The limits to open innovation and its impact on innovation performance

Technovation 119 (2023) 102519

Contents lists available at ScienceDirect

Technovation

journal homepage: www.elsevier.com/locate/technovation

The limits to open innovation and its impact on innovation performance

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

[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, 12 rue Alexandre Parodi, Paris, 75010, France
[d] Alpen-Adria-Universität Klagenfurt, Austria

ARTICLE INFO

Keywords:
Knowledge sourcing
Transaction costs
Resource-based view
Regional collaboration
Global collaboration
Product innovation

ABSTRACT

This study focuses on the sectoral and geographical differences in open knowledge collaboration for the innovation performance of UK firms. Drawing on transaction cost theory and appropriability of knowledge, we adopt a resource-based view to focus on limits to open innovation. We use a generalized multi-level mixed model to test our hypotheses, controlling for time, regional and firm unobserved characteristics. Our sample includes 19,510 observations and 17,859 firms, with a small panel element of 1651 firms mainly from the UK Innovation Survey and Business Registry. Our results demonstrate that limits to open innovation differ across knowledge-intense sectors and at different geographic dimensions, with creative sectors experiencing the greatest limits to knowledge collaboration in both national and international markets. We discuss why and how this occurs, and conclude with several theoretical and policy implications.

1. Introduction

The major motivation for open innovation (Dahlander and Gann, 2010; West and Bogers, 2014, 2017; Obradovic et al., 2021) is that it improves a firm's ability to generate knowledge spillovers (Grilitches, 1979; Jaffe et al., 1993; Audretsch and Feldman, 1996; Griffith et al., 2006) and create new products internally and in collaboration with external partners (Cappelli et al., 2014; Bogers et al., 2018, 2019; Granstrand and Holgersson, 2020). In this context, we draw on West et al. (2014a,b) and Bogers et al. (2018) in defining open innovation as a concept that encompasses the novel challenges, norms and practices of innovation processes. Open innovation strategies increase the likelihood of knowledge complementarities, leading to faster and higher-quality innovation along with greater firm productivity (Hall et al., 2013 Audretsch and Belitski, 2020). It has become a "key innovation strategy" (Frenz and Ietto-Gillies, 2009; Hsieh et al., 2018; Kobarg et al., 2019) as small and large firm, start-ups and incumbents promote open collaborative activities, deepening and broadening the portfolio of activities with innovation partners (Roper et al., 2017; Audretsch et al., 2021).

While the open innovation model has demonstrated substantial benefits to both product and process innovation (Chesbrough, 2003; Chesbrough et al., 2006, 2018; Bogers et al., 2018, 2019), we still lack a clear understanding of the downsides of open innovation (Saura et al., 2022).

Underlying the theoretical positioning of this strategy is the assumption that collaboration has a positive impact on innovation (Denicolai et al., 2016; Roper et al., 2017), which in practice results in the proposition that knowledge collaboration is often an 'objective in itself' (Del Giudice and Maggioni, 2014). The downside of collaboration includes resource redeployment and relocation, along with the use of time and effort (Stadler et al., 2022), in addition to operational, technological, cognitive, cultural and regulatory barriers that limit open innovation. Knowledge collaboration may shift resources and focus away from experimentation and in-house innovation, preventing internal investment in R&D and training (Mention, 2011; Barham et al., 2020).

Scholars have acknowledged the importance of external knowledge in the form of knowledge transfer or spillovers for firm's innovation and productivity (Jaffe, 1989; Griliches, 1992; Dahlander and Gann, 2010; Bogers et al., 2018). However, relatively little empirical research has investigated the limits to open innovation across different contexts. This gap is unfortunate because several authors have argued that the limits of open innovation must be studied and discussed using the risk management perspective (Hervas-Oliver et al., 2021), resources perspective (García-Quevedo et al., 2018; Stadler et al., 2022; Saura et al., 2022), institutional perspective (Hsieh et al., 2018), organizational perspective

* Corresponding author. Henley Business School, University of Reading, Whiteknights campus, Reading, RG6 6UD, UK.
E-mail addresses: daudrets@indiana.edu (B.D. Audretsch), m.belitski@reading.ac.uk (M. Belitski).

https://doi.org/10.1016/j.technovation.2022.102519
Received 13 August 2021; Received in revised form 18 February 2022; Accepted 22 March 2022
Available online 27 March 2022

(Vanhaverbeke et al., 2017) and technology perspective (Noh and Lee, 2020).

The novelty of this study lies in the fact that, owing to the various matched micro-level datasets, and by filling the gap in the available research, we identify and discuss the boundaries of knowledge collaboration evidenced by the sectoral and geographical contexts of open innovation.

This study addresses two research questions. First, what are the limits of open innovation for knowledge-intensive and other industries? Second, what is the role of geography in limiting knowledge collaboration between innovators and external partners locally, nationally, and internationally? To answer these two questions, we aim to achieve the following objectives:

- To create knowledge about limits to open innovation by discussing theories and explaining the boundary conditions for knowledge collaboration and open innovation more broadly;
- To explore the differences between industries with different levels of knowledge in the relationship between knowledge collaboration and firm innovation;
- To outline the way partner location affects returns to knowledge collaboration for innovation and the industry context;
- To establish future directions for overcoming the limitations of open innovation research.

The next section of this study will discuss the theoretical framework and set out the research hypotheses. Section 3 discusses the data matching and sample, and outlines the econometric modelling. Section 5 reports the main findings and examines the main developments in the extent literature. Section 6 concludes with a discussion of the theoretical and practical implications, and makes suggestions for future research.

2. Theoretical framework

2.1. Collaboration and innovation performance

The concept of open innovation is central to this study (Bogers et al., 2019). As firms aim to accelerate the process and product innovation, firms require external knowledge in a form of knowledge collaboration (West and Bogers, 2014, 2017) and access to knowledge spillovers (Griliches, 1992).

Theoretically, while the mechanism of a knowledge collaboration seems clear (Roper et al., 2017), its empirical identification is rather complex (Mention, 2011; Alassaf et al., 2020). Collaboration is defined as "the process through which two or more actors engage in a constructive management of differences in order to define common problems and develop joint solutions based on provisional agreements that may coexist with disagreement and dissent" (Hartley et al., 2013: 826). Knowledge collaboration includes mutual innovation activities with shared goals and the active participation of external stakeholders, and hence represents a distinct type of open innovation (Enkel et al., 2009). Working collaboratively on innovation allows for the acquisition of additional resources and the greater avoidance of negative contingencies, and increases the likelihood of goal achievement (Audrestch and Belitski, 2020).

Knowledge collaboration may target a variety of external partners in collaboration (Frenz and Ietto-Gillies, 2009; Hsieh et al., 2018; Kobarg et al., 2019; Granstrand and Holgersson, 2020) as well as a selection of specific partners (e.g. customers, competitors, suppliers) deepening knowledge collaboration with them (Laursen and Salter, 2006).

Given the high heterogeneity of partners' knowledge (Belderbos et al., 2004) and their distinct impact on different types of innovation (incremental and radical) (Denicolai et al., 2016), the diversity of collaboration partners has been seen as an important strategy in building a portfolio of firm innovation (Van Beers and Zand, 2014).

The resource-based view (Grant, 1996; Barney, 1996) applied to open innovation could be useful in explaining the costs and benefits of collaboration. Firstly, knowledge collaboration is associated with the acquisition of knowledge that is not available within a firm (Chesbrough et al., 2006; Bogers et al., 2018). This knowledge may include but is not limited to customer preferences, technological developments and infrastructure, fundraising channels, and market needs (Belderbos et al., 2004). Knowledge collaboration expands the knowledge base of a firm available for redeployment of knowledge or knowledge transfer (Kobarg et al., 2019; Stadler et al., 2022). Secondly, from an organizational learning perspective (Argote, 2013), knowledge collaboration enables innovators to exchange experiences and competences, and to develop new procedures, routines and norms of collaboration related to the technology and market aspects, thus increasing innovation output (Almeida and Kogut, 1999; Van Beers and Zand, 2014). Finally, the resource-based view (Grant, 1996) integrated with organizational learning theory (Belderbos et al., 2004; Argote, 2013) explains how access to the resources owned by external partners can shorten and reduce uncertainty during the innovation process, in particular in high-technology contexts.

While open innovation research has long focused on its positive impacts (Chesbrough and Moedas, 2018), studies have also explored the potential negative aspects of open innovation (Knudsen and Mortensen, 2011; Chesbrough and Bogers, 2014; Kobarg et al. 2019; Saura et al. 2022), as well as beneficial and limiting effects of open innovation, with the evidence still limited at the microlevel (Salge et al., 2013).

Cost-benefit analyses of collaborations for innovation are not well developed in the organizational learning and open innovation theories. There is a widespread assumption that collaboration is a superior approach to pursuing strategic objectives (such as innovation) based on an "implicit" cost-benefit analysis; indeed, it is commonly thought that collaboration partners expect the benefits of collaboration will outweigh the costs (Tartari and Breschi, 2012). Collaborators may experience information asymmetry (they might not know all the costs and benefits related to collaboration), but they often underestimate collaboration costs (Simon, 1976). This challenges the assumption that innovation outputs can be achieved only in collaboration (Edmondson, 2016).

Open innovation scholars have only recently demonstrated that there are risks relating to a lack of internal investment in absorptive capacity (Denicolai et al., 2016; Roper et al., 2017; Barham et al., 2020). Prior research has underestimated the role of managers and their strategic approach to decision-making in supporting knowledge collaboration (Audretsch and Belitski, 2020). The strategic orientation of managers is crucial, as external knowledge needs to be integrated in form routines and innovation processes to enhance innovation (Enkel et al., 2009). Managerial decision-making as it relates to identifying and then managing the risks related to over-searching for partners and projects or going through additional legal protection of collaboration (Hall and Sena, 2017) may add to the costs associated with resource allocation (Laursen and Salter, 2006) and redeployment (Stadler et al., 2022), negatively affecting open innovation (Knudsen and Mortensen, 2011; Keijl et al., 2016). Authors distinguish between different levels of transfer and recombination of knowledge (low, intermediate, high) and determine their differential impact on innovation with the highest level of technological impact. We argue that the degree to which limits to open innovation accrue in collaborations depends on various factors, including the appropriability of knowledge, managerial decision-making and readiness, and the breadth and the depth of collaboration, to name a few (Kobarg et al., 2019).

