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Knowledge spillover of innovation: Entrepreneurial difference

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ABSTRACT

This paper extends the knowledge spillover theory of entrepreneurship and innovation to explain how firms of different ages (startups vs. incumbents) and sizes (small vs. medium/large) benefit differently from external knowledge collaboration. Drawing on the distinction between *active* (formal) and *passive* (informal) spillovers, we examine how the intensity of knowledge collaboration influences two key innovation outcomes: product innovation and new market entry. Using a panel dataset of 27,685 UK firms (2005–2015), we show that the gains from knowledge spillovers for all types of firms are subject to diminishing marginal returns as collaboration intensity increases, while the findings between startups and incumbents are more nuanced than between small and medium/large firms. The benefits from knowledge spillover of innovation vary by knowledge spillover type, intensity, and mode of engagement, as well as innovation outcome. These findings refine the knowledge spillover theory by emphasizing the importance of firm age over size (entrepreneurial difference) in moderating innovation outcomes.

1. Introduction

Knowledge spillovers of innovation and entrepreneurship are a positive externality—the process through which knowledge generated by one entity (such as a firm, university, or research institution) is transferred to another entity, leading to innovation, enhanced innovative capabilities, or new market entry (Acs et al., 2009; Braunerhjelm et al., 2010; Audretsch and Belitski, 2022; Becker et al., 2023). Knowledge spillovers occur when knowledge created is not fully appropriated by the firm (Arrow, 1962) or (and) transferred to other firms as a result of formal (Belderbos et al., 2006) and informal knowledge collaboration (Griliches, 1991; Jaffe, 1986). Audretsch and Feldman (1996: 630) describe the process of knowledge spillovers as follows "investment in R&D by private corporations and universities "spills over" for third-party firms to exploit".

Prior research on the knowledge spillover of entrepreneurship and innovation has been limited in two key ways. Firstly, it lacks robust empirical evidence on how the heterogeneous knowledge created at universities, conferences, by customers, competitors, patents, and others sources may become "spillovers" and affect a firm's innovation activity (Van Beers and Zand, 2014; Aghion and Jaravel, 2015; Roper et al., 2017; Audretsch et al., 2021). Secondly, it lacks both a strong theoretical foundation for the knowledge spillover of innovation and an examination of the entrepreneurial difference in the size of the effect, distinguishing between firm size and firm age (Audretsch and Lehmann, 2006; Agarwal et al., 2010; Ghio et al., 2015). Bloom et al. (2013: 2) argues that: "Econometric estimates of technology spillovers in the literature may be severely contaminated by product market rivalry effects, and it is difficult to ascertain the direction and magnitude of potential biases without building a model that incorporates both types of spillovers". With a few exceptions, gaps remain in the literature in understanding the mechanisms that facilitate heterogeneous knowledge spillovers of innovation and in measuring them between firm size and age (Stolpe, 2002; Audretsch and Feldman, 1996; Audretsch and Belitski, 2024; Audretsch et al., 2025a), including intensity and sources of knowledge collaboration (Kobarg et al., 2019), type of spillover (active or passive) (Giovannetti and Piga, 2017), and innovation outcomes. Despite the gaps, scholars seem to agree that the emergence of knowledge spillovers is rare and often unexpected in direct and indirect interactions between firms (Cassiman and Veugelers, 2002; Bloom et al., 2013).

Therefore, this paper has two objectives. The first is to examine firm's returns from knowledge spillovers through direct and indirect knowledge collaboration and their impact on the propensity to innovate

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new products and new market entry. The second objective of this study is to examine the differences in benefits and costs of the knowledge spillover of innovation for different intensity of collaboration, firm age and size and innovation outcomes. This could better inform the choices of managers regarding which sources of knowledge and collaboration partner a firm needs to engage and the level of collaboration intensity to achieve specific innovation outcomes. We consider two key groups of knowledge spillovers. The first group is active knowledge spillovers defined by direct collaboration or knowledge exchange with specific external actors. These spillovers include vertical and horizontal collaboration, as well as collaboration with consultants and competitors. The second group is passive knowledge spillovers which are informal or semi-informal, derived from public or semi-public information sources without active collaboration with the partner or formal agreement (Love et al., 2014; Kafouros et al., 2020). These spillovers include knowledge engagement and collaboration within conferences, academic and technical publications, trade and industry associations, and industry standards (West and Bogers, 2014; Bernal et al., 2022; Stouras et al., 2022).

Methodologically, we operationalize knowledge spillovers using data on intensity of collaborations with variety of knowledge sources (Chesbrough et al., 2006; Cassiman et al., 2008; Lucking et al., 2018; Braunerhjelm et al., 2018), controlling for intra- and inter-industry regional knowledge production capacity (Bernal et al., 2022).

Using regression analysis and firm-level longitudinal data (2005–2015) from the United Kingdom—covering 27,685 UK firms and 35,223 firm-year observations to test our research hypotheses, this study makes three main contributions to the knowledge spillover theory of entrepreneurship and innovation literature (KSTE&I). Our first contribution is in advancing open innovation literature (Bogers, 2011; West and Bogers, 2014) by explicitly theorizing the heterogeneity of spillover effects by firm size and age. Prior research has suggested that small firms benefit more from open innovation practices due to their reliance on external knowledge (Audretsch and Vivarelli, 1996; Acs et al., 1994), while our findings demonstrate that it is not firm size but firm age which moderates the knowledge spillover of innovation and new market entry (entrepreneurial difference). This study refines the KSTE by showing that both small and large firms equally benefit from knowledge collaboration, but they experience diminishing marginal returns as intensity of knowledge collaboration increases.

Our second contribution to the knowledge spillover and open innovation literature (Laursen and Salter, 2006; Love et al., 2014; Audretsch and Belitski, 2020, 2022) by introducing the heterogeneity of knowledge spillovers and variety of engagement modes that shape innovation outcomes. Active (formal) and passive (informal) knowledge supports innovation and new market entry propensity. However, the effects are nuanced and depend on the intensity of collaboration, source of knowledge spillover; firm age and size, and innovation outcome, showcasing the strong presence of diminishing returns to spillovers for innovation (Laursen and Salter, 2006, 2014; Denicolai et al., 2016; Kobarg et al., 2019; Audretsch and Belitski, 2022), and suggesting the existence of optimal levels of intensity and breadth of knowledge collaboration.

Finally, our third contribution is in revising and refining the knowledge spillover theory of entrepreneurship (KSTE) by emphasizing firm age rather than size as the core factor determining how knowledge spillovers shape firm's innovation propensity and new firm entry. These contributions align with recent calls to revisit structural assumptions in innovation theory (Petruzzelli et al., 2018; Kobarg et al., 2019; Audretsch et al., 2025b).

The remainder of this paper is structured as follows. In the next section we discuss knowledge spillover across four literature streams and develop our research hypotheses. We describe the various data sources and regression in Section 3 and proceed in Section 4 with the econometric analysis. Section 5 discusses this paper's key findings, contributions, and policy implications, and Section 6 concludes.

2. Theoretical framework

2.1. The knowledge spillover of innovation theory

While there is wide agreement on the importance of knowledge externalities for innovation performance (Jaffe, 1986; Griliches, 1991), the sources of knowledge spillovers remain under-investigated (Laursen and Salter, 2014; Becker et al., 2023), in particular across firm size and age (Acs and Audretsch, 1987). The knowledge spillover literature distinguishes four streams explaining how knowledge spills over for innovation. The first stream suggests that knowledge spillovers originate from third parties within the industry, such as the Marshall–Arrow–Romer externalities (Marshall, 1920; Beaudry and Schiffauerova, 2009; Caragliu et al., 2016) between industries (Jacobs, 1970), where incumbent firms invest in knowledge that is sometimes uncommercialized or underutilized by the inventor and then picked up by other firms that integrate, appropriate, and commercialize knowledge via new market entry and new product sales.

This approach is closely related to the role of knowledge cross-fertilization within and between industries (Jaffe, 1986; Audretsch and Feldman, 1996), especially when a firm is co-located in a cluster or is part of an agglomeration economy (Caragliu et al., 2016). Temporary knowledge communities—such as associations developing technical standards, academic teams, trade and industry associations and fairs, conferences and exhibitions—function as clusters of knowledge spillovers (Santamaría et al., 2009).

The second stream distinguishes between horizontal spillovers—primarily among competitors—and vertical spillovers with suppliers and customers. Horizontal spillovers within the industry—mainly from competitors—involve technologically and cognitively proximate knowledge which can be understood and integrated by recipient firms (Park et al., 2014). The cost of knowledge adoption and appropriation within the same industry can be lower than the cost of information from the technologically distant sectors, but there still is a cost (Mansfield et al., 1981; Mansfield, 1985). On the positive side, knowledge from competitors can support innovation through mechanisms such as co-development, resource acquisition, and the stimulation of internal capabilities (Park et al., 2014). This is particularly beneficial for young and small firms that oftentimes lack experience in developing new-to-market products (Mariani and Belitski, 2023).

