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Effects of open innovation in startups: Theory and evidence

David B. Audretsch [a], Maksim Belitski [b,c,*], Rosa Caiazza [d], Donald Siegel [e]

[a] School of Public and Environmental Affairs, Indiana University Bloomington, 1315 E. 10th Avenue SPEA, Bloomington, IN 47405, USA
[b] Henley Business School, University of Reading Whiteknights, Reading RG6 6UD, UK
[c] ICD Business School Paris, France Rue Alexandre Parodi, 12, Paris 75010, France
[d] Parthenope University of Naples via Ammiraglio Ferdinando Acton, 38, 80133 Napoli, NA, Italy
[e] Global Center for Technology Transfer, School of Public Affairs, Arizona State University, 411 N Central Ave Suite 400/Office 461, Phoenix, AZ 85004, USA

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ABSTRACT

A robust literature has provided compelling evidence showing how open innovation impacts incumbent firms. However, only a paucity of research has linked open innovation strategies to different types of innovation in startups. This paper fills this gap in the literature by focusing on if, how and why open innovation enhances innovative activity in newly created firms. In particular, the paper examines how the role of both the specific external partner as well as the geographical location of partner matters in how product and process innovation is shaped in startups. The empirical evidence garnered in this paper suggest that not only do startups benefit from open innovation, but also the extent of product innovation and the propensity to innovate new processes in startups are significantly affected by specific external partner and its geographical location. The positive impact of open innovation reflects the heterogeneous effects of knowledge embedded in different partner types and the role that technological, institutional, and competitive arrangements play domestically and internationally in startup innovation. This study provides new light on how and why open innovation benefits not just incumbents but also startups as well.

1. Introduction

It is important to understand the effects of open innovation for innovation activity in startups. First, the rise of globalization and the growth of new digital technologies, and the evolution of knowledge in the field of engineering, technology and management (Cunningham and Kwakkel, 2011), have contributed to the emergence of open innovation models (Chesbrough, 2006, 2007; Kafouros et al., 2020) and the rise of inter-firm collaboration and knowledge spillovers (Schilling and Phelps, 2007; Tucci et al., 2016). However, the returns to open innovation differ between startups and incumbent firms (Audretsch and Belitski, 2021). Second, ever-increasing innovation costs and a lack of resources push startups to search for external knowledge collaborators to co-create knowledge together and reduce innovation costs (van Beers and Zand, 2014).

Despite the theoretical underpinning and importance of knowledge collaboration for innovation, the entrepreneurship and management literatures (Tambe et al., 2012; Roper et al., 2017; Knoben and Bakker, 2019) have not identified the impact that knowledge partner type and location may have on a startup.

This theoretical empirical evidence is important for entrepreneurial decision-making and recognition of entrepreneurial opportunities for new product creation. These opportunities may exist beyond startups and can come from customers, suppliers, other units within enterprise groups, and even competitors (Foss et al., 2011, 2013; Foss and Saebi, 2017; Desyllas et al., 2022).

Given the attention that the entrepreneurship and management literatures pay to open innovation (Chesbrough, 2006; Spithoven et al., 2010), and how knowledge is transferred (Audretsch and Feldman, 1996; Ritala et al., 2015; Asimakopoulos et al., 2020), recent research has overwhelmingly examined the sources of open innovation, mainly for high-tech, high-growth firms, and incumbent firms (Stephan et al., 2019; Kobarg et al., 2019).

Few studies have examined the joint effects of heterogeneous external partners such as suppliers, customers, competitors, consultants, universities, government and other startups within a group on innovation activity in startups. The extant literature has primarily focused on one specific collaboration partner (e.g. competitor, customer, supplier,

* Corresponding author at: Henley Business School, University of Reading, Whiteknights, Reading RG6 6UD, UK.
E-mail addresses: daudrets@indiana.edu (D.B. Audretsch), m.belitski@reading.ac.uk, mbelitski@groupe-igs.fr (M. Belitski), rosa.caiazza@uniparthenope.it (R. Caiazza), donald.siegel.1@asu.edu (D. Siegel).

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university) and specific innovation strategy (e.g. exploration vs. exploitation; incremental vs. radical innovation; imitation vs. first mover advantage) (Kobarg et al., 2019; Audretsch and Belitski, 2022) limiting the complex understanding and interdependencies between the type of collaboration partner and the importance of co-location between collaboration partner and a startup. There is a paucity of research has linked open innovation to startups. This paper fills this gap in the literature by focusing on if, how and why open innovation enhances innovative activity in newly created firms using sample of 4401 firm-year observations and 405 innovative startups observed during 2002–2016 in the United Kingdom.

Therefore, our research question is how does knowledge collaboration with different types of external partners (customers, suppliers, units within enterprise groups and competitors) regionally and internationally shape innovation activity in startups?

Our study makes several important contributions. First, we extend the knowledge-based view (Grant, 2006; Kobarg et al., 2019) on the geographical perspective of open innovation in startups (Tucci et al., 2016; Cunningham, 2022), and contribute to the literature on the visualization and analysis of the role of geography for innovation and technology forecasting (Kwakkel et al., 2014). Second, while prior studies on open innovation focus on a specific collaborator type, we assess the returns to knowledge collaboration across four types of knowledge collaborators: enterprise groups (internally); suppliers; customers; and competitors (externally). We also assess returns across different locations: regionally; nationally; within Europe; and internationally. In doing so we further recent research on geographical aspects of knowledge collaboration (Audretsch et al., 2022). Our findings have important implications for entrepreneurs and policymakers in the sense that entrepreneurs choosing an innovation strategy need to choose a partner type and location simultaneously.

2. Theoretical framework

2.1. Knowledge collaboration within an enterprise group

Several types of collaborators can help startups innovate: enterprise groups, clients and customers, suppliers, competitors, consultants, universities, and government (van Beers and Zand, 2014). Startups do not work independently and could be part of a larger enterprise group, including corporate entrepreneurship. An enterprise group means two or more enterprises are interconnected under joint ownership. Enterprises within the group generally belong to similar or complementary industry segments and share a close intra-organizational relationship (Rosenkopf and Almeida, 2003).

Knowledge collaboration between startups and other units within the enterprise group is beneficial as firms share similar organizational contexts, production contexts, and in many cases, similar industry contexts. For startups, collaboration within enterprise groups can enhance needed intra-firm management and quality control systems, as single small units often lack the financial and labour resources needed for quality control and product development. Startups will benefit from facilitated production circles, knowledge transfers, and collaboration with more experienced counterparts within the group. Given their joint ownership, it will also be easier to receive legal access to coded and tacit knowledge (Un and Asakawa, 2015).

Following the knowledge-based view theory of a firm (Grant, 2006), exchanges of knowledge within enterprise groups create incentives and mindsets that enable startups or less experienced units to integrate and convert tacit knowledge into explicit knowledge (Kogut and Zander, 1992). The enterprise group's knowledge is made available across all startups and incumbents (Rosenkopf and Almeida, 2003).