2.2. Sector, collaboration and innovation performance

One may expect that different industries will have different limits in open innovation. Transaction cost theory of collaborative innovation can be used to explain the mechanisms behind the theorizing the limits to open innovation for firms in knowledge-intensive sectors. Transaction cost theory argues that partners incur coordination costs of monitoring, controlling and managing knowledge transfers (Camacho, 1991), and that they will seek to optimize collaboration governance (Williamson, 1981). Authorn explains that the analysis considers the comparative costs of planning, adapting, and monitoring collaboration under alternative governing structures. Transaction cost theory can be employed by assuming that the open innovation management structures have to be applied that best fit a particular knowledge transfer and transaction, and that knowledge collaboration is approximated to a set of transactions between partners.

Due to differences in absorptive capacity across industries with different levels of R&D investment (e.g. high-tech manufacturing, knowledge intense services, ICT, creative) and the different costs of knowledge creation in-house, one may expect significant heterogeneity between industries in terms of coordination ability and working together effectively (Vural et al., 2013). Differences in investment, protection and maintaining knowledge led to differences in transaction costs in the form of higher (for knowledge-intensive sectors) or lower (for low-intensity sectors) coordination and knowledge-treatment costs of open innovation. Transaction costs could be viewed within two broader categories: costs related to the nature of the innovation, and costs related to knowledge collaboration management. Autonomy, communication, and waiting costs, managerial efforts are part of the costs related to the nature of innovation. Formal and informal institutions, organizational hierarchy and firm size, productivity and geographical location are related to management collaboration costs. Both types of costs are likely to be higher in industries rich in knowledge than in industries with a paucity of knowledge, given that the value added per unit of time and by a unit of labour force (including top managers and head of innovation units) is significantly higher.

Open innovation may be limited in sectors where the cost of knowledge transfer between collaborators is high and where intellectual property protection requires additional coordination and transaction costs (Hall and Sena, 2017). Knowledge has the attributes of a public good and cannot be fully appropriated by the knowledge producer, meaning firms who invest in knowledge will bear higher costs to protect and commercialize it. Meanwhile some knowledge may still outflow to competitors and collaborators involuntarily (Cassiman and Veugelers, 2002; Chesbrough, 2003; Dahlander and Gann, 2010), creating additional risks and costs. Knowledge-intensive sectors with weak appropriability conditions may contain firms that are reluctant to invest in R&D and hence will have to invest in knowledge protection to appropriate the outcomes of R&D and technological search. This will again increase the costs of open innovation (Hall et al., 2014).

In addition, knowledge-intensive industries have higher levels of cross-sectoral collaboration (Jaffe et al. 1993), in which the innovation problems are usually complex and across many dimensions (e.g., technical, economical, and social). Complex problems have low degrees of decomposability due to a high degree of task interdependence, and will therefore require additional effort in coordination between different external partners. This is because each partner may need to understand the complexity of a problem and interdependency of the elements, as well as the role of other partners in dealing with the problem before starting to work on new solutions. This requires both more time to proceed with innovation and additional investment in absorptive capacity. More complex tasks (Alassaf et al., 2020) related to knowledge generation and recombination mean external partners and focal firms will have less autonomy in carrying out their own tasks, and coordination and management costs will increase significantly. Open innovation mechanisms will require more frequent and intensive in-depth communication with external partners, thus increasing monetary and time costs (MacMillan et al., 2004).

Open innovation demands coordination of innovation between a variety of partner types (Kobarg et al., 2019; Audretsch et al., 2021) as it may involve heterogeneous vertical (suppliers and customers) and horizontal (competitors) structures of collaboration (Van Beers and Zand, 2014). For knowledge-intensive firms who source and combine knowledge from various partner types, a multi-partner collaborations are more expensive to coordinate and monitor (Camacho, 1991). This is not the case for low-intensity firms. Firms will need cross-partner structures to be clear and well-defined in order to secure effective sourcing of knowledge between partners, leading to additional costs. Firms in low-tech sectors are less likely to establish rigid control structures over intellectual property due to the low risk of infringement, as well as the reduced ability and interest of competitors to imitate or reverse-engineer their products (Roper et al., 2017). This will reduce the degrees of formality and hierarchy (Gazley, 2010) in, for example, low-tech projects and non-profit sector services, which will reduce the transaction costs of open innovation. Due to uncertainty about the future value of knowledge, and the willingness to formally appropriate future knowledge, knowledge-intensive firms are more likely than firms in other sectors to apply formal arrangements, as formality is often associated with rigidity. This will further increase the transaction costs of collaboration (Rawley, 2010).

We therefore argue that the highest cost of collaboration will occur when sourcing knowledge from sectors that have invested heavily in R&D and possess a high concentration of knowledge workers, and where open innovation includes an increased depth and breadth of collaboration partners. External collaborators are likely to be most interested in learning from and reverse-engineering, when collaborating with firms in KIBS, high-tech manufacturing, ICT and the creative industries. The benefits of collaboration with different partner types and across different structures are higher for these four sectors. However, the risk of knowledge outflows and imitation remains high, as does the need to protect knowledge while investing in absorptive capacity, knowledge management and managerial decision-making. We thus hypothesise:

H1. Firms in knowledge-intensive sectors will have larger limits to open innovation than firms in other sectors.

2.3. Geography of collaboration

Learning from external partners and knowledge transfers remains a primary rationale for firm knowledge search strategies. Costs are incurred when acquiring and accessing relevant external knowledge, and also for the retention and management of internal knowledge. Collaborative innovation has been the core factor pushing innovators to move away from innovating internally and expanding the technological and geographical boundaries of open innovation (Chesbrough, 2003; West et al., 2014a,b). However, there remains an unresolved tension in the geography of innovation literature from the consideration of the role of localization economies vs. global networks in firm innovation (Hervas-Oliver et al., 2018; Ascani et al., 2020). With few exceptions (Cui et al., 2006), most prior research on technology transfers globally has focused on macro-economic or institutional factors as determinant of technology transfers, while micro-economic factors such as the market or cultural environment have remained unexplored. Furthermore, significant differences in appropriating knowledge internationally may be industry-specific, with knowledge intensive sectors have more to lose and less to gain from localization (McCann and Folta, 2011).

Research on the geography of knowledge collaboration has focused on the positive externalities of localization economies on firm performance (Hervas-Oliver and Albors-Garrigos, 2009, 2014; McCann and Folta, 2011). This has advanced the earlier line of research in the knowledge spillover literature (Saxeinan, 1994; Audretsch and Feldman, 1996), suggesting that knowledge is locally bounded and cannot be easily replicated in other locations (Munari et al., 2012). The most recent evidence (Hervas-Oliver et al., 2018) in the geography of innovation literature (Jaffe, 1989) also emphasizes that engagement in knowledge collaboration within a close spatial proximity increases the diffusion of tacit knowledge and knowledge spillovers. That said, criticism of localization economies and regional knowledge collaborations focuses on "the lock-in effect" of knowledge for innovation as a negative externality of localization economies (Boschma, 2005; Balland et al., 2015).

As economies gradually expand their digital infrastructure (Caputo et al., 2021; Belitski et al., 2021), the geographical boundaries of collaboration are becoming more blurred, and more global knowledge can be made available quickly via digital technologies. To further this discussion, we adopt the resource-based view of collaborative innovation (Barney, 1996) and argue that despite the international benefits of global knowledge collaborations and open innovation, geographical proximity still matters as global access to knowledge raises the cost of collaboration and required resources (Barney, 2001), limiting open innovation strategies. Consistent with the economics theory of bounded rationality (Simon, 1976), knowledge sourcing and acquisition are expensive and uncertain: firms have limited resources when looking for relevant external knowledge and selecting potential collaboration partner types. This also includes the cost-benefit analysis with size of collaboration, distance, institutional and legal idiosyncrasies and cognitive differences to be taken into account, as together they either reduce or increase collaboration cost (Nooteboom et al., 2007; Ascani et al., 2020).

Innovators may choose to collaborate locally and nationally when they have limited resources to avoid an increase in collaboration and other miscellaneous costs. Firstly, appropriation of knowledge co-created with external partners matters. This limitation can be exacerbated by the location of an external partner as it requires them to solve regulatory burdens of appropriation of knowledge co-created together. Differences in regulation and laws may prevent companies from collaborating (Balland et al., 2015). The risks increase if investors are unaware of the location of relevant knowledge (Felin and Zenger, 2014) as the cost to access and sourcing knowledge cannot be directly calculated. Secondly, if the knowledge for the innovation process resides beyond national boundaries, knowledge transfers will require permanent updates on information, skills, and ideas to effectively develop and transfer knowledge, increasing the cost of knowledge creation and diffusion. International knowledge collaboration increases the complexity of operations and reduces communication effectiveness due to cultural and cognitive distance, resulting in information asymmetries and miscommunications that will affect every aspect of open innovation (Cui et al., 2006).

Thirdly, access and assimilation of global knowledge requires further investment in internal capabilities and collaborative arrangements and trust, directly affecting the firm's cost of investment in expertise, routines, market knowledge, legal issues, organization systems and knowledge diffusion mechanisms (Denicolai et al., 2016). Interrelationships and synergies need to be created to an extent which will enable joint integration of heterogeneous knowledge that originated within different cultural and institutional contexts and that will increase costs of capacity building, as the RBV and dynamic capabilities suggest (Hervas-Oliver et al., 2021). Fourthly, new knowledge created in a different cognitive and technological context via global networks (Nooteboom et al., 2007) needs to be adapted to local specifications and regulations, and may require different testing and approvals procedures and further resources (Ascani et al., 2020). Institutional variations when collaborating internationally increase adaptation costs for products and services, as well as costs related to ongoing technical and legal support (Ahuja and Katila, 2004). These caveats to open innovation (Barney, 2001) will make it difficult for innovators with limited resources (mainly micro and small firms) to finance value creation and value capture internationally. Finally, moving to localized collaborations for innovators may reduce the cost of accessing knowledge globally and across multiple locations. This reduces the cost of knowledge searches (Kobarg et al., 2019) and shifts open innovation product development to localized economies (Hervas-Oliver et al., 2018). We hypothesise:

H2. The limits of open innovation are higher in international markets.

