Received: 21 April 2021 | Revised: 1 March 2023 | Accepted: 7 June 2023

DOI: 10.1111/jpim.12696

ORIGINAL ARTICLE

JOURNAL OF PRODUCT INNOVATION MANAGEMENT pdma

Your innovation or mine? The effects of partner diversity on product and process innovation

Maksim Belitski[1,2] | **Blanca L. Delgado-Márquez**[3] | **Luis Enrique Pedauga**[4]

[1]Henley Business School, University of Reading, Reading, UK

[2]ICD Business School, IGS-Groupe, Rue Alexandre Parodi, Paris, France

[3]Department of International and Spanish Economics, School of Economics, University of Granada, Granada, Spain

[4]Department of Economics, University of Leon (Spain), León, Spain

Correspondence
Maksim Belitski, Henley Business School, University of Reading, Whiteknights, Reading RG6 6UD, UK.
Email: m.belitski@reading.ac.uk

Associate Editor: Andrea Ordanini

Abstract

Despite a fundamental revolution in digital technology, along with an ancillary reduction in the cost of transmitting knowledge, the innovation literature on knowledge collaboration continues to hold on to the spatial localization of knowledge collaboration as a truism. Drawing on the open innovation literature and knowledge-based view of firm innovation, this study explores key boundary conditions affecting the relationship between research and development (R&D) collaboration breadth, and product and process innovation. Using a large-scale survey consisting of 25,813 observations of 14,784 firms in the United Kingdom during 2004–2020, we demonstrate that the breadth of knowledge collaboration with regional, national, and international partners directly affects product and process innovation. However, this relationship depends on the geographical location of the collaboration partner, the type of partner, and the firm's absorptive capacity. We found diminishing marginal returns to knowledge collaboration breadth for regional partners in product innovation, and an inverted U-shaped relationship in R&D collaboration breadth with regional partners for process innovation and for national and international partners for product and process innovation. While investment in digital technologies only shifts the curve upwards, it is unlikely to change the direction of the relationship between R&D collaboration and a type of innovation outcome. On the contrary, an increase in the share of science, technology, engineering, and math graduates enables firms to leverage the negative effect of R&D collaboration breadth nationally and specifically for process innovation. Investment in digital technology and human capital increases absorptive capacity and reduces the transaction costs associated with oversearch and limited managerial capabilities and resources.

KEYWORDS

innovation strategy, knowledge collaboration, knowledge spillover, open innovation, partner diversity

1 | INTRODUCTION

The open innovation literature insists on the increasing role of research and development (R&D) collaboration with a variety of external partners in firm innovation (Chesbrough, 2006; Faems et al., 2005; Ritala et al., 2015). Therefore, understanding how the strategic choice of collaboration partner affects the innovation efforts and directions of firms (Spanjol et al., 2012), as well as why product and process innovation varies so much across different types of collaboration partners and when the portfolio of partners becomes more diverse, have been central concerns in the open innovation literature (Asimakopoulos et al., 2020; Belderbos et al., 2004, 2006). Despite the positive returns to R&D collaborations (Un et al., 2010), there is a paucity of knowledge about the mechanisms that lead to the positive effects of knowledge collaboration and trigger the negative effects (Katila & Ahuja, 2002; Laursen & Salter, 2006; Vanhaverbeke et al., 2002) and for different innovation outcomes and partner types (Audretsch & Belitski, 2020; Kobarg et al., 2019). In addition, only a few studies have examined the effects of partner diversity in open innovation on product innovation (Audretsch et al., 2021; Mowery et al., 1998; Van Beers & Zand, 2014) with limited evidence across geographies of collaboration (Hsieh et al., 2018), and product and process innovation (Kobarg et al., 2019).

Over the last decade, a few studies have started to look beyond single-partner R&D collaboration (Colen et al., 2022; Laursen & Salter, 2006), researching R&D collaboration with two or more external partners simultaneously (Cheng & Huizingh, 2014; Gallié & Roux, 2010). The insights derived from these studies on the role that R&D collaboration breadth plays in product innovation (Belderbos et al., 2015) may not translate directly into innovation outcomes, because the type of knowledge transfer mechanism differs with geographical proximity to the source of knowledge (Crescenzi et al., 2016; Guenther et al., 2023) and between firms with different knowledge endowments. Hence, insights from R&D collaboration breadth and depth for product innovation (Kobarg et al., 2019) may not be directly applicable to process innovation (Pisano & Shih, 2012; Stadler, 2011; Un & Asakawa, 2015). Therefore, understanding the mechanisms and boundary conditions that facilitate or impede the effects of R&D collaboration breadth on product and process innovation remains of interest to open innovation scholars and is the purpose of this study. In addition, this study aims to distinguish the mechanisms which shape the effect of R&D knowledge collaboration breadth on different innovation outcomes, such as investment in digital technologies, employing science, technology, engineering, and math (STEM) workers and geography of R&D collaboration partners.

Practitioner points

- Managers should carefully analyze and identify the appropriate mix of regional and international knowledge collaboration, considering whether their objective is product or process innovation or both. The selection of partner types (e.g., competitor, university, suppliers) must be made with consideration of the geography of research and development (R&D) collaboration and to ensure alignment with organizational goals.
- To capitalize on the link between hiring science, technology, engineering, and math (STEM) graduates employees and innovation, managers should prioritize investment in STEM graduates over digitalization when resources are scarce as well as provide specialized training on innovation which further accelerate innovation capabilities.
- Managers should balance R&D collaboration strategies. Managers should heed the recommendation to keep the number of regional collaborations under four and international collaborations under three. Such an approach can ensure an optimal combination of knowledge breadth and depth as well as focus, avoiding the diminishing and often negative returns to over-collaboration and maximizing the benefits of various partner types.
- Investment decisions in areas such as advanced machinery, digital equipment, and software must be customized based on the selected R&D collaboration strategy as they shape process and product innovation differently. By aligning technological investments with the firm's unique combination of the geographic location of knowledge partners, knowledge breadth and depth, and use of digital technology, managers can direct resources to the most impactful areas, enhancing the likelihood of innovation and innovation sales.

This study contributes to the knowledge-based view (KBV) and open innovation literature in two important ways. To begin with, this is the first study to focus on the complexity and heterogeneity in the relationship between R&D collaboration breadth and process and product innovation furthering Laursen and Salter (2006), Kobarg et al. (2019), and Colen et al. (2022) studies on the impact of R&D collaboration breadth and different single collaboration partners on product innovation. Second, we apply the KBV of inter-firm collaboration (Grant, 1996; Grant & Baden-Fuller, 1995; Kogut & Zander, 1992) to the open innovation literature (Chesbrough, 2006; Un et al., 2010; Un & Asakawa, 2015), and argue that the impact of R&D collaborations breadth on innovation outcomes depends on several boundary conditions related to type of partner, geography, and the firm's absorptive capacity. We draw on and extend prior knowledge (Kobarg et al., 2019; Laursen & Salter, 2006) by developing and empirically testing the boundary conditions of this relationship, using a sample of the most innovative U.K. firms during 2004–2020. This is the first study to examine the role of the geographical proximity of collaboration partners and the extent of investment in digital technologies and STEM workers as important boundary conditions in the relationship between knowledge collaboration and firm innovation.

Our key finding is that the extent of investment in employing STEM graduates, the number of collaboration partners, and their location shape the relationship between R&D collaboration breadth and innovation outcomes.

The remainder of this study is organized as follows. The next section discusses the different external knowledge sources and their characteristics and sets out the research hypotheses. Section 3 introduces the data and methodology, while Section 4 presents the results. Section 5 discusses the findings and Section 6 concludes.

2 | THEORETICAL FRAMEWORK

2.1 | Collaboration diversity and firm innovation

Firms collaborate with various external partners locally, nationally, and internationally. A highly diverse collaborator portfolio indicates access to heterogeneous knowledge, diverse pools of information, different perspectives, and ideas (Asimakopoulos et al., 2020; Baum et al., 2000; Spanjol, Qualls, et al., 2011). Knowledge collaboration with customers and competitors can affect a firm's strategic and technological orientation and influence the front end of innovation (Spanjol, Qualls, et al., 2011).

The depth (intensity) and the breadth (diversity of partners) in R&D collaboration are guided by two mechanisms (Katila & Ahuja, 2002). First, R&D collaboration enriches a firm's knowledge pool and adds new variations to knowledge for problem-solving (Bogers & Horst, 2014). Second, R&D collaboration increases innovation activity, adding to new product creation and market access (Frenz & Ietto-Gillies, 2009; Mariani & Belitski, 2022). This becomes likely as R&D collaboration enables recombinatory knowledge search (Nelson & Winter, 1982) and creates new associations and linkages (Cohen & Levinthal, 1989), leading to further exploration activity (March, 1991).

From an organizational learning perspective, R&D collaboration allows firms to learn skills and competencies related to the technology and market aspects (Kogut & Zander, 1992; Van Beers & Zand, 2014).

Prior research has suggested that R&D cooperation has a positive impact on innovation outcomes (Branstetter & Sakakibara, 2002; Katila & Ahuja, 2002). However, a challenging task for firm managers remains, as they must organize R&D collaboration in such a way as to minimize redundancies and costs when knowledge transfer occurs (Vanhaverbeke et al., 2002), as an increase in the number of collaboration partners does not always generate more innovation outcomes (Kobarg et al., 2019). Katila and Ahuja (2002) argue that complementarities between different R&D cooperation strategies might be limited due to the increased costs associated with managing an increasing breadth of R&D collaboration and synchronizing the business objectives and strategies of all partners. Some of these concerns are greater for small firms (Katila & Ahuja, 2002) due to their limited resources and absorptive capacities. Katila and Ahuja (2002) focus on searches inside firms (as reflected in patent citations), while Laursen and Salter (2006) focus on the external innovative search efforts of firms. They describe the search channels (e.g., customers, suppliers, universities) shifting attention toward the partner type (breadth) rather than toward the degree of interaction within each partner (depth) and their impact on product innovation. Laursen and Salter (2006, p. 135) state "Although we hypothesize that external search breadth is associated with innovative performance, we also argue that firms may 'over-search' and that this will have negative consequences for their innovation performance."

Drawing on prior research on open innovation (Laursen & Salter, 2006) and KBV (Grant, 1996), we may distinguish the following aspects which are pertinent to the utilization of knowledge within the firm to create new value.

The first aspect is transferability. There are two types of knowledge: tacit and explicit. The critical distinction between the two lies in transferability and the transfer mechanisms across individuals, space, and time (Grant, 1996). Explicit knowledge is revealed by communication, and this ease of communication is the fundamental property of explicit knowledge. Tacit knowledge is revealed through its application, and its transfer is spatially bounded. The cost of tacit knowledge transfer increases with distance. If tacit knowledge cannot be codified, and can only be observed through application, then face-to-face contact becomes an essential and necessary condition of transfer (Kogut & Zander, 1992). Face-to-face contact, and hence geographical proximity between collaboration partners, increases the speed of tacit knowledge transfer and reduces costs and uncertainty.

The second aspect is capacity. Drawing on Laursen and Salter (2006) highlighted different institutional norms, habits, and rules that need to be taken into consideration for each partner type and the different organizational practices required to render the knowledge transfer effective. Firms have limited absorptive capacities to apply different organizational practices. Absorptive capacity needs to be increased to enable the complementarity of new knowledge to existing knowledge. This may require establishing links between different elements of tacit and codified knowledge (Zobel, 2017). As each firm's absorptive capacity is limited (Audretsch & Belitski, 2023), an increase in knowledge collaboration breadth limits the ability to process, aggregate and integrate knowledge, reducing the share of knowledge that can be further implemented for new product creation. Every additional knowledge partner, ceteris paribus, will reduce the marginal added value to innovation as the ability to absorb external knowledge starts to decrease (Deeds & Hill, 1996; Faems et al., 2005). Firms with high compatibility in processes and partner-specific absorptive capacity may enable more effective knowledge transfer. However, as the number of R&D collaboration partners increases, the overlapping knowledge increases as well (Dyer & Singh, 1998), along with the managerial effort invested in filtering and selecting relevant knowledge. This will lead to a diminishing marginal return to knowledge collaboration breadth.

The third aspect is appropriability. When firms invest in R&D collaboration, they expect to receive a return equal to or greater than the cost of the collaboration. The transaction cost of enforcing appropriability increases with the number of collaboration partners, as it is unclear whose knowledge contributed most to the final product and how R&D contributions could be calculated and weighted. The leakage of sensitive knowledge to competitors (Nieto & Santamaría, 2007) and unintended knowledge spillovers to other collaborators may lead to further security concerns (Belitski, 2019; Cassiman & Veugelers, 2002; Kafouros et al., 2008). Thus, an increasing cost and uncertainty about "who owns new knowledge" reduces the incentives for collaboration, and raises the risk of legal claims reducing the expected returns from knowledge collaboration.