Vertical spillovers, particularly through suppliers, provide rapid diffusion of novel inputs and technologies (Scherer, 1982), often yielding more radical innovations due to knowledge complementarity (Arora and Gambardella, 2010), enabling new combinations of knowledge (Audretsch and Belitski, 2023). Two mechanisms facilitate vertical spillovers of innovation (Bernstein, 1988; Vanderwerf, 1992). First, vertical knowledge spillovers from upstream suppliers offer tried and tested knowledge related to inputs and can be further added and integrated into existing knowledge to enable complementarity (Scherer, 1982). Second, downstream vertical knowledge spillovers from collaboration with customers allow valuable insights on product and service co-creation with customers (Von Hippel, 2009).

A third stream of literature is associated with the works of economic and management scholars (Guerrero and Urbano, 2014; Guerrero et al., 2016; Audretsch et al., 2022) who described how knowledge spillovers university–industry collaborations facilitate the emergence of new technologies, spinouts, and new-to-market products. Furthermore, scholars such as Patton and Kenney (2010) and Kenney and Patton (2011) have argued that universities are an integral part of the genesis and evolution of research-based clusters and that university-research-driven entrepreneurs per se are a source of knowledge. Prior research discussed how firm–university collaborations boost knowledge creation and commercialization through joint R&D, conferences, associations, and patent activity (Bradley et al., 2013; Audretsch and Link, 2019) as well as commercial labs and consultants (Klofsten et al., 2019; Fini et al., 2022; Radko et al., 2023).

The final stream—open innovation—frames knowledge spillovers as increasingly decentralized, transcending geographical clusters (Chesbrough, 2003; Chesbrough et al., 2006; Cassiman et al., 2008; Feldman et al., 2023). While the field has grown significantly since the work of Chesbrough (2003), few studies have examined the role that variety of open knowledge sources play in innovation activity (Bogers, 2011; Audretsch et al., 2023). According to the open innovation literature, knowledge spillovers may be an outcome of more explicit (active) forms of knowledge collaboration vertically (customers and suppliers), and horizontally (competitors) and with universities, but also more implicit (passive) forms of knowledge engagement, such as through knowledge exchange at fairs, conferences, access to open scientific publications and patents, industrial standards, and membership of associations (Stouras et al., 2022).

Given the emergence of new platforms of e-working and channels to knowledge transfer (e.g., Zoom, Teams, Google Meet, and other videoconference platforms) (Zysman and Kenney, 2016; Kenney et al., 2019) as well as and hybrid ways of work organization (Zhang et al., 2022), the cost of knowledge transfer over time has also been significantly reduced, leading to intensified knowledge co-creation nationally and internationally.

2.2. Heterogeneity of the knowledge spillover of innovation

Knowledge spillovers offer managers and entrepreneurs the chance to learn new skills and competencies, and also improve absorptive capacity (Roper et al., 2017) and oftentimes the efficiency of a firm's own investment in R&D and innovative training. Drawing on earlier studies of Bloom et al. (2013), Roper et al. (2017) and Giovannetti and Piga (2017) we group knowledge spillovers into active and passive types subject to the source of knowledge. Interactive (active) knowledge spillovers are defined by direct collaboration with external partners, such as vertical collaboration spillovers—knowledge from suppliers and customers; horizontal collaboration spillovers—knowledge from competitors (coopetition); consultant collaboration spillovers—knowledge from consultants, commercial labs, and private R&D institutes; and university collaboration spillovers—knowledge from universities or higher education institutions (regional, national, or international).

These spillovers are typically bidirectional and co-evolving, relying on ongoing interaction, feedback loops, and mutual adaptation (Chesbrough et al., 2006; Audretsch et al., 2025b). Effective collaboration requires trust and absorptive capacity (Cohen and Levinthal, 1990), and is often influenced by the history of prior partnerships (Love et al., 2014; Kafouros et al., 2020). These relationships frequently involve tacit knowledge, such as routines, design ideas, and problem-solving strategies (Helfat and Martin, 2015). This form of collaboration may or may not require spatial proximity for knowledge transfer (Balland et al., 2015), especially with the development of new digital tools. Interactive (active) knowledge spillovers are dependent on network structures and relationship intensity, and may be protected via contracts or non-disclosure agreements (Bogers, 2011). While active knowledge spillovers have higher operational, transactional, and coordination costs (Audretsch and Belitski, 2020), these spillovers have higher innovation impact (Giovannetti and Piga, 2017).

Informal (passive) knowledge spillovers arise from public or semi-public information sources without the need for active collaboration or formal agreements. These spillovers are typically not spatially constrained (Audretsch and Feldman, 1996) and often involve one-directional, codified knowledge flows, where the recipient firm neither compensates nor reciprocates the knowledge provider (Laursen and Salter, 2014; Feldman et al., 2023).

Following Cassiman and Veugelers (2002, 2006), we include a range of passive spillover mechanisms, such as participating in or presenting at conferences, trade fairs, and exhibitions; accessing academic and technical publications; engaging in sectoral forums, industry groups, and associations; and involvement in standard-setting processes and technical certification (Bernal et al., 2022). These are often characterized as pure spillovers, requiring minimal or no negotiation (Audretsch and Keilbach, 2007, 2015; Audretsch and Belitski, 2022).

While accessing such knowledge may involve modest costs (e.g., conference fees, association dues, or exhibition space), the knowledge remains broadly accessible. These spillovers include both codified and tacit elements such as benchmarking data, published research, patents, and industry norms. These spillovers represent a form of public knowledge which is useful for benchmarking or keeping up with industry and market trends (Operti and Carnabuci, 2014), but which may expose a firm to a rapid dissemination or imitation of knowledge (Mariani and Belitski, 2023). Firms require investment in absorptive capacity that can internalize and adapt codified knowledge (Kafouros et al., 2020; Audretsch and Belitski, 2022), transforming new ideas and creativity into new products and services (Bogers, 2011; Van Beers and Zand, 2014).

2.3. Benefits and costs of knowledge spillover of innovation

The extant literature has demonstrated that knowledge spillovers from collaboration with diverse external partners foster learning and enhance a firm's absorptive capacity (Denicolai et al., 2016), supporting innovation and idea generation (Van Beers and Zand, 2014). Furthermore, we know that external knowledge is a critical input for innovation performance, accelerating new product development and strengthening competitive advantage (von Hippel, 2009; Kenney and Patton, 2011; Audretsch et al., 2021). Milton Friedman, a Nobel Prize-winning economist, is credited with observing, "There's no such thing as a free lunch." To generate output, (costly) inputs are needed, notably knowledge. Knowledge spillovers offer valuable inputs, but sustained innovation effort and new product development depends on continued investment in internal and buying R&D, skills development, and absorptive capacity (Alvarez and Busenitz, 2001). These investments allow firms to recognize, assimilate, and apply external knowledge effectively (Cohen and Levinthal, 1990; Roper et al., 2017), but they also contribute to rising marginal costs of collaboration. This occurs due to rising costs of sourcing, coordination, and adaptation (Audretsch and Belitski, 2020), as well as redundant or outdated knowledge inputs (Ter Wal et al., 2016; Kobarg et al., 2019) and competition effects, such as product market rivalry effects (Bloom et al., 2013). In particular, in intra-industry and in technologically close sectors (Balland et al., 2015), high levels of knowledge spillovers disincentivize firms to further invest in R&D (Cassiman and Veugelers, 2002). Similarly, knowledge from downstream partners—such as customers—may improve demand awareness, meeting buyer needs and promoting incremental rather than radical innovation, constraining originality (Tether, 2002).

Initially, increase in intensity of knowledge collaboration enhances innovation by bringing in diverse, novel ideas, reducing uncertainty, and accelerating product development (Cohen and Levinthal, 1990; Belitski et al., 2024). However, as firms integrate more external knowledge, and the intensity of knowledge collaboration increases, firms reach a saturation point beyond which additional inputs yield limited returns. This saturation point may depend on the type and source of knowledge, with the effect of the knowledge spillover varying and becoming harder to predict. As intensity of collaboration increases, less novel knowledge is created and assimilated, which is harder to integrate or more expensive to coordinate depending on the model of engagement and the source of the knowledge spillover, it reduces innovation activity (Laursen and Salter, 2006; Bloom et al., 2013; Kobarg et al., 2019). Cognitive and technological misalignments may arise specifically for active knowledge spillovers and the incongruence between internal and external knowledge may grow asymmetrically (Balland et al., 2015), increasing the risk of inefficiencies as well as the coordination complexity (Laursen and Salter, 2014; Saura et al., 2023). This leads to heterogeneous effects and affects the shape of the knowledge spillover of innovation curve. We develop our first hypothesis:

Hypothesis 1. The positive effect of heterogeneous knowledge spillovers on innovation is subject to diminishing marginal returns as the intensity of knowledge collaboration increases.