3. Methodology and data

3.1. Data and sample

We used three data sources taken from the Business Registry (BSD) and the UK Innovation Survey (UKIS) within six waves during the period 2002–2014. The UKIS data covers six consecutive periods (2002–04, 2004–06, 2006–08, 2008–10, 2010–12 and 2012–14), while the BSD was matched to the respective years for the periods 2002, 2004, 2006, 2008, 2010 and 2012 respectively. The BSD offers data on the business accounting, employment, firm status, industry and firm location, while the UKIS provides innovation data. The most valuable information was related to innovation inputs and outputs, as well as different types of innovations, barriers to innovation and knowledge collaboration breadth and depth (Van Beers and Zand, 2014; Denicolai et al., 2016).

After cleaning for the missing values in our variables of interest and product innovation, we were left with 17,859 available firms and 19,510 observations during 2002–2014. All non-applicable answers and missing values were not included and w did not substitute missing values to zeroes. The list of variables used in this study is provided in Table 1, while the industry, size and regional distribution can be seen in Tables 2A–2C. Our sample includes sixteen aggregated industries. The left sides of Tables 2A–2C demonstrate the distribution of firms in the estimated sample,[1] while the right sides illustrate the distribution of firms by industry, region and size. The distribution remains stable during 2002–2014, demonstrating the generalizability of our results across various samples. The correlation between variables is included in Table 3.

3.2. Dependent and explanatory variables

We measure innovation output as a percentage of product sales which were new to market (Santamaría et al., 2009; Laursen and Salter, 2006). Our explanatory variables are "UK regional", "UK national", "Europe" and "Other countries" which reflect knowledge collaboration with at least one external collaboration partner (e.g. enterprise group, suppliers, clients or customers, competitors, consultants, commercial labs, universities, government) and across four geographical markets (Frenz and Ietto-Gillies, 2009; Kobarg et al., 2019). Interestingly, while 16.7 percent of firms collaborate regionally and 21.7 percent collaborate on innovation nationally, only 10.6 percent collaborate with European partners and 9.2 percent collaborate on innovation with partners outside Europe (other world.) Collaboration across multiple geographical markets for one firm is possible (Boschma and Frenken, 2010; Cappelli et al., 2014). We include four binary variables which represent industries where firms operate and are used to test our H1 and H2: ICT, high-tech manufacturing, KIBS and the creative industry. Table 4 presents the geographical distribution of knowledge collaboration or non-collaboration between four of the most innovative UK industries.

3.3. Econometric modelling

A modification of a multilevel generalized linear approach which is a multi-level (mixed-effect) logistic model was used to test our research hypothesis. This approach was chosen based on the multi-level structure of the UKIS across industry, region and wave. There are several issues with the sample which also guided us to use the multilevel generalized linear approach. First, each wave of the UKIS is a stratified sample, and

[1] Table 2A illustrates a significant decrease in a sample size in the UKIS 8 (2010–12) and UKIS 9 (2012–14) survey rounds which is explained of missing values in our dependent variables as a result of financial crises. We deal with it later using correction for selection bias Heckman procedure. We evidence a significant increase in non-reporting on questions of product and process innovation starting from UKIS 8 and UKIS 9 as compared to previous years.

Table 1
Descriptive statistics.

Label		Survey question		Mean	Std. Dev.
				Product innovation sample 19,510 obs.	
Product innovation (DV1)		% of firm's total turnover from goods and services that were new to the market (%), radical product innovation		0.048	0.136
Independent variables: Collaboration (UKIS)	*UK Regional*	Binary variable equal one if business collaborates on any innovation activities with at least one of the following partners within specific geographical boundaries: businesses within enterprise group, suppliers, clients or customers, competitors, consultants, commercial labs, universities, government	Regionally	0.167	0.37
	UK National		Nationally	0.217	0.41
	European Countries		Europe	0.106	0.30
	Other Countries		World	0.092	0.28
Sectors (BSD)	*High-tech Manufacturing*	Binary variable equal one if firms belongs to one of the following SIC 2007 (2 digit): 19–22, 26–27, 29, 32, 33.20, zero otherwise		0.112	0.31
	ICT	Binary variable equal one if firms belongs to one of the following SIC 2007 (2 digit): 58–63, zero otherwise		0.072	0.25
	KIBS	Binary variable equal one if firms belongs to one of knowledge intensive business services sectors SIC 2007 (2 digit): 64–66, 69–71, 74.20, 74.30 and 74.90, zero otherwise		0.104	0.30
	Creative	Binary variable equal one if firms belongs to one of SIC2007 (2 digit): 70.21, 71.11, 71.20, 73.11, 73.12, 74.10, 74.20, 85, zero otherwise		0.043	0.20
Firm size (BSD)	*small*	Binary variable equal one if number of FTEs is $<$ 50, zero otherwise		0.447	0.49
	medium	Binary variable equal one if number of FTEs is between 50 and 249, zero otherwise		0.277	0.44
	large	Binary variable equal one if number of FTEs is $\geq$ 250, zero otherwise		0.275	0.44
Technological intensity (UKIS)	*Manufacturing High-tech*	Binary variable equal one if SIC2007 (2 digit): 21, 26, 30, zero otherwise		0.004	0.07
	Manufacturing Med-tech	Binary variable equal one if SIC2007 (2 digit): 20, 22–25, 27–29, 32, zero otherwise		0.063	0.24
	Manufacturing Low-tech	Binary variable equal one if SIC2007 (2 digit): 10–19, 33, zero otherwise		0.082	0.27
	High/Med-tech services	Binary variable equal one if SIC2007 (2 digit): 59, 60–62, 72, zero otherwise		0.068	0.25
	Low-tech services	Binary variable equal one if SIC2007 (2 digit): 35, 38, 41–43, 49–56, zero otherwise		0.781	0.41
Exploration (UKIS)	*New product*	Binary variable equals one if a firm states the importance of increasing range of goods or services is high to innovate, zero otherwise		0.408	0.49
	New Market	Binary variable equals one if a firm states the importance of increasing market share is high to innovate, zero otherwise		0.166	0.37
Constraining factor (UKIS)	*Cost*	Binary variable equals one if firm states the factors has severely constrained innovation:	excessive perceived economic risks, direct innovation costs too high, cost and availability of finance, zero otherwise	0.331	0.47
	Knowledge		lack of qualified personnel, lack of information on markets, lack of information on technology and markets, zero otherwise	0.137	0.34
	Others		market dominated by established businesses, uncertain demand for innovative goods or services, zero otherwise	0.173	0.37
Ownership Status (BSD)	*Company*	Binary variable = 1 if firm's legal status is limited liability company, 0 otherwise		0.844	0.36
	Sole proprietor	Binary variable = 1 if firm's legal status is Sole-proprietor, 0 otherwise		0.041	0.20
	Partnership	Binary variable = 1 if firm's legal status is partnership, 0 otherwise		0.099	0.29
	Public corporation	Binary variable = 1 if firm's legal status is *Public corporation*, 0 otherwise		0.001	0.03
	Non-for-profit body	Binary variable = 1 if firm's legal status is *Non for profit*, 0 otherwise		0.013	0.11
R&D intensity (BERD and UKIS)		Internal Research and Development expenditure (£) to total sales (£) ratio		0.013	0.05
Foreign (BSD)		Binary variable = 1 if a firm has a headquarter in a foreign country, zero otherwise		0.467	0.49
Scientist, % of FTE (UKIS/BERD)		The proportion of employees that hold a degree or higher qualification in science and engineering at BA/BSc, MA/PhD, PGCE levels		7.673	17.52
Exporter (UKIS)		Binary variable = 1 if a firm sells its products in foreign markets, 0 otherwise		0.396	0.48
Part of a group (BSD)		Binary variable = 1 if a firm is a part of an enterprise group, 0 otherwise		0.149	0.35
Age of firm (BSD)		Age of a firm (years since the establishment)		17.40	9.82

Source ONS: BSD - Business Register (2002–2014); UKIS – UK Innovation Survey (2002–2014); Number of observations 19,510 except of process innovation variables which is 23,070 obs.

although there is a panel element across each of the six waves, several firms only appear in one wave. The panel element in a sample, if any, is treated using a multilevel estimation approach. This model specification has its origin in Papke and Wooldridge (2008).

Second, while this is not a hierarchical model, it is often referred to as a mixed-effect model, and the data structure in the population is viewed as a multi-stage estimation (Goldstein, 2003). Consequently, firms are nested in a three-level model that relates to the innovation output (Luke, 2004).

Third, the macro-level containing the six waves of the BSD-UKIS dataset 128 borough locations were identified and used in the estimation. Our dependent variable is innovation performance distributed between zero and 100 percent of innovation sales [0,100].

We estimate the following model (1) with the dependent variable y_{ijk} and the independent variable x_{ijk} such that:

$$g\left[E\left(y_{ijk}\right)\right] = \beta_0 + \beta_1 x_{ijk} + \beta_2 \tau_{ijk} + \varepsilon_{ijk} \quad (1)$$

where i is the firm level-1, j is the region level-2 and k serves to index the wave survey level-3. y_{ijk} relates to innovation output and x_{ijk} relates to the vector of knowledge collaboration, our independent variables. Our control variables τ_{ijk} related to innovation output and driven by the prior

Table 2A
Sample split by industrial divisions (by SIC 2007).

Description	Sample of the regressions (DV: Product innovation)							Population sample original: (DV: Product innovation)						
	2005	2007	2009	2011	2013	2015	Total	2005	2007	2009	2011	2013	2015	Total
1 - Mining & Quarrying	144	<10	11	<10	<10	<10		159	13	16	46	<10	<10	
2 - Manufacturing basic	815	141	92	102	21	14		883	341	148	460	136	135	
3 - High-tech manufacturing	2600	491	424	265	66	66		2803	1038	591	1235	397	363	
4 - Electricity, gas and water supply	93	<10	16	26	<10	<10		107	46	26	112	22	18	
5 - Construction	1617	91	74	124	<10	<10		1871	372	124	747	62	47	
6 - Wholesale, retail trade	2417	138	130	279	39	58		2770	588	269	1507	205	408	
7 - Transport, storage	918	36	31	53	<10	<10		1079	264	78	359	44	38	
8 - Hotels & restaurants	794	29	46	120	17	<10		991	197	93	595	56	39	
9 - ICT	898	169	196	86	28	44		994	452	279	352	131	138	
10 - Financial intermediation	578	39	49	28	<10	<10		673	176	74	190	33	44	
11 - Real estate & business activities	1701	169	199	262	63	86		1916	600	307	1179	245	285	
12 – Admin and support services, defence	1519	84	98	185	18	15		1737	459	168	779	80	81	
13 - Education	61	<10	11	<10	<10	<10		71	31	13	<10	<10	<10	
16 - Other community, social activities	355	53	47	<10	<10	<10		389	118	65	<10	<10	<10	
Total							19,510							33,969

Note: The totals of rows, which could be used to calculate the number of enterprises in cells (<10) across sectors were suppressed for disclosure control.