Finally, the fourth aspect is specialization. Managerial and firm absorptive capacity is limited (Grant, 1996), mainly by time and human intellectual capacity. The success of knowledge transfer depends on a firm's specialization in particular areas of knowledge, and this accelerates the integration of external knowledge with existing internal knowledge. This implies that expert knowledge in a firm may be limited, and only a fraction of the new knowledge transferred within the R&D collaboration can be absorbed by a firm and finally implemented. Over-search and over-exploration of external knowledge will increase the costs of R&D collaboration across different channels and types of partners (Laursen & Salter, 2006). An increase in collaboration breadth leads to increased complexity of new knowledge and requires investment in absorptive capacity, such as employing STEM workers, investing in digital technology and equipment, while managers must learn new skills and invest in multiple specializations as strategic alliances do (Eisenhardt & Schoonhoven, 1996). This will raise the transaction and operational costs of collaboration breadth and knowledge transfer (Knudsen & Mortensen, 2011; Reichstein & Salter, 2006).

Once a certain degree of R&D collaboration breadth is reached, any further increase may add more to the cost of collaboration than to value creation from R&D collaboration. Prior research has already demonstrated both positive and negative innovation outcomes as the breadth of collaboration increases (Audretsch & Belitski, 2020; Kobarg et al., 2019).

2.2 | Knowledge collaboration and firm innovation: Hypotheses formulation

While the shape of the relationship between the breadth of R&D collaboration and innovation outcomes has been widely examined (Laursen & Salter, 2006), a critical discussion of the role that geographical proximity plays in this relationship is missing (Crescenzi et al., 2016). The geographical and related institutional proximity may be important boundary conditions enabling or impeding R&D collaboration and finally shaping innovation outcomes. For example, the negative effect of R&D collaboration on innovation outcomes may differ if the collaboration is spatially localized. Prior research has demonstrated that in close geographical proximity, the diminishing returns to knowledge collaboration are due to the internalization of knowledge and redundancy of information (Reichstein & Salter, 2006). In inter-regional and international knowledge collaborations, the diminishing returns to collaboration are due to the increased transaction and operational costs of managing new knowledge and collaborations; limited firm capabilities, skills, and resources; and the very diverse nature and applicability of the knowledge, given the institutional context where the knowledge originated (Crescenzi et al., 2016).

The positive effect of an increase in the breadth of R&D collaboration is likely to be more persistent for localized knowledge transfers than for distant knowledge transfers, mainly due to the advantages of tacit knowledge transfers via face-to-face interactions (Kogut & Zander, 1992). Firms with high resource constraints (e.g., small firms, startups, etc.) will significantly benefit from co-location with the source of the knowledge (Audretsch et al., 2023; Belderbos et al., 2004). Localized knowledge transfers are efficient, as tacit knowledge can be transferred due to the greater transparency, trust, and social capital found within localized networks (Tödtling et al., 2009). Localized R&D collaborations also minimize transportation and coordination costs, and increase customer loyalty. Schilling and Phelps (2007) found that firms embedded in alliance collaborations that exhibit both high clustering and high reach will have greater innovative outputs than firms with low clustering and low reach.

The diminishing returns to such collaborations will be constrained by the internalization of knowledge and the "lock-in effect" (Balland et al., 2015; Boschma, 2005), which significantly limits the availability of diverse knowledge available internationally (Rugman & Verbeke, 2001). We hypothesize:

> **Hypothesis 1a.** Within a close geographic proximity, R&D collaboration breadth on firm innovation has a curvilinear shape and is subject to diminishing marginal returns.

The positive slope of the R&D collaboration breadth on innovation outcomes is expected for both regional and international partners and is grounded in four conceptual channels. First, drawing on the KBV (Grant, 1996; Spender & Grant, 1996), R&D collaboration with international partners is associated with access to knowledge that is not present either within the firm (Chesbrough, 2006) or within the national boundaries (Belderbos et al., 2006; Tödtling et al., 2009). Knowledge collaboration with international partners extends the regional and national knowledge base. Second, according to the KBV (Das & Teng, 2000; Mowery et al., 1998), firms aiming to internationalize consider R&D collaboration to be an important factor in reducing the risk and uncertainty associated with international market entry. Third, international R&D collaboration has the potential to mitigate internalization issues resulting from the limited geographical scope of learning, in particular when external knowledge is available, transferrable, and adaptable to the firm's innovation (Lane et al., 2006).

At high levels of R&D collaboration breadth, the negative effect on firm innovation will be stronger in R&D collaboration with partners outside the region where the firm is located. First, the increase in knowledge complexity is higher when collaborating with partners across different geographical and cognitive contexts (Un & Asakawa, 2015), even within the same country, increasing the costs associated with accessing and understanding the knowledge (Badir & O'Connor, 2015). Second, an increase in the portfolio of R&D collaboration partners inter-regionally and internationally raises the opportunity and search costs as the number of partners increases (Kobarg et al., 2019; Salge et al., 2013). The origins of the transaction costs are in the risk of over-searching (Laursen & Salter, 2006), which is higher with international partners versus local partners. Third, collaborating with partners outside of a region raises issues of culture and trust, value sharing, norms, and values between collaboration partners as heterogeneity between partners' increases with distance (Boschma, 2005). Fourth, applied to international collaboration, the outcomes of R&D collaboration are harder to appropriate as international collaboration raises issues of intellectual property rights, such as which country's regulations should be considered primary for intellectual property rights protection (Bogers et al., 2012).

We hypothesize:

> **Hypothesis 1b.** Within distant geographic proximity, R&D collaboration breadth on firm innovation has a curvilinear shape and is subject to negative returns.

2.3 | The role of investment in information technology in knowledge collaboration

Despite a massive and fundamental revolution in digital technology, along with the ancillary reduction in the cost of transmitting tacit knowledge using the latest digital technologies such as Skype, Microsoft Teams, WebEx, and Zoom, the literature continues to hold on to the spatial localization of knowledge transfer as a truism (Audretsch & Belitski, 2022).

The transaction and operational costs of R&D collaboration with partners inter-regionally and internationally could be sufficiently reduced if information processing was optimized (Williamson & Masten, 1995) and storage, computation, and data transmission costs were reduced

(Goldfarb & Tucker, 2019). Many managerial functions could then be automated and outsourced to digital technology. This economizing rationale appears to play a particular role in multistep production, capital-intensive firms, and international alliances, where managers are involved in multiple operations and data requires synchronization and adaptation. Since the early 2000s, and in particular, over the last decade, the way tacit knowledge is transferred has changed as the digitization of knowledge transfer has become a reality. In particular, investment in digital technologies has changed the way knowledge is processed, recombined, and systemized (Haefner et al., 2021; Keding & Meissner, 2021). For example, the adoption of smart mobile technology reduced search costs and price dispersion (Jensen, 2007). The following mechanisms enable digital technologies to reduce the cost of R&D collaboration inter-regionally and internationally, and therefore minimize the diminishing returns to scale for R&D collaboration in close proximity, and the negative effect of R&D collaboration in distant geographical proximity.

First, the use of digital technologies challenges the traditional way of knowledge organization and management in firms (Haefner et al., 2021). The use of digital technologies substantially reduces the operational and transaction costs of searching, collecting, processing, and transferring new knowledge (Goldfarb & Tucker, 2019).

Second, investment in and adoption of new digital technology has increased the speed of knowledge search and transfer, while enabling the use of algorithms, including artificial intelligence, for filtering out redundant knowledge (Keding & Meissner, 2021). In addition to making sense of data by synchronization, adaptation, and clustering, digital tools can follow-up managerial decisions, track collaboration activities, and provide interactive and timely feedback to managers on the outcomes of decision-making, enabling the improvement of decision-making processes over time.

Third, beyond knowledge filtering and transfer, artificial intelligence in particular can create a simulation algorithm that can help to choose a type of partner to collaborate without a portfolio of collaboration partners for each and every specific operation and task (Akerkar, 2019; Paschen et al., 2020). Investment in digital technologies facilitates speedy decision-making, partner selection in R&D collaborations, and reduces managerial procedures related to data collection, analysis, and sense-making (Paschen et al., 2020).

Once the transaction and operation costs for managers are reduced, teams can coordinate knowledge transfer in a more sensible and structured way and collaborate on projects while outsourcing complex cognitive functions to machines (Dixit et al., 2021). For the relationship between R&D collaboration breadth and innovation outcomes, this means that the diminishing marginal returns to R&D collaboration breadth locally and the negative effect of the R&D collaboration breadth outside of a region can be reduced, increasing innovation outcomes. An example of reducing cost can be Zoom conferences, which enable up to 300 participants to join a single meeting independently of their physical location. We hypothesize:

> **Hypothesis 2a.** Investment in digital technologies reduces the diminishing marginal returns of regional R&D collaboration breadth on firm innovation.

> **Hypothesis 2b.** Investment in digital technologies reduces the negative returns of national and international R&D collaboration breadth on firm innovation.

3 | METHODOLOGY AND DATA

3.1 | Data

We test the hypotheses using three datasets (Business Registry [BSD], Business Enterprise Research and Development Survey [BERD], U.K. Innovation Survey [UKIS]), and eight cross-sectional surveys with a panel element over 2004–2020 (Office for National Statistics, 2021a, 2021b). Although three datasets were pooled together and constructed from three different sources, they are matchable by identifying a reporting unit. First, we collected and matched eight consecutive UKIS waves between 2004 and 2020, each conducted every second year by the Office of National Statistics (ONS) in the United Kingdom. Second, we used BSD and BERD data for the years 2004, 2006, 2008, 2010, 2012, 2014, 2016, and 2018. The data were matched to a correspondent CIS survey wave for the initial year of the UKIS period. The Business Structure Database has data on firms' legal status, ownership (foreign or national), alliance information, exports, turnover, employment, industry, and postcodes.

The UKIS offers the most comprehensive data, including direct measures of innovation performance and a wide variety of factors influencing innovation.

Our match resulted in 25,813 observations with 14,784 firms. In our sample, 8984 firms were observed only once; 3071 firms were observed twice; 1712 firms were observed three times; 510 firms were observed four times; 289 firms were observed in five surveys; 122 firms were observed in six surveys; 69 firms were observed in seven surveys; and 29 firms were observed in all eight surveys.

All questions related to the variables of interest need to be completed with no missing values to be included in a sample. All missing values and nonapplicable answers were labeled as missing and were therefore not included in our sample. A full list of variables is provided in Table 1 for the product innovation sample of 25,813 observations.

3.2 | Sample description

The data embraces a wide spectrum of industries, with most firms coming from basic manufacturing (21.43%), the wholesale retail trade (16.26%), professional and scientific services (10.94%), administration and public service (10.57%), and construction (10.15%).

The most underrepresented sectors are real estate (1.93%) and education (0.40%). Table 2 demonstrates the distribution of firms by industry divisions adopted by the ONS, region, survey wave, and firm size. Most firms come from the South East of England (10.95%), London (9.81%), and the North West of England with a center in Manchester (9.38%). At the same time, Northern Island (7.78%) and the North East of England (5.50%) are less represented. Most observations come from the first survey available 2004–2006 (30.81%); the share of observations dropped significantly in 2016–2018 (5.79%) and 2018–2020 (5.46%). Finally, Table 2 illustrates the distribution of firms across various sizes; up to 44.97% are small firms (10–49 FTEs), 13.61% are micro firms (<10 employees), 13.78% are medium firms (50–99 employees), 10.43% are medium–large firms (100–249 employees), and 17.20% are large firms with more than 250 employees.

3.3 | Variables

3.3.1 | Dependent variables

Our first dependent variable is product innovation (innovative sales), which varies from 0 (no innovation sales) to 100 (all sales are made of new to market products). This does not measure technological innovation but is more biased toward the commercialization of the new products through market sales. A turnover-based measure enables us to integrate the highly variable commercial value of these innovations (Kobarg et al., 2019; Laursen & Salter, 2006).

Our second dependent variable is process innovation, which is measured as a binary variable that takes a value of one if the firm introduced any new or significantly improved processes which were new to the industry, and zero otherwise (Salge et al., 2013; Terjesen & Patel, 2017). It is important that the process innovation is new to the industry, and is not only an incrementally improved method new to the business (Frenz & Ietto-Gillies, 2009).

3.3.2 | Independent variables

To test our hypotheses, we created a new variable, "collaboration breadth," that represents the number of external partners a firm collaborates with externally on R&D and innovation. These are ordinal variables bounded between zero (if a firm has zero collaboration partners within a specific region) to a maximum of seven types of external collaboration partners (enterprise groups, suppliers, customers, competitors, consultants and commercial labs, universities, governments) (Love et al., 2014). The breadth of knowledge collaboration is measured: (a) within close geographical proximity as the number of collaboration partners within the region the firm is located, with a maximum radius of 80 miles (regional collaboration breadth); (b) within distant geographical proximity within the country, but not within the same region (national collaboration breadth); and (c) within distant geographical proximity outside the country (international collaboration breadth).

Our second explanatory variable is digital intensity. This is the ratio of expenditure on advanced machinery, information technology equipment, hardware, and software for innovation to total sales in pound sterling multiplied by 100.

3.3.3 | Control variables

We included several control variables to test our hypotheses on the inverted U-shaped effect of collaboration breadth and innovation output. First, we controlled for the size of the firm by creating four binary variables (small, medium, medium–large, and large firms, with large firms used as a reference category). We control for the firm's absorptive capacity by controlling for the share of employees who hold a degree or higher qualification at BA/BSc, MA/PhD, or PGCE in statistics, technology, engineering, or mathematics (Zobel, 2017). In addition, we include internal R&D intensity calculated as a ratio of internal R&D expenditure to sales. It is also important to control for one type of innovation (e.g., process innovation, organizational innovation) when predicting the other (e.g., product innovation) and vice versa, as companies might have engaged in more than one innovation

TABLE 1 Descriptive statistics.