First, the knowledge collaboration of startups with other units within enterprise groups increases all enterprise group knowledge inputs into the innovation process. This enables the startup to leverage its contributions to an innovation pool at various levels and different knowledge cognitive distances through intensive intra-firm collaboration tools (Kogut and Zander, 1992). Knowledge collaboration within an enterprise group means that each partner (enterprise unit) can receive more knowledge from a collaborative innovation effort than they contribute to the project independently. Second, cooperation within enterprise groups within close technological and cognitive proximity (Balland et al., 2015) makes spatial proximity obsolete Startups will collaborate with other startups and incumbents to diversify their skills and resources, enhancing product and process innovation and leveraging any contingencies related to differences in regulation across countries. Each enterprise unit can benefit from complementarity, in addition to the knowledge-sharing benefits (Belderbos et al., 2004, 2015). An open innovation strategy within an enterprise group will eliminate the geographical limits to collaboration. Third, suppose the technology of research is characterized by increasing returns to scale. In that case, even minor enhancements in firms' knowledge through collaboration can lead to significant increases in innovation output (Terjesen et al., 2011). These intra-organizational networks are usually supported by information technology, intra-organizational visits, and sharing documentation and competencies which enables the transfer of knowledge independently of spatial proximity. Thus, startups that collaborate within an enterprise group will be able to benefit from such collaboration both regionally and internationally. We hypothesize:

H1. Domestic and international knowledge collaboration within an enterprise group has a positive effect on innovation in startups.

2.2. Knowledge collaboration with customers and suppliers

In addition to knowledge collaboration within an enterprise group, collaboration on innovation with upstream and downstream partners has remained an attractive source of external knowledge for startups (Spithoven et al., 2010; West and Bogers, 2014).

Collaborations with suppliers and customers are the most important form of R&D collaboration for startups for the following reasons. Firstly, knowledge collaboration in the form of R&D agreements, R&D partnerships, and knowledge spillovers with suppliers enables startups to learn about input-output conversion technologies (Griliches, 1991) and is conducive to innovation and productivity (Hall et al., 2013; Audretsch and Belitski, 2020b). Secondly, industries in the vertical value chain affect the 'degrees of freedom' in raw material inputs, operational processes, and product innovations. Knowledge collaborations with suppliers improve knowledge complementarity (Cassiman and Veugelers, 2006; Arora and Gambardella, 2010), facilitate faster integration (Lafontaine and Slade, 2007), and provide a locus of coherent knowledge combinations that align with the capabilities of suppliers and buyers (Foros, 2004). Thirdly, the acquisition of firm-specific knowledge from suppliers helps startups to better understand the customers and market (Belitski and Rejeb, 2022). Fourthly, knowledge collaboration with suppliers might involve activities upstream in the value chain, such as R&D and manufacturing, and knowledge collaboration with customers will facilitate downstream activities, such as product marketing (Peng and Bourne, 2009). Startups have few resources and little time, and collaborations with customers generate validated learning that could be conducive to an improvement of the value proposition, helping startups to create prototypes and reducing experimentation time (McGrath, 2010; Audretsch and Belitski, 2020a). Furthermore, collaborations with suppliers may improve the startup's supply chain management and increase the adaptation of ready-made innovation and solutions, shortening the time needed for market entry.

Collaborations with suppliers in close geographical proximity and within localized markets may be most important for the development of new products, as well as reducing the cost of innovation by reducing the cost of raw materials, logistics, and supply-chain combinations (Schilling and Phelps, 2007). Startups acquire deeper firm- and market-specific knowledge from local suppliers, knowledge which is likely to have been tested for many years (March, 1991), and knowledge about the product that is available and ready to use for specific markets (Audretsch and Belitski, 2020a). Local vis-a-vis global suppliers can provide direct new inputs in terms of materials, knowledge (suppliers), feedback, advice and co-creation (customers) in the production flow adjusted for local customer needs and local markets which startups are more likely to target first due to resource and knowledge limitations (Zahra, 2021).

Collaboration with local vis-a-vis international suppliers may be a useful way to exchange innovation capabilities within close cognitive-cultural proximity (Balland et al., 2015). Startups can use suppliers' ready-made solutions for specific markets and customers to increase the visibility and flexibility of local offerings. In addition, knowledge sourced from local suppliers via direct collaboration or spillovers can be readily integrated into existing routines. Drawing on technologically distant knowledge from other regions and sectors is associated with knowledge integration challenges, such as the need to increase R&D and operational costs to integrate technologically and cognitively distant knowledge available in other countries (Audretsch and Belitski, 2023). Localized knowledge requires less adaptation and hence lowers the internal R&D costs startups must pay to access, appropriate, assimilate, and integrate external knowledge (Audretsch et al., 2021), which may increase startup profitability (Chesbrough, 2007). Start-up productivity benefits from the complementarities of existing knowledge in a firm adapted to a specific geographical location, and knowledge from suppliers that improves productivity (Kugler, 2006; Cunningham, 2022). Collaboration with suppliers internationally may be limited for startups given the logistics and complexity of supply chains. The need to deal with certifications, product regulation and contracts internationally leads to additional operational and transaction costs that startups may be unable to pay given their resource constraints (De Massis et al., 2018).

We hypothesize:

H2a. Domestic knowledge collaboration with suppliers has a positive effect on innovation in startups.

Innovation is also a systemic process, with startups facing greater challenges to systemically innovating due to their lack of capabilities and knowledge. Building on the contemporary literature on open innovation and technology (Cunningham and Kwakkel, 2011; Kafouros et al., 2020), we indicate that spillovers and knowledge from customers will increase demand for startup products and services (Vanderwerf, 1992) through the cross-fertilization of knowledge among value chain participants. We outline three mechanisms through which collaboration with customers will lead to an increased innovation output.

Firstly, knowledge collaboration with customers increases marginal returns to innovators and knowledge producers (Henderson and Cockburn, 1996), and increases the synchronization of the startup's knowledge with that of the customers, improving awareness of and efforts toward meeting customer needs. Secondly, collaboration with customers independently of where the customers are located accentuates existing products and how they could be further changed and modified to match customer needs, complementing the firm's internal knowledge capabilities (Kafouros et al., 2020). New innovation efforts that are more complementary to customer expectations require fewer adjustments within the startup and with buyers (Tether, 2002), and will reduce the search and operationalization costs of new product development (Audretsch and Belitski, 2023; Saura et al., 2023). Thus, knowledge from suppliers increases the incentive for startups to engage in further exploratory searches, as it complements their market knowledge with specific customer needs and reduces experimentation and knowledge search costs.

Thirdly, knowledge collaboration with customers will reduce the time of product creation and facilitate entrepreneurial judgment (Foss et al., 2011, 2013, 2019). We hypothesize:

H2b. Domestic and international knowledge collaboration with customers has a positive effect on innovation in startups.