Table 2B
Sample split by twelve UK regions.

Description	Sample of the regressions (DV: Product innovation)							Population sample original: (DV: Product innovation)						
	2005	2007	2009	2011	2013	2015	Total	2005	2007	2009	2011	2013	2015	Total
North East	830	93	85	61	<20	17		950	298	135	262	61	76	
North West	1341	129	117	174	32	23		1498	380	198	767	139	130	
Yorkshire and The Humber	1179	110	133	126	<20	17		1348	363	203	640	116	125	
East Midlands	1178	145	121	121	<20	23		1329	397	189	570	112	128	
West Midlands	1285	146	122	143	21	19		1456	409	207	650	114	138	
Eastern	1252	143	128	159	25	34		1419	421	176	750	132	152	
London	1401	104	111	170	36	32		1615	495	196	1006	205	183	
South East	1543	162	157	203	48	45		1738	465	248	1084	228	226	
South West	1196	127	141	128	27	18		1361	380	213	637	139	107	
Wales	975	106	97	74	<20	19		1100	338	155	344	51	97	
Scotland	1115	116	122	104	<20	38		1270	360	176	583	78	167	
Northern Ireland	1215	84	90	73	<20	22		1359	389	155	268	40	75	
Total							19,510							33,969

Table 2C
Sample split by firm size (Micro and Small, Medium and Large).

Description	Sample of the regressions (DV: Product innovation)							Population sample original: (DV: Product innovation)						
	2005	2007	2009	2011	2013	2015	Total	2005	2007	2009	2011	2013	2015	Total
Micro and Small 1-49	6380	513	558	912	184	178		6970	1934	838	2166	356	389	
Medium 50-249	4098	362	389	404	61	105		4408	1034	579	1016	117	174	
Large >249	4032	590	477	220	23	24		4324	1452	779	524	58	46	
Total							19,510							27,164

innovation research are in Table 1 (Laursen and Salter, 2006; Santamaria et al., 2009; Van Beers and Zand, 2014). The error term is ε_{ijk} and is calculated as:

$$\varepsilon_{ijk} = \gamma_i + \mu_{j.} + t_{k.} + \nu_{ijk} \tag{2}$$

where γ_i is related to the omitted variables that vary across firms but not over regions and waves, $\mu_{ij.}$ relates to the omitted variables that vary over regions but are constant across firms and time, $t_{k.}$ relates to the omitted variables which vary across waves but not across firms and regions, while finally ν_{ijk} is the error term. Additionally, a multilevel model enables us to control for the effect by which a region in each survey wave shapes firm innovation performance. It also demonstrates that firm performance is not independent from the influences of time and regional characteristics.

Furthermore, when estimating equation (1), it was necessary to control for a sample selection bias by carrying out a two-stage Heckman approach. Stage one of the analysis, also known as selection equation identified, using a probit regression, all observations for which the innovation output was observed in the original sample, those that implement intellectual property rights (IPR) protection measures (Table 5). This bias originates due to the firm's willingness to report a share an information on collaboration with external partners in the reduced UKIS sample. This response and collaboration per se may be conditional on applying various IPR protection mechanisms while knowledge transfer. Observations knowledge collaboration can be affected for those observations that adopt the IPR protection measures.

$$\text{Selection step: } \Pr\left(D = 1 \middle| z_{ijk}\right) = \Phi\ (\alpha' z\ ) \tag{3}$$

where D indicates that the firm adopts IPR protection measures (D = 1 if $p_{ijk} > 0$ and D = 0 otherwise), where p_{ijk} is a dependent variable measures the degree of IPR protection, α is a vector of unknown parameters,

Table 3
Correlation matrix.

Variables …		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Product innovation	1														
2	UK Regional	0.14*	1													
3	UK National	0.22*	0.39*	1												
4	European Countries	0.21*	0.34*	0.57*	1											
5	Other Countries	0.20*	0.26*	0.43*	0.58*	1										
6	New product	0.24*	0.15*	0.24*	0.18*	0.16*	1									
7	New market	0.05*	0.10*	0.11*	0.08*	0.06*	0.20*	1								
8	Cost	0.13*	0.14*	0.17*	0.12*	0.11*	0.22*	0.12*	1							
9	Knowledge	0.09*	0.09*	0.11*	0.06*	0.06*	0.15*	0.07*	0.32*	1						
10	Others	0.07*	0.09*	0.10*	0.07*	0.06*	0.14*	0.07*	0.36*	0.36*	1					
11	R&D intensity	0.36*	0.10*	0.21*	0.22*	0.26*	0.16*	−0.01*	0.12*	0.08*	0.07*	1				
12	Foreign	0.06*	0.09*	0.06*	0.09*	0.07*	0.01	0.01	−0.07*	−0.08*	−0.04*	−0.03*	1			
13	Scientist	0.28*	0.09*	0.22*	0.23*	0.26*	0.15*	0.00	0.12*	0.08*	0.08*	0.42*	0.02*	1		
14	Exporter	0.17*	0.06*	0.21*	0.28*	0.25*	0.23*	0.03*	0.10*	0.04*	0.08*	0.18*	0.18*	0.25*	1	
15	Part of a group	0.19*	0.50*	0.63*	0.47*	0.45*	0.20*	0.10*	0.14*	0.09*	0.08*	0.14*	0.07*	0.16*	0.16*	1
16	Age	−0.11*	0.03*	0.01*	0.03*	0.00	0.05*	0.03*	−0.03*	0.04*	−0.01*	−0.11*	0.23*	−0.10*	0.09*	0.01*

Note: * significant at 5% significance level. Source ONS: matched Business Register (2002–2014) and UK Innovation Survey (2002–2014). Number of observations 19,510.

Table 4
Knowledge collaboration across four geographical dimensions across four major UK sectors (N = 19,510).

Number of firm in the sample															
Regional															
High Tech	*Collaboration*		Total	ICT	*Collaboration*		Total	KIBS	*Collaboration*			Creative	*Collaboration*		
	No	Yes			No	Yes			No	Yes			No	Yes	
No	83.6%	16.4%	**17305**	No	83.5%	16.5%	**18089**	No	83.3%	16.7%	**17463**	No	83.7%	16.3%	**18654**
Yes	80.3%	19.7%	**2205**	Yes	80.5%	19.5%	**1421**	Yes	83.1%	16.9%	**2047**	Yes	72.7%	27.3%	**856**
Total	**17422**	**2088**	**19510**	Total	**17422**	**2088**	**19510**	Total	**17422**	**2088**	**19510**	Total	**17422**	**2088**	**19510**
Nation															
High Tech	*Collaboration*		Total	**ICT**	*Collaboration*		Total	**KIBS**	*Collaboration*			**Creative**	*Collaboration*		
	No	Yes			No	Yes			No	Yes			No	Yes	
No	79.2%	20.8%	**17305**	No	79.2%	20.8%	**18089**	No	78.4%	21.6%	**17463**	No	79.1%	20.9%	**18654**
Yes	70.7%	29.3%	**2205**	Yes	66.5%	33.5%	**1421**	Yes	76.6%	23.4%	**2047**	Yes	59.3%	40.7%	**856**
Total	**17422**	**2088**	**19510**	Total	**17422**	**2088**	**19510**	Total	**17422**	**2088**	**19510**	Total	**17422**	**2088**	**19510**
Europe															
High Tech	*Collaboration*		Total	**ICT**	*Collaboration*		Total	**KIBS**	*Collaboration*			**Creative**	*Collaboration*		
	No	Yes			No	Yes			No	Yes			No	Yes	
No	90.3%	9.7%	**17305**	No	89.7%	10.3%	**18089**	No	89.0%	11.0%	**17463**	No	90.0%	10.0%	**18654**
Yes	81.1%	18.9%	**2205**	Yes	84.8%	15.2%	**1421**	Yes	92.0%	8.0%	**2047**	Yes	73.9%	26.1%	**856**
Total	**17422**	**2088**	**19510**	Total	**17422**	**2088**	**19510**	Total	**17422**	**2088**	**19510**	Total	**17422**	**2088**	**19510**
Europe															
High Tech	*Collaboration*		Total	**ICT**	*Collaboration*		Total	**KIBS**	*Collaboration*			**Creative**	*Collaboration*		
	No	Yes			No	Yes			No	Yes			No	Yes	
No	91.9%	8.1%	17305	No	91.4%	8.6%	**18089**	No	90.7%	9.3%	**17463**	No	91.4%	8.6%	**18654**
Yes	82.1%	17.9%	2205	Yes	82.4%	17.6%	**1421**	Yes	91.8%	8.2%	**2047**	Yes	76.7%	23.3%	**856**
Total	**17711**	**1799**	**19510**	Total	**17711**	**1799**	**19510**	Total	**17711**	**1799**	**19510**	Total	**17711**	**1799**	**19510**

and Φ is the cumulative distribution function. A vector containing the independent and control variables is z.

The first stage follows the generalized Heckman approach as developed by Greene (2003), and we compute the inverse Mills ratio (λ_{ijk}) by predicting the likelihood of innovation to appear in both the reduced and the original samples. The selection bias was corrected by including Mills ratio in the final equation (4). We can now re-write equation (1) as follows:

$$g\left[E\left(y_{ijk}\right)\middle|x_{ijk},\ D=1\right] = \beta_0 + \beta_1 x_{ijk} + \beta_2 \tau_{ijk} + \rho\sigma_\varepsilon\lambda_{ijk} + \left(\gamma_{i..} + \mu_{j.} + t_{k.} + \nu_{ijk}\right) \tag{4}$$

where ρ is the correlation between unobserved determinants of propensity to apply Mills ratio and the observed error term ε_{ijk}, and σ_ε is the standard deviation of ε_{ijk}. The presence of a selection bias was observed if the Mills ratio coefficient in equation (4) was significant.