Label	Description of variables	Mean	Std. dev.	Min	Max
Product innovation	Dependent variable: % of firm's total turnover from goods and services that were new to the market (%), radical product innovation	4.52	13.48	0	100
Process innovation	Dependent variable: Binary variable = 1 if firm introduced any new or significantly improved processes for producing or supplying goods or services, zero otherwise.	0.12	0.32	0	1
Regional breadth	The number of partners a firm cooperates on innovation regionally (enterprise group, suppliers, clients and customers, competitors, consultants and private R&D labs, universities, local and national government (0—no collaborators, max. 7—collaboration with all seven types of partners)	0.41	1.22	0	7
National breadth	The number of partners a firm cooperates on innovation nationally—outside the region (enterprise group, suppliers, clients and customers, competitors, consultants and private R&D labs, universities, local and national government (0—no collaborators, max. 7—collaboration with all seven types of partners)	0.56	1.40	0	7
International breadth	The number of partners a firm cooperates on innovation abroad (enterprise group, suppliers, clients and customers, competitors, consultants and private R&D labs, universities, local and national government (0—no collaborators, max. 7—collaboration with all seven types of partners)	0.24	0.91	0	7
Small	Binary variable equal one if number of FTEs is <50, zero otherwise	0.56	0.49	0	1
Medium	Binary variable equal one if number of FTEs is between 50 and 99, zero otherwise	0.14	0.35	0	1
Medium–large	Binary variable equal one if number of FTEs is between 100 and 249, zero otherwise	0.09	0.29	0	1
Exploration	A firm states the importance of increasing range of goods or services from not applied (0), to low importance (1), medium (2), and high importance (3) for innovation	1.28	1.23	0	3
Organizational innovation internal	Binary variable equal one if firm has introduced new business practices for organizing procedures (i.e., supply chain management, business engineering, knowledge management, lean production, quality management, etc.), as well as firm has introduced new methods of organizing work responsibilities and decision-making (e.g., system of employee responsibilities, team work, decentralization, integration, etc.), zero otherwise	0.14	0.34	0	1
Organizational innovation external	Binary variable equal one if firm used new methods of organizing external relationships with other firms or public institutions (i.e., firms use of alliances, partnerships, outsourcing or subcontracting, etc.), zero otherwise	0.27	0.44	0	1
Ownership: Company	Binary variable = 1 if firm's legal status is limited liability company, 0 otherwise	0.34	0.36	0	1

(Continues)

TABLE 1 (Continued)

Label	Description of variables	Mean	Std. dev.	Min	Max
Ownership: Sole proprietor	Binary variable = 1 if firm's legal status is sole proprietor, 0 otherwise	0.041	0.20	0	1
Ownership: Partnership	Binary variable = 1 if firm's legal status is partnership, 0 otherwise	0.099	0.29	0	1
Ownership: Public corporation	Binary variable = 1 if firm's legal status is public corporation, 0 otherwise	0.001	0.03	0	1
Ownership: Non-for-profit body	Binary variable = 1 if firm's legal status is non for profit, 0 otherwise	0.013	0.11	0	1
Foreign	Binary variable = 1 if a firm has a headquarter in a foreign country, zero otherwise	0.34	0.47	0	1
Age	Age of a firm (years since establishment), in logarithms	2.82	0.68	0	3.85
STEM share	The proportion of employees that hold a degree or higher qualification in science, technology, engineering, and math at BA/BSc, MA/PhD, PGCE levels	7.06	16.79	0	100
R&D intensity	Expenditure on Internal Research and Development expenditure (£) to total sales (£) ratio × 100%	1.20	6.04	0	66
Part of a group	Binary variable = 1 if a firm is a part of an enterprise group, 0 otherwise	1.59	4.01	0	112
Digital intensity	Expenditure on advanced machinery, information technology equipment, software and hardware (£) to total sales (£) ratio × 100%	1.38	4.58	0	40
Enterprise group	Binary variable =1 if firm cooperates on innovation with an enterprise group, zero otherwise	0.65	0.47	0	1
Suppliers	Binary variable = 1 if firm cooperates on innovation with suppliers of equipment, materials, services, zero otherwise	0.67	0.46	0	1
Customers	Binary variable = 1 if firm cooperates on innovation with clients customers, zero otherwise	0.68	0.46	0	1
Competitors	Binary variable = 1 if firm cooperates on innovation with competitors and other businesses in the industry, zero otherwise	0.63	0.48	0	1
Consultants	Binary variable = 1 if firm cooperates on innovation with consultants, commercial labs, or private R&D institutes, zero otherwise	0.42	0.49	0	1
Universities	Binary variable = 1 if firm cooperates on innovation with universities or other higher education institutes, zero otherwise	0.28	0.45	0	1
Government	Binary variable = 1 if firm cooperates on innovation with regional and national government, zero otherwise	0.29	0.45	0	1

Source: Office for National Statistics (2021a), hereinafter named UKIS—U.K. Innovation Survey (2004–2020). Office for National Statistics (2021b), hereinafter named BSD—Business Register (2004–2020). Business Strategy and Practices Include all new and significantly improved forms of organization, business structures or practices aimed at raising internal efficiency or the effectiveness of approaching markets and customers. U.K. Innovation Survey (2004–2020) and Business Register (2004–2020). Number of observations: 25,813.

effort. This point is addressed by adding process innovation and organizational innovation (internal and external) in the regression model predicting product innovation. We also added product innovation and organizational innovation (internal and external) in the model where we predict process innovation. We included

TABLE 2 Sample distribution by ONS industrial sectors, survey year, and U.K. region.

	Number of observations	%, total		Number of observations	%, total
Industry			U.K. region		
Basic manufacturing	5397	21.43	Northeast England	1385	5.50
High-tech manufacturing	781	3.10	Northwest England	2361	9.38
Construction	2556	10.15	Yorkshire and the Humber	2052	8.15
Wholesale, retail trade	4096	16.26	East Midlands	2026	8.05
Transport, storage	1423	5.65	West Midlands	2211	8.78
Accommodation and food	1533	6.09	Eastern England	2253	8.95
Information and communication techs.	1712	6.80	London	2470	9.81
Financial intermediation and insurance	846	3.36	South East England	2757	10.95
Real estate	486	1.93	South West England	2126	8.44
Professional and scientific services	2756	10.94	Wales	1627	6.46
Administration and public service	2661	10.57	Scotland	1955	7.76
Education	101	0.40	Northern Ireland	1960	7.78
Other community, social activities	835	3.32			
Survey year			Firm size		
			Micro (<10 employees)	3428	13.61
2004–2006	7760	30.81	Small (10–49 employees)	11,326	44.97
2006–2008	4012	15.93	Medium (50–99 employees)	3470	13.78
2008–2010	2366	9.40	Medium–large (100–249 employees)	2627	10.43
2010–2012	3772	14.98	Large (250+ employees)	4332	17.20
2012–2014	2485	9.87			
2014–2016	1957	7.77			
2016–2018	1457	5.79			
2018–2020	1374	5.46			
Total	25,813	100	Total	25,813	100

Source: U.K. Innovation Survey (2004–2020) and Business Register (2004–2020). Number of observations: 25,813.

in our models the variables of internal and external organizational innovation. In addition, we control for firm ownership—foreign firm, which equals one if a firm is owned by a foreign company, and zero if a firm is owned by a local firm (Love et al., 2014). We add the variable "part of a group," which represents the number of units within an enterprise group, which is also a measure of a firm's group size if the firm is part of a larger enterprise group. A firm's location in the enterprise group may affect its ability to engage in innovation and the speed of its innovation. Firm age is measured as a logarithm of firm age since establishment, which may change a firm's propensity to innovate (Coad et al., 2016). We control for exploration activity (March, 1991), which states the importance of increasing the range of goods or services between zero (not applied) to low (1), medium (2), and high importance (3) for innovation. Finally, the type of collaboration partner matters for innovation, as each type has a specific set of expertise and networks (Spanjol, Qualls, et al., 2011) and is involved differently in the value chain (Belderbos et al., 2015; Mariani & Belitski, 2022). We include seven binary variables to control for the type of external partner for knowledge collaboration: enterprise groups, suppliers, customers, competitors, consultants, universities, and government (Salge et al., 2013).

Further, we included industry (two-digit) dummies (agriculture as reference category), survey time period (wave) dummies (2004–2006 as reference years), and regional dummies for 128 regions in the United Kingdom (York as a reference category). For the full list of variables used in this study, please refer to Table 1. The correlation between variables is illustrated in Table 3.

3.4 | Methodology

The choice of model is often determined by the construction of the dependent variable and the available data. We estimated our knowledge production function (Crépon et al., 1998) for product and process innovation, and we used Tobit and logistic multiple regression to predict product and process innovation, respectively. The issue with the product innovation model is related to the characteristics of our dependent variable, which is double censored with the lowest limit of zero and a maximum of 100% (all sales are new to the market). There are several different ways of estimating such models with censored dependent variables using parametric techniques (Wooldridge, 2015). The main benefit of concentrating on the Tobit estimation is that it provides a finer understanding of the potential selection of the firms which innovate new products and those which do not. The underlying assumptions of the method are that the disturbances are normally distributed and that the same data-generating process that determines the censoring is the same process that determines the outcome variable. Our econometric model for product innovation is a Tobit estimation (Wooldridge, 2015):

$$y_{it} = \beta_0 + \beta_1 x_{it} + \beta_2 \tau_{it} + u_{it}, \quad (1)$$

where y_{it} represents innovation sales for firm i, that varies between zero and 100 at time t; x_{it} is a vector of exogenous variables related to R&D collaboration breadth and investment in IT; τ_{it} is a vector of control exogenous variables describing the characteristics of a firm i in year t, including year, industry and region fixed effects and firm ownership status; u_{it} is the error term and is assumed to be identically and independently distributed with mean zero and constant variance σ^2.

We estimate the knowledge production function for process innovation as our dependent variable using a multivariate logistic regression model where process innovation is a dependent variable. Process innovation is a binary variable that equals one if a firm introduced a new process, and zero otherwise. The model (2) estimates the probability of one event (out of two alternatives) taking place by having the log-odds (the logarithm of the odds) for the event be a linear combination of one or more independent variables ("predictors") (Wooldridge, 2015):

$$\Pr(y_{it} = 1) = \beta_0 + \beta_1 x_{it} + \beta_2 \tau_{it} + u_{ijt}, \quad (2)$$

where y_{it} represents the probability of process innovation by firm i, which could be either zero or one at time t; x_{it} is a vector of exogenous variables related to R&D collaboration breadth and investment in IT; τ_{it} is a vector of control exogenous variables describing the characteristics of a firm i in year t; u_{it} is the error term and is assumed to be identically and independently distributed with mean zero and constant variance σ^2. The multicollinearity test examined the variance inflation factors for all variables, finding each is between 2 and 5.

4 | RESULTS

4.1 | Results related to main hypotheses

Our estimation is reported in Table 4, as we also use predictive margins to plot the expected values of product and process innovation for each of the explanatory variables while controlling for all other characteristics from Equation (1). We find that there is a diminishing marginal return for regional collaboration breadth on product innovation, supporting Hypothesis 1a ($\beta = 0.747$, $p < 0.01$; Specification 2, Table 4). In economic terms, this means that an increase in one type of collaboration partner on a scale between zero and seven increases product innovation sales between 0.74% and 0.82% (Specifications 2–4, Table 4). The relationship between regional collaboration breadth and process innovation is subjected to an inverted U-shaped relationship and does not support Hypothesis 1a ($\beta = 1.230$, $p < 0.001$; $\beta^2 = 0.981$, $p < 0.05$; Specification 6, Table 4). The coefficients of logistic estimation for process innovation are reported in an odd ratio, with <1 meaning a reduction in the likelihood of process innovation and >1 meaning an increase in the likelihood of process innovation. We find support for Hypothesis 1b, which states that the relationship between national and international collaboration breadth and product and process innovation is an inverted U-shape, which consists of the positive knowledge collaboration effect and negative cost effect.

As shown in Table 4 (Specification 6), an inverted U-shape effect for partner diversity holds when collaborating with national partners for process innovation ($\beta = 1.392$, $p < 0.001$; $\beta^2 = 0.961$, $p < 0.001$; Specification 6, Table 4) and with international partners for process innovation ($\beta = 1.182$, $p < 0.001$; $\beta^2 = 0.982$, $p < 0.001$; Specification 6, Table 4).