2.4. Knowledge spillover of innovation in startups and small firms

The choice of knowledge collaboration partner and the intensity of collaboration are important factors that may shape innovation outcome, subject to specific firm idiosyncratic characteristics. There are several reasons to believe smaller and younger firms benefit more from knowledge spillovers (Acs et al., 1994; Audretsch and Vivarelli, 1996). Drawing on the literature on how knowledge spillovers lead to innovation across firms of different size and age (Acs and Audretsch, 1987; Audretsch, 1995; Coad et al., 2018), we observe four key mechanisms. Firstly, new knowledge is uncertain, asymmetric, and costly. While established older firms aim to reduce uncertainty and calculate risks, smaller and younger firms are more tolerant of uncertainty (Knight, 1921). Arrow (1962) emphasized that knowledge differs from other production inputs—its returns are uncertain, and only domain experts can accurately assess its value. Established firms may overlook valuable external knowledge that does not align with their existing technological or cognitive frames. In contrast, startups and smaller firms are more flexible in exploring and integrating novel knowledge into their routines, even if such knowledge appears redundant or low-value to incumbents (Audretsch et al., 2021). Unlike large established firms, startups actively engage in knowledge-sharing activities such as conferences, industry associations, and university collaborations, which is typical of an exploratory entrepreneurial regime (Audretsch and Acs, 1990). Larger established firms may find external knowledge partnerships redundant or non-complementary, due to the "not invented here syndrome".

Second, smaller firms are better positioned to overcome the "knowledge filter", which is the gap between knowledge creation and commercial application (Audretsch, 1995). Large firms often fail to act on new ideas that do not align with existing routines or are undervalued due to bureaucratic inertia and rigid evaluation criteria. Although university and industry collaboration can be important sources of competitive advantage (Siegel et al., 2003; Guerrero et al., 2016), incumbents may be deterred by long experimentation periods or procedural barriers, slowing down knowledge adoption (Audretsch and Keilbach, 2007; Audretsch and Lehmann, 2006). Individuals (e.g., engineers, scientists) with knowledge that is underutilized or not yet tested within incumbent organizations and universities may leave incumbents to start new firms and enter newly created markets before incumbents.

Thirdly, smaller and younger firms are less bureaucratic and more agile. They are less constrained by internal hierarchies, allowing for quicker decision-making on knowledge collaborations, including "trying collaborations" and learning by doing. Smaller and younger firms focus on niche markets (Pahnke et al., 2023) and engage in knowledge collaboration to achieve radical innovations that incumbents may consider highly risky and uncertain (Audretsch, 2009). These firms actively seek external knowledge sources to reduce costs and gain a competitive edge, often by building networks through universities, conferences, and industry associations.

Finally, startups and small firms have limited internal resources to invest in R&D and technology, train employees, and hire talent (Audretsch et al., 2021). They rely on knowledge spillovers for innovation (Bloom et al., 2013). It may be difficult to draw a line and argue that smaller vs. younger firms have higher (or lower) internal capacity, higher (or lower) returns from engaging in knowledge spillovers (Audretsch and Feldman, 1996), and that the marginal costs of knowledge collaborations are different. However, the above characteristics are definitely distinct from larger established firms. We develop our second hypothesis:

Hypothesis 2. The positive effect of knowledge spillovers on innovation is greater for startups and smaller firms, as they experience smaller diminishing marginal returns to the intensity of knowledge collaboration and are more willing to take risks.

3. Data and method

3.1. Sample

To test our hypotheses, we use an unbalanced panel dataset that covers the innovation activity of 27,685 UK firms and 35,223 firm-year observations constructed from six consecutive waves of a community innovation survey (UKIS) and the Business Structure Database (BSD) (also known as the Business Register and Business Enterprise Research and Development (BERD)) for the period 2005–2015. We produce four subsamples: a subsample of startups (5878 firms and 6559 firm-year observations), incumbents (21,807 firms and 28,664 firm-year observations), small firms (16,323 firms and 19,688 firm-year observations), and medium/large firms (11,362 firms and 15,535 firm-year observations).

We collected and matched UKIS data to the initial year of BSD and BERD data for 2003, 2005, 2007, 2009, 2011, and 2013.

The UK context of innovative firms is particularly well-suited for this study for several reasons. The UK demonstrates diverse innovation activity—including radical and incremental innovation—and a rich and varied innovation ecosystem across regions, characterized by a mix of startups and incumbent firms across numerous industries. This diversity allows for a comprehensive examination of how firm age and size affect the knowledge spillover of innovation, thus providing robust ground to test our hypotheses.

Table A1 in Appendix A shows the industry, regional, time, and firm-size distribution of our sample.

3.2. Variables

3.2.1. Dependent variable

We measure innovation using two variables which capture the newness of a product (service) and a firm's ability to introduce new products to market. Our first variable is the binary "product (service) innovation" which comes from the UK Innovation Survey question: "During the past 3 years this business had turnover from goods and services that were new to the market" (Van Beers and Zand, 2014; Kobarg et al., 2019; Audretsch et al., 2021). Our second variable is the binary "New market entry", also from the UK Innovation Survey question: "During the past 3 years, did this business introduce a new good or service to the market before competitors?" This variable, in addition to firm's innovation, demonstrates a firm's ability to enter new markets faster than its competitors (Laursen and Salter, 2014; Santamaría et al., 2009; Mariani and Belitski, 2023). The new market entry variable imposes additional conditions to new product introduction, demonstrating a firm's ability to be a first-mover in the market and commercialize new knowledge.

3.2.2. Explanatory variables

We use a set of explanatory variables to measure a variety of knowledge spillovers and emphasize their heterogeneity for a firm. We use the UK Innovation Survey to source data on knowledge collaboration with diverse external partners (Van Beers and Zand, 2014; Belitski et al., 2024) within two groups of knowledge spillovers (passive and active) depending on the source of knowledge input.

We measure knowledge spillovers using the intensity of knowledge collaboration with external partner (supplier and customer, competitor, consultant, university, conferences, associations, technical standards, and scientific publications) with the intensity of collaboration varying between 0 and 3 (0—not used, 1—importance low, 2—importance medium, and 3—very important). While selected measures of knowledge collaboration have been used in prior research (Van Beers and

Zand, 2014; Audretsch and Link, 2019; Kobarg et al., 2019), all eight types of knowledge spillovers have never been analyzed jointly in one model.

Finally, we use two binary variables—startup and small-sized firms (Coad et al., 2018)—to split the sample into (i) startups vs. incumbent firms, and (ii) small firms vs. medium and large firms. Startup is a binary variable equal to one if a firm has been incorporated for a maximum of 7 years, has no subsidiaries, and is an independent firm and not a subsidiary of a larger firm. The maximum number of employees at the establishment year (year of incorporation) is between 2 and 49 (Freel, 2000). A small-sized firm is a binary variable equal to one if a firm has between 2 and 49 full-time employees (FTEs), zero otherwise. We also excluded firms that are subsidiaries of large firms, if, together with another unit, the number of FTEs exceeds 49. As part of a robustness check, we use firm age and size and interact them with each type of knowledge spillovers, specifically to test our hypothesis 2.

3.2.3. *Control variables*

Our control variables include firm and industry characteristics that predict firm innovation performance. We control for firm age and size which is associated with changes in innovation strategy and firm's growth (Coad et al., 2018). We control whether or not a firm is an exporter, which is a binary variable that equals one if a firm sells its products and services in foreign markets, and zero otherwise (Belderbos et al., 2015), and whether a firm is a foreign firm subsidiary and has headquarters abroad (Audretsch et al., 2021). We control for the inverted U-shaped effect of knowledge collaboration breadth and innovation output (Belitski et al., 2024) by including collaboration breadth as the number of types of external partners a firm simultaneously collaborates between zero to eight knowledge partners. Prior research has demonstrated that collaboration with a broader range of external partners enables innovating firms to acquire required information from a variety of sources and leads to more synergies (Belderbos et al., 2006; Van Beers and Zand, 2014) but has a cost effect diminishing returns of functional diversity (Belitski et al., 2024). We control for the firm's absorptive capacity by controlling for the share of employees who hold a degree or higher qualification (Zahra and George, 2002) as well as R&D intensity (Belderbos et al., 2015), digital intensity (Hall et al., 2013), and training intensity (Belitski et al., 2020). It is also important to control for process innovation when predicting the other (e.g., product innovation) and vice versa, as companies might have engaged in more than one innovation type. We control for market uncertainty of demand for firm products and economic risks (Knight, 1921), changing from zero—none to three—high risk (uncertainty).