4. Results and discussion

4.1. Sector, collaboration and innovation performance

We used a generalized linear mixed model to test our hypotheses, with the major results presented in Table 6. It is important to mention

Table 5
Random-effects probit estimates (N = 67, 162 obs) (First stage).

Two-step Heckman approach – stage 1		Protection (D = 1)		
		Coef.	SE	
Age of firm	*Age, log*	−0.005	0.001	***
Employment, in logs	*Employment, log*	0.238	0.011	***
Scientist, % of employments	*Scientist*	0.016	0.001	***
R&D intensity to sales	*RD internal*	4.439	0.300	***
Context for Innovation				
Increasing range of goods or services .	*New product*	0.331	0.016	***
Increasing market share	*New market*	0.241	0.016	***
Constant		−2.968	0.196	***
sigma u		1.024	0.050	
rho		0.512	0.024	
Sectoral dummies		Yes		
Regional dummies		Yes		
Likelihood ratio test Wald chi2		1353.85		

Note: ***,** and * Significance at the 1%, 5% and 10% levels, respectively.

that the method used and logistic transformation of our dependent variable in Table 6 means that the product innovation variable was rescaled between zero and one.

The results are reported in Table 6 and illustrate the direct effect of knowledge collaboration regionally (Model 1), nationally (Model 2), Europe (Model 3) and in other countries internationally (Model 4) on firm's innovation sales across four knowledge intensive industries (with other sectors as a reference category). We interpret our hypotheses based on the sign and significance of the interaction coefficient for each sector and knowledge collaboration across four geographical dimensions. Although the benefits from external knowledge collaboration are different across four sectors, the direct effect of regional, national and European and international knowledge collaboration on innovation is consistently positive and significant. The size of the UK national collaboration coefficients is greater than for regional and international collaboration and varies between 0.14 and 0.16 ($\beta = 0.144$–0.159, $p < 0.05$) (Models 1–4, Table 6), which means that firms that collaborate on innovation with national partners have on average a 14.4–15.9% higher share of products that are new to the market in sales.

This finding provides further support to Boschma and Frenken (2010) on the role of optimal proximities of knowledge collaboration. This becomes important when there is a variety of knowledge outside the region, but national cultural distance enables collaborators to avoid institutional and cognitive barriers associated with international collaboration, expanding the argument of international knowledge transfer caveats (Cui et al., 2006). This finding is intriguing, as it demonstrates that sourcing knowledge from within national boundaries is optimal for firms in knowledge-intensive sectors. These findings also contrast with earlier studies which found that knowledge collaboration and transfer is most efficient in the immediate proximity of collaborators (Saxenian, 1994; Audretsch and Feldman, 1996).

There are no additional benefits or costs for firms in high-tech manufacturing, ICT and KIBS from external knowledge collaboration regionally (Model 1) nationally (Model 2) and internationally (Models 3–4, Table 6) compared to firms in olow-intensity sectors. . Our H1 which states that firms in the knowledge-intensive sectors will have larger limits to open innovation than firms in other sectors is not supported. If H1 is true, then one would expect negative values of the interaction coefficients for high-tech manufacturing, creative, ICT and KIBS sectors. This finding contrasts with the widespread assumption that collaboration is a superior way to pursue strategic objectives (such as innovation) and that knowledge-intense firms achieve greater benefits from knowledge collaboration than firms with low capabilities and absorptive capacity (Nooteboom et al., 2007). In fact, we found that the benefits of collaboration are likely to outweigh the costs (Tartari and Breschi, 2012), and that this holds true for knowledge collaborators across all geographical proximities and for firms in KIBS, high-tech manufacturing and ICT as well as other sectors (Edmondson, 2016). Our results demonstrate that the benefits of open innovation may be achieved across different sectors (Van Beers and Zand, 2014) and that sectors with a paucity of knowledge also rely on knowledge collaboration in creating their new products (Roper et al., 2017; Kobarg et al., 2019). This finding also supports the argument that knowledge collaboration as a form of open innovation is not the set of complex processes and challenges, supporting Mention (2011) and what was described in Alassaf et al. (2020), Saura et al. (2022) as negative externalities of collaboration. Our findings also extend the work of Fischer et al. (2021) who argued that networks can serve as a relevant source of knowledge creation and we showed they are able to drive change in organizations with different focuses on investment in knowledge. As Chesbrough and Bogers (2014) argued, we find that knowledge collaboration is becoming more and more accessible to all firms, and this is how these firms may rip the benefits of open innovation along with other more specialised or knowledge-intensive firms.

Interestingly, the findings in Table 6 (Models 2–4) support H1 for the creative sector. The size of the interaction coefficient with a binary variable of creative industry varies between the minimum for national collaboration partners −0.13 ($\beta = -0.13$, $p < 0.05$) (Model 2, Table 6) to a maximum of −0.21 ($\beta = -0.21$, $p < 0.05$) (Model 4, Table 6) for collaboration with international partners. This result means that firms in creative sectors who collaborate on knowledge with external partners nationally and internationally have a 13–21 percent average lower share of innovative products in sales compared to other industries. The results demonstrate the challenges of appropriability of knowledge in the creative industries, extending the sectoral specificities of formal and informal mechanisms of knowledge protection, and extend the earlier works of Hall et al. (2014); Hall and Sena (2017) and Bogers et al. (2017, 2019). Creative industry firms are less able to retain intellectual property rights on investment in knowledge than other sector firms, and thus are less able to prevent knowledge outflows in other sectors (Cassiman and Veugelers, 2002). Knowledge is harder to protect in the creative industries (Shipilov et al., 2017).

4.2. *Geography of collaboration*

Our H2 states that the limits of open innovation are higher in international markets, and is not supported for ICT, KIBS and high-tech manufacturing. This because i) these sectors are not more or less likely to achieve innovation output if they engage in open collaboration compared to other sectors; and ii) the significance of the interaction coefficients does not change across four geographical proximities. This demonstrates that the ICT, KIBS and high-tech manufacturing sectors are not more or less likely to experience limits to open innovation than any other sectors. While the interaction coefficients of the creative industries and knowledge collaboration across three geographical dimensions are significant, the confidence intervals and standard errors overlap which demonstrates that limits to open innovation are not higher in international markets than nationally. Interestingly, in regional markets the interaction coefficient is insignificant (Model 1, Table 6), while it is negative for Models 1–3 (Table 6). This demonstrates that the limits to open innovation for firms in the creative industries are higher outside of a region where the firm is located and internationally. This is an unexpected finding which supports the knowledge spillovers literature that advocates the importance of spatial proximity in tacit knowledge diffusion (Audretsch and Feldman, 1996; Audretsch et al., 2015) and as a way to benefit from localized externalities (Hervas-Oliver and Albors-Garrigos, 2014; Hervas-Oliver et al., 2018). Limits to open innovation are associated with two boundary conditions: the geography of knowledge collaboration, and the industry. This finding extends prior research on differences in returns to investment in R&D across industries (Hall et al., 2013) and the role of intra- and inter-industry collaboration

Table 6
Generalized linear mixed model: innovation performance and knowledge collaboration (second stage).

..	Model 1			Model 2			Model 3			Model 4		
	Coef.	SE	p-value	Coef.	SE	p-value	Coef.	SE	p-value	Coef.	SE	p-value
Sectors												
High-tech manufacturing	−0.112	0.067	*	−0.125	0.071	*	−0.102	0.060	*	−0.137	0.067	**
ICT	0.298	0.083	***	0.306	0.087	***	0.320	0.081	***	0.331	0.081	***
KIBS	−0.203	0.080	**	−0.142	0.083	*	−0.160	0.077	**	−0.194	0.077	**
Creative	−0.259	0.148		−0.057	0.124		−0.153	0.114		−0.130	0.112	
Other	reference			reference			reference			reference		
Collaboration												
UK Regional	***0.052***	***0.023***	**	***0.065***	***0.020***	***	***0.065***	***0.020***	***	***0.063***	***0.020***	***
× *High-tech*	0.004	0.059										
× *ICT*	0.075	0.077										
× *KIBS*	0.044	0.054										
× *Creative*	0.025	0.068										
× *Other*	reference											
UK National	***0.144***	***0.019***	***	***0.159***	***0.022***	***	***0.145***	***0.019***	***	***0.144***	***0.019***	***
× *High-tech*				0.019	0.042							
× *ICT*				0.018	0.055							
× *KIBS*				−0.046	0.047							
× *Creative*				−0.137	0.049	***						
× *Other*				reference								
European Countries	***0.019***	***0.033***		***0.025***	***0.033***		***0.055***	***0.041***		***0.028***	***0.033***	
× *High-tech*							−0.033	0.069				
× *ICT*							0.010	0.098				
× *KIBS*							−0.080	0.087				
× *Creative*							−0.163	0.076	**			
× *Other*							reference					
Other Countries	***0.016***	***0.004***	*	***0.019***	***0.000***	**	***0.026***	***0.004***	**	***0.032***	***0.007***	**
× *High-tech*										0.075	0.075	
× *ICT*										−0.040	0.086	
× *KIBS*										0.053	0.089	
× *Creative*										−0.211	0.081	***
× *Other*										reference		
Firm size												
Small	reference			reference			reference			reference		
Medium	−0.375	0.055	***	−0.374	0.055	***	−0.372	0.055	***	−0.371	0.055	***
Large	−0.704	0.066	***	−0.706	0.066	***	−0.704	0.066	***	−0.707	0.066	***
Exploration												
New products	0.596	0.046	***	0.594	0.046	***	0.595	0.046	***	0.597	0.046	***
New markets	−0.098	0.053		−0.096	0.053		−0.097	0.053		−0.097	0.053	
Hampering factor												
Cost	0.220	0.046	***	0.220	0.046	***	0.220	0.046	***	0.220	0.046	***
Knowledge	0.134	0.061	**	0.129	0.061	**	0.132	0.061	**	0.133	0.061	**
Others	0.033	0.056		0.034	0.056		0.033	0.056		0.032	0.056	
Legal Status												
Company	reference			reference			reference			reference		
Sole proprietor	−0.165	0.131		−0.162	0.131		−0.162	0.131		−0.163	0.131	
Partnership	−0.133	0.086		−0.131	0.086		−0.132	0.086		−0.130	0.086	
Public corporation	0.356	0.651		0.335	0.652		0.350	0.651		0.341	0.650	
Non-profit making body	−0.421	0.210	**	−0.378	0.207	*	−0.377	0.208	*	−0.384	0.208	*
R&D intensity to sales	0.832	0.488	*	0.995	0.488	**	0.951	0.490	*	1.004	0.489	**
Foreign firm	−0.211	0.051	***	−0.208	0.051	***	−0.208	0.051	***	−0.210	0.051	***
Scientist, % of employments	−0.004	0.001	***	−0.004	0.001	***	−0.004	0.001	***	−0.004	0.001	***
Exporter firm	0.600	0.046	***	0.597	0.046	***	0.596	0.046	***	0.597	0.046	***
Part of a group	0.434	0.072	***	0.413	0.072	***	0.409	0.072	***	0.411	0.072	***
Age of firm	0.004	0.002	*	0.004	0.002	*	0.004	0.002	*	0.004	0.002	*
Mill's ratio	−1.410	0.052	***	−1.408	0.052	***	−1.407	0.052	***	−1.406	0.052	***
Constant	−0.203	0.101	**	−0.219	0.102	**	−0.219	0.102	**	−0.212	0.101	**
Number of obs.	19510			19510			19510			19510		
Log likelihood	−7641			−7637			−7639			−7636		
Chi2	3000.0			3002.6			3001.3			3003.3		
LR Vs Log Chi2	1527.8			1518.6			1522.0			1525.4		