Furthermore, we argue that collaboration with suppliers and customers is the most beneficial channel of open innovation (Chesbrough, 2006), and has a greater effect on innovation in startups compared to other types of collaboration partner, such as enterprise groups (with limited novelty and close technological proximity of knowledge) (Balland et al., 2015) and competitors (with the likelihood of involuntary knowledge outflows (Cassiman and Veugelers, 2002) and competitive tensions) (Mariani and Belitski, 2022). Un and Asakawa (2015) argued that upstream R&D collaborators, such as suppliers dealing with the input side of firm operations, are more important than downstream and horizontal collaborations dealing with the final output side of firm operations. However, this is not the case for startups. In addition to collaboration upstream and with competitors, collaboration with customers is likely to reduce the financial and time costs of new product creation, particularly in more innovative startups (Audretsch et al., 2023). It will also likely reduce the time period from product idea to customer testing, as well as the time needed to validate the idea and commercialize the final product, better addressing customer needs and expectations (Felin et al., 2020). We hypothesize that:

H2c. Knowledge collaborations with suppliers and customers will have a stronger effect on innovation in startups compared to other types of external knowledge partners.

2.3. Knowledge collaboration with competitors

A vast body of research has examined the role of coopetition in firm innovation (e.g., Bouncken and Kraus, 2013; Le Roy et al., 2016; Park et al., 2014; Ritala and Hurmelinna-Laukkanen, 2009, 2013; Ritala, 2012). Empirical studies seem to display mixed findings in terms of the benefits of coopetition for startups. Most empirical studies (e.g., Estrada et al., 2016; Le Roy et al., 2016; Ritala and Hurmelinna-Laukkanen, 2013) have found coopetition positively influences innovation.

Bouncken and Fredrich's (2012) empirical study demonstrates that coopetition enhances radical innovation by means of assisting knowledge combination across partner firms, and also found that the effect of coopetition on radical innovation is persistent. Ritala and Hurmelinna-Laukkanen (2009) developed theoretical propositions suggesting that coopetition increases innovation by facilitating the accumulation of a common knowledge base within the same industry. In a later study, Ritala and Hurmelinna-Laukkanen (2013) found that firms' absorptive capacity and appropriability regimes are crucial when firms achieve innovation through coopetition. This has an important implication for startups, who have low absorptive capacities and are therefore less attractive for competitors to collaborate with. This results in incumbents avoiding or pursuing only low-intensity collaboration with startups, especially when they compete for the same customers. Ritala (2012) used the resource-based view to study 212 Finnish firms and found that coopetition leads to superior innovation performance under high market uncertainty conditions. Steinicke et al. (2012) analysed 225 firms in the German logistics industry and found that different forms of cooperation governance can determine the mechanisms of coopetition and their effect on innovation. Finally, Le Roy et al. (2016) used a sample of 3933 firms from the innovation survey to demonstrate how international cooperation with competitors fosters innovation. Bouncken et al. (2018) studied 1049 new product development alliances in the German machinery and medical sectors and found that coopetition intensity positively influences innovation in both the product pre-launch and launch phases. Several other studies have found that the relationship between coopetition and innovation is more complex and there is an optimal level of coopetition which improves innovation performance (e.g., Bouncken et al., 2016; Park et al., 2014). For instance, Bouncken et al. (2016) analysed 372 German firms in the medical device industry, finding that product innovativeness declines as coopetition increases due to greater transactional governance, and that coopetition has no direct effect on innovation performance when governance is absent. Scholars also found coopetition has a neutral or no effect on innovation unless certain conditions are present (Tomlinson and Fai, 2013).

The mechanisms which enable startups to collaborate with competitors and enhance their innovation include the following. Firstly, close technological proximity (Hall et al., 2014) and contextual knowledge distance (Un and Asakawa, 2015) enable startups to better understand technologies, products and processes developed by their competitors within the industry, therefore allowing them to introduce new-to-market products quicker. Secondly, best practices and knowledge spillovers from competitors that have been present in the market could be useful for startups seeking to compete for customers and better understand customer preferences. Startups could use the tested knowledge of their competitors to improve their processes and the designs of products positioned for markets where their competitors have been present (Tsai, 2009). These factors will positively affect the innovation performance of startups.

Coopetition with firms within the same geographical markets might be risky due to the possible leakage of sensitive information to competitors and loss of their competitive advantage, as well as impediments to appropriating novel knowledge (Cassiman and Veugelers, 2002). Mariani and Belitski (2022) found that the relationship between coopetition and innovation is more complex and even negative, while the localized effects of coopetition were not analysed. Therefore, the risks and challenges of coopetition may be hidden and complex. Coopetition also requires significant preparation and research, including legal arrangements for non-disclosure agreements and other forms of strategic and legal knowledge protection that may be costly for startups, who may opt out of coopetition in local markets (Bouncken et al., 2018). Should these impediments and risks be eliminated, for example in coopetition with international partners that do not compete in the same market, then the exchange of knowledge could take place more easily.

Therefore, coopetition is particularly unlikely in regionally close markets where startups and incumbents may voluntarily withdraw or limit their coopetition, while coopetition with international partners is not considered to be a direct threat and may enable a deeper and more intense exchange of knowledge and experiences (Vanyushyn et al., 2018). International coopetition may be used as a network extension and a new market opportunity for larger incumbents with no or little conflict of interest, potentially furthering the development of new products for different local markets (Schilling and Phelps, 2007). Startups may prioritize international coopetition to access unique knowledge and technologies, which may lead to entirely new-to-market products in domestic markets. We hypothesize:

H3. International knowledge collaboration with competitors positively affects innovation in startups, while co-location between startups and competitors limits their knowledge collaboration.

3. Data and method

3.1. Sample

To test our hypotheses, we analysed seven pooled cross-sectional datasets from the Business Structure Database (BSD) and the UK Community Innovation Survey (CIS) during 2002–2016. Although the two datasets were pooled together and constructed from two different sources, both the BSD and CIS datasets are matchable by reference unit ID number and year, tracked with the VAT number. First, seven consecutive CIS waves (CIS5 2002–2004, CIS5 2004–2006, CIS6 2006–2008, CIS7 2008–2010, CIS8 2010–2012, CIS9 2012–2014, CIS9 2014–2016) conducted every two years by the Office of National Statistics (ONS) in the UK on behalf of the Department of Business Innovation and Skills (BIS) were included in this study. Second, Business Structure Database (BSD) data for the years 2002, 2004, 2006, 2008, 2010, 2012 and 2014 were matched to the correspondent CIS survey, with the data from the BSD taken for the initial year of the Innovation survey period.

The Business Structure Database is a version of the Inter-Departmental Business Register for research use, taking full account of changes in ownership, size, sales, age, and restructuring of businesses. The BSD is the key sampling frame for UK business statistics and is maintained and developed by the Business Registers Unit (BRU) within the ONS. The construction of our data specifically used Value Added Tax (VAT) businesses and Company Registration (for businesses that wish to operate with limited liability).