The degree of industry competition is measured using the Herfindahl index of sales. Localized knowledge production capacity within and between industries facilitates the creation of new ideas and leads to potential incremental productivity gains for co-located firms (Audretsch and Feldman, 1996; Bloom et al., 2013). Finally, we use year, time, and region fixed effects. Table B1 provides a description of variables, Table B2 has summary statistic for the overall sample and subsamples, and Table B3 is a correlation matrix.

3.3. *Method*

In our identification strategy, we account for the type of dependent variable. We use logistic regression for both dependent variables to predict the effect of knowledge spillovers on the likelihood of product (service) innovation and new market entry (Wooldridge, 2009). In econometric form, the first model has y_{it} as a binary variable, and firm's i product innovation (firm's new-to-market entry) in time t, which varies between zero and one. Vector S_{ijt} is the knowledge spillover of firm i at time t with a type of knowledge source j. We use the level and squared terms for each knowledge spillover to control for diminishing marginal returns; vector φ_{it} is a vector control variable of firm i at time t.

$$y_{it} = \beta_0 + \beta_1 S_{ijt} + \beta_2 S_{ijt}^2 + \beta_3 \varphi_{it} + \delta_r + \tau_t + \lambda_r + u_{it} \quad (1)$$

We can also call it a structural equation to emphasize that we are interested in β_1-β_2 for the effect of each type of knowledge spillover on the propensity to innovate and enter new markets. Additionally, β_3 is the effect of firm and industry/regional characteristics on the propensity to innovate and new market entry. Vector φ_{it} is a list of exogenous control variables, and S_{ijt} is a vector of knowledge collaboration not correlated with u_{it}, an error term. δ_r, τ_t, and λ_r are the industry, year of survey, and regional fixed effects (Wooldridge, 2009: 517).

4. Results

We estimated an innovation production function using logistic regression, reporting results as odds ratios for startups (Table C1, spec. 1–10) and incumbents (Table C2, spec. 1–10). A likelihood-ratio test supported the use of logistic estimation over linear regression.

Specifications 1–8 in Tables C1 and C2 estimate the effect of each type of knowledge spillover—both in level and squared terms—on firms' propensity to engage in product innovation. Specification 9 includes all spillover types simultaneously. Specification 10 assesses the effect on firms' likelihood of entering new markets before competitors.

For startups, we find diminishing marginal returns to innovation from vertical, horizontal, and university spillovers (squared terms <1 and significant in spec. 9, Table C1), supporting our first hypothesis (H1). Consultant spillovers are insignificant. For incumbents, all active knowledge spillovers, including consultants, show diminishing returns, also supporting H1. However, the effects for new market entry differ: for startups, consultant spillovers remain insignificant (specs. 9–10, Table C1), whereas for incumbents, consultant collaboration supports product innovation but not new market entry. Notably, vertical spillovers for incumbents exhibit no diminishing returns (squared term insignificant, spec. 9, Table C2). This finding does not support H1, and demonstrates that, for incumbents, the more knowledge collaboration with suppliers and customers, the merrier is innovation. It also demonstrates that when analyzing the extent of knowledge collaboration, it is the source of knowledge—along with a firm's capabilities—that matters (Audretsch et al., 2024).

To illustrate these differences, we plot predictive margins in Fig. 1A–D based on spec. 9 (Tables C1 and C2). Predictive margins show that startups benefit more strongly from vertical, horizontal, and university spillovers than incumbents. The initial returns are steeper and more positive for startups, supporting our second hypothesis (H2) of a higher positive effect of knowledge spillover innovation for startups compared to incumbents. This extends prior research of Aghion and Jaravel (2015) on the heterogeneity of knowledge spillovers effects.

We then evaluate passive knowledge spillovers (Tables C1–C2, specs. 9–10). Conference participation significantly enhances innovation for both startups and incumbents, with no evidence of diminishing returns. Scientific journal participation is positive but insignificant for startups and significantly negative for incumbents (b = 0.797, $p < 0.01$, spec. 9, Table C2). Membership in trade or industry associations is initially negative across both groups but improves at higher levels of engagement, suggesting a U-shaped relationship.

Participation in technical standards shows no significant effect on innovation for either group (spec. 9, Tables C1–C2).

For new market entry (spec. 10), passive spillover effects differ. The overall effect is insignificant for startups but positive and significant for incumbents (b = 1.216, $p < 0.05$, Table C2). Journal participation is again insignificant, while industry association membership for incumbents shows a U-shaped pattern, suggesting increased market entry at higher involvement levels (spec. 10, Table C2). This finding suggests that low-to-moderate participation may hinder innovation, but high involvement in trade and industry associations reverses the negative effect, and knowledge contributes to innovation. Finally, there is no

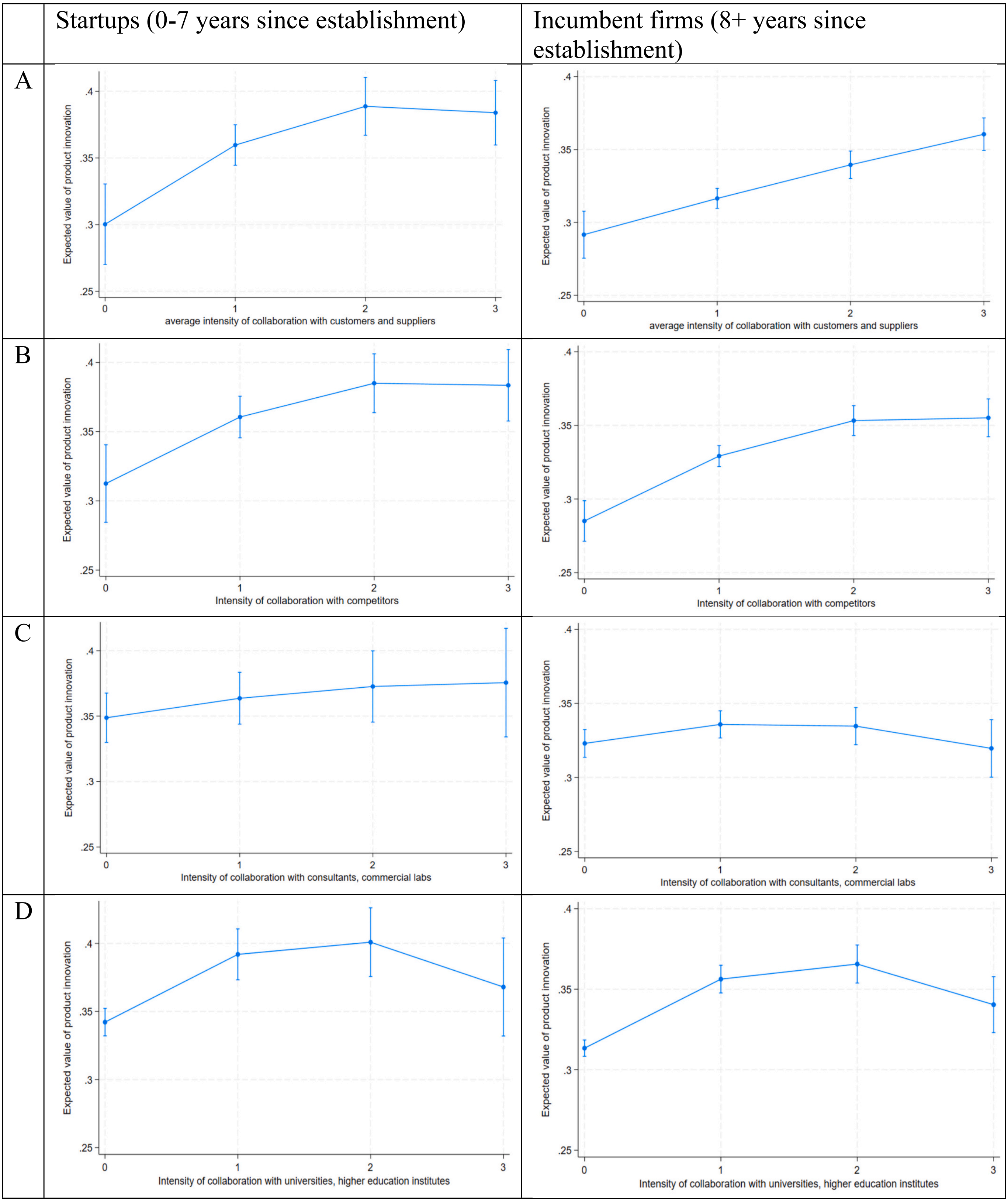

Fig. 1. Predictive margins for knowledge spillover of innovation with 95 % confidence intervals for startups (0–7 years) (left column) and incumbent firms (8+ years) (right column).
Source: UKIS—UK Innovation Survey; BSD—Business Structure Database; BERD—Business Expenditure on research and development.