Note: reference category for legal status = Company (limited liability company); for firm size = small firms <49 FTEs); for industries = Other industries. Robust standard errors are in parenthesis. Significance level: *p < 0.10; **p < 0.05, ***p < 0.01.
Source: UKIS- UK Innovation survey; BSD- Business Structure Database.

for innovation (Griliches, 1992). Our findings demonstrate that firms in creative industries are more successful in appropriating their innovation in collaboration with regional partners and are at a higher risk of limits to open innovation in the form of collaboration nationally and internationally.

We argue that the unique characteristics of the creative industries make them better able to govern knowledge collaborations with suppliers, customers, universities and government and others in close regional proximity than those outside their familiar environment–nationally and internationally. They are able to develop the same ability to collaborate as other sectors without experiencing limits to open innovation. These unique characteristics that enable levelling up innovation in creative industries compared to other industries originate in open innovation strategies in localization economies, extending the findings of Hervas-Oliver et al. (2018). The higher trustworthiness and the associated knowledge advantage of creative industry firms are primarily based on their stronger connections to local customers, communities and development localized networks, supported by the community embeddedness of creative artists (Belitski and Herzig, 2018). Frequent interactions, gaining firsthand experience "on the floor", as well as personal and informal relationships (Miller et al., 2011), are the key ingredients to increasing returns to open innovation in a region. However, the levelling up effect of the creative industries in knowledge collaboration in a region is bound for two main reasons.

First, the spatial proximity of collaboration partners is a prerequisite for regular face-to-face interactions, in particular with people in creative professions and in the context of the severe resource constraints often experienced by creative-sector firms (Khlystova et al., 2021). Mutual trust relationships, intense knowledge exchanges and spillover effects between the collaboration partners are stronger in creative sector firms and in spatial proximity (Boschma and Frenken, 2010). Secondly, firms in the creative industries are more likely to invest their resources in open partnerships if the goal of the partnership is both economic and noneconomic (Chapain and Comunian, 2010). This situation is more likely to occur in partnerships with stakeholders within the close local communities, so they can also easily observe their partners with little or no cost. These two factors enable the creative industries to level up their limits to collaboration in a region compared to creative industry firms who are more likely to experience limits to open innovation outside their local communities.

4.3. Differences in knowledge collaboration between sectors

While we hypothesized that limits to open innovation will be higher in international markets, we do not find support for this hypothesis for knowledge-intensive and other sectors. One reason for this could be the ever-growing ability of firms across different industries to protect knowledge outcomes within and beyond national boundaries (Hall et al., 2014). Our study adds to the discussion of Cassiman and Veugelers (2002) and Hall and Sena (2017) on differences in appropriability conditions across sectors. As we do not find differences in limits to open innovation across industries and geographical dimensions, this could mean that appropriability conditions could be enforced efficiently within national and international knowledge collaborations. It could also indicate that informal knowledge protection may be as efficient for knowledge-intensive sectors as for other sectors across all geographical dimensions, expanding the forms of knowledge protection discussion of Hall and Sena (2017). We also argued that transaction cost theory will incur higher coordination costs to monitor, control and manage knowledge transfers (Camacho, 1991), with the effect being stronger for knowledge-intensive sectors which is not the case. This means that knowledge-intensive sectors may have automated their monitoring and knowledge management process (Li et al., 2016) and will seek to optimize collaboration governance and reduce coordination costs adding to what we know from Williamson (1981) for the use of digital technologies in modern industry (Belitski et al., 2021). At the same time differences in the absorptive capacity across industries still remain an issue as investment in capabilities is required (Nooteboom et al., 2007) to access, assimilate and integrate external knowledge efficiently (Vural et al., 2013). Industries such as high-tech manufacturing, KIBS, ICT, and creative will still require higher investment in absorptive capacity, meaning higher collaboration costs, while they also aim to enjoy the greater benefits of knowledge collaboration (Denicolai et al., 2016; Kobarg et al., 2019; Audretsch and Belitski, 2020). This means than even though knowledge-intensive industries are characterised by relatively greater investment in R&D and higher knowledge collaboration costs (Laursen and Salter, 2006; Keijl et al., 2016; Stadler et al., 2022), the amount and quality of knowledge which is created, co-created and commercialized is also higher compared to other sectors. This is why our H1 is not supported: because the profit margins between the costs and benefits of open innovation as described by Tartari and Breschi (2012) and Simon (1976) may not be statistically significant between knowledge-intensive and other sectors. Other sector firms will have lower investment in R&D and absorptive capacity, while the value of innovation output is also lower. The result of the estimation is that the elasticities of an increased investment in open innovation in knowledge-intensive sectors will not be different from the elasticities of open innovation for other sectors.

4.4. Other factors for firm innovation

Firms in high-tech manufacturing have on average lower product innovation across all models which tested the limits to open innovation across four geographical regions ($\beta = -0.10$-0.13, $p < 0.10$); ICT firms have on average higher product innovation ($\beta = 0.29$–0.33, $p < 0.01$); KIBS firms have on average lower product innovation ($\beta = -0.14$-0.20, $p < 0.10$); and creative industry firms have on average the same level of product innovation as firms in the other sectors when controlling for various firm, regional and time characteristics ($\beta = 0.00$–0.20, $p > 0.10$). Firm size is important, with small and micro firms being more likely to achieve higher product innovation than medium firms ($\beta = -0.371$ – (-0.375), $p < 0.01$) and large firms ($\beta = -0.704$-(-0.707), $p < 0.01$) with the results consistent across various geographical dimensions. The exploration activity of firms is positively associated with innovation performance with the results varying between $\beta = 0.594$ and $\beta = 0.597$ ($p < 0.01$). The coefficient of internal R&D intensity is positive and significant ($\beta = 0.832$–1.004, $p < 0.01$) with a consistent effect across all geographical dimensions. A firm's internal R&D intensity and exploration activities play an important role in increasing the likelihood of innovation, the development of new product ranges and market entry.

Factors which impede innovation, such as high innovation costs and lack of market knowledge have both positive and significant effects on innovation performance. While this may sound counterintuitive, firms which report major obstacles to innovation are those which introduce new products. Firms which report that innovation activities are expensive ($\beta = 0.22$, $p < 0.01$) or that they lack knowledge on markets ($\beta = 0.13$, $p < 0.01$) are likely to have higher product innovation.

Firms that are part of an enterprise group have higher levels of innovation output ($\beta = 0.409$, $p < 0.01$) as well as firms that export to Europe and internationally ($\beta = 0.59$–0.60, $p < 0.01$). Firm age has a positive but weakly significant effect on product innovation ($\beta = 0.004$, $p < 0.10$), suggesting that more mature firms have lower resource constraints which may be used to develop and introduce new-to-market products. Non-profit firms are likely to innovate less than companies. The share of employees with a college degree or above in fact impedes product innovation.

5. Conclusions

5.1. Main findings and contribution to theory

Drawing on the open innovation literature (Chesbrough, 2003; Chesbrough et al., 2006; West et al., 2014a,b; Bogers et al., 2018), this study used a generalized linear mixed model to examine the limits to open collaboration for innovation with external partners located across four geographical dimensions (regionally, nationally, Europe and world) and across firms in the most innovative UK sectors (high-tech manufacturing, ICT, KIBS, creative, and other). Based on the results of our data analysis, we identified that the returns to open innovation in the knowledge-intensive sectors and across all geographical proximities are not statistically different from the returns to open innovation in other sectors.

Our first research question was "what are the limits of open innovation for industries with a paucity of knowledge and for knowledge-intensive industries?" We applied the foundations of transaction costs theory (Camacho, 1991; Williamson, 1981) and the knowledge-based view of a firm (Grant, 1996; Barney, 1996) to the open innovation literature in order to examine the mechanisms behind knowledge collaboration, as well as the benefits and costs. We also examine idiosyncrasies as they relate to industries, which may change the limits to knowledge collaboration.

We theoretically debated and empirically demonstrated how the costs of collaboration and value creation across industries differ, cancelling out the effects of differences in limits to open innovation between knowledge-intensive sectors and other sectors. We provided evidence that the creative industries have limits to open innovation in all regions, except in the regions where they are located. In addition, this study further supports a number of previous studies on tacit knowledge diffusion and the role of industrial clusters for innovation (Hervas-Oliver and Albors-Garrigos, 2007, 2014; Hervas-Oliver et al., 2018).

Our second research question was "What is the role of geography in limiting knowledge collaboration between innovators and external partners locally, nationally and internationally?" Our findings demonstrated that limits to knowledge collaboration do not increase with the geographical markets where this collaboration takes place. This is because the development of digital technologies and the development of various informal mechanisms of knowledge appropriation enables enabled us to effectively apply the open innovation model (Bogers et al., 2018) across different geographical proximities. Our findings demonstrated that sectoral differences and geographical proximity are two boundary conditions which leverage cognitive, technological and institutional proximities (Boschma, 2005; Nooteboom et al., 2007; Balland et al., 2015) of knowledge collaboration regionally and internationally. Based on the characteristics of each model applied in our analysis, we extracted insights that can help to create new knowledge and reduce the limits to open innovation (West and Bogers, 2014, 2017).

