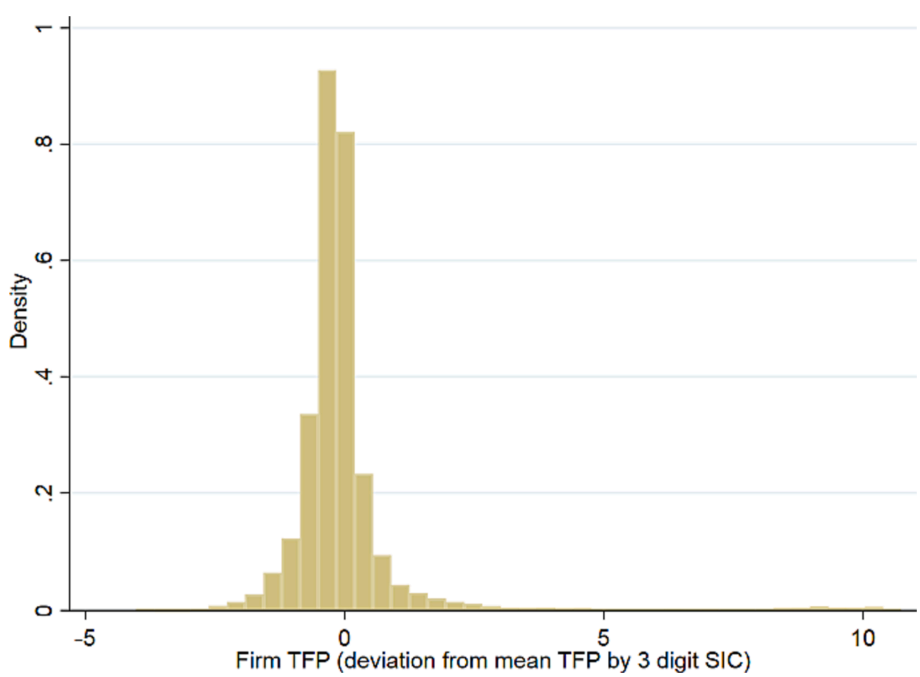

Fig. 3. Firm TFP as deviation from the industry average TFP (3 digit SIC). Source: Annual Business Survey, 2008–2014.

5. Discussion

5.1. Implications for theory

Drawing on open innovation literature (Chesbrough, 2003; Chesbrough et al., 2006; Audretsch and Belitski, 2022) and resource-based view (Penrose, 1959; Grant, 1996; Pitelis and Wahl, 1998), this study has found several novel and compelling findings. The first involves the role of geography, but also embeddedness into the institutional context in shaping social networks (Leyden and Link, 2015) and knowledge collaboration for innovation (Ascani et al., 2020). The empirical results suggest that the geographic location of the knowledge partner matters. If the firm and knowledge partner are located within national institutional boundaries, innovation can be enhanced in firms with different levels of productivity. By contrast, greater disparities across national and international borders change innovative activity. This suggests that geographic and institutional context (Audretsch et al., 2019) provides a valuable platform for the co-development of new economic knowledge, and is more inclusive for both low and high-productivity forms. Interestingly, we also find that embeddedness in a European institutional context increases returns to knowledge collaboration to a greater extent compared to collaboration with partners outside of Europe, which can be thwarted by geographic distance, national boundaries, but also the regulation and institutional context of the European Union. Thus for firms with lower productivity levels, knowledge collaboration for innovation is effective, but only with the important caveat of geographic proximity within the same regional and national borders. Just as knowledge spillovers for innovation have been found to be geographically bounded (Audretsch and Feldman, 1996; Audretsch and Belitski, 2013), so too is fruitful knowledge cooperation between firms and external knowledge partners.

The institutional context of European countries facilitates knowledge collaboration between innovative firms in the UK and in Europe, so that firms with lower levels of productivity can still benefit from knowledge collaboration. It may be that the importance of national and European institutions are requisite for the co-development of knowledge conducive to innovative firms in the UK.

This study has demonstrated the increasing role of productivity in knowledge collaboration as knowledge collaboration requires an investment in absorptive capacity and resources. Firms that are more productive are better able to engage with external collaboration partners for innovation, which supports prior research on the role of firm's resources and capabilities in knowledge collaboration depth and breadth (Kobarg et al., 2019; Belitski et al., 2023). In addition, by matching four levels of geographical proximities of knowledge collaboration – regional, national, European and other countries, this study furthers prior research on the geography of open innovation (Laursen and Salter, 2006; Terjesen and Patel, 2017) and applying it to innovation outcomes at different levels of productivity (Vedula and Kim, 2019).