Several questions were excluded from the CIS because they changed over the years CIS data are used in >60 academic publications (Laursen and Salter, 2006), with the popularity of the data growing exponentially among policymakers, scholars, and practitioners. The CIS contains data on several firm innovation activities, e.g. product and process innovation, barriers to innovation and major innovation sources, human capital, partner type, partner location, and collaboration networks, including investment in R&D, training and other external knowledge. The BSD contains data on firms' legal status, ownership (foreign or national firm), alliance information, exports, turnover, employment, industry at the 5-digit level, and firm location by postcode. All missing values and non-applicable answers were labelled as missing and therefore not included in our data.

Table 1 demonstrates the distribution of firms by the industry divisions adopted by the ONS, as well as region, survey year, and startup size. Most firms come from the South East of England (11.25 %), London

Table 1
sample description by industry, region, firm size, survey wave.

Industry	Total	Share, %	Region	Total	Share, %
Mining and Quarrying	17	0.39	North-East	282	6.41
Manufacturing basic	510	11.59	North-West	418	9.50
High-tech manufacturing	459	10.43	Yorkshire and The Humber	314	7.13
Electricity, gas and water supply	647	14.70	East Midlands	358	8.13
Construction	141	3.20	West Midlands	370	8.41
Wholesale, retail trade	464	10.54	Eastern	401	9.11
Transport	218	4.95	London	472	10.72
Hotels and restaurants	394	8.95	South-East	495	11.25
Information technology	467	10.61	South-West	369	8.38
Financial intermediation	297	6.75	Wales	311	7.07
Real estate and other business activities	547	12.43	Scotland	308	7.00
Public administering, defence consultancy	138	3.14	Northern Ireland	303	6.88
Education	39	0.89			
Other community, social active	63	1.43			

Firm size	Total	Share, %	Survey year	Total	Share, %
2–9 FTE	105	2.39	2002–2004	977	22.20
10–49 FTEs	2965	67.37	2004–2006	562	12.77
50–99 FTEs	759	17.25	2006–2008	405	9.20
100–249 FTEs	572	13.00	2008–2010	703	15.97
			2010–2012	709	16.11
			2012–2014	560	12.72
			2014–2016	485	11.02
Total	4401	100	Total	4401	100

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

(10.72 %), and the North West of England (9.50 %). Meanwhile, Northern Island (6.88 %) and the North East of England (6.43 %), Wales (7.07 %) and Scotland (7.00 %) are less represented. Most observations come from the first survey available 2002–2004 (22.20 %); the share of observations dropped significantly in 2006–2008 (9.20 %) and 2014–2016 (11.02 %). The startups were distributed across various sizes: 2.39 % were micro firms (2–9 full-time employees (FTEs)); 67.37 % were small firms (10–49 FTEs), 17.25 % were medium firms (50–99 FTEs); and 13.00 % were medium-large firms (100–249 FTEs).

3.2. Variables

3.2.1. Dependent variables

We use two dependent variables as measures of innovation: product and process innovation. To measure a firm's innovative performance, we use the CIS question asking firms to indicate the percentage of total turnover over the last three years from goods and services that are new to the market. The new product share (question 810 in the survey) varies from 0 to 100, with 3.7 % on average and a standard deviation of 11.99 (see Table 2). This measure is also known as radical innovation (Kobarg et al., 2019; Mariani and Belitski, 2022).

To measure firm process innovation, we use the CIS question that asks firms to indicate if the business had introduced any new or significantly improved processes for producing or supplying goods or services during the last 3 years. The proportion of process innovators in our sample is 22.9 (question 900 in a survey) with a mean of 0.22 and a standard deviation of 0.42. Unlike the product innovation measure, which varies from 0 to 100, process innovation is measured as a binary

Table 2
Descriptive statistics.

Label	Description		Mean	Std. Dev.
Dependent variables				
Process innovation	Firm has introduced process innovation = 1, zero otherwise		0.25	0.42
Product innovation	% of firm's total turnover from goods and services, that were new to the market (%)		6.46	18.16
Explanatory variables				
UK Regional	Enterprise group	Binary variable =1 if firm uses information for business's innovation activities from within enterprise group and if it interacts with other firms in the enterprise group, zero otherwise	0.06	0.23
	Suppliers	Binary variable =1 if firm uses information for business's innovation activities from suppliers of equipment, materials, services or software and if it interacts with suppliers, zero otherwise	0.07	0.25
	Customers	Binary variable =1 if firm uses information for business's innovation activities from clients or customers from the private and public sector and if it interacts with clients, zero otherwise	0.10	0.29
	Competitors	Binary variable =1 if firm uses information for business's innovation activities from competitors and if it interacts with competitors in the industry, zero otherwise	0.04	0.19
UK National	Enterprise group	Collaboration with enterprise group businesses in national market = 1, zero otherwise	0.05	0.22
	Suppliers	Collaboration with suppliers in national market = 1, zero otherwise	0.10	0.30
	Customers	Collaboration with customers in national market = 1, zero otherwise	0.12	0.32
	Competitors	Collaboration with competitors in national market = 1, zero otherwise	0.05	0.23
European Countries	Enterprise group	Collaboration with enterprise group in Europe =1, zero otherwise	0.03	0.17
	Suppliers	Collaboration with suppliers in Europe =1, zero otherwise	0.04	0.19
	Customers	Collaboration with customers in Europe =1, zero otherwise	0.04	0.20
	Competitors	Collaboration with competitors in Europe =1, zero otherwise	0.02	0.13
Other Countries	Enterprise group	Collaboration with enterprise group businesses in otherworld market = 1, zero otherwise	0.03	0.17
	Suppliers	Collaboration with suppliers internationally =1, zero otherwise	0.03	0.18
	Customers	Collaboration with customers internationally =1, zero otherwise	0.04	0.20
	Competitors	Collaboration with competitors internationally =1, zero otherwise	0.02	0.13
Control variables				
UK regional	Consultants	Binary variable =1 if firm uses information for business's innovation activities from consultants, commercial labs or private R&D institutes and if it interacts with consultants, zero otherwise	0.05	0.20
	Universities	Binary variable =1 if firm uses information for business's innovation activities from universities or other higher education institutes and if it interacts with university, zero otherwise	0.05	0.21
	Government	Binary variable =1 if firm uses information for business's innovation activities from government or public research institutes and if it interacts with government, zero otherwise	0.02	0.16
UK national	Consultants	Collaboration with consultants in national market = 1, zero otherwise	0.05	0.24
	Universities	Collaboration with university in national market = 1, zero otherwise	0.04	0.20
	Government	Collaboration with government in national market = 1, zero otherwise	0.04	0.19
European Countries	Consultants	Collaboration with consultants in Europe =1, zero otherwise	0.02	0.11
	Universities	Collaboration with university in Europe =1, zero otherwise	0.01	0.09
	Government	Collaboration with government in Europe =1, zero otherwise	0.01	0.08
Other Countries	Consultants	Collaboration with consultants internationally =1, zero otherwise	0.02	0.12
	Universities	Collaboration with university internationally =1, zero otherwise	0.01	0.10
	Government	Collaboration with government internationally =1, zero otherwise	0.01	0.07
Foreign		Binary variable = 1 if a firm has headquarters abroad, zero otherwise	0.21	0.40
Age		Age of a firm (years since the establishment)	1.39	0.50
Employment		Number of full-time employees, in logarithms	3.49	1.2
Scientists		The proportion of employees that hold a university degree and above in science and engineering	9.13	20.93
R&D intensity		R&D investment to sales ratio	0.021	0.07
Exporter		Binary variable = 1 if a firm sells goods and services abroad, zero otherwise	0.28	0.45

Source: ONS data.

variable. The value of zero means no significant improvement in processes of manufacturing new products (services), while one means significant improvement occurred (Salge et al., 2013; Terjesen and Patel, 2017). Product innovation and process innovation are not mutually exclusive, and companies doing both types of innovation vary from 60 to 70 % of a sample. Product innovation is defined as technologically new products and services that are new to the market and operationalized at a firm level (Kobarg et al., 2019).