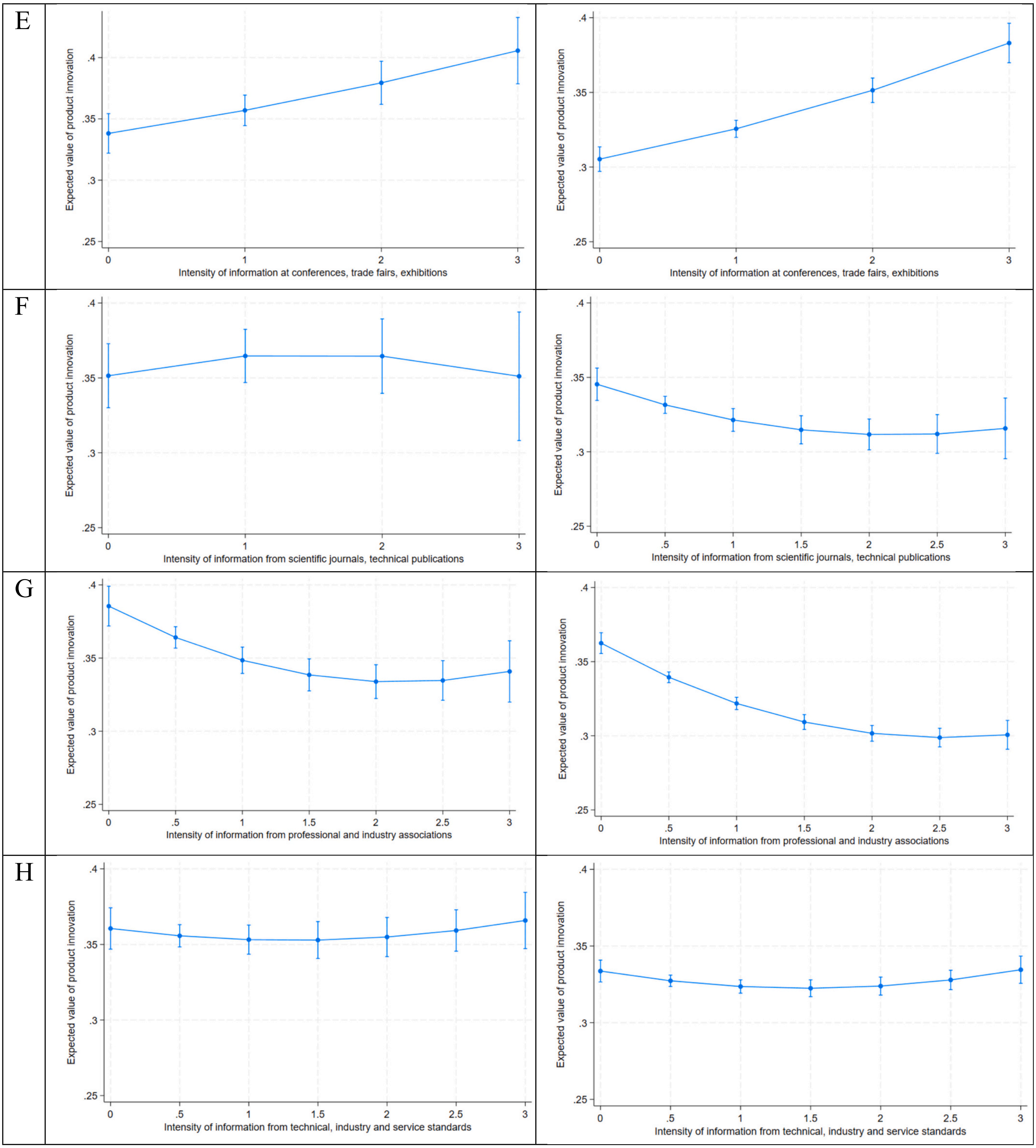

Fig. 1. (*continued*).

Table 1
Summary of the hypotheses testing and key findings.

Knowledge spillover type	Variation of spillover	Significant for Startups	Significant for Incumbents	Diminishing Returns	Support for H1	Support for H2	Significant for small firms	Significant for medium and large firms	Diminishing Returns	Support for H1	Support for H2
Interactive (Active)	Vertical	Yes	Yes (positive)	Yes, startups only	Yes	Yes	Yes (positive)	Yes (positive)	No (Both)	No	No
	Horizontal	Yes	Yes	Yes (Both)	Yes	Yes	Yes	Yes	Yes (Both)	Yes	No
	Consultants	No	No	No (Both)	No	No	No	No	No (Both)	No	No
	University	Yes	Yes	Yes (Both)	Yes	Yes	Yes	Yes	Yes (Both)	Yes	No
Informal (Passive)	Conferences	Yes (positive)	Yes (positive)	No (Both)	No	No	Yes (positive)	Yes (positive)	No (Both)	No	No
	Scientific Journals	No	Yes(negative)	No (Both)	No	No	No	No	No (Both)	No	No
	Professional Associations	Yes	Yes	No, (U-shaped, both)	No	No	Yes	Yes	No, (U-shaped, both)	No	No
	Technical Standards	No	No	No (Both)	No	No	No	No	No (Both)	No	No

Source: Regression results.

evidence that spillover from participating in technical standards increases the propensity to innovate in startups and incumbent firms.

Fig. 1E–H plot the predictive margins for passive spillovers. These results show no diminishing returns and no significant difference in effect size between startups and incumbents for passive knowledge spillovers, thus not supporting our H1 and H2 in the context of passive spillovers. Table 1 summarizes our findings by knowledge spillover type and across firm age and size, and indicates whether our hypotheses are supported.

4.1.1. *Other results*

Larger firms have lower innovation likelihood for startups (b = 0.94–0.97, $p < 0.01$, spec. 1–9, Table C1), but not for incumbents (Table C2). Each 1 % increase in startup employment is associated with a 2.2–5.3 percentage point decline in product innovation propensity. In contrast, older incumbents are less likely to innovate (b = 0.81–0.86, $p < 0.01$, Table C2), with no significant effect observed for startup age. Internal R&D significantly increases innovation for both groups, but to a greater extent for incumbents (b = 29.26–41.20, Table C2) than for startups (b = 3.84–5.08, Table C1). Digital intensity has a negative effect for incumbents (b = 0.56–0.77, $p < 0.05$, Table C2), but is insignificant for startups—possibly due to overlapping effects from other firm capabilities like training and R&D. This result is surprising and may be confounded by positive and statistical significance of other firm's capabilities measures such as training and R&D, and remits future research. Training intensity increases innovation propensity more strongly for startups (b = 3.27–4.62, $p < 0.01$, Table C1) than for incumbents (b = 2.34–2.88, Table C2). A higher share of university-educated FTEs enhances innovation among incumbents (b = 1.004–1.006, $p < 0.01$, Table C2), but not startups. Economic and demand uncertainty risks raise innovation likelihood for both startups (b = 1.12–1.18, Table C1) and incumbents (b = 1.07–1.20, Table C2), consistent with prior findings on risk perception and innovation outcomes (Knight, 1921). Process innovation positively predicts product innovation—it increases the propensity to innovate between 5.1 and 5.3 times for startups (Table C1), and between 4.1 and 4.4 times for incumbents (Table C2). Exporting firms are more likely to innovate, with similar positive effects in startups (b = 1.98–2.09, $p < 0.01$) and in incumbents (b = 1.82–1.91, $p < 0.01$). Foreign ownership also increases innovation in startups (b = 1.12–1.17, $p < 0.01$) and incumbents (b = 1.15–1.19, $p < 0.01$). Industry competition fosters innovation in startups (b = 1.46–1.77, $p < 0.10$, Table C1) but discourages it in incumbents. Intra-industry local knowledge capacity shows no significant effect, while high inter-industry capacity may inhibit innovation—an unexpected finding, warranting further research.

Finally, collaboration breadth exhibits an inverted U-shaped relationship with innovation in both groups. While diversity increases absorptive capacity (Van Beers and Zand, 2014; Denicolai et al., 2016), excessive breadth may reduce focus and raise costs, confirming prior observations (Belitski et al., 2024).

4.1.2. *Robustness check*

The classic literature on knowledge spillover innovation, led by Audretsch (1995) and his collaborators in the 1980s–2000s (Acs and Audretsch, 1987, 1988; Acs et al., 2009), used the lens of small firms vs. large firms to explain the KSTE. While we control for firm size in our model, one may feel that the classic approach was ignored in this study.

We estimate Eq. (1) for both groups (spec. 11–12, Table C1 for small firms, Table C2 for medium/large firms), using product innovation propensity (spec. 11) and early market entry with new products (spec. 12) as outcomes.