Our results mirror the theoretical predictions, and provide novel insights into two important aspects. Firstly, we inform on open innovation literature that focuses on the role of knowledge partners and their geographical location (Faems et al., 2005; Balland et al., 2015; Audretsch et al., 2023), and on potential collaboration strategies which innovative firms may apply aiming to boost innovation outcomes. For example, startups which experience lack of financial resources and managerial capabilities (Helfat and Martin, 2015) may want initiate collaboration using knowledge with partners in the closer proximity, such as universities (Laursen et al., 2011), however engaging in knowledge collaboration nationally is a way forward for the least productive firms to increase the propensity and size of innovation outputs. Secondly, our finding informs on business research literature about the importance of a firm's productivity as a requisite for increasing returns to knowledge collaboration (MacGarvie, 2006; Paiva et al. 2020; Saura et al., 2023).

5.2. Implications for policy and practice

This research has important implications for practitioners and policymakers. Economists and managers in startups and multinational firms, as well as regional and international policymakers, have long observed that a firm's innovation has become increasingly dependent on the type of knowledge (explicit or implicit; industry or university, etc.), type of knowledge partner and its geographical location, firm capacity, productivity and social capital.

The concerted efforts should be taken by policy-makers to promote firms that aim to collaborate with European and international partners to increase their productivity and capabilities to be able to benefit from knowledge collaboration internationally. At the same time, managers in the least productive firms in the industry should focus on internalizing knowledge collaboration and limiting it to local partners to minimize transaction and operational costs (Laursen and Salter, 2006; Saura et al., 2023). Firms are more likely to innovate when knowledge inputs are increasingly novel and diverse, such as when a firm outreaches to knowledge partners outside of its region and internationally, for example in global entrepreneurial ecosystems (Audretsch and Belitski, 2021b; Belitski and Büyükbalci, 2021). Enhancing innovation in firms could be achieved at the lower level of productivity and investment in R&D if firms are able to combine both knowledge spillovers and collaboration with external partners, drawing on the argument of knowledge spillover of innovation where firms with low R&D investment may still benefit from an increased knowledge spillover and collaboration, in particular within the industry (Laursen et al., 2011; Audretsch and Belitski, 2022). Knowledge spillover can be used by low productive firms to increase their resource availability and innovate.

While most productive firms are able to better assimilate and absorb different sources of external knowledge (Cohen and Levinthal, 1989; Vega-Jurado et al., 2009; Saura et al., 2023), the least productive firms may require targeted policy tools to support them in increasing their productivity, before targeting international partnerships. The risk of international collaboration for the least productive firms could be wasting precious resources, whilst they are attempting to make international collaboration work for them.

6. Conclusion

The extant research on open innovation has argued that engaging in knowledge collaboration internationally is positively associated with innovation outputs for domestic firms and industries (Faems et al., 2005; MacGarvie, 2006; Cantwell and Mudambi, 2011; Driffield et al., 2014). These findings should not be taken at face value. In this study we empirically demonstrate that knowledge collaboration internationally contributes to innovation outputs only in firms with high levels of productivity, which is a requisite and a boundary condition for international knowledge collaboration. Our findings confirm the positive role that resources and capabilities of internationally networked firms play in innovation outputs via a system of firm-to-firm knowledge exchanges, social embeddedness in knowledge collaboration and ability to outreach and absorb external knowledge. This study provides a coherent theoretical framework which brings together enablers and boundary conditions of knowledge collaboration across different geographical dimensions and its direct and indirect effect on innovation in firms.

7. Limitations and future research

This study has several limitations to discuss. Firstly, the decision on knowledge collaboration and observing innovation outputs does not happen simultaneously. While we used a two-step variable approach to deal with potential endogeneity in a model, all future research will examine the willingness and ability of firms with different levels of firm productivity to collaborate domestically and internationally. Secondly, the relationship between knowledge collaboration across different geographical and institutional dimensions and innovation output is not static, and it evolves over time with the development of a country's institutional systems and the resources available to firms for knowledge collaboration. Future research will include more specific regional and national socio-economic and institutional controls and perform a multilevel analysis (firm-region-country). This will enable to better understand the decision-making by firms and the multilevel effect of a region and country on innovation outputs at each level of firm productivity.

Further research will include other measures of innovation performance, across different types of innovators, innovation strategies and policy responses (Tödtling et al., 2009; Martínez et al., 2022) and using different productivity and performance measures such as return on investment, assets, gross value added. This is important to examine to what extent firm productivity can explain different micro and macro boundary conditions related to knowledge collaboration and innovation output.