By definition, both process and product measures of innovation are characterized by a lower bound of zero with no negative values. Firms report zero when innovation projects related to either type of innovation were not completed over the three-year period. They were asked if it was for one of the following reasons: the project was abandoned or seriously suspended; the project was seriously delayed with respect to initial planning; the project requires more than three years to complete. All these factors may mean a project may be ongoing at the end of the three-year period.

3.2.2. *Explanatory variables*

Following Laursen and Salter (2014) and Belitski (2019), we operationalize collaboration partner types and geographies of collaboration using the set of binary variables which identify the type of vertical and horizontal collaboration partner (competitor, supplier, customer) and if a startup is part of an enterprise group it collaborates with. The survey data also identifies where the collaboration partner is located geographically: regionally (within a distance of up to 80 miles), nationally (the UK), in Europe or other countries (internationally).

Looking at the patterns of collaboration within enterprise groups, we found that 5–6 % of startups collaborate within enterprise groups domestically, and only 3 % internationally. Suppliers and customers are the most common types of external collaborators, with 7 % of startups collaborating with suppliers and 10 % collaborating with customers regionally. Approximately 10 % of startups collaborate with suppliers and 13 % with customers within the national market. On average, 4 % of startups collaborate with customers and suppliers in Europe and internationally.

On average, between 3 and 4 % of startups collaborate with competitors domestically, and 2 % collaborate internationally.

3.2.3. *Control variables*

We control for other types of collaboration: with consultants, universities, and local and national governments (Audretsch et al., 2022). We are able to identify where the collaboration partner is located geographically: regionally (within a borough of up to 80 miles), nationally (the UK), in Europe, or in other countries. On average, 4–5 % of startups collaborate with national universities, with only 2 % collaborating with international universities. Collaboration with consultants, a form of horizontal cooperation for startups, makes up 5 % of collaborations domestically and 2 % internationally. <2 % of startups collaborate with governments domestically or internationally. In addition, we control for in-house R&D intensity, measured as the ratio of in-house R&D to total sales (averaged over three years) as a measurement of absorptive capacity and knowledge capital (Cohen and Levinthal, 1989; Kafouros et al., 2020).

In addition, we control for startup size as the total number of employees taken in logarithms. Although larger startups rely on already developed products and exploit their innovations (March, 1991), they startups also demonstrate superior levels of new product development thanks to economies of scale and risk diversification advantages (Gesing et al., 2015). Small startups are more flexible and adaptive to market changes (Roper et al., 2017) and may outperform their larger counterparts while lacking resources for growth and innovation (Audretsch and Belitski, 2021). Startup age in years since establishment is used in logarithms. Age increases a startup's ability to draw knowledge from their collaborators and use it for R&D and innovation activities (Laursen and Salter, 2006).

We use the proportion of startup employees that hold a university degree in science and engineering subjects as a human capital control. Foreign ownership control is represented by a binary variable which equals one if the firm is foreign-owned, e.g. its headquarters is not in the UK, and zero otherwise. Finally, we use a binary exporter taking a value of one if the firm exports, and zero otherwise.

Following Hall et al.'s (2013) study which estimated the knowledge production function, we control for seven survey periods (2002–2004 as a reference wave), 12 UK regions (with North East England as a reference category), and 14 aggregated industries (with agriculture as a reference category) using the fixed effects. Table 2 presents the summary statistics and description of each dependent, explanatory, and control variable used in this study.

3.3. *Model specification and estimation*

We used the Tobit estimation method for our model, with product innovation (Model 1) as dependent variable (q_810) and the "xttobit" option in Stata controlling for unobserved heterogeneity in firms within the panel element. The option "xttobit" in Stata 16 fits random-effects Tobit models for panel data where the outcome variable is censored.

We requested that a likelihood–ratio test comparing the panel Tobit model with the pooled Tobit model be conducted at estimation time, with our choice for the panel Tobit model given 405 panel elements. Although random-effects Tobit estimation was used, regional, sector, and time fixed effects were included in the estimation model. We used the logit estimation method for our model with process innovation as a dependent variable (q_900) taking a value of one for process innovation and zero otherwise (Model 2). The option "xtlogit" fits the random-effects model for a binary dependent variable, with process innovation controlling for unobserved heterogeneity in firms within the panel element. The probability of a positive outcome is assumed to be determined by the logistic cumulative distribution function. The results may be reported as odds ratios rather than coefficients.

The following innovation function using Tobit and logit regressions with dependent variables y_{it} (innovation performance) and m_{it} (knowledge collaboration) is estimated:

$$y_{it} = \beta_0 + \beta_1 m_{it} + \beta_2 z_{it} + \lambda_t + \tau_s + a_j + u_{it} \tag{1}$$

We are interested in β_1 which is the size of the effect of knowledge collaboration related to our H1–H3. The variable z_{it} is an exogenous control variable not correlated with u_{it} (Wooldridge, 2002), where u_{it} is an error term; are time and industry fixed effects, and a_j is the region fixed effect where the startup is located. We use a multivariate Tobit regression model when predicting product innovation performance as our dependent variable is left-censored.

Four columns in Tables 3 and 4 illustrate four different geographical areas of knowledge collaboration.

We used a maximum number of 4401 firm-year observations with non-missing values for 405 startups observed over at least three consecutive waves of innovation survey and a maximum of seven waves across 2002–2016. The Wald test on joint non-significance of model coefficients is rejected in both models. We treat all non-applicable, non-identified, and other responses as missing values and do not replace them with zeros.

4. Results

Table 3 reports the results of the random-effects Tobit regression for product innovation (Model 1) and Table 4 reports the results of the logistic regression for process innovation (Model 2). As mentioned, specifications 1–4 demonstrate the relationships between different types of knowledge collaboration partners and innovation outcomes regionally (spec. 1), nationally (spec. 2), in Europe (spec. 3), and internationally (spec. 4). Additionally, we also control for other types of collaboration

Table 3
Product innovation (Model 1).