TABLE 3 Correlation matrix.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Product innovation	1															
2. Process innovation	0.23*	1														
3. Regional breadth	0.15*	0.24*	1													
4. National breadth	0.20*	0.29*	0.54*	1												
5. International breadth	0.19*	0.25*	0.59*	0.64*	1											
6. Small	0.03*	−0.02*	−0.03*	−0.09*	−0.07*	1										
7. Medium	−0.02*	−0.01	0.09	−0.08	−0.01	−0.46*	1									
8. Medium–large	−0.03	0.01*	0.07*	0.03*	0.02*	−0.35*	−0.12*	1								
9. Exploration	0.25*	0.27*	0.25*	0.33*	0.26*	−0.09*	0.01*	0.03*	1							
10. Organizational innovation internal	0.13*	0.24*	0.26*	0.28*	0.28*	−0.09*	0.06	0.04*	0.23*	1						
11. Organizational innovation external	0.15*	0.17*	0.21*	0.28*	0.25*	−0.18*	0.04	0.04*	0.27*	0.44*	1					
12. Foreign	−0.09	−0.03*	−0.09*	0.05*	0.04*	−0.43*	0.04*	0.09*	0.10*	0.04*	0.18*	1				
13. Age	−0.11*	−0.08*	−0.09*	0.09	0.04*	−0.26*	0.04*	0.04*	−0.07	−0.02*	−0.05*	0.15*	1			
14. STEM share	0.25*	0.14*	0.12*	0.22*	0.23*	0.01*	0.01*	−0.06*	0.17*	0.11*	0.17*	0.07*	−0.07*	1		
15. R&D intensity	0.30*	0.14*	0.14*	0.19*	0.23*	0.03*	−0.02*	−0.01*	0.14*	0.08*	0.11*	0.02	−0.07*	0.37*	1	
16. Digital intensity	0.12*	0.10*	0.06*	0.07*	0.06*	0.05*	−0.04	−0.02*	0.10*	0.05*	0.06*	−0.02*	−0.04*	0.07*	0.22*	1
17. Part of group	−0.04	0.01*	0.01*	0.07*	0.03*	−0.15*	−0.04*	−0.03*	0.02*	0.03*	0.08*	0.17*	0.11*	0.15*	−0.07*	−0.09*

Note: Significance *0.05% does not include zero.
Source: U.K. Innovation Survey (2004–2020) and Business Register (2004–2020). Number of observations: 25,813.

TABLE 4 Tobit and logistic regression for the effect of knowledge collaboration breadth on innovation.

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	Product innovation				Process innovation			
Estimation method	Tobit regression				Logistic regression			
Regional breadth (Hypothesis 1a)	4.801*** (0.66)	0.747*** (0.39)	0.830*** (0.43)	0.802*** (0.38)	1.455*** (0.06)	1.230*** (0.05)	1.290*** (0.06)	1.200*** (0.06)
Regional breadth squared (Hypothesis 1a)	−0.491*** (0.12)	−0.038*** (0.11)	−0.044*** (0.12)	0.002*** (0.13)	0.965*** (0.00)	0.981*** (0.00)	0.976*** (0.00)	0.986*** (0.00)
National breadth (Hypothesis 1b)	11.790*** (0.61)	4.238*** (0.55)	4.576*** (0.58)	4.541*** (0.64)	1.887*** (0.07)	1.392*** (0.05)	1.369*** (0.06)	1.460*** (0.01)
National breadth squared (Hypothesis 1b)	−1.531*** (0.11)	−0.628*** (0.10)	−0.693*** (0.11)	−0.645*** (0.12)	0.927*** (0.00)	0.961*** (0.00)	0.963*** (0.00)	0.951*** (0.00)
International breadth	11.330*** (0.82)	6.445*** (0.75)	6.230*** (0.80)	6.739*** (0.93)	1.249*** (0.06)	1.182*** (0.06)	1.174*** (0.07)	1.460*** (0.10)
International breadth squared (Hypothesis 1b)	−1.295*** (0.15)	−1.057*** (0.14)	−1.032*** (0.15)	−1.160*** (0.17)	0.994*** (0.00)	0.982*** (0.01)	0.984** (0.01)	0.953** (0.01)
Small		3.762*** (0.81)	3.774*** (0.81)	3.801*** (0.80)		0.856** (0.05)	0.856** (0.06)	0.895*** (0.05)
Medium		1.062 (0.94)	1.080 (0.94)	1.090 (0.94)		0.810** (0.06)	0.808** (0.06)	0.816** (0.06)
Medium–large		0.993 (1.01)	0.981 (1.01)	0.996 (1.01)		0.966 (0.08)	0.967 (0.08)	0.966 (0.08)
Exploration		7.060*** (0.26)	7.064*** (0.26)	7.048*** (0.27)		1.441*** (0.03)	1.442*** (0.03)	1.433*** (0.03)
Process innovation		11.840*** (0.70)	11.850*** (0.70)	11.840*** (0.70)				
Product innovation						1.016*** (0.00)	1.016*** (0.00)	1.016*** (0.00)
Organizational innovation internal		0.801 (0.74)	0.797 (0.74)	0.791 (0.74)		2.336*** (0.13)	2.331*** (0.13)	2.332*** (0.13)
Organizational innovation external		6.066*** (0.62)	6.066*** (0.62)	6.044*** (0.61)		1.033 (0.05)	1.033 (0.05)	1.020 (0.05)
Foreign		−2.790*** (0.65)	−2.797*** (0.65)	−2.772*** (0.65)		0.555*** (0.03)	0.556*** (0.03)	0.545*** (0.03)
Age		−2.681** (0.41)	−2.680*** (0.41)	−2.671*** (0.41)		0.956 (0.03)	0.955 (0.03)	0.954 (0.03)
STEM share		0.192*** (0.01)	0.192*** (0.01)	0.221*** (0.01)		1.003*** (0.00)	1.002*** (0.00)	1.002*** (0.00)
R&D intensity		0.539*** (0.04)	0.534*** (0.04)	0.550*** (0.04)		1.001 (0.00)	1.001 (0.00)	1.002 (0.00)
Digital intensity		0.185*** (0.05)	0.205** (0.06)	0.186*** (0.05)		1.024*** (0.00)	1.029*** (0.00)	1.024*** (0.00)
Part of group		−0.014 (0.06)	−0.013 (0.06)	−0.013 (0.06)		1.003 (0.00)	1.003 (0.00)	1.003 (0.00)
Enterprise group		11.730*** (1.10)	11.710*** (1.10)	11.740*** (1.10)		1.846*** (0.19)	1.848*** (0.19)	1.794*** (0.18)
Suppliers		−1.391 (1.10)	−1.403 (1.10)	−1.385 (1.10)		0.903 (0.08)	0.897 (0.08)	0.898 (0.08)
Customers		4.984*** (1.30)	4.979*** (1.30)	4.889*** (1.30)		1.199 (0.13)	1.196 (0.13)	1.188 (0.13)

TABLE 4 (Continued)

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Competitors		2.185* (1.02)	2.177** (1.02)	2.157** (1.01)		0.856 (0.07)	0.855 (0.07)	0.850 (0.07)
Consultants		0.137 (0.70)	0.158 (0.70)	0.063 (0.70)		1.134* (0.06)	1.136** (0.06)	1.131** (0.06)
University		1.770* (0.82)	1.780* (0.82)	1.797** (0.82)		1.226** (0.08)	1.223** (0.08)	1.222** (0.08)
Government		1.263 (0.79)	1.247 (0.49)	1.260 (0.79)		0.984 (0.06)	0.987 (0.06)	0.986 (0.06)
Digital intensity × regional breadth (Hypothesis 2a)			−0.037 (0.10)				0.979** (0.00)	
Digital intensity × regional breadth squared (Hypothesis 2a)			0.003 (0.01)				1.002 (0.00)	
Digital intensity × national breadth (Hypothesis 2b)			−0.163 (0.09)				1.009 (0.00)	
Digital intensity × national breadth squared (Hypothesis 2b)			0.030 (0.01)				0.999 (0.00)	
Digital intensity × international breadth (Hypothesis 2b)			0.128 (0.02)				1.002 (0.00)	
Digital intensity × international breadth squared (Hypothesis 2b)			−0.018 (0.02)				1.000 (0.00)	
STEM share × regional breadth				−0.009* (0.00)				1.002* (0.00)
STEM share × regional breadth squared				−0.003 (0.00)				0.999*** (0.00)
STEM share × national breadth				−0.030 (0.00)				0.996* (0.00)
STEM share × national breadth squared				0.003 (0.00)				1.002** (0.00)
STEM share × international breadth				−0.002 (0.03)				0.760 (0.08)
STEM share × international breadth squared				0.005 (0.01)				1.041 (0.03)
Constant					0.041*** (0.00)	0.040*** (0.00)	0.037*** (0.00)	0.036*** (0.00)
χ^2	3128.23	7480.67	7486.33	7492.04	2214.90	3909.26	3925.09	3951.08

Note: Reference category for sector is SIC = 1 (basic manufacturing), for legal status is Company (limited liability company), for firm size (large firm >250 FTEs). Statiatical significance is *0.05%, **0.01% and ***0.001% does not include zero.
Source: U.K. Innovation Survey (2004–2020) and Business Register (2004–2020). Number of observations: 25,813.

Figure 1a illustrates the diminishing marginal returns to regional collaboration breadth for product innovation and the inverted U-shaped relationship between regional collaboration breadth and process innovation.

The curvilinear shape of the knowledge collaboration breadth with national and international partners and product innovation is illustrated in Figure 1b,c (left column) and process innovation in Figure 1b,c (right column). Firms achieve a maximum expected value of product innovation when collaborating with a minimum of three (product innovation) and a maximum of four different partner types (process innovation).

Our Hypothesis 2a, which states that an investment in digital technologies reduces the diminishing marginal

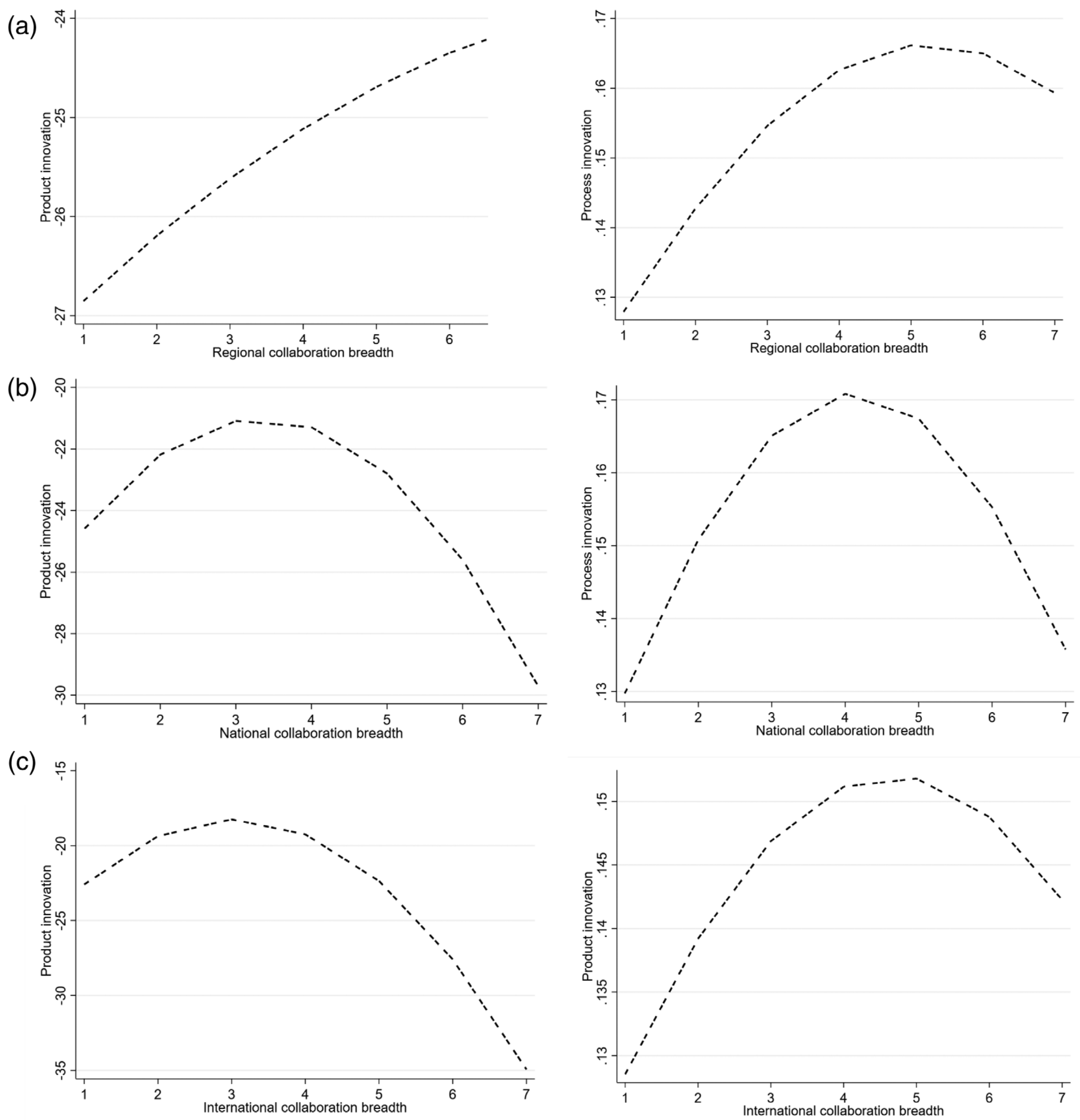

FIGURE 1 Predictive margins of the effect of R&D collaboration on product innovation for (a) regional partners, (b) national partners, (c) European and international partners with 95% confidence intervals. *Source*: U.K. Innovation Survey (2004–2020) and Business Register (2004–2020). Number of observations: 25,813.

returns of regional R&D collaboration breadth on firm innovation, is not supported. Both interaction coefficients between digital intensity and regional collaboration breadth in levels and squared are not statistically significant (Specifications 3 and 7, Table 4). The direct effect of digital intensity is positive and significant for product innovation ($\beta = 0.185$–0.205, $p < 0.001$) (Specifications 2 and 3, Table 4) and for process innovation ($\beta = 1.002$–1.003, $p < 0.01$) (Specifications 6 and 7, Table 4). In economic terms, this means that an increase in investment in digital intensity by one standard deviation does not change a firm's propensity to innovate new processes and products if regional R&D collaboration breadth changes by one unit. Figure 2a illustrates this relationship diagrammatically, with little difference between product and process innovation. Firms with higher digital intensity do not receive innovation premiums if collaborating on R&D regionally. and their average level of product and process innovation is lower than for firms that do not invest or invest less in digital intensity.