5.2. Theoretical implications

According to our results, the main limits of open innovation are transaction costs, investment in knowledge internally and the ability to appropriate knowledge outputs from open innovation. However, they also offer further channels to manage knowledge collaboration. While collaborative strategies between different sectors matter, this remained beyond the focus of this study and may become a fruitful direction for future research. The creation of collective knowledge should positively contribute to innovation outcomes, and if transaction costs can be balanced and automated, managerial decision-making and complexity of dealing with external knowledge combinations and interdependencies will be paid off by additional returns to innovation and profits. Similarly, drawing on Saura et al. (2022) and with longitudinal data over 2002–2014, this study expanded the method of studying limitations to open innovation by applying a generalized linear mixed model to quantify empirically the costs and benefits of the innovation process across four knowledge-intensive sectors and other sectors.

Furthermore, our results also highlighted the influence of process innovation, R&D investment, uncertainty, and financial support to innovation as important firm-level characteristics for the development of open innovation. Furthermore, as revealed by our results, community support for ideas, trust and "on the floor" knowledge collaboration strategy in regions could become an efficient mechanism for knowledge collaboration and attracting funding, and activities to keep idea-generating in place. Although the only positive effect was found for creative sectors, identifying other fine-grained sectors which may also rely on regional markets and communities in leveraging limits to innovation could become an avenue for future research.

At the same time, our study also suggests that firms driving open innovation must be guided by structure to reduce transaction costs. This is particularly the case for knowledge-intensive sectors which may encourage further adoption of digital technologies to reduce collaboration costs. Another important insight derived from our data analysis is that creative ideas are less likely to be appropriated while they generate knowledge outflows to other sectors. This may play a fundamental role in open innovation in other sectors, which in most cases is the driving force behind open innovation in regions. Finally, the success of open innovation when developing and experimenting with new products is the ability of knowledge redeployment and recombination within the enterprise group (Stadler et al., 2022). This is to reduce rigidities and transaction costs (Rawley, 2010).

5.3. Practical implications

The results of the present study are eminently practical. Accordingly, managers of firms across all sectors and firms of different size can meaningfully use our results as a guide for the elaboration of new communication or organizational mechanisms of knowledge transfer regionally, nationally and internationally. The findings demonstrate that managers in knowledge-intensive sectors may not need to consciously limit their external knowledge and technology search. This is because the high-tech manufacturing, ICT and KIBS sectors are all equally likely to be affected when performing knowledge sourcing across i) different geographical dimensions or ii) different partner types (Van Beers and Zand, 2014; Kobarg et al., 2019).

Furthermore, the different feelings identified in this research provide a deeper understanding of employees who are on the ground and engaging in open innovation with external partners such as suppliers and universities. Our results also provide meaningful insights concerning how firms across different sectors should organize or promote their innovation ideas, and the potential challenges and risks they could consider drawing on RBV and the transaction cost theory. Managers in creative industries have to be open and to engage with local communities and do project management together with customers and other partners within close proximity.

We demonstrated that open innovation within a region is positively associated with innovation for creative industry firms, while limits to such collaboration emerge when they collaborate nationally and internationally. Support programmes designed to bestow innovation activities via open innovation for creative industries locally may therefore need to differentiate between support tools and networks for creative firms and firms in other sectors, including other knowledge-intensive sectors. While firm managers in the creative sectors may need assistance in accessing the relevant networks and facilitating long-term relationship management, they may also need support in overcoming the perceived threats associated with such collaborations in national markets. This suggestion can also be extended to other institutional settings where the limits to open innovation for creative firms are particularly strong (e.g. Europe and international markets).

5.4. Future research

We call for further research on knowledge sourcing and limits to open innovation in KIBS, ICT and high-tech manufacturing, as well as other sectors. This could involve adding the different boundary conditions of such collaborations (e.g. process innovation, first mover advantage, access to finance and intra-organizational knowledge redeployment, skills and capabilities). Although the limits to open innovation may not exist, they could be amplified or further reduced when different innovation and collaboration strategies are applied and when the depth of collaboration increases. This study focused only on the fact and the breadth of collaboration (Kobarg et al., 2019), while future research needs to measure the depth of collaboration across different collaboration partners. It is possible that the data we used and sample size were not enough to measure the evidence of the limits to open innovation across all sectors. Limits to open innovation can also be explained by collaboration intensity, type of collaboration partner, horizontal vs vertical collaboration strategies, and the economic phenomenon of opportunity costs which are higher in industries rich in knowledge. We encourage future research on all sectors and comparative studies across country and micro level data.

Given that our main limitation was our inability to measure the quality of knowledge collaborations, further research could focus on understanding how various combinations of knowledge can generate complementarities and substitute effects. This research could further build on Bogers and West (2012) and Bogers et al. (2018)m who emphasized that different ecosystem actors (universities, supplies, customers) may have different effects on the exploration and exploitation behaviour of firms.