Dependent variable:	Product innovation											
Geographical Diversity and specification:	1 - UK Regional Specification			2 - UK National Specification			3 - European Countries Specification			4 - International Specification		
Method:	Random-effects Tobit			Random-effects Tobit			Random-effects Tobit			Random-effects Tobit		
Variables	Coef.	S.E.	P > |z|	Coef.	S.E.	P > |z|	Coef.	S.E.	P > |z|	Coef.	S.E.	P > |z|
Enterprise group (H1)	2.16	3.23	0.40	2.06	3.11	0.55	5.90	4.38	0.33	11.81	4.42	0.00
Suppliers (H2a)	5.10	1.20	0.09	11.84	2.97	0.00	3.73	2.24	0.15	8.10	4.01	0.01
Customers (H2b)	9.74	1.11	0.00	15.81	2.93	0.00	−1.49	4.24	0.60	2.39	3.32	0.50
Competitors (H3)	7.73	5.62	0.19	−2.79	2.18	0.38	−0.22	0.76	0.54	−5.93	5.65	0.54
Consultants	3.12	2.43	0.25	0.65	1.17	0.58	−2.68	6.06	0.49	0.11	5.39	0.82
University	7.57	1.35	0.00	2.40	2.33	0.37	−17.72	7.54	0.03	−15.39	7.03	0.03
Government	−1.33	1.75	0.45	8.48	4.37	0.00	−11.19	8.83	0.34	4.54	8.40	0.64
Foreign	1.86	0.61	0.00	−6.33	2.68	0.00	−6.37	1.68	0.00	−6.51	0.69	0.00
Age	−5.28	1.03	0.00	−4.29	1.03	0.00	−4.29	1.03	0.00	−4.29	0.03	0.00
Employment	−1.93	0.50	0.00	−2.25	0.79	0.00	−2.43	0.22	0.02	−2.50	102	0.03
Scientists	0.40	0.02	0.00	0.37	0.02	0.00	0.40	0.02	0.00	0.39	0.02	0.00
R&D intensity	92.58	4.90	0.00	93.40	9.89	0.00	98.05	4.92	0.00	91.88	4.95	0.00
Exporter	9.07	1.52	0.00	17.63	1.51	0.00	17.58	2.51	0.00	17.81	1.51	0.59
UK 12 Regions, 7 time waves, and 14 industry controls	Yes			yes			Yes			Yes		
Controls for partner types in other locations	Yes			Yes			Yes			Yes		
Constant	−37.22	3.75	0.00	−36.94	3.78	0.00	−36.39	3.77	0.00	−36.63	3.78	0.00
Sigma u	17.15	0.65	0.00	16.55	0.66	0.00	16.68	0.67	0.00	16.96	0.67	0.00
Sigma e	24.26	0.47	0.00	24.35	0.47	0.00	24.51	0.48	0.00	24.44	0.48	0.00
rho	0.333	0.023		0.316	0.023		0.317	0.024		0.325	0.024	
Number of obs.	4401			4401			4401			4401		
Number of unique firms	405			405			405			405		
Log likelihood	-31,342			-31,177			-31,368			-31,409		
Wald chi2	3577			3790			3595			3529		
Prob > chi2	0.00			0.00			0.00			0.00		
left-censored	3330			3330			3330			3330		
uncensored	1071			1071			1071			1071		

Source: ONS data.

Table 4
Process innovation model (Model 2).

Dependent variable:	Process innovation											
Geographical Diversity and specification:	1 - UK Regional Specification			2 - UK National Specification			3 - European Countries Specification			4 - International Specification		
Method:	Random effects Logistic			Random effects Logistic			Random effects Logistic			Random effects Logistic		
Variables	Coef.	S.E.	P > |z|	Coef.	S.E.	P > |z|	Coef.	S.E.	P > |z|	Coef.	S.E.	P > |z|
Enterprise group (H1)	1.36	0.11	0.09	1.38	0.10	0.08	1.66	0.13	0.06	1.26	0.13	0.08
Suppliers (H2a, H2c)	2.12	0.11	0.00	2.44	0.09	0.00	1.21	0.12	0.40	1.39	0.53	0.30
Customers (H2b, H2c)	1.79	0.10	0.00	1.65	0.08	0.00	0.87	0.12	0.20	1.73	0.12	0.21
Competitors (H3)	0.83	0.14	0.37	1.20	0.11	0.21	1.62	0.10	0.04	1.60	0.15	0.53
Consultants	0.92	0.13	0.25	1.29	0.11	0.30	0.25	0.21	0.01	0.87	0.23	0.17
University	1.10	0.12	0.12	1.17	0.13	0.28	0.78	0.28	0.90	2.14	1.32	0.15
Government	1.19	0.16	0.50	1.35	0.23	0.21	1.75	0.30	0.25	0.28	0.01	0.04
Foreign	1.01	0.05	0.12	0.91	0.05	0.30	0.94	0.34	0.60	0.95	0.45	0.30
Age	0.88	0.05	0.18	0.91	0.00	0.30	0.93	0.45	0.35	0.90	0.52	0.40
Employment	1.13	0.10	0.01	1.13	0.00	0.00	1.12	0.00	0.02	1.13	0.00	0.01
Scientists	1.02	0.00	0.00	1.02	0.00	0.02	1.01	0.00	0.00	1.01	0.00	0.00
R&D intensity	18.38	10.55	0.00	8.76	0.55	0.00	22.07	0.56	0.00	20.04	0.56	0.00
Exporter	−0.07	0.11	0.53	1.45	0.15	0.00	1.42	0.11	0.02	1.49	0.11	0.02
UK 12 Regions, 7 time waves, and 14 industry controls	Yes			Yes			Yes			Yes		
Controls for partner types in other locations	Yes			Yes			Yes			Yes		
Constant	−1.98	0.25	0.00	−1.88	0.25	0.00	−1.82	0.24	0.00	−1.84	0.25	0.00
lnsig2u	0.521	0.121		0.46	0.12		0.51	0.12		0.53	0.12	
Sigma u	1.30	0.08		1.26	0.08		1.29	0.08		1.30	0.08	
rho	0.338	0.027		0.325	0.027		0.336	0.027		0.341	0.027	
Number of obs	4401			4401			4401			4401		
Number of unique firms	405			405			405			405		
Log likelihood	2070			2058			2203			2160		
Wald chi2	788			848			685			636		
Prob > chi2	0.00			0.00			0.00			0.00		

Source: ONS data.

partners, firm-specific characteristics, industries, regions, and time-fixed effects. Our results indicate that there is a clear distinction between the factors which predict two innovation types, namely process and product innovation. In addition, the effect of open innovation varies depending on the partner type and geographical location of the collaboration partner.

Hypothesis 1, which states that domestic and international knowledge collaboration within an enterprise group has a positive effect on innovation in startups, is supported for process innovation (β = 1.26–1.66, $p < 0.05$) (specifications 1–4, Table 4). Startup collaboration on innovation within an enterprise group increases product innovation by 11.86% age ($\beta = 11.86$, $p < 0.05$) (specification 4, Table 3), partly supporting H1. We argue that product innovation requires novel knowledge and new approaches to innovation, and that knowledge within an enterprise group in close geographical proximity is internalized and limited. Innovation conducted in cooperation subsequently needs to be internalized by the parent firm, and affecting such a knowledge transfer from the collaborative innovation project to the firm may have a high cost. In addition, enterprise group collaboration has a risk of not completely eliminating the duplication of research efforts. In economic terms, this means that startup collaboration with partners within the enterprise group increases product innovation sales by 11.86 percent compared to startups that do not collaborate within enterprise groups internationally. The effect is not statistically significant for other geographical locations.