The most interesting finding is that regardless of the extent of a firm's digital intensity, the negative effect of R&D collaboration breadth on product and process innovation does not change for regional partners nor for partners in distant geographical proximity, which does not support Hypothesis 2b. An increase in digital intensity

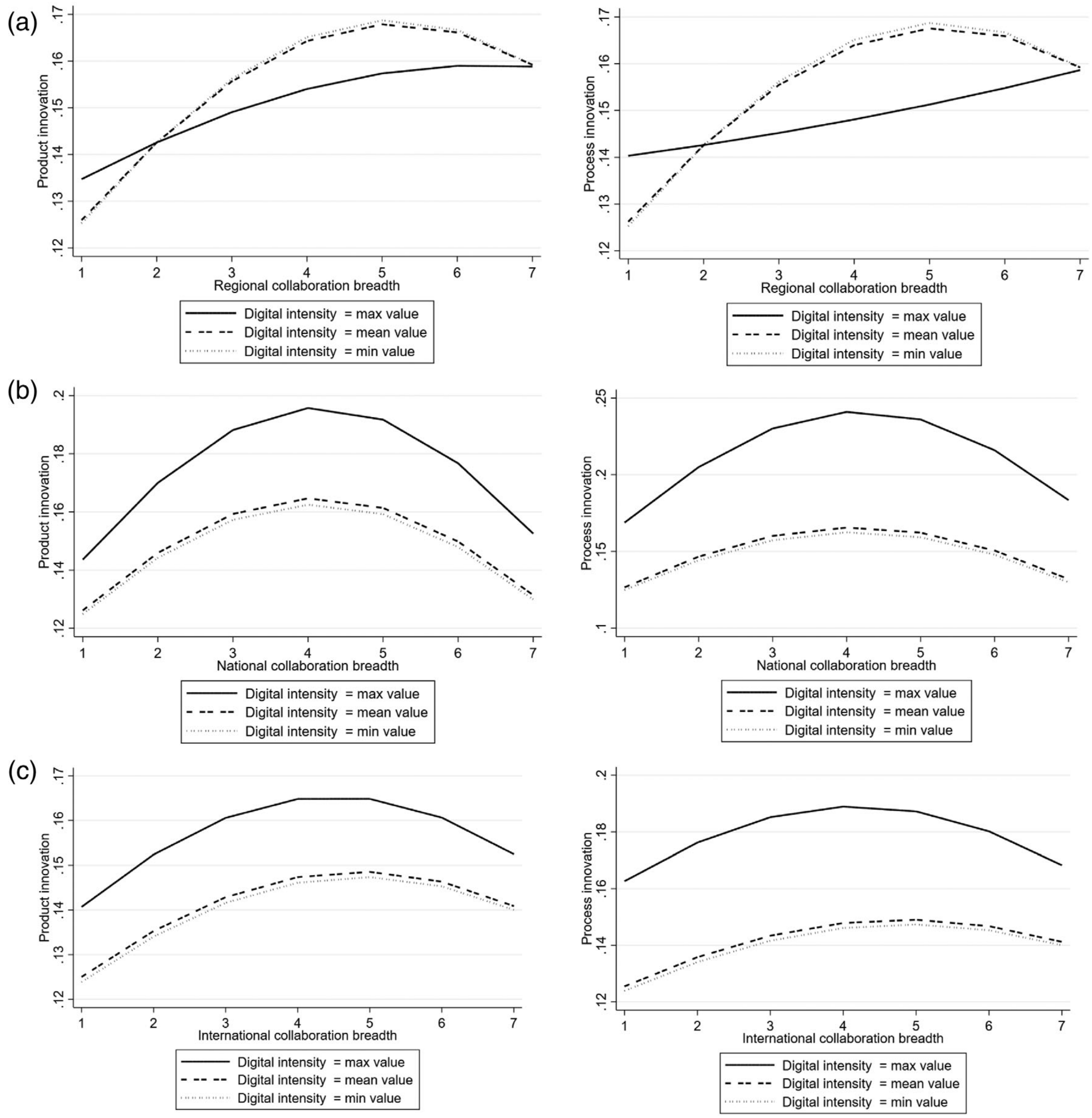

FIGURE 2 Predictive margins of the effect of R&D collaboration breadth on product innovation (left column) and process innovation (right column) for firms that used (a) regional partners, (b) national partners, (c) international partners and for firms with different digital intensity (95% confidence intervals). *Source*: U.K. Innovation Survey (2004–2020) and Business Register (2004–2020). Number of observations: 25,813.

shifts the inverted U-shaped curve of national and international R&D collaboration breadth upwards, with the negative effect persisting for both product (Figure 2b,c, left column) and process innovation (Figure 2b,c, right column) Table 4 (Specifications 3 and 7) demonstrates that the interaction coefficients are insignificant. Firms achieve a maximum expected value of product and process innovation when collaborating with a minimum of five partner types regionally without investment in digital technologies. The maximum product and process innovation can be achieved with four different partner types (see Figure 2b,c). Interestingly, the same maximum level of product and process innovation can be achieved with a smaller number of national and international partner types compared to regional partners.

4.2 | Other results

Table 4 also demonstrates that additional factors can affect product and process innovation in our model. Firm size is associated with innovation outcomes, with smaller firms being more likely to introduce product innovation. In contrast, small and medium firms were less likely to introduce process innovation than large firms. This demonstrates that larger firms are less adaptive and flexible at introducing new products; however, they develop high productivity and efficiency levels in operations, which allows them to introduce process innovation. Firm age is not associated with process innovation, demonstrating that process innovation can take place equally in startups and mature firms. The coefficients for exploration activity related to the development of new product ranges and entering new markets (March, 1991) are positive and significant for the product ($\beta = 7.064$, $p < 0.01$) (Specification 3, Table 4) and process innovation ($\beta = 1.4420$, $p < 0.001$) (Specification 7, Table 4). Firms that introduce process innovation have an average 11.84% higher share of new-to-market products (Specification 2, Table 4), while firms that innovate new products increase their propensity for process innovation by 1.6% for every percentage point increase in new product sales (Specification 6, Table 4). Internal organizational innovation is positively associated with process innovation, while organizational innovation with external partners is positively associated with product innovation. R&D intensity is positive and statistically significant for product innovation ($\beta = 0.539$, $p < 0.01$), but is not associated with process innovation. This demonstrates that process innovation is about changes in efficiency and organization, and may not require additional R&D expenditure.

Firms that are part of an enterprise group are not more or less likely to innovate. However, engaging in collaboration within an enterprise group increases both product ($\beta = 11.73$, $p < 0.001$) and process ($\beta = 1.846$, $p < 0.001$) innovation. A one percentage point increase in the employment of STEM workers is associated with an additional 0.19% ($\beta = 0.192$, $p < 0.001$) growth of new product sales and an increase in the propensity of process innovation of between 2% and 3% ($\beta = 1.003$, $p < 0.001$) (Specification 6, Table 4).

In addition, we control for different external partner types, with collaboration with enterprise groups and with universities increasing both process and product innovation. Collaboration with suppliers reduces both process and product innovation, as it offers readymade solutions. Collaboration with customers and competitors is an important conduit for product innovation (Mariani & Belitski, 2022; Ritala et al., 2015), while it is unlikely to change the process by which innovation is created (Bohlmann et al., 2013). Collaboration with consultants increases process innovation but is not associated with product innovation. Collaboration with the government is not associated with product and process innovation (Van Beers & Zand, 2014).

4.3 | Post hoc analysis

Firm managers rely on highly qualified labor and new product development teams to carry out their directives and make decisions (Spanjol, Tam, et al., 2011). As the first step of the post hoc analysis, we wanted to discuss how investment in a firm's human capital may increase its absorptive capacity (Cohen & Levinthal, 1990) and reduce the cost of knowledge transfer for product and process innovation (Williamson & Masten, 1995). By employing talented individuals who possess relevant knowledge in technology, and are aware of digital tools, a firm could increase its dynamic capabilities (Eisenhardt & Martin, 2000). This could help it to overcome the negative effect of R&D collaboration breadth on firm innovation. Despite the promise of this mechanism, relatively little research has examined how the STEM knowledge and expertise of individuals can facilitate innovation and reduce the transaction and managerial costs (Audretsch & Belitski, 2023) associated with an increased R&D collaboration breadth (Kobarg et al., 2019). In this part of the analysis, we examine whether an increase in the share of STEM employees in a firm may reduce the negative effect and sustain the positive effect of R&D collaboration breadth on innovation outcomes. We use the share of full-time STEM employees in the total number of employees to test how the relationship between R&D collaboration breadth and innovation may change. We interact STEM with the R&D collaboration breadth for regional, national, and international collaborations (Specifications 4 and 8, Table 4).

Based on Specification 4 (Table 4) we use the "margins" command to calculate and plot the predictive margins of regional, national, and international collaboration breadth and innovation outcomes using the mean, one standard deviation below and above the mean share of STEM employees. The interaction coefficient of STEM and regional collaboration breadth is negative, meaning that an increase in regional collaboration breadth and employing more STEM workers than average leads to a reduction in product innovation ($\beta = -0.009$, $p < 0.05$) (Specification 4, Table 4). Diagrammatically the effect is plotted in Figure 3a (left column). Our results for process innovation are different. Firms with more STEM employees than average will be able to initially increase their propensity to process innovation when the number of collaboration partners increases regionally ($\beta = 1.002$, $p < 0.05$ and $\beta^2 = 0.999$, $p < 0.05$; Specification 8, Table 4). However, the positive effect is only valid until four collaboration partner types and reduces after.

Interestingly, firms that have more STEM employees than average will be able to increase their propensity to process innovation when the number of collaboration partners increases nationally ($\beta = 0.996$, $p < 0.05$ and $\beta^2 = 1.002$, $p < 0.01$; Specification 8, Table 4) (Figure 3b, right column). An increase in STEM employees does not change the inverted U-shaped relationship between

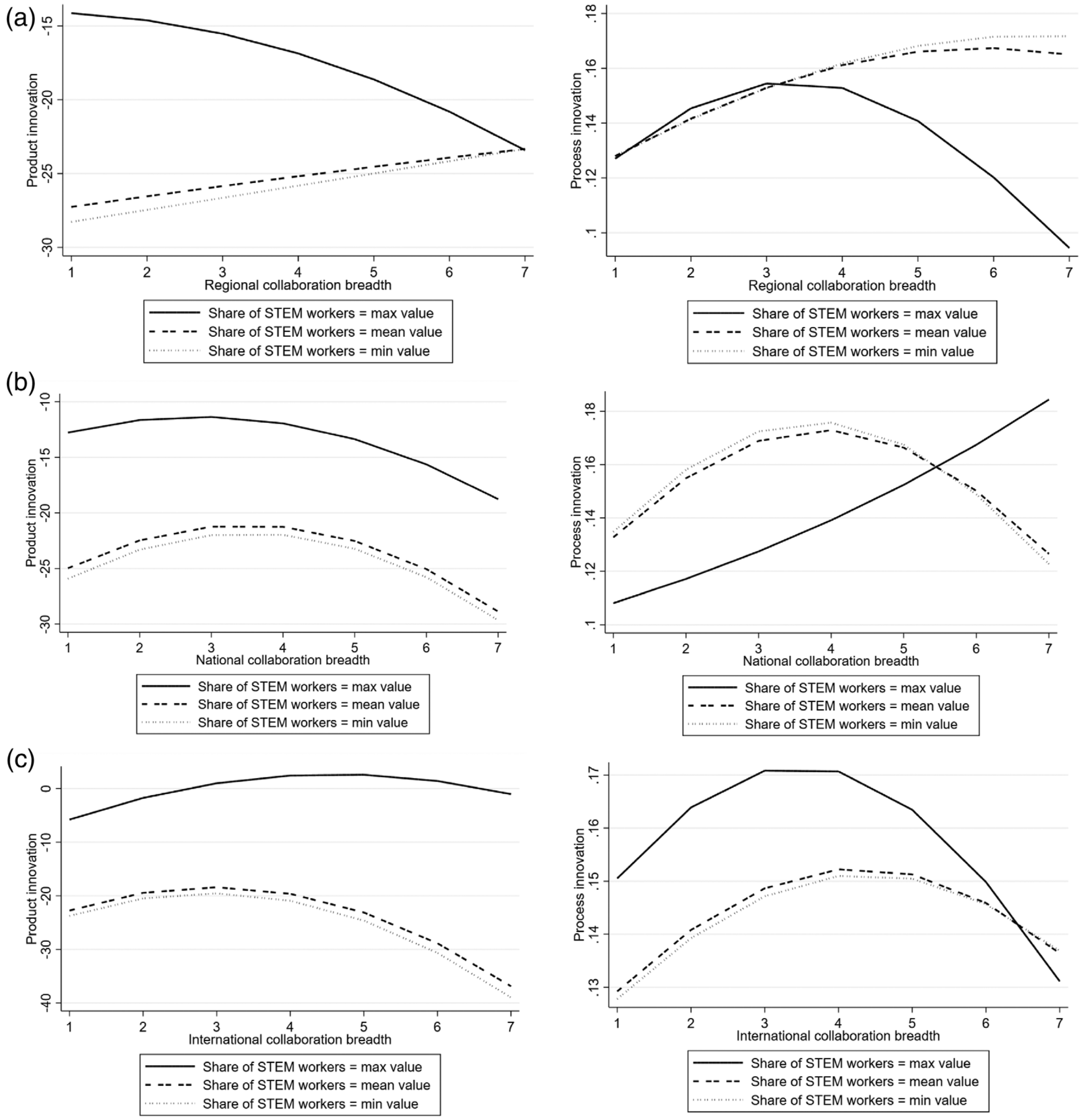

FIGURE 3 Predictive margins of R&D collaboration on product (left) and process innovation (right) for firms that used (a) regional partners; (b) national partners; (c) international partners and a share of STEM employees (95% confidence intervals). *Source*: U.K. Innovation Survey (2004–2020) and Business Register (2004–2020). Number of observations: 25,813.

regional and international R&D collaboration and process innovation (Figure 3a,c, right column). The curve shifts upward in the case of international knowledge collaboration breadth and more STEM employees, however, the negative effect on firm innovation is persistent.