To further explore interaction effects, we test how firm size and age interact with each type of knowledge spillover in Table D1 (Appendix D), providing additional estimates for innovation and market entry (spec. 1–4, Table D1).

Regarding active knowledge spillovers, we find that vertical spillovers significantly predict product innovation in both groups (small: b = 1.23, large: b = 1.21, $p < 0.01$, spec. 11, Tables C1–C2), with no evidence of diminishing returns or size differences, not supporting H1 and H2. The effect on new market entry is similarly significant and comparable across firm sizes (spec. 12, Tables C1-C2).

Horizontal spillovers (from competitors) also significantly enhance innovation propensity (small: b = 1.21, large: b = 1.17, $p < 0.01$), with diminishing returns, supporting H1 and H2. The effect of knowledge spillover from consultants is only significant and positive for innovation propensity in medium/large firms (b = 1.09, $p < 0.01$) (spec 11, Table C2), but not in startups.

University collaboration spillovers increase the propensity to innovate in both groups (small firms: b = 1.19; medium/large: b = 1.12; $p < 0.01$), again with diminishing returns, supporting H1 but not H2. University spillovers also enhance early market entry across all firm sizes. Fig. 2 illustrates predictive margins for active and passive knowledge spillovers across firm sizes, confirming broadly similar effects, and not supporting H2.

Regarding passive knowledge spillovers, we find that conference participation increases innovation for both small (b = 1.39, $p < 0.10$) and large firms (b = 1.07, $p < 0.10$), though the effect emerges at lower

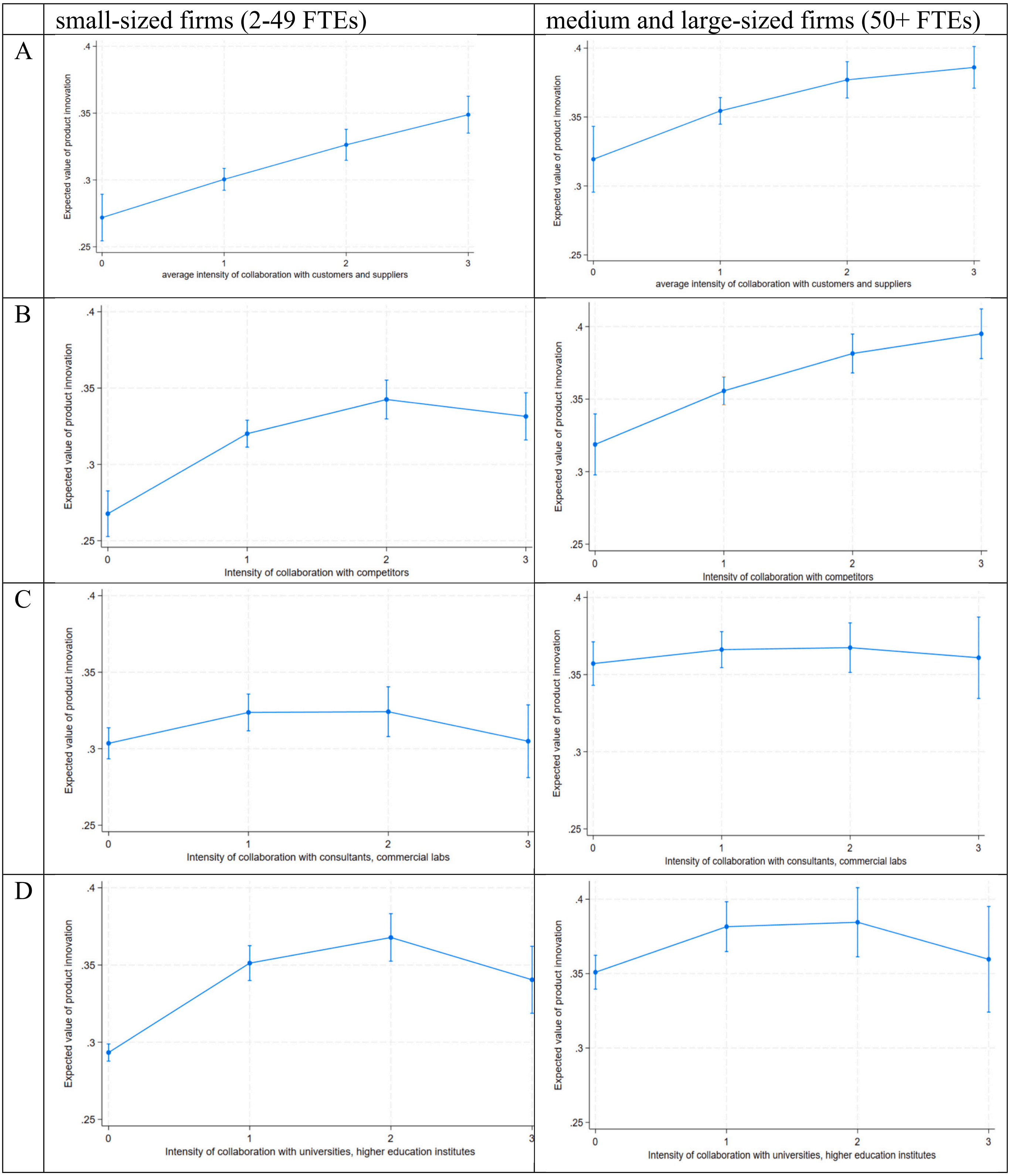

Fig. 2. Predictive margins for knowledge spillover of innovation with 95 % confidence intervals for small-sized firms (2–49 FTEs) (left column) and for medium and large-sized firms (50+ FTEs) (right column).
Source: UKIS—UK Innovation Survey; BSD—Business Structure Database; BERD—Business Expenditure on research and development.

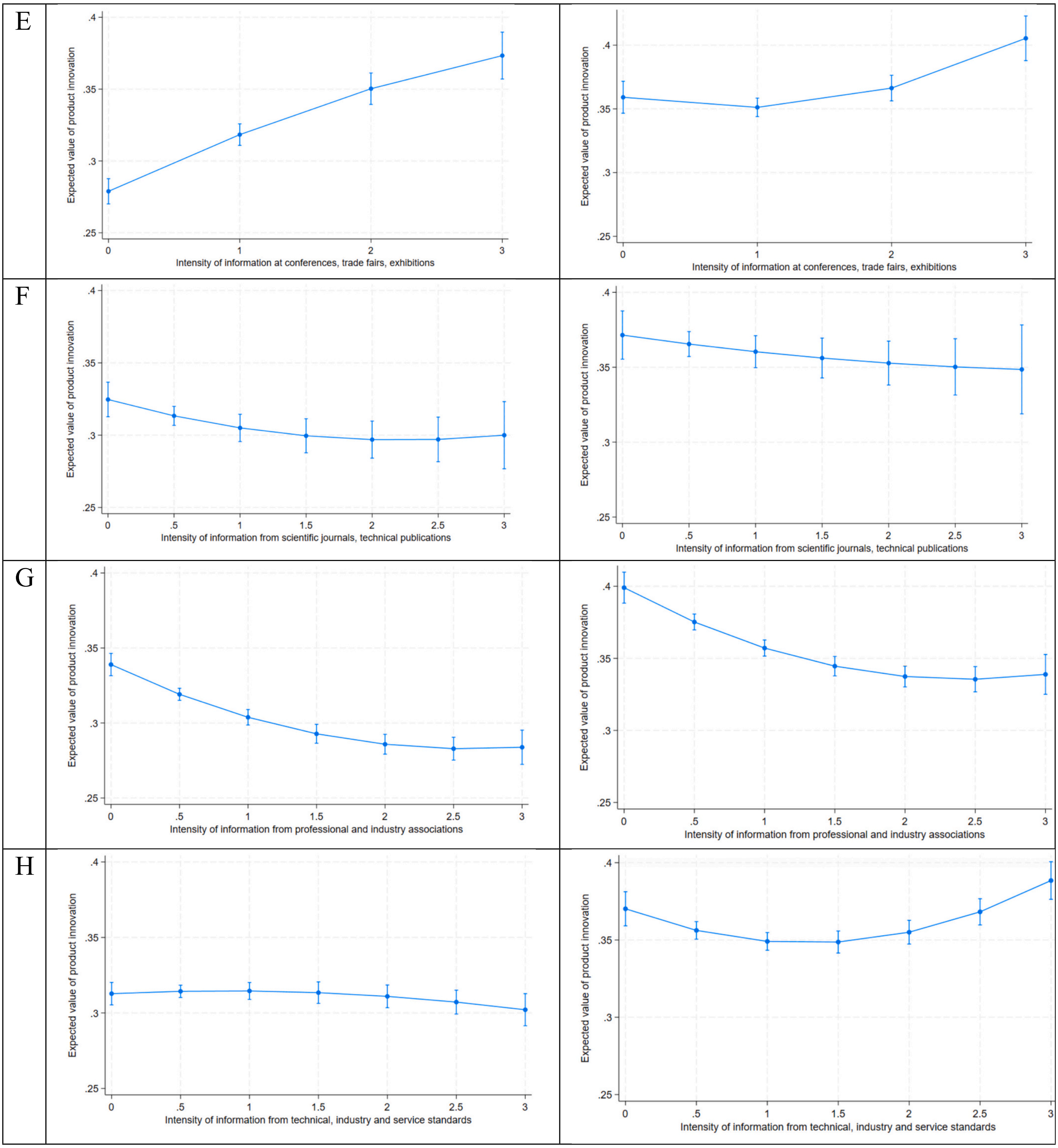

Fig. 2. (*continued*).