Knowledge collaboration with suppliers regionally ($\beta = 5.10$, $p < 0.01$) (specification 1, Table 3) and nationally ($\beta = 11.84$, $p < 0.01$) (specification 2, Table 3) increases product innovation, supporting H2a, while collaboration in Europe has no effect on product innovation (spec. 3, Table 3). Interestingly, collaboration with suppliers internationally also increases product innovation in startups (spec. 4, Table 3), which extends what we know about the role that international suppliers play in product innovation in startups. The results for process innovation support H2a, which states that regional collaboration with suppliers increases the propensity to innovate new processes ($\beta = 2.12$, $p < 0.01$) (specification 1, Table 4), as does national collaboration with suppliers ($\beta = 2.44$, $p < 0.01$) (specification 2, Table 4). It is likely easier for a startup to alter its production system, adapting and adjusting to suppliers' R&D and logistics within close geographical proximity, creating a "comfort zone" limited to the institutional arrangement of a region and a country (Balland et al., 2015). The results for collaboration with suppliers internationally and process innovation are not statistically significant.

Collaboration with customers regionally ($\beta = 9.74$, $p < 0.01$) (specification 1, Table 3) and nationally ($\beta = 15.81$, $p < 0.01$) (specification 2, Table 3) increases product innovation, partly supporting H2b, while collaboration with customers internationally has no effect on product innovation. Collaboration with customers regionally ($\beta = 1.74$, $p < 0.01$) (specification 1, Table 4) and nationally ($\beta = 1.65$, $p < 0.01$) (specification 2, Table 4) increases process innovation (1.6–1.7 times), partly supporting H2b. We do not find evidence of startups collaborating with international suppliers to facilitate process and product innovation, not supporting H2b. One would expect that startups need to know potential customers wherever they sell their products and independently of geographical proximity. Unlike collaboration with suppliers, which often enables firms to benefit from the close proximity while reducing their logistics, supply chain, and delivery costs, collaboration with customers and servitization in a digital era enables the use of state-of-the-art digital technology (Li et al., 2016) to transfer knowledge and learn from customers internationally. Our results demonstrate that the digitalization of the open innovation literature, innovative startups still focus on regional markets. The value of international knowledge collaborations with customers, as well as international knowledge transfers between startups and customers, is therefore limited. Belitski and Rejeb (2022) clearly demonstrate that the open customer innovation model mainly explains family strategy in a close geographical proximity and that startups prefer localized collaborations as they are embedded in the local markets.

To test our H2c we performed a *t*-test on the estimated beta coefficient to examine whether the coefficient on collaboration with suppliers and customers is higher than and statistically different from coefficients of collaboration with other types of external partners, including competitors, enterprise groups, consultants, universities and government and across all proximities. Our H2c is only supported for regional and national knowledge collaborations with suppliers and customers, as companies collaborating domestically with suppliers and customers have on average 11–15 % more innovation sales compared to domestic collaborations with any other partner.

Our H2c is also supported for regional and national knowledge collaborations with suppliers and customers and the likelihood of process innovation, but not international collaborations. Interestingly, it appears that in regional and national country contexts, collaborations with customers and suppliers are an important source of knowledge for product and process innovation. Our findings could be explained by differences in knowledge cognitive distance in intra- and inter-firm collaborations (Kogut and Zander, 1992). International collaborations with customers and suppliers do not provide additional benefits due to the cost of collaborating (Saura et al., 2023). Innovative small firms at the start-up stage traditionally target local markets to test their product and gain a customer base and visibility before going international (Guenther et al., 2023). For international knowledge collaboration, neither suppliers nor customers facilitate process innovation, and H2c is not supported.

Hypothesis 3, which states that international knowledge collaboration with competitors positively affects innovation in startups, while domestic knowledge collaboration with competitors is unlikely, is supported for product innovation (specifications 1–4, Table 3), while partly supported for process innovation ($\beta = 1.64$, $p < 0.05$) (specification 3, Table 4). Neither domestic nor international coopetition facilitates product innovation, which extends the findings of Mariani and Belitski (2022) on the negative effect of innovation with competitors related to the risk of involuntary knowledge flows and limited knowledge spillovers from competitors. Although competitors share similar industrial knowledge and generally have close technological proximity, incumbents perceive startups as lacking industry-related knowledge and technology, and hence as highly risky collaborative partners. This expands what we know about localized coopetition effects (Bouncken et al., 2016, 2018). While positive with international partners for process innovation, coopetition remains a challenging perspective for innovative startups (Ritala, 2012; Ritala and Hurmelinna-Laukkanen, 2013; Ritala et al., 2015).

The impact of internal R&D intensity is positive and statistically significant for both product and process innovation, supporting Roper et al. (2017). In addition, startups that are foreign-owned as well as exporters have on average higher product and process innovation compared to startups that do not export. Human capital proxied by share of scientists is positively associated with product and process innovation. In economic terms, this means that a 1 % increase in the share of university graduates increases product innovation by 0.4 %. An increase in employment and startup age is negatively associated with the likelihood of process and product innovation. Younger startups were more likely to introduce new products and services compared to startups more established in the market.

4.1. Robustness check

We performed two robustness checks. First, we treated our dependent variable in the product innovation model with as non-censored and used a logistic model with robust standard errors, correcting for the heteroskedasticity of the error term. The results were robust and statistical significance was at the same level, including the signs of the coefficients of all variables of interest. Second, we ran a weighted regression analysis using innovation survey weights by firm size, region and industry. The qualitative results on the direction of impact, sign, and statistical significance of the coefficients of interest related to our main hypothesis remain the same.

5. Discussion

5.1. Implications for theory

Several novel impactions for theory emanate from our findings. The first involves the role of geography in shaping knowledge collaboration in startups. The empirical results suggest that the geographic location of the knowledge partner matters. If the startup and knowledge partner are located within spatial proximity, as reflected by national boundaries, both product and process innovation is enhanced. Thus, collaboration between a startup and a knowledge partner yields innovations, with the effects stronger when a knowledge partner and a startup are co-located within the same geographic context. This suggests that geographic context provides a valuable platform for the co-development of new economic knowledge, which can be thwarted by geographic distance and national boundaries. Thus, knowledge collaboration is effective in the context of open innovation for startups, but only with the important caveat of geographic proximity within the same national boarders. Just as knowledge spillovers for innovation have been found to be geographically bounded (Audretsch and Feldman, 1996; Audretsch and Stephan, 1996), so too is fruitful knowledge cooperation between startups and external knowledge partners. It may be that the importance of local and national institutions are requisite for the co-development of knowledge conducive to innovative startups.