As the second part of the post hoc analysis, we estimated a multilevel (mixed-effect) logistic model (Goldstein, 2003), which is illustrated in Table 5 and can be compared with the results in Table 4. The selection of a multilevel estimation approach was important in our case and was based on the fact that the innovation survey is not a panel survey. Consequently, firms from one wave may not always participate in the next survey. Each wave is selected as a stratified sample of a pull of firms by industry, region, and size. The panel element in a sample is treated using a multilevel estimation approach.

Multilevel analysis is sometimes called a hierarchical, random coefficient, or mixed-effect model. First, the macro-level contains the eight waves of the BDS–BERD–UKIS dataset; there are 12 U.K. regions at the meso-level. Finally, there are 14,516 firms in the sample assumed to be randomly sampled per unit (micro-level).

Given that the dependent variable is "product innovation," it was measured as a fraction of the firm's annual sales of new-to-market products. The resulting dependent variable was defined on the interval [0, 100]

TABLE 5 Mixed-effect GLS estimation for the effect of knowledge collaboration breadth on innovation.

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	Product innovation				Process innovation			
Regional breadth (Hypothesis 1a)	0.280*** (0.04)	0.067*** (0.03)	0.058*** (0.03)	0.070*** (0.03)	1.375*** (0.06)	1.095* (0.05)	1.137* (0.05)	1.037 (0.06)
Regional breadth squared (Hypothesis 1a)	−0.033*** (0.01)	−0.009 (0.01)	−0.007 (0.01)	−0.011 (0.11)	0.975*** (0.00)	1.000 (0.00)	0.997 (0.00)	1.010 (0.00)
National breadth (Hypothesis 1b)	0.573*** (0.04)	0.215*** (0.04)	0.244*** (0.04)	0.223*** (0.05)	1.736*** (0.07)	1.257*** (0.05)	1.218*** (0.05)	1.345*** (0.06)
National breadth squared (Hypothesis 1b)	−0.069*** (0.01)	−0.027*** (0.00)	−0.032*** (0.00)	−0.028*** (0.00)	0.965*** (0.01)	0.974* (0.01)	0.976 (0.01)	0.972 (0.01)
International breadth	0.662*** (0.05)	0.406*** (0.06)	0.406*** (0.06)	0.434*** (0.07)	1.381*** (0.08)	1.206*** (0.07)	1.201*** (0.07)	1.229*** (0.09)
International breadth squared (Hypothesis 1b)	−0.092*** (0.01)	−0.072*** (0.01)	−0.072*** (0.01)	−0.074*** (0.01)	0.965*** (0.01)	0.974* (0.01)	0.976 (0.01)	0.972 (0.01)
Small		0.306*** (0.05)	0.306*** (0.05)	0.307*** (0.05)		0.785** (0.05)	0.786** (0.06)	0.789*** (0.05)
Medium		0.174** (0.06)	0.175** (0.06)	0.175** (0.06)		0.777** (0.06)	0.773** (0.06)	0.779** (0.07)
Medium–large		0.128 (0.07)	0.128 (0.07)	0.127 (0.07)		0.810* (0.08)	0.812* (0.08)	0.812* (0.07)
Exploration		0.521*** (0.02)	0.521*** (0.01)	0.522*** (0.02)		1.392*** (0.03)	1.385*** (0.03)	1.391*** (0.03)
Process innovation		1.031*** (0.05)	1.033*** (0.05)	1.031*** (0.05)				
Product innovation						1.019*** (0.00)	1.019*** (0.00)	1.019*** (0.00)
Organizational innovation internal		0.135** (0.05)	0.136** (0.05)	0.133** (0.05)		1.843*** (0.11)	1.782*** (0.10)	1.845*** (0.11)
Organizational innovation external		0.289*** (0.04)	0.289*** (0.04)	0.290*** (0.04)		1.247*** (0.06)	1.238*** (0.06)	1.247*** (0.07)
Foreign		0.082 (0.05)	0.082 (0.05)	0.081 (0.05)		1.017 (0.06)	1.032 (0.06)	1.016 (0.06)
Age		−0.048 (0.03)	−0.049 (0.03)	−0.048 (0.04)		0.930* (0.03)	0.923* (0.03)	0.931* (0.03)
STEM share		0.009*** (0.00)	0.009*** (0.00)	0.009*** (0.00)		1.001* (0.03)	1.001 (0.00)	1.002*** (0.04)
R&D intensity		0.022*** (0.00)	0.022*** (0.00)	0.022*** (0.00)		0.999 (0.00)	1.000 (0.00)	1.001 (0.00)
Digital intensity		0.004** (0.00)	0.007** (0.00)	0.004** (0.00)		1.031*** (0.00)	1.028*** (0.00)	1.031*** (0.00)
Part of group		−0.001 (0.00)	−0.001 (0.00)	−0.001 (0.01)		1.005 (0.01)	1.005 (0.00)	1.004 (0.00)
Enterprise group		0.808*** (0.08)	0.806*** (0.08)	0.807*** (0.08)		1.836*** (0.20)	1.764*** (0.19)	1.836*** (0.20)
Suppliers		0.019* (0.00)	0.018** (0.00)	0.020** (0.00)		1.307* (0.14)	1.181** (0.13)	1.313** (0.14)
Customers		0.246*** (0.09)	0.244*** (0.09)	0.246*** (0.09)		1.381** (0.16)	1.367** (0.16)	1.370** (0.16)
Competitors		0.085 (0.07)	0.085 (0.07)	0.082 (0.07)		0.880 (0.08)	0.876 (0.08)	0.881 (0.08)
Consultants		−0.022 (0.05)	−0.022 (0.05)	−0.024 (0.05)		1.135* (0.07)	1.127 (0.07)	1.132* (0.07)
University		0.117** (0.05)	0.116** (0.05)	0.117** (0.05)		1.228** (0.07)	1.225** (0.07)	1.229** (0.08)
Government		0.030 (0.05)	0.030 (0.05)	0.032 (0.05)		0.968 (0.06)	0.970 (0.07)	0.969 (0.07)
Digital intensity × regional breadth (Hypothesis 2a)			0.005 (0.01)				0.980** (0.00)	
Digital intensity × regional breadth squared (Hypothesis 2a)			−0.001 (0.00)				1.002** (0.00)	
Digital intensity × national breadth (Hypothesis 2b)			−0.014 (0.00)				1.011 (0.00)	
Digital intensity × national breadth squared (Hypothesis 2b)			0.002 (0.00)				0.999 (0.00)	
Digital intensity × international breadth (Hypothesis 2b)			0.001 (0.01)				0.999 (0.01)	

TABLE 5 (Continued)

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Digital intensity × international breadth squared (Hypothesis 2b)			0.001 (0.01)				1.000 (0.00)	
STEM share × regional breadth				−0.011* (0.00)				1.004* (0.00)
STEM share × regional breadth squared				0.001 (0.00)				0.998* (0.00)
STEM share × national breadth				−0.001 (0.00)				0.995* (0.00)
STEM share × national breadth squared				0.001 (0.00)				1.003** (0.00)
STEM share × international breadth				−0.001 (0.00)				0.999 (0.00)
STEM share × international breadth squared				0.001 0.00)				1.001 (0.00)
Constant	−0.402* (0.16)	−2.660*** (0.20)	−2.659*** (0.20)	−2.671*** (0.20)	−3.422*** (0.20)	−3.471*** (0.20)	−3.492*** (0.20)	−3.470*** (0.19)
Variance (region-year)	1.320*** (0.24)	1.211*** (0.22)	1.211*** (0.23)	1.217*** (0.23)	1.826*** (0.22)	2.196*** (0.33)	2.263*** (0.35)	2.205*** (0.33)
χ^2	1749.79	3588.57	3592.37	3595.37	1452.79	2342.42	2377.51	2349.51
Log-likelihood	−12,305.89	−10,177.84	−10,173.82	−10,173.99	−8134.85	−7289.22	−7247.26	−7284.53

Note: Reference category for sector is SIC = 1 (basic manufacturing), for legal status is Company (limited liability company), for firm size (large firm >250 FTEs). Statiatical significance is *0.05%, **0.01% and ***0.001% does not include zero.
Source: U.K. Innovation Survey (2004–2020) and Business Register (2004–2020). Number of observations: 25,813.

(Goldstein, 2003). For the product innovation model, we applied the logistic transformation to change the coded interval between 0 and 1.

Formally, a generalized linear three-level model was estimated with the fractional dependent variable y_{ijk} and the independent variable x_{ijk} such that:

$$y_{ijk} = \beta_0 + \beta_1 x_{ijk} + \beta_2 \tau_{ijk} + \varepsilon_{ijk}, \quad (3)$$

where i is the firm Level 1, j is the region Level 2, and k serves to index the wave survey Level 3. The dependent variable y_{ijk} gathers product (process) innovation. The explanatory variables, which were described previously, are presented by x_{ijk}. Other control variables which represent firm-specific characteristics described in Table 1 are presented by τ_{ijk}. Finally, ε_{ijk} is an error term that consists of three components in the hierarchical model:

$$\varepsilon_{ijk} = \gamma_i + \mu_j + t_k + \nu_{ijk}, \quad (4)$$

where $\gamma_i$represents the omitted variables that vary across firms but not over regions and waves; μ_j denotes the omitted that vary over regions but are constant across firms and time; t_k represents omitted variables that vary across waves but not across firms and regions; and ν_{ijk} is the error term. In addition, a multilevel model specification also controls for the assumption of the independence of observations in grouped data.

The results of the mixed-effect estimation for product innovation are reported in Table 5 (Specifications 1–4) and for process innovation in Table 5 (Specifications 5–8). Our Hypothesis 1a is supported for product innovation, as we observed diminishing marginal returns, but is not supported for process innovation where the relationship is an inverted U-shape. Our Hypothesis 1b is supported, as we find an inverted U-shaped relationship between national and international R&D collaboration breadth and innovation outcomes across all specifications in Table 5. The higher digital intensity and a larger share of STEM employees directly and positively affect product innovation sales and increases the propensity to introduce process innovation. As the regional R&D collaboration breadth increases, an increase in digital intensity is not associated with product innovation but facilitates process innovation when the number of partners increases (Specification 7, Table 5). Finally, an increase in the share of STEM employees reduces the effect of regional R&D collaboration breadth on process innovation but increases the effect of national R&D collaboration breadth (Specification 8, Table 5), consistent with the findings outlined in Table 4.

5 | DISCUSSION

Prior research on the role that R&D collaboration breadth plays in innovation outcomes has been often limited to product innovation and investigating the associations and direct relationships (Brunswicker & Vanhaverbeke, 2015; Laursen & Salter, 2006; Nieto & Santamaría, 2007). Using longitudinal survey data on U.K.-based firms during the period 2004–2020, we theoretically debate and empirically test the nuanced inverted U-shape relationship between R&D collaboration breadth and two types of innovation outcomes: product and process innovation. In addition, we explain why knowledge collaboration may experience positive, diminishing, and finally negative returns to product and process innovation Drawing on Laursen and Salter (2006) and Audretsch and Belitski et al. (2020), this study considers the role of geographical proximity, digital intensity and employment of STEM graduates as additional boundary conditions for this relationship. Although the results do not always support our hypotheses, they provide important and novel insights into the impact of R&D collaboration breadth on product and process innovation, putting STEM employment and digital intensity across different geographical proximities of R&D collaboration to the competitive test. The estimation results are particularly important because prior studies have not investigated the mechanisms which enable firms to sustain the positive effect of R&D collaboration breadth for product and process innovation when the number of types of collaboration partners increases. Neither has prior research examined a combination of up to seven types of knowledge partners or the extent to which firms invest in digital technologies and recruit STEM graduates. Our findings have four main aspects.

First, our results reveal that the returns from R&D collaboration breadth depend on the geographical location of collaboration partners and the extent of digital technology investment, and the ability to attract STEM workers.