intensity levels for small firms and only at higher levels for medium/large firms, not supporting our hypotheses. Scientific journal engagement has no significant effect for either group, consistent with prior work suggesting such knowledge may be too academic and abstract, and must be turned into applied knowledge before industry can benefit (Audretsch, 2014). Participation in professional and trade associations demonstrates a U-shaped effect, which means low involvement reduces innovation propensity, but higher intensity of collaboration in associations increases innovation propensity. Technical standards show no significant impact on innovation in both groups of firms. Fig. 2E–H show no evidence of diminishing returns or size-based differences for passive spillovers, so neither hypothesis is supported.

As an additional robustness check, we interact firm age and size with each type of knowledge spillover (Table D1). We find that when interacting firm age with knowledge spillovers, a 1 % increase in age combined with one unit change in intensity of vertical spillover reduces innovation by 2.7 % and market entry by 6.1 %, indicating younger firms benefit more from vertical spillovers (spec. 1–2, Table D1). On the contrary, older firms benefit more from consultant spillovers, increasing market entry propensity by 7.2 %. Firm age does not affect the innovation impact of university collaboration but reduces its effect on market entry by 4.7 %, demonstrating that startups rely on university technology and collaboration when entering new markets.

When interacting firm size with knowledge spillovers, we find that larger employment combined with one unit increase in intensity of vertical spillover reduces innovation by 2.4 % and market entry by 1 %, demonstrating that smaller firms benefit more from vertical spillover (spec. 3–4, Table D1) (Von Hippel, 2009). Larger firms benefit less from conference participation (reduction of 4 % in innovation and 3.6 % in market entry), while they benefit more from scientific journal use (increase in propensity to innovate by 4.7 % and 2 % in market entry propensity). Industry association participation increases market entry by 2.5 % in larger firms, confirming our findings in Fig. 2.

5. Discussion

5.1. Theoretical contribution

This study offers three main contributions to the knowledge spillover theory of entrepreneurship and open innovation literature. Firstly, this paper extends open innovation theory (Chesbrough et al., 2006; West and Bogers, 2014) by differentiating the role of firm size and firm age in knowledge spillover innovation (Acs and Audretsch, 1988; Acs et al., 1994; Coad et al., 2018). While prior research has acknowledged that smaller firms can be highly effective in innovation (Acs and Audretsch, 1988; Audretsch et al., 2021)—particularly when adopting multiple practices simultaneously (Bogers, 2011)—it has also argued that resource constraints of smaller firms may limit their capacity to innovate (Acs et al., 2009; De Massis et al., 2018). Our empirical results refine this view by demonstrating that small firms can simultaneously leverage a diverse set of active knowledge spillovers—vertical, horizontal, and university spillovers, and informal (passive) spillovers—conferences, trade fairs and exhibitions, participation in industry and trade associations with innovation outcomes that are statistically comparable to those of larger firms. Notably, the magnitude of these effects on product innovation is not significantly different between smaller and larger firms. This finding challenges the prevailing assumption that only resource-rich, large firms with high absorptive capacity can effectively capitalize on open innovation (Belderbos et al., 2006; Lichtenthaler and Lichtenthaler, 2009). In addition, the assumption that smaller firms benefit more from knowledge spillovers than large firms (Audretsch, 1995; Audretsch and Feldman, 1996, 2004) does not hold for knowledge spillovers of innovation, as the main differences in their effects are more due to firm age rather than size.

Interestingly, while both small and large firms benefit from multiple types of knowledge spillovers, we observe stronger effects among startups specifically for active spillovers, despite the fact that diminishing marginal returns are found for both startups and incumbents. This adds a new layer to open innovation theory (Chesbrough, 2003) and KSTE (Acs et al., 2009): although small firms are generally more reliant on external sources, the innovation returns and leading market entry before competitors by utilizing knowledge spillovers are not necessarily amplified for them. Instead, medium and large firms, if they actively engage in open innovation practices, can have innovation benefits comparable to those of smaller firms. In contrast, incumbents show weaker returns to knowledge spillovers compared to startups, especially under low-intensity knowledge collaboration—likely due to organizational inertia, structural inefficiencies, and a need for greater resource mobilization to incorporate external insights into organizational routines.

These findings suggest that firm size alone does not rigidly constrain the capacity to benefit from knowledge spillovers. Rather, our analysis contributes to economics of innovation literature by highlighting the contingent nature of knowledge spillovers, depending in addition to firm size (i) on the degree of engagement with the external source of knowledge intensity; (ii) source of knowledge, such as university, conferences, suppliers, customers, competitors, etc.; and (iii) firm age, namely startups vs. incumbents. Agile small firms can extract value from knowledge collaboration more quickly than incumbents, having a steeper knowledge spillover of innovation slope. However, unlike incumbents, they are more constrained by scale and commitment of resources and time. We find that larger incumbent firms may require a higher intensity of collaboration and more persistent commitment to engagement.

Our second theoretical contribution is by introducing the heterogeneity of knowledge spillovers and the role of intensity and the model of knowledge collaboration. Our results further contribute to the open innovation and knowledge spillover innovation literature (Love et al., 2014; Lucking et al., 2018; Audretsch and Belitski, 2022) by emphasizing the importance of both the intensity of knowledge collaboration and mode of knowledge engagement shaping two innovation outcomes—new product innovation and new market entry before competitors. We distinguish between passive (informal) and active (interactive) knowledge spillovers and demonstrate the limits to knowledge collaboration within each type of collaboration partner and for different innovation outcomes, arguing for the presence of diminishing marginal returns in spillovers. This means that engaging with too many partners or combining overly heterogeneous and conflicting information across different partner types can increase operational and transaction costs, competitive tensions, and information crowding, leading to lower returns to knowledge spillovers and eventually lower propensity to innovate (Laursen and Salter, 2006, 2014; Saura et al., 2023).

This insight contributes to the refinement of open innovation by underscoring that open knowledge sources are not “a free lunch,” as earlier conceptualized in the open innovation literature (Bogers, 2011; West and Bogers, 2014) and the knowledge spillover of entrepreneurship literature, both of which assume a linear effect of knowledge spillovers. To benefit from knowledge spillovers, firms must invest in absorptive capacity through R&D, training, digital infrastructure, and human capital, and strategically select the type of knowledge engagement, intensity level, and the innovation outcome a firm wants to achieve.

Thirdly, we contribute to knowledge spillover literature by revisiting the foundations of the Knowledge spillover theory of innovation (Audretsch and Belitski, 2022). Our findings extend this literature and address the recent call by Audretsch et al. (2025b) to unpack the heterogeneity of external knowledge sources and show how their benefits vary systematically by firm age, firm size, source of knowledge, mode of engagement, and intensity of collaboration. Contrary to classical formulations of the knowledge spillover theory of entrepreneurship (Acs et al., 2009; Audretsch, 2009), we argue that firm age, not size is the more decisive factor in shaping the impact of knowledge spillovers on innovation. In doing so, we challenge prior research on KSTE, which relied on differences in firm size than firm age (Audretsch and Vivarelli, 1996; Audretsch and Keilbach, 2015; Petruzzelli et al., 2018).

This perspective challenges the assumptions of prior literature that often equates small-sized firms with superior absorptive flexibility (Ghio et al., 2015; Audretsch et al., 2025a) and instead our study advances a more nuanced view. Specifically, we demonstrate that the magnitude and direction of knowledge spillover effects are non-linear and have various effects depending on firm age and size, the type of external knowledge spillovers, and the model of engagement (passive or active). This nuanced view allows us to refine the boundaries of the knowledge spillover theory of entrepreneurship and innovation (Audretsch et al., 2025b), introducing empirical granularity of the effect of firm size and the magnitude of the diminishing marginal returns. Hence, we argue that the optimal configurations of external knowledge spillovers may exist and are subject to knowledge spillover type, firm size and age, and the specific innovation output—new market entry or new product commercialization—that is expected.

5.2. Managerial and policy implications

We derive implications for innovation managers and policy-makers based on four streams of literature in the knowledge spillover of entrepreneurship and innovation, and our findings.