References

Ahuja, G., Katila, R., 2004. Where do resources come from? The role of idiosyncratic situations. Strat. Manag. J. 25 (8-9), 887–907.
Almeida, P., Kogut, B., 1999. Localization of knowledge and the mobility of engineers in regional networks. Manag. Sci. 45 (7), 905–917.
Alassaf, D., Dabic, M., Daim, T., Shifrer, D., 2020. The impact of open-border organization culture and employees' knowledge, attitudes, and rewards with regards to open innovation: an empirical study. J. Knowl. Manag. 24 (9), 2273–2297.
Argote, L., 2013. Organization learning: a theoretical framework. In: Organizational Learning. Springer, Boston, MA, pp. 31–56.
Ascani, A., Bettarelli, L., Resmini, L., Balland, P.A., 2020. Global networks, local specialisation and regional patterns of innovation. Res. Pol. 49 (8), 104031.
Audretsch, D.B., Belitski, M., Desai, S., 2015. Entrepreneurship and economic development in cities. Ann. Reg. Sci. 55 (1), 33–60.
Audretsch, D.B., Belitski, M., 2020. The role of R&D and knowledge spillovers in innovation and productivity. Eur. Econ. Rev. 123, 103391.
Audretsch, D.B., Belitski, M., Caiazza, R., 2021. Start-ups, innovation and knowledge spillovers. J. Technol. Tran. 46 (6), 1995–2016.
Audretsch, D.B., Feldman, M.P., 1996. R&D spillovers and the geography of innovation and production. Am. Econ. Rev. 86 (3), 630–640.
Barham, H., Dabic, M., Daim, T., Shifrer, D., 2020. The role of management support for the implementation of open innovation practices in firms. Technol. Soc. 63, 101282.
Barney, J.B., 1996. The resource-based theory of the firm. Organ. Sci. 7.
Barney, J.B., 2001. Resource-based theories of competitive advantage: a ten-year retrospective on the resource-based view. J. Manag. 27 (6), 643–650.
Balland, P.-A., Boschma, R., Frenken, K., 2015. Proximity and innovation: from statics to dynamics. Reg. Stud. 49 (6), 907–920.
Belderbos, R., Carree, M., Lokshin, B., 2004. Cooperative R&D and firm performance. Res. Pol. 33, 1477–1492.
Belitski, M., Herzig, M., 2018. The jam session model for group creativity and innovative technology. J. Technol. Tran. 43 (2), 506–521.
Belitski, M., Korosteleva, J., Piscitello, L., 2021. Digital affordances and entrepreneurial dynamics: new evidence from European regions. Technovation 102442.
Bogers, M., Zobel, A.-K., Afuah, A., Almirall, E., et al., 2017. The open innovation research landscape: established perspectives and emerging themes across different levels of analysis. Ind. Innovat. 24 (1), 8–40.
Bogers, M., Chesbrough, H., Moedas, C., 2018. Open innovation: research, practices, and policies. Calif. Manag. Rev. 60 (2), 5–16.
Bogers, M., Sims, J., West, J., 2019. What is an ecosystem? Incorporating 25 years of ecosystem research. Working Paper. In: Paper Presented at the 2019 Meeting of the Academy of Management. Available at: https://ssrn.com/abstract=3437014.
Boschma, R., 2005. Proximity and innovation: a critical assessment. Reg. Stud. 39 (1), 61–74.
Boschma, R., Frenken, K., 2010. The spatial evolution of innovation networks. A proximity perspective. In: The Handbook of Evolutionary Economic Geography, pp. 120–135.
Camacho, A., 1991. Adaptation costs, coordination costs and optimal firm size. J. Econ. Behav. Organ. 15 (1), 137–149.
Cappelli, R., Czarnitzki, D., Kraft, K., 2014. Sources of spillovers for imitation and innovation. Res. Pol. 43 (1), 115–120.
Caputo, A., Pizzi, S., Pellegrini, M.M., Dabić, M., 2021. Digitalization and business models: where are we going? A science map of the field. J. Bus. Res. 123, 489–501.
Cassiman, B., Veugelers, R., 2002. R&D cooperation and spillovers: some empirical evidence from Belgium. Am. Econ. Rev. 92 (4), 1169–1184.
Chapain, C., Comunian, R., 2010. Enabling and inhibiting the creative economy: the role of the local and regional dimensions in England. Reg. Stud. 44 (6), 717–734.
Chesbrough, H., 2003. The era of open innovation. Sloan Manag. Rev. 35–41.
Chesbrough, H., Vanhaverbeke, W., West, J., 2006. Open Innovation: Researching a New Paradigm. Oxford University Press, Oxford.
Chesbrough, H., Bogers, M., 2014. Explicating open innovation: clarifying an emerging paradigm for understanding innovation. In: Chesbrough, H., Vanhaverbeke, W., West, J. (Eds.), New Frontiers in Open Innovation. Oxford University Press, Oxford, pp. 3–28.
Cui, A.S., Griffith, D.A., Cavusgil, S.T., Dabic, M., 2006. The influence of market and cultural environmental factors on technology transfer between foreign MNCs and local subsidiaries: a Croatian illustration. J. World Bus. 41 (2), 100–111.
Dahlander, L., Gann, D.M., 2010. How open is innovation? Res. Pol. 39 (6), 699–709.
Del Giudice, M., Maggioni, V., 2014. Managerial practices and operative directions of knowledge management within inter-firm networks: a global view. J. Knowl. Manag. 18 (5), 841–846.
Denicolai, S., Ramirez, M., Tidd, J., 2016. Overcoming the false dichotomy between internal R&D and external knowledge acquisition: absorptive capacity dynamics over time. Technol. Forecast. Soc. Change 104, 57–65.
Edmondson, A.C., 2016. Wicked problem solvers. Harv. Bus. Rev. 94 (6), 52–59.
Enkel, E., Gassmann, O., Chesbrough, H., 2009. Open R&D and open innovation: exploring the phenomenon. R D Manag 39 (4), 311–316.
Felin, T., Zenger, T.R., 2014. Closed or open innovation? Problem solving and the governance choice. Res. Pol. 43 (5), 914–925.
Frenz, M., Ietto-Gillies, G., 2009. The impact on innovation performance of different sources of knowledge: vidence from the UK Community Innovation Survey. Res. Pol. 38 (7), 1125–1135.
García-Quevedo, J., Segarra-Blasco, A., Teruel, M., 2018. Financial constraints and the failure of innovation projects. Technol. Forecast. Soc. Change 127, 127–140.
Gazley, B., 2010. Linking collaborative capacity to performance measurement in government—nonprofit partnerships. Nonprofit Voluntary Sect. Q. 39 (4), 653–673.
Granstrand, O., Holgersson, M., 2020. Innovation ecosystems: a conceptual review and a new definition. Technovation 90, 102098.
Greene, W.H., 2003. Econometric Analysis. Pearson Education India.
Griffith, R., Harrison, R., Van Reenen, J., 2006. How special is the special relationship? Using the impact of US R&D spillovers on UK firms as a test of technology sourcing. Am. Econ. Rev. 96, 1859–1875.
Goldstein, H., 2003. Multilevel Statistical Models Arnold. London, UK.
Grant, R.M., 1996. Toward a knowledge-based theory of the firm. Strat. Manag. J. 17 (S2), 109–122.
Griliches, Z., 1992. The search for R&D Spillovers. Scand. J. Econ. 94, 29–48.
Hall, B.H., Lotti, F., Mairesse, J., 2013. Evidence on the impact of R&D and ICT investments on innovation and productivity in Italian firms. Econ. Innovat. N. Technol. 22 (3), 300–328.
Hall, B., Helmers, C., Rogers, M., Sena, V., 2014. The choice between formal and informal intellectual property: a review. J. Econ. Lit. 52 (2), 375–423.
Hall, B.H., Sena, V., 2017. Appropriability mechanisms, innovation, and productivity: evidence from the UK. Econ. Innovat. N. Technol. 26 (1–2), 42–62.
Hartley, J., Sørensen, E., Torfing, J., 2013. Collaborative innovation: a viable alternative to market competition and organizational entrepreneurship. Publ. Adm. Rev. 73 (6), 821–830.
Hervas-Oliver, J.-L., Albors-Garrigos, J., 2009. The role of the firm's internal and relational capabilities in clusters: when distance and embeddedness are not enough to explain innovation. J. Econ. Geogr. 9 (2), 263–283.
Hervas-Oliver, J.-L., Albors-Garrigos, J., 2014. Are technology gatekeepers renewing clusters? Understanding gatekeepers and their dynamics across cluster life cycles. Enterpren. Reg. Dev. 26, 5–6.
Hervas-Oliver, J.L., Sempere-Ripoll, F., Rojas Alvarado, R., Estelles-Miguel, S., 2018. Agglomerations and firm performance: who benefits and how much? Reg. Stud. 52 (3), 338–349.
Hervas-Oliver, J.L., Sempere-Ripoll, F., Boronat-Moll, C., 2021. Technological innovation typologies and open innovation in SMEs: beyond internal and external sources of knowledge. Technol. Forecast. Soc. Change 162, 120338.
Hsieh, W.L., Ganotakis, P., Kafouros, M., Wang, C., 2018. Foreign and domestic collaboration, product innovation novelty, and firm growth. J. Prod. Innovat. Manag. 35 (4), 652–672.
Jaffe, A.B., 1989. Characterizing the 'Technological Position' of firms, with application to quantifying technological opportunity and research spillovers'. Res. Pol. 18, 87–97.
Jaffe, A.B., Trajtenberg, M., Henderson, R., 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. Q. J. Econ. 108, 577–598.
Keijl, S., Gilsing, V.A., Knoben, J., Duysters, G., 2016. The two faces of inventions: the relationship between recombination and impact in pharmaceutical biotechnology. Res. Pol. 45 (5), 1061–1074.
Khlystova, O., Kalyuzhnova, Y., Belitski, M., 2022. The impact of the COVID-19 pandemic on the creative industries: a literature review and future research agenda. J. Bus. Res. 139, 1192–1210.
Knudsen, M.P., Mortensen, T.B., 2011. Some immediate–but negative–effects of openness on product development performance. Technovation 31 (1), 54–64.
Kobarg, J., Stumpf-Wollersheim, S., Welpe, I.M., 2019. More is not always better: effects of collaboration breadth and depth on radical and incremental innovation performance at the project level. Res. Pol. 48 (1), 1–10.
Laursen, K., Salter, A.J., 2006. Open for innovation: the role of openness in explaining innovation performance among UK manufacturing firms. Strat. Manag. J. 27, 131–150.
Li, W., Liu, K., Belitski, M., Ghobadian, A., O'Regan, N., 2016. e-Leadership through strategic alignment: an empirical study of small-and medium-sized enterprises in the digital age. J. Inf. Technol. 31 (2), 185–206.
MacMillan, J., Entin, E.E., Serfaty, D., 2004. Communication overhead: the hidden cost of team cognition. In: Salas, E., Fiore, S.M. (Eds.), Team Cognition: Understanding the Factors that Drive Process and Performance. American Psychological Association, pp. 61–82.
McCann, B.T., Folta, T.B., 2011. Performance differentials within geographic clusters. J. Bus. Ventur. 26 (1), 104–123.
Mention, A.L., 2011. Co-operation and co-opetition as open innovation practices in the service sector: which influence on innovation novelty? Technovation 31 (1), 44–53.
Miller, D., Le Breton-Miller, I., Lester, R.H., 2011. Family and lone founder ownership and strategic behaviour: social context, identity, and institutional logics. J. Manag. Stud. 48 (1), 1–25.

Munari, F., Sobrero, M., Malipiero, A., 2012. Absorptive capacity and localized spillovers: focal firms as technological gatekeepers in industrial districts. Ind. Corp. Change 21 (2), 429–462.
Noh, H., Lee, S., 2020. What constitutes a promising technology in the era of open innovation? An investigation of patent potential from multiple perspectives. Technol. Forecast. Soc. Change 157, 120046.
Nooteboom, B., Van Haverbeke, W., Duysters, G., Gilsing, V., Van den Oord, A., 2007. Optimal cognitive distance and absorptive capacity. Res. Pol. 36 (7), 1016–1034.
Obradović, T., Vlačić, B., Dabić, M., 2021. Open innovation in the manufacturing industry: a review and research agenda. Technovation 102, 102221.
Papke, L.E., Wooldridge, J.M., 2008. Panel data methods for fractional response variables with an application to test pass rates. J. Econom. 145 (1), 121–133.
Rawley, E., 2010. Diversification, coordination costs, and organizational rigidity: evidence from microdata. Strat. Manag. J. 31 (8), 873–891.
Roper, S., Love, J.H., Bonner, K., 2017. Firms' knowledge search and local knowledge externalities in innovation performance. Res. Pol. 46 (1), 43–56.
Salge, T.O., Farchi, T., Barrett, M.I., Dopson, S., 2013. When does search openness really matter? A contingency study of health-care innovation projects. J. Prod. Innovat. Manag. 30 (4), 659–676.
Santamaria, L., Nieto, M., Barge-Gil, A., 2009. Beyond formal R&D: taking advantage of other sources of innovation in low-and medium-technology industries. Res. Pol. 38 (3), 507–517.
Saxenian, A., 1994. Regional Advantage: Culture and Competition in Silicon Valley and Route 128. Harvard Univ. Press, Cambridge, MA.
Shipilov, A., Godart, F.C., Clement, J., 2017. Which boundaries? How mobility networks across countries and status groups affect the creative performance of organizations. Strat. Manag. J. 38 (6), 1232–1252.
Saura, H.R., Palacios-Marqués, D., Ribeiro-Soriano, D., 2022. Exploring the boundaries of open innovation: evidence from social media mining. Technovation. https://doi.org/10.1016/j.technovation.2021.102447. In press.
Simon, H.A., 1976. Administrative Behavior. Free Press, New York.
Stadler, C., Helfat, C.E., Verona, G., 2022. Transferring knowledge by transferring individuals: innovative technology use and organizational performance in multiunit firms. Organ. Sci. 33 (1), 253–274.
Tartari, V., Breschi, S., 2012. Set them free: scientists' evaluations of the benefits and costs of university–industry research collaboration. Ind. Corp. Change 21 (5), 1117–1147.
Van Beers, C., Zand, F., 2014. R&D cooperation, partner diversity, and innovation performance: an empirical analysis. J. Prod. Innovat. Manag. 31 (2), 292–312.
Vanhaverbeke, W., Roijakkers, N., Lorenz, A., Chesbrough, H., 2017. The importance of connecting open innovation to strategy. In: Strategy and Communication for Innovation. Springer, pp. 3–15.
Vural, M., Dahlander, L., George, G., 2013. Collaborative benefits and coordination costs: learning and capability development in science. Strategic Entrepreneurship Journal 7 (2), 122–137.
West, J., Bogers, M., 2014. Leveraging external sources of innovation: a review of research on open innovation. J. Prod. Innovat. Manag. 31, 814–831.
West, J., Salter, A., Vanhaverbeke, W., Chesbrough, H., 2014a. Open innovation: the next decade. Res. Pol. 43, 805–811.
West, J., Bogers, M., 2017. Open innovation: current status and research opportunities. Innovation 19 (1), 43–50.
West, J., Salter, A., Vanhaverbeke, W., Chesbrough, C., 2014b. Open innovation: the next decade. Res. Pol. 43, 805–811.
Williamson, O.E., 1981. The economics of organization: the transaction cost approach. Am. J. Sociol. 87 (3), 548–577.