Second, R&D collaboration breadth regionally has diminishing marginal returns on product innovation and both positive (knowledge effect) and negative (cost effect) impacts on process innovation. As the geographical proximity between collaboration partners increases, the negative effects increase and begin to reduce process and product innovation.

Third, we found that the slope of the predicted margins for national and international R&D collaboration breadth shifts upwards for product and process innovation for firms with higher than average digital intensity. The negative effect remains unchanged, demonstrating that returns to R&D collaboration breadth are subject to managerial and transaction costs which cannot be leveraged with investment in digital tools alone.

Finally, an increase in R&D collaboration with national partners and investment in absorptive capacity by employing more STEM graduates is the unique combination that facilitates process innovation at the highest partner diversity. An increase in STEM workers and partner diversity is not associated with product innovation or process innovation when collaborating internationally. This may be limited to absorptive capacity and significant cognitive and institutional differences limiting the efficiency of R&D collaboration breadth.

The most under-researched phenomenon in the prior literature is the boundary condition which reduces the negative effect of R&D collaboration breadth on a variety of innovation outcomes. While the transfer of knowledge inter-regionally and internationally may lead to increasing protection and engagement costs, firms and even regions (e.g., Silicon Valley) may be very highly specialized in terms of the knowledge pertinent to product and process innovation and will be able to benefit from collaboration with international partners of different types. Firms that invest in digital tools and have higher absorptive capacities are more likely to waste their resources if they focus on local collaborations. Thus, there may be limits to collaborating with regional proximity, resulting in diminished marginal returns as a firm prioritizes the internalization of knowledge. Furthermore, regionally proximal firms may use relatively similar tools and have common knowledge of the market and technology, making their collaboration obsolete. This is unlikely to happen with international collaboration partners.

A diversity of knowledge from inter-regional and international collaboration partners significantly increases the benefits of such collaborations for product and process innovation. The differences in returns to R&D collaboration between product and process innovation may be explained by the essential differences between the two innovation types. First, process innovation aims at efficiency in operations and not at creating a new product or service per se; this is often achieved through benchmarking with international partners. Process innovation is very industry-specific, and learning from foreign competitors may serve to establish new processes in the local industry but may not apply to the new products. Second, process innovation is systemic. This means partner diversity may be needed to complete the complexity of the process and understand the exact elements of the knowledge package coming from different partners and not just one specific partner, increasing the demand for collaboration breadth. Finally, process innovation is less visible, contrary to product innovation. Because it is embedded in firm routines, it will not repeat the processes applied by any specific collaborator. This may reduce the risk of intellectual property disputes, as processes can be introduced more rapidly and in a more ad hoc fashion compared to the invention and commercialization of new products (Davenport, 1993). These differences between innovation types are important as they may directly affect the choice of the mechanisms used to facilitate the returns from knowledge collaboration breadth. For example, investment in digital tools without understanding the type of partner and context may not transfer into innovation outcomes. Meanwhile, employing STEM graduates is likely to increase managerial and absorptive capacities, as well as knowledge of how to use technology, which will eventually be used in knowledge collaborations.

6 | CONCLUSION

The findings of this study suggest a fundamental rethinking of the imperative of local proximity is required, as well as the extent of investment in absorptive capacity and managerial capabilities for accessing knowledge collaboration and shaping product and process innovation. As earlier studies on the geography of R&D collaboration (Balland et al., 2015; Boschma, 2005; Crescenzi et al., 2016) on the role of spatial proximity have demonstrated, geographic proximity is indeed conducive to positive returns to knowledge collaboration breadth for product innovation, but not for process innovation. However, spatial proximity internalizes knowledge collaboration and reduces the positive returns from R&D collaboration breadth compared to inter-regional and international collaborations. Knowledge collaboration breadth may have both positive and negative effects on product and process innovation; however, the effects may be partly leveraged by the share of STEM employees in a firm. STEM employees have greater compared to non-STEM employees, managerial and absorptive capacity and are trained to deal with very diverse and technical knowledge, enabling firms to further explore R&D collaborations and increase innovation outcomes.

Our findings call for a fundamental rethinking about the primacy of geographic proximity, cognitive and institutional knowledge distance, and how knowledge can be transferred across international borders facilitating innovation outcomes. The results of our study seem to be a common sense garnered in an era of face-to-face communication made possible by technological platforms such as Zoom. Further advancements in digital technologies and STEM education and training may reduce the cost of knowledge transfer nationally and internationally, and be the next best thing to being there in innovation (Belitski et al., 2020).

6.1 | Policy and managerial implications

Two aspects of this study make it especially useful for managers. First, prior research suggested two types of relationships: between knowledge collaboration and product innovation (Kobarg et al., 2019; Laursen & Salter, 2006), and between knowledge collaboration and process innovation (Un & Asakawa, 2015). This study's arguments and results draw managers' attention to the notion that the most fruitful approach lies at the intersection of regional and international knowledge collaboration, investment in digital technology and tools, along with investment in STEM graduates and training for existing employees in STEM-related disciplines. It is important to keep the number of R&D collaboration types under five for regional collaborations, and under four when engaging in R&D collaboration between regions and internationally. This reminder of the importance of balance between various knowledge partner types, and the role of each collaboration partner type in product and process innovation, is especially relevant in the context of the three conflicting strategies related to R&D collaboration. These include the choice of partner type (e.g., competitor, university, suppliers, etc.); how many partners to collaborate with; and where they are located. Depending on the choice of strategy, the next step is to choose the extent of investment in advanced machinery, digital equipment, hardware, and software, as well as the share of STEM workers. External factors such as the geographic location of knowledge partners and their diversity, as well as firm-specific factors such as the extent of investment in digital technology and the share of STEM employees, ultimately determine the type of innovation (process or product) a firm is likely to achieve.

A firm's innovation strategy should be designed to leverage the negative effect of the breadth of R&D based on the findings of this study.

6.2 | Limitations and future research

Our findings pave the way for several future studies that may address this study's limitations. As our study uses a sample of U.K. innovative firms, our findings are contextually limited and may not be generalizable to other developing and middle-income countries. They may be partly generalized for other OECD countries with similar levels of firm innovation and investment in digital technology, R&D, and STEM education. Future studies can examine the ecological validity of our results by collecting data from other countries and comparing findings. As this study is based on quantitative work, longitudinal case studies could be conducted to explore how the requirements for routines/capabilities develop and evolve at different stages of open innovation.

Future research will jointly examine the breadth and depth of collaboration for product and process innovation at the project level instead of the firm level, and search for different combinations of partner types that may be especially efficient in specific markets and industries. Given the availability of data on the depth of R&D collaboration across each innovation partner type, future researchers using the UKIS data may want to examine the complementarity between specific pairs of R&D collaboration partners that may be especially efficient in product, process, and organizational innovation.

ACKNOWLEDGMENTS

We would like to thank a distinguished Professor David Bruce Audretsch, American economist and Ameritech Chair of Economic Development for his valuable contribution to our resrearch and understanding the knowlege spillover of innovation. Furthemore, we thank the JPIM Editor-in-Chief Professor Jelena Spanjol and the three anonymous reviewers for their valuable comments and suggestions throughout the manuscript developemnt. This research was funded by the British Academy within the project titled Tackling the UK's International Challenges number IC160084 from 17/02/2017.

CONFLICT OF INTEREST STATEMENT

The authors have no conflict of interest to declare.

ETHICS STATEMENT

The authors have read and agreed to the Committee on Publication Ethics (COPE) international standards for authors.

ORCID

Maksim Belitski https://orcid.org/0000-0002-9895-0105

REFERENCES

Akerkar, R. 2019. *Artificial Intelligence for Business*. Cham: Springer.

Asimakopoulos, G., A. J. Revilla, and K. Slavova. 2020. "External Knowledge Sourcing and Firm Innovation Efficiency." *British Journal of Management* 31(1): 123–140.

Audretsch, D. B., and M. Belitski. 2020. "The Limits to Collaboration across Four of the Most Innovative UK Industries." *British Journal of Management* 31(4): 830–855.

Audretsch, D. B., and M. Belitski. 2022. "The Knowledge Spillover of Innovation." *Industrial and Corporate Change* 31(6): 1329–57.

Audretsch, D. B., and M. Belitski. 2023. "The Limits to Open Innovation and its Impact on Innovation Performance." *Technovation* 119: 102519.

Audretsch, D. B., M. Belitski, and R. Caiazza. 2021. "Start-Ups, Innovation and Knowledge Spillovers." *The Journal of Technology Transfer* 46(6): 1995–2016.

Audretsch, D. B., M. Belitski, R. Caiazza, and D. Siegel. 2023. "Effects of Open Innovation in Startups: Theory and Evidence." *Technological Forecasting and Social Change* 194: 122694.

Badir, Y. F., and G. C. O'Connor. 2015. "The Formation of Tie Strength in a Strategic alliance's First New Product Development Project: The Influence of Project and partners' Characteristics." *Journal of Product Innovation Management* 32(1): 154–169.

Balland, P.-A., R. Boschma, and K. Frenken. 2015. "Proximity and Innovation: From Statics to Dynamics." *Regional Studies* 49(6): 907–920.

Baum, J. A., T. Calabrese, and B. S. Silverman. 2000. "Don't Go it Alone: Alliance Network Composition and startups' Performance in Canadian Biotechnology." *Strategic Management Journal* 21(3): 267–294.

Belderbos, R., M. Carree, and B. Lokshin. 2004. "Cooperative R&D and Firm Performance." *Research Policy* 33(10): 1477–92.

Belderbos, R., M. Carree, and B. Lokshin. 2006. "Complementarity in R&D Cooperation Strategies." *Review of Industrial Organization* 28(4): 401–426.

Belderbos, R., M. Carree, B. Lokshin, and J. Fernández Sastre. 2015. "Inter-Temporal Patterns of R&D Collaboration and Innovative Performance." *Journal of Technology Transfer* 40: 123–137.

Belitski, M. 2019. "Innovation in Schumpeterian-Type Firms: Knowledge Collaboration or Knowledge Spillover?" *Foundations and Trends in Entrepreneurship* 15(3–4): 368–390.

Belitski, M., R. Caiazza, and Y. Rodionova. 2020. "Investment in Training and Skills for Innovation in Entrepreneurial Start-Ups and Incumbents: Evidence from the United Kingdom." *International Entrepreneurship and Management Journal* 16: 617–640.

Bogers, M., R. Bekkers, and O. Granstrand. 2012. "Intellectual Property and Licensing Strategies in Open Collaborative Innovation." In *Open Innovation in Firms and Public Administrations: Technologies for Value Creation*, edited by C. de Pablos Heredero and D. Lopez, 37–58. Hershey: IGI Global.

Bogers, M., and W. Horst. 2014. "Collaborative Prototyping: Cross-Fertilization of Knowledge in Prototype-Driven Problem Solving." *Journal of Product Innovation Management* 31(4): 744–764.

Bohlmann, J. D., J. Spanjol, W. J. Qualls, and J. A. Rosa. 2013. "The Interplay of Customer and Product Innovation Dynamics: An Exploratory Study." *Journal of Product Innovation Management* 30(2): 228–244.

Boschma, R. 2005. "Proximity and Innovation: A Critical Assessment." *Regional Studies* 39(1): 61–74.

Branstetter, L. G., and M. Sakakibara. 2002. "When Do Research Consortia Work Well and why? Evidence from Japanese Panel Data." *American Economic Review* 92(1): 143–159.

Brunswicker, S., and W. Vanhaverbeke. 2015. "Open Innovation in Small and Medium-Sized Enterprises (SMEs): External Knowledge Sourcing Strategies and Internal Organizational Facilitators." *Journal of Small Business Management* 53(4): 1241–63.

Cassiman, B., and R. Veugelers. 2002. "R&D Cooperation and Spillovers: Some Empirical Evidence from Belgium." *American Economic Review* 92(4): 1169–84.

Cheng, C. C., and E. K. Huizingh. 2014. "When Is Open Innovation Beneficial? The Role of Strategic Orientation." *Journal of Product Innovation Management* 31(6): 1235–53.

Chesbrough, H. 2006. "Open Innovation: A New Paradigm for Understanding Industrial Innovation." Paper presented at 10th Anniversary Summer Conference on Dynamics of Industry and Innovation: Organizations, Networks and Systems, Copenhagen

Coad, A., A. Segarra, and M. Teruel. 2016. "Innovation and Firm Growth: Does Firm Age Play a Role?" *Research Policy* 45(2): 387–400.

Cohen, W. M., and D. A. Levinthal. 1989. "Innovation and Learning: The Two Faces of R&D." *The Economic Journal* 99(397): 569–596.

Cohen, W. M., and D. A. Levinthal. 1990. "Absorptive Capacity: A New Perspective on Learning and Innovation." *Administrative Science Quarterly* 35(1): 128–152.

Colen, L., R. Belderbos, S. Kelchtermans, and B. Leten. 2022. "Reaching for the Stars: When Does Basic Research Collaboration between Firms and Academic Star Scientists Benefit Firm Invention Performance?" *Journal of Product Innovation Management* 39(2): 222–264.

Crépon, B., E. Duguet, and J. Mairessec. 1998. "Research, Innovation and Productivity: An Econometric Analysis at the Firm Level." *Economics of Innovation and New Technology* 7(2): 115–158.