A second important insight for theory is that not all external knowledge partners are created equal. Certain types of partners yield a greater innovative impact than do others. Specific types of partners, such as customers and suppliers, are more conducive to product and process innovation in startups than are other types of external partners. An explanation for the lower yield, in terms of innovative activity emanating from collaboration between startups and competitors may be the relatively small size and power vis-à-vis their larger and incumbent competitors, putting them in a disadvantage bargaining position to appropriate the fruits of knowledge collaboration. A second interpretation may be that trust is harder to achieve between competitors than between complementary organizations that do not directly compete.

Non-market partners, who are not competitors in any way, such as university and government may be particularly important in achieving product and process innovation by startups, in contrast to prior research on incumbent innovative firms (Martin, 1998; Spencer, 2003). Universities have been long considered an essential source of new ideas and scientific knowledge for highly innovative firms (Belderbos et al., 2004, 2006), but the results for startups have been inconclusive (Tsai, 2009). We contributed to knowledge transfer literature by demonstrating the extent of product and process innovation can be achieved in startups when those collaborate with universities in a close geographical proximity (Guenther et al., 2023).

A third insight for theory is that different types of innovative activity respond differently to external knowledge partnerships. is in understanding the degree of concentration and localization of heterogeneous knowledge sources which can stem from two distinct knowledge characteristics – depth and breadth of knowledge. Notably, the breadth of organizational collaboration (Belitski et al., 2023) relates to the variety of external knowledge partners and can be considered as the number of different partners regionally, nationally and internationally. Knowledge depth is a choice and the extent of collaboration with each specific partner types. This study has demonstrated the increasing role of breadth and depth of knowledge collaboration for innovation in startups adding to prior research on knowledge dept. hand breadth by innovative firms (Kobarg et al., 2019), as well as by matching both type of partner and its variety across different geographical dimensions furthering prior research on inbound open innovation strategies (Laursen and Salter, 2006; Terjesen and Patel, 2017) and applying it to two types of innovation outcomes in startups.

5.2. Implications for practice

The findings from this paper suggest important implications for practice. We have shown that startups are not doomed by a lack of knowledge and absorptive capacity. Rather, by engaging in a compensatory open innovation strategy which leverages in knowledge collaborations for innovation within a specific geographical proximity and with a specific type of external collaboration partner, startups can generate robust innovative activity. Overall startups are able to increase their product innovation by engaging in regional collaboration with universities, government, suppliers and customers and internationally by collaboration within enterprise group and suppliers. For process innovation, startups will benefit from regional collaboration within enterprise group, suppliers, and customers. Startups are more likely to be disadvantaged by international collaboration with universities, that provide a very specific knowledge and despite visible technological and market readiness, innovations from universities internationally bear high costs and require additional time for traction, market validation, knowledge testing and experimentation before commercialization and profits appear (Colombo et al., 2010).

Our findings across type of partner and localization of knowledge collaboration have strong implications for the UK's small business and innovation policy. In particular, policymakers and entrepreneurs are called to incentivize startups to collaborate with other units within the enterprise group, suppliers and customers in their local markets and internationally, as those startups who do so will achieve higher product and process innovation.

In doing so startup context is viewed as a springboard to place-related innovation policy (Audretsch et al., 2022), where a variety of knowledge collaboration strategies cold be applied to foster product and process innovation in the UK. Across partner types and internationally of knowledge required for startups to achieve process and product innovation conditions that increase innovation in firms.

Our study has direct practical implications for startup owner-managers to complements their strategy on product and process innovation in the first seven years since firm establishment (Colombelli et al., 2020). New market development, along with new product innovation and process improvements, rendering the creation of such an understanding highly relevant.

Furthermore, our practical implication enables owner-managers of startups to differentiate the effects of knowledge collaboration for each innovation type (Salge et al., 2012, 2013; Audretsch and Belitski, 2020a) and for each external partner (Chesbrough, 2006; van Beers and Zand, 2014). We thereby add to recent knowledge on open inbound innovation in firms and how this external partnership should be managed, particularly across a set of internal characteristics of startups.

A more nuanced understanding of the hidden trade-offs confronting startups face when reaching out for external knowledge collaborators are discussed, along with the combination of aiming inbound open innovation strategies which configuration enables to shape innovation outcomes in startups - process or (and) product innovation. While prior research illustrated that sourcing external knowledge has both positive and negative effects on innovation efficiency (Roper et al., 2017; Audretsch and Belitski, 2020b; Asimakopoulos et al., 2020), our study demonstrated that it is partner type and location which shapes product and process innovation in startups.

6. Conclusions

This study investigated the returns from knowledge collaboration across different partner types and geographical locations for innovation performance in startups. Knowledge collaboration with external partners directly affects the propensity for process innovation and the share of innovation sales. This study provides new insights on open innovation theory for entrepreneurs, by comparing how startups use the knowledge spillover of innovation (Audretsch and Belitski, 2022) across different partner types and locations.

Our findings pave the way for future studies that may address this study's limitations. Firstly, our study was based on a sample of UK firms. Our findings are contextually limited and may not be generalizable to other countries, particularly developing countries and other developed countries. Future studies can expand the longitudinal dimension of data, aiming for longer lags as well as switching to internationalization vs. de-internationalization of collaboration for startups. Further research is needed to explore the breadth and depth of knowledge collaboration for startups and incumbent firms.

Secondly, due to the anonymous nature of the UK Innovation Survey, we were unable to track the number of contacts and the length of engagements between collaboration partners. Thirdly, we are aware that claiming the causality of collaboration partners on innovation performance may be limited as a result of the limited time-series data. In addition, we highlight possible endogeneity issues as a concern here, even after controlling for time, regional and industry fixed effects in Tobit and logit models. For example, R&D intensity and share of scientists as measurements of internal innovation capacity and human capital could be correlated with other unobserved factors that are not captured by the model. Given that R&D intensity and share of scientists were controls and not our variables of interest, we did not perform endogeneity correction using instrumented estimation. Further research may include a set of robustness checks on endogeneity using balanced longitudinal data.

Future research may also include industry-based studies, as the intensity and the volume of collaboration partners may be industry-related. The role of different partner types and intensities of collaboration across different external partners and in national vis-a-vis international contexts can be important in understanding the mechanisms of knowledge collaboration and spillovers. Studying this may provide further insights to managers and policymakers developing support tools and policies for entrepreneurship and when using open innovation as a tool for productivity and market growth. Startup owners may want to know how various combinations of external knowledge partners and their locations (Cunningham, 2022) may complement innovation and productivity, extending knowledge spillover of innovation research. Policymakers and entrepreneurs need to better understand why knowledge collaboration with certain external partners is associated with specific internationalization and localization strategies, and why it can be geographically biased. In addition, differences in the portfolio of knowledge collaboration partners and their intensity may change how (re)combination of knowledge inputs take place (Belderbos et al., 2006, 2015).

Data availability

The authors do not have permission to share data.

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