Future research could introduce a greater complexity of knowledge creation, recombination and commercialization by introducing further boundary conditions which will combine knowledge collaboration across four geographical dimensions with knowledge partner types, drawing on some recent research (Audretsch and Belitski, 2023a, 2023c). Future research might expand this. We would like to further understand the generalizability of our results, across innovator types and regions and countries with different levels of economic development (Audretsch et al., 2015). Further research will look into firms with foreign subsidiaries, and whether they are more likely than firms without foreign subsidiaries to innovate and use knowledge collaboration as a strategy of value creation and innovation (Driffield et al., 2016). This positive effect of knowledge collaboration between multinational subsidiaries is likely to be further moderated by firm productivity and managerial capabilities available across different institutional contexts. Our results are likely generalizable to innovators in other developed countries. Future research will use a broader context and cross-country analysis (Bloom & Van Reenen, 2010) to validate and consolidate our findings.

CRediT authorship contribution statement

David B. Audretsch: Conceptualization, Investigation, Resources, Supervision. **Maksim Belitski:** Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

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.

Appendix A1. Three samples sector divisions (by SIC 2007)

Sector divisions	Innovative sales sample	Share of total	Product innovator sample	Share of total
1 – Mining & Quarrying	175	0.81	205	0.69
2 - Manufacturing basic	1277	5.88	1738	5.83
3 - High-tech manufacturing	4218	19.44	5479	18.38
4 – Utility	170	0.78	228	0.76
5 – Construction	2229	10.27	2925	9.81
6 - Wholesale, retail trade	3481	16.04	4789	16.07
7 - Transport, storage	1195	5.51	1654	5.55
8 - Hotels & restaurants	1174	5.41	1572	5.27
9 – ICT	1434	6.61	1980	6.64
10 - Financial intermediation	850	3.92	1480	4.97
11 - Real estate & other business activities	2682	12.36	3844	12.90
12 - Public admin, defence	2196	10.12	3093	10.38
13 – Education	152	0.70	212	0.71
16 - Other community, social activity	469	2.16	656	2.20
Total observations	21,702	100.00	29,805	100.00

Source: UK Innovation Survey, 1994–2016; Business Structure Database, 1997–2017.

Appendix A2. Three samples regional distribution (by 10 UK regions, Scotland and Northern Ireland) and distribution over survey waves

Regions	Innovative sales sample	%	Product innovator sample	%
North East	1171	5.40	1752	5.88
North West	1997	9.20	2707	9.08
Yorkshire and Humber	1758	8.10	2455	8.24
East Midlands	1749	8.06	2364	7.93
West Midlands	1890	8.71	2549	8.55
Eastern England	1946	8.97	2708	9.09
London	2064	9.51	2898	9.72
South East	2367	10.91	3242	10.88
South West	1813	8.35	2510	8.42
Wales	1432	6.60	2000	6.71
Scotland	1700	7.83	2395	8.04
Northern Ireland	1815	8.36	2225	7.47
Total	21,702	100.00	29,805	100.00
Years				
UKIS4 (2005)	12,557	57.86	12,554	42.12

(*continued on next page*)

(*continued*)

Regions	Innovative sales sample	%	Product innovator sample	%
UKIS5 (2007)	2425	11.17	6264	21.02
UKIS6 (2009)	1454	6.70	4734	15.88
UKIS7 (2011)	2773	12.78	2853	9.57
UKIS8 (2013)	1174	5.41	1509	5.06
UKIS9 (2015)	1319	6.08	1891	6.34
Total observations	21,702	100.00	29,805	100.00

Source: UK Innovation Survey, 1994–2016; Business Structure Database, 1997–2017.

Appendix A3. First stage probit regression used for constructing the predicted values of knowledge collaboration with regional, national, European and international partners for Tables 2-4