Crescenzi, R., M. Nathan and A. Rodríguez-Pose. 2016. "Do Inventors Talk to Strangers? on Proximity and Collaborative Knowledge Creation." *Research Policy* 45(1): 177–194.

Das, T. K., and B. S. Teng. 2000. "A Resource-Based Theory of Strategic Alliances." *Journal of Management* 26(1): 31–61.

Davenport, T. H. 1993. *Process Innovation: Reengineering Work through Information Technology*. Boston: Harvard Business Press.

Deeds, D. L., and C. W. Hill. 1996. "Strategic Alliances and the Rate of New Product Development: An Empirical Study of Entrepreneurial Biotechnology Firms." *Journal of Business Venturing* 11(1): 41–55.

Dixit, A., J. Quaglietta, and C. Gaulton. 2021. "Preparing for the Future: How Organizations Can Prepare Boards, Leaders, and Risk Managers for Artificial Intelligence." *Healthcare Management Forum* 34(6): 346–352.

Dyer, J. H., and H. Singh. 1998. "The Relational View: Cooperative Strategy and Sources of Interorganizational Competitive Advantage." *Academy of Management Review* 23(4): 660–679.

Eisenhardt, K. M., and J. A. Martin. 2000. "Dynamic Capabilities: What Are they?" *Strategic Management Journal* 21(10–11): 1105–21.

Eisenhardt, K. M., and C. B. Schoonhoven. 1996. "Resource-Based View of Strategic Alliance Formation: Strategic and Social Effects in Entrepreneurial Firms." *Organization Science* 7(2): 136–150.

Faems, D., B. Van Looy, and K. Debackere. 2005. "Interorganizational Collaboration and Innovation: Toward a Portfolio

Approach." *Journal of Product Innovation Management* 22(3): 238–250.

Frenz, M., and G. Ietto-Gillies. 2009. "The Impact on Innovation Performance of Different Sources of Knowledge: Evidence from the UK Community Innovation Survey." *Research Policy* 38(7): 1125–35.

Galliè, E. P., and P. Roux. 2010. "Forms and Determinants of R&D Collaborations: Evidence Based on French Data." *Industry and Innovation* 17(6): 551–576.

Goldfarb, A., and C. Tucker. 2019. "Digital economics." *Journal of Economic Literature* 57(1): 3–43.

Goldstein, H. 2003. *Multilevel statistical models*. Arnold: London, UK.

Grant, R. M. 1996. "Toward a Knowledge-Based Theory of the Firms." *Strategic Management Journal* 17: 109–122.

Grant, R. M., and C. Baden-Fuller. 1995. "A Knowledge-Based Theory of Inter-Firm Collaboration." *Academy of Management Proceedings* 1: 17–21.

Guenther, C., M. Belitski, and N. Rejeb. 2023. "Overcoming the Ability-Willingness Paradox in Small Family Firms' Collaborations." *Small Business Economics* 60: 1409–29.

Haefner, N., J. Wincent, V. Parida, and O. Gassmann. 2021. "Artificial Intelligence and Innovation Management: A Review, Framework, and Research Agenda." *Technological Forecasting and Social Change* 162: 120392.

Hsieh, W. L., P. Ganotakis, M. Kafouros, and C. Wang. 2018. "Foreign and Domestic Collaboration, Product Innovation Novelty, and Firm Growth." *Journal of Product Innovation Management* 35(4): 652–672.

Jensen, R. 2007. "The Digital Provide: Information (Technology), Market Performance, and Welfare in the South Indian Fisheries Sector." *The Quarterly Journal of Economics* 122(3): 879–924.

Kafouros, M. I., P. J. Buckley, J. A. Sharp, and C. Wang. 2008. "The Role of Internationalization in Explaining Innovation Performance." *Technovation* 28(1–2): 63–74.

Katila, R., and G. Ahuja. 2002. "Something Old, Something New: A Longitudinal Study of Search Behavior and New Product Introduction." *Academy of Management Journal* 45(6): 1183–94.

Keding, C., and P. Meissner. 2021. "Managerial Overreliance on AI-Augmented Decision-Making Processes: How the Use of AI-Based Advisory Systems Shapes Choice Behavior in R&D Investment Decisions." *Technological Forecasting and Social Change* 171: 120970.

Knudsen, M. P., and T. B. Mortensen. 2011. "Some Immediate—But Negative—Effects of Openness on Product Development Performance." *Technovation* 31(1): 54–64.

Kobarg, S., J. Stumpf-Wollersheim, and I. M. Welpe. 2019. "More Is Not Always Better: Effects of Collaboration Breadth and Depth on Radical and Incremental Innovation Performance at the Project Level." *Research Policy* 48(1): 1–10.

Kogut, B., and U. Zander. 1992. "Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology." *Organization Science* 3(3): 383–397.

Lane, P. J., B. R. Koka, and S. Pathak. 2006. "The Reification of Absorptive Capacity: A Critical Review and Rejuvenation of the Construct." *Academy of Management Review* 31(4): 833–863.

Laursen, K., and A. Salter. 2006. "Open for Innovation: The Role of Openness in Explaining Innovation Performance among UK Manufacturing Firms." *Strategic Management Journal* 27(2): 131–150.

Love, J. H., S. Roper, and P. Vahter. 2014. "Learning from Openness: The Dynamics of Breadth in External Innovation Linkages." *Strategic Management Journal* 35(11): 1703–16.

March, J. G. 1991. "Exploration and Exploitation in Organizational Learning." *Organization Science* 2(1): 71–87.

Mariani, M. M., and M. Belitski. 2022. "The Effect of Coopetition Intensity on First Mover Advantage and Imitation in Innovation Related Coopetition: Empirical Evidence from UK Firms." *European Management Journal*. https://doi.org/10.1016/j.emj.2022.05.001.

Mowery, D. C., J. E. Oxley, and B. S. Silverman. 1998. "Technological Overlap and Interfirm Cooperation: Implications for the Resource-Based View of the Firm." *Research Policy* 27(5): 507–523.

Nelson, R. R., and S. G. Winter. 1982. "The Schumpeterian Tradeoff Revisited." *The American Economic Review* 72(1): 114–132.

Nieto, M. J., and L. Santamaría. 2007. "The Importance of Diverse Collaborative Networks for the Novelty of Product Innovation." *Technovation* 27(6–7): 367–377.

Office for National Statistics. 2021a. *UK Innovation Survey, 1994–2020: Secure Access*, 6th ed. London: UK Data Service. https://doi.org/10.5255/UKDA-SN-6699-6.

Office for National Statistics. 2021b. *Business Structure Database, 1997–2020: Secure Access*, 9th ed. London: UK Data Service. https://doi.org/10.5255/UKDA-SN-6697-9.

Paschen, U., C. Pitt, and J. Kietzmann. 2020. "Artificial Intelligence: Building Blocks and an Innovation Typology." *Business Horizons* 63(2): 147–155.

Pisano, G. P., and W. C. Shih. 2012. "Does America Really Need Manufacturing." *Harvard Business Review* 90(3): 94–102.

Reichstein, T., and A. Salter. 2006. "Investigating the Sources of Process Innovation among UK Manufacturing Firms." *Industrial and Corporate Change* 15(4): 653–682.

Ritala, P., H. Olander, S. Michailova, and K. Husted. 2015. "Knowledge Sharing, Knowledge Leaking and Relative Innovation Performance: An Empirical Study." *Technovation* 35: 22–31.

Rugman, A. M., and A. Verbeke. 2001. "Subsidiary-Specific Advantages in Multinational Enterprises." *Strategic Management Journal* 22(3): 237–250.

Salge, T. O., T. Farchi, M. I. Barrett, and S. Dopson. 2013. "When Does Search Openness Really Matter? A Contingency Study of Health-Care Innovation Projects." *Journal of Product Innovation Management* 30(4): 659–676.

Schilling, M. A., and C. C. Phelps. 2007. "Interfirm Collaboration Networks: The Impact of Large-Scale Network Structure on Firm Innovation." *Management Science* 53(7): 1113–26.

Spanjol, J., S. Mühlmeier, and T. Tomczak. 2012. "Strategic Orientation and Product Innovation: Exploring a Decompositional Approach." *Journal of Product Innovation Management* 29(6): 967–985.

Spanjol, J., W. J. Qualls, and J. A. Rosa. 2011. "How Many and What Kind? The Role of Strategic Orientation in New Product Ideation." *Journal of Product Innovation Management* 28(2): 236–250.

Spanjol, J., L. Tam, W. J. Qualls, and J. D. Bohlmann. 2011. "New Product Team Decision Making: Regulatory Focus Effects on Number, Type, and Timing Decisions." *Journal of Product Innovation Management* 28(5): 623–640.

Spender, J.-C., and R. M. Grant. 1996. "Knowledge of the Firm: Overview." *Strategic Management Journal* 17: 5–9.

Stadler, C. 2011. "Process Innovation and Integration in Process-Oriented Settings: The Case of the Oil Industry." *Journal of Product Innovation Management* 1: 44–62.

Terjesen, S., and P. C. Patel. 2017. "In Search of Process Innovations: The Role of Search Depth, Search Breadth, and the Industry Environment." *Journal of Management* 43(5): 1421–46.

Tödtling, F., P. Lehner, and A. Kaufmann. 2009. "Do Different Types of Innovation Rely on Specific Kinds of Knowledge Interactions?" *Technovation* 29(1): 59–71.

Un, C. A., and K. Asakawa. 2015. "Types of R&D Collaborations and Process Innovation: The Benefit of Collaborating Upstream in the Knowledge Chain." *Journal of Product Innovation Management* 32(1): 138–153.

Un, C. A., A. Cuervo-Cazurra, and K. Asakawa. 2010. "R&D Collaborations and Product Innovation." *Journal of Product Innovation Management* 27: 673–689.

Van Beers, C., and F. Zand. 2014. "R&D Cooperation, Partner Diversity, and Innovation Performance: An Empirical Analysis." *Journal of Product Innovation Management* 31(2): 292–312.

Vanhaverbeke, W., G. Duysters, and N. Noorderhaven. 2002. "External Technology Sourcing through Alliances or Acquisitions: An Analysis of the Application-Specific Integrated Circuits Industry." *Organization Science* 13(6): 714–733.

Williamson, O., and S. Masten. 1995. *Transaction Cost Economics*. Brookfield, VT: Edward Elgar Publishing.

Wooldridge, J. M. 2015. *Introductory Econometrics: A Modern Approach*. Boston: Cengage Learning.

Zobel, A. K. 2017. "Benefiting from Open Innovation: A Multidimensional Model of Absorptive Capacity." *Journal of Product Innovation Management* 34(3): 269–288.

AUTHOR BIOGRAPHIES

Maksim Belitski is a Professor in Entrepreneurship and Innovation at Henley Business School, University of Reading, Research Fellow at the Institute for Development Strategies, Indiana University Bloomington (USA), Professor of Entrepreneurship at ICD Business School, IGS-Groupe, France, Professor in Entrepreneurship and Innovation at Loyola University New Orleans (USA). Maksim holds a PhD in Applied Economics from the University of Leicester and another PhD in Economics from the University of Milan, Italy. He is a "Trusted" researcher and has worked with microfoundations data from the U.K. Secure Data Service and Office of National Statistics since 2011. His research interests lie in the area of Entrepreneurship, innovation, and regional economics, with a particular focus on Entrepreneurship as a spillover of knowledge and creativity. Maksim is an editor of the *Small Business Economic* Journal and a member of the Editorial Review Board for the *Entrepreneurship and Regional Development* journal.

Blanca L. Delgado Márquez is a Professor of Economics at the University of Granada (Spain). Her expertise is related to several topics, such as the analysis of the relationships between businesses and their environmental/internationalization/innovation strategies, as well as the construction of indicators for social capital (trust and networks, especially). Blanca has published a number of works in top-tier research journals, including *Business Strategy and the Environment*, *Organization & Environment*, *Journal of Business Research*, *Decision Support Systems*, *Management International Review*, *Journal of Business Economics and Management*, *Social Indicators Research*, and *Regional Studies*, among others. Also, she has published several book chapters edited by Springer, IGI Global, and so forth. She was a Visiting lecturer at different international universities in the United Kingdom, Germany, Portugal, Poland, and Romania, among others. Blanca has participated in several international and national research competitive projects related to the implementation of sustainability in higher education, businesses, and regions.

Luis E. Pedauga, PhD in Economics is a Research Fellow at the Joint Research Centre (European Commission). He has worked for the European Commission in the Joint Research Centre. He is also an Associate Professor at Universidad de León in Spain. His prior experiences include a Professorship at Universidad de Granada in Spain and an Economic analyst at Analista Económico in the Central Bank of Venezuela. His research is on various aspects of international business, digitalization, and environmental performance. It sheds light on the complex relationship between multinational enterprises' international diversification and environmental outcomes, challenging conventional linear assumptions. His research outlines disaster analysis, particularly assessing the impacts on supply chains, and a focus on the relative importance of small- and medium-sized enterprises in Spain's economic landscape, especially during the COVID-19 pandemic.

How to cite this article: Belitski, Maksim, Blanca L. Delgado-Márquez, and Luis Enrique Pedauga. 2024. "Your Innovation or Mine? The Effects of Partner Diversity on Product and Process Innovation." *Journal of Product Innovation Management* 41(1): 112–137. https://doi.org/10.1111/jpim.12696