Dependent variable	CollaborationRegional	Collaborationnational	CollaborationEurope	CollaborationRest of the world
Model	(1)	(2)	(3)	(4)
Collaboration regional industry ϱ_2 (instrument)	4.283***			
	(0.27)			
Collaboration national industry ϱ_2 (instrument)		3.220***		
		(0.14)		
Collaboration international – Europe ϱ_2 (instrument)			3.242***	
			(0.20)	
Collaboration international – rest of the world ϱ_2 (instrument)				3.779***
				(0.03)
Protection industry ϱ_1 (instrument)	−0.440*	−0.095	0.687**	0.558***
	(0.19)	(0.19)	(0.24)	(0.02)
Age	−0.012**	−0.011**	−0.006*	−0.007**
	(0.00)	(0.00)	(0.00)	(0.00)
Age squared	0.001*	0.001*	0.001*	0.002**
	(0.00)	(0.00)	(0.00)	(0.00)
Firm size	0.059***	0.155***	0.153***	0.211***
	(0.00)	(0.01)	(0.01)	(0.00)
High-tech manufacturing	−0.198	−0.187	−0.144	−0.103
	(0.14)	(0.13)	(0.14)	(0.01)
Med-tech manufacturing	−0.057	−0.038	−0.005	−0.011
	(0.04)	(0.04)	(0.07)	(0.01)
Risk	0.152***	0.192***	0.138***	0.037***
	(0.01)	(0.01)	(0.01)	(0.00)
Technology	0.135***	0.182***	0.031***	0.055***
	(0.01)	(0.01)	(0.01)	(0.00)
Scientist	0.004***	0.009***	0.014***	0.002***
	(0.00)	(0.00)	(0.00)	(0.00)
Exporter	0.179***	0.440***	0.933***	0.521***
	(0.02)	(0.02)	(0.03)	(0.00)
Scientist	0.091***	0.012	0.015**	0.007*
	(0.02)	(0.02)	(0.00)	(0.00)
Constant	−2.503***	−3.062***	−3.824***	−3.447***
	(0.07)	(0.08)	(0.11)	(0.00)
Number of observations	21,702	21,702	21,702	21,702
Industry, year and city-region fixed effects	Yes	Yes	Yes	Yes
chi2	2012.34	2896.85	2111.62	2351.62
LR test of rho = 0 (chi2)	243.67	354.67	325.15	275.35
Log-likelihood	−14905.03	−15682.77	−13495.37	−14245.37

Note: reference category for legal status is Company (limited liability company), Industry (mining), city-region (Newcastre) Robust standard errors are in parenthesis. The coefficients of the regressions (1–3) are the marginal effect of the independent variable on the knowledge collaboration rescaled variable, ceteris paribus. The coefficients of the regression (4) are the marginal effect of the independent variable on the Incoming knowledge spillover, ceteris paribus. For dummy variables, it is the effect of a discrete change from 0 to 1.

Significance level: * $p < 0.05$; ** $p < 0.01$, *** $p < 0.001$.

Source: UK Innovation Survey, 1994–2016; Business Structure Database, 1997–2017.

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David Audretsch is a Distinguished Professor and the Ameritech Chair of Economic Development at Indiana University, where he also serves as Director of the Institute for Development Strategies. He is an Honorary Professor of Industrial Economics and Entrepreneurship at the WHU-Otto Beisheim School of Management in Germanyand a Research Fellow of the Centre for Economic Policy Research in London. Audretsch's research has focused on the links between entrepreneurship, government policy, innovation, economic development, and global competitiveness. He is co-author of *The Seven Secrets of Germany*, published by Oxford University Press. He is co-founder and Editor-in-Chief of *Small Business Economics: An Entrepreneurship Journal*. He was awarded the Global Award for Entrepreneurship Research by the Swedish Entrepreneurship Forum(*Entreprenörskapsforum*). He has received honorary doctorate degrees from the University of Augsburg in Germany and Jonköping University in Sweden. Audretsch was also awarded the Schumpeter Prize from the University of Wuppertal in Germany. Audretsch has served as an advisory board member to a number of international research and policy institutes, including Chair of the *Deutsches Institut für Wirtschaftsforschung Berlin* (German Institute for Economic Analysis Berlin); Chair of the *Stifterverband für die Deutsche Wissenschaft* (Foundation for the Promotion of German Science) in Berlin, Germany; the Center for European Economic Research (*Zentrum für Europäische Wirtschaftsforschung*) in Mannheim, Germany; National Academies of Sciences, Engineering and Medicine; New York Academy of Sciences; the Swedish Entrepreneurship Forum in Stockholm, Sweden; and the Jackstädt Centre for Entrepreneurship in Wuppertal, Germany.

Maksim Belitski is a Professor in Entrepreneurship and Innovation at Henley Business School and a Research Fellow at the Institute for Development Strategies, Indiana University, US. Before joining Henley he has worked in the University of Bolzano, Italy, Bratislava, Slovakia, Vilnius University, Lithuania, Loughborough University, UK and Brunel University West London, UK. He holds a PhD in Social Sciences from the University of Leicester and University of Milan. He is teaching Innovation and market entry, Financing for Entrepreneurship, MBA in Entrepreneurship and couching start-ups and SMEs in the Thames Valley region. He is an Editor, Small Business Economics Journal, Editor, Journal of Management Development and Associate Editor, Electronic Commerce Research and Applications Journal. Maksim has worked with local UK businesses across sectors, with an emphasis on IT, finance, creative sectors and with the local borough councils to enhance university-private-public collaborations.