The first stream of literature on intra- and inter-industry knowledge spillovers and agglomeration spillovers, originating from the foundational work of Marshall (1920) on localization economies and Jacobs (1970) on diversity-based innovation, posits that new knowledge created by universities and incumbent firms is often underutilized, allowing entrepreneurial firms to absorb and transform it into innovation outputs (Acs and Audretsch, 1988; Freel, 2000; Acs et al., 2009; Link, 2015). Our results align partially with this view.

In contrast to the extant literature (Audretsch and Feldman, 1996; Roper et al., 2017; Audretsch and Belitski, 2022, 2023), we find that measures of intra- and inter-industry regional knowledge capacity—such as internal R&D spending—are not significantly associated with product innovation or new market entry. This result implies that commonly used proxies may reflect local knowledge production rather than actual spillovers (Jaffe, 1986). When controlling for active and passive collaboration, the direct effect of regional knowledge capacity on a firm's innovation predicted by the literature dissipates, suggesting that knowledge spillovers emerge through interaction rather than localized intra- or inter-industry knowledge capacity or geographical proximity alone.

Innovation managers should not rely solely on regional co-location for spillover benefits. Instead, strategic co-location should aim at establishing direct active collaboration with universities, suppliers, customers, and competitors. Tacit knowledge flows from active partnerships more than geographical proximity, furthering the recent research of Feldman et al. (2023). Passive knowledge spillovers like conferences or associations only become effective through repeated, persistent, and high-intensity collaboration.

Policymakers should reevaluate their over-reliance on regional R&D investment by innovative firms. Policy could shift towards facilitating inter-industry collaboration rather than accumulating regional knowledge capability and R&D, and utilize hybrid innovation platforms more actively (e.g., hackathons, innovation fairs, mixed-industry clusters such as manufacturing and IT or biotech and creative sectors). Promoting collaborative R&D (Belderbos et al., 2006) and fostering cross-sector knowledge interactions will be more effective if enabling active knowledge spillovers, rather than developing traditional clusters or financing R&D (e.g., R&D breaks, tax holidays, etc.).

The second stream of literature focuses on horizontal and vertical knowledge spillovers. Our findings confirm that horizontal spillovers significantly increase the propensity for product innovation across both startups and incumbents, as well as across small and large firms. This supports the argument that coopetition facilitates knowledge transfer and innovation (Ritala and Hurmelinna-Laukkanen, 2013). However, we also find diminishing marginal returns to horizontal collaboration, suggesting the existence of an optimal level of intensity of collaboration with competitors, beyond which innovation benefits start to diminish.

Vertical spillovers from suppliers and customers demonstrate strong positive effects on the propensity to innovate and enter markets. Suppliers offer domain-specific insights, including technical innovations (Bernstein, 1988), and innovation with customers raises awareness of user needs (Von Hippel, 2009). Our analysis reveals that when startups benefit from vertical spillover, they face diminishing marginal returns, likely due to limited absorptive capacity or coordination challenges. In contrast, incumbents do not experience diminishing returns, implying stronger absorptive capacity (Cohen and Levinthal, 1990) and greater ability to leverage supply-chain innovation. Consultants, a form of active knowledge spillover, positively impact innovation in medium/large firms, but not in small firms. This contradicts assumptions that startups rely heavily on external mentorship (Audretsch et al., 2021). Instead, small firms may lack the financial or managerial capacity to integrate consultant insights, or the consultant's advice may be too generic to apply.

Managers must choose the intensity of knowledge collaboration carefully, subject to the source of knowledge, mode of engagement, and firm size and age. High intensity of collaboration with competitors can lead to knowledge leakage and unintended spillovers. Startups should engage selectively in active knowledge spillovers and reduce the intensity of collaboration if the saturation point is achieved. Larger firms can leverage their organizational slack to scale and formalize vertical spillovers. Consultants should be used by startups only when absorptive capabilities and skills are sufficient to engage in this model of collaboration.

Innovation policies should encourage vertical collaboration via such tools as innovation vouchers, the Catapult accelerator in the UK, where firms are given the opportunity to use equipment and grants to validate their knowledge, and collaborate with partners within the accelerator. For horizontal spillovers, policies could support "controlled" knowledge-sharing forums that prevent freeriding and promote the creation of new products, including imitations, which could be useful for startups and small firms that lack organizational slack, absorptive capacity, and internal resources. Training and support schemes for small firms should focus on developing internal capabilities to better absorb vertical knowledge, including support for identifying consultants and using external tools to facilitate consultant collaborations.

Our third literature stream focuses on the role of universities and public research institutions in the knowledge spillover of innovation. While prior literature emphasized the importance of these spillovers for small firms and startups (Siegel et al., 2003; Guerrero et al., 2016; Audretsch and Link, 2019), our results show that university spillovers significantly benefit firms across size and age groups. Contrary to Acs et al. (2009) and Audretsch and Keilbach (2007), the effect is not limited to small firms, but is ubiquitous. Innovation managers should be aware that both startups and incumbents experience diminishing marginal returns to university collaboration, suggesting that high-intensity collaborations may generate coordination and transaction costs, and firms should keep up with the uncertainty of product co-creation, validation, and commercialization (Bradley et al., 2013). Passive knowledge spillovers through participation in scientific journals have no effect on innovation propensity and market entry. This aligns with Cassiman and Veugelers (2002) and Fini et al. (2022), who argue that without active engagement or internal capabilities, scientific knowledge does not translate into new products.

Firms should shift from passive to active collaboration with universities, engaging directly with research teams and technology transfer offices (Bradley et al., 2013). Startups show greater dependence on university-originated knowledge, which is a substitute for the lack of internal R&D and capabilities (Klofsten et al., 2019; Audretsch et al., 2025b), while incumbents see it as complementary knowledge. Managers must balance collaboration intensity to avoid over-commitment and optimize the intensity of collaboration on knowledge.

Policymakers should support differentiated engagement models based on firm age and size. Creating "matching platforms" for universities and firms of different sizes and ages is money well spent, as it can facilitate more effective and active collaboration, which is needed for innovation, and we know all types of firms can benefit equally. Hence, policy support for university spillovers to industry should be ubiquitous, and not focus solely on smaller, younger firms.

The fourth stream of open innovation literature emphasizes that knowledge spillovers are accessible through open collaborations and external networks (Chesbrough et al., 2006; Bogers, 2011). Our findings confirm the innovation value of open knowledge flows but make managers aware that excessive breadth (multiple partner types) and depth of collaboration (high intensity) may lead to diminishing returns. As shown in Belitski et al. (2024) and Laursen and Salter (2006), collaboration intensity beyond a certain point reduces innovation propensity due to information overload, redundancy, and coordination costs.

Innovation managers should decide on optimal intensity and breadth of knowledge spillovers and the model of engagement by partner type. Not all knowledge is equally valuable, and too many partnerships can overwhelm a firm's capacity and resources. Combining passive and active spillovers, with clear goals and limits, can maximize innovation propensity and lead to new market entry. Innovation policies may include investment in a firm's absorptive capacity via training, internal R&D, digital skills, and talent development. It is important for the policy to differentiate between supporting active and passive knowledge spillovers, but the support should have clear guidelines on the intensity of engagement, type of knowledge, and type of firm. Policies may also emphasize what type of innovation outcome is sought and suggest specific collaboration partners across firm size and age. Incentives could be given across all types of firms for sustained participation in associations and networks, as we find that it is only high intensity of participation in associations, conferences, and exhibitions that increases innovation propensity. Those participating in exhibitions need to ensure the exchange of contact information between exhibits, organize follow-up events to exchange best practices and knowledge, and engage with visitors to understand their business needs and how strong their innovation is compared to other conference members and exhibitors. Organizers and policy-makers should promote the intensity of exchange of knowledge, including grants for association memberships, access to resources by both exhibitors and participants, and encourage attendees to engage with them. They should also co-organize conferences and exhibits for various stakeholders across regions and types of institutions on a specific topic, inviting the exchange of ideas at the individual level. It is important to stimulate high persistence and high intensity of interaction between exhibits and participants, and also within associations, avoid minimal attendance or random engagements, and allow each participant enough time to present their case, stall, exhibit, or prototype. It is important to focus on building trust between organizers and participants, and ensuring committed and persistent engagement with passive spillovers for both startups and incumbents.

6. Conclusions

This study extends the knowledge spillover of entrepreneurship and innovation (Audretsch, 1995; Audretsch and Feldman, 2004; Acs et al., 2009; Aghion and Jaravel, 2015; Audretsch et al., 2025b) by theorizing and empirically examining the heterogeneity of formal (active) and informal (passive) knowledge spillovers and their impact on firms' propensity to innovate and new market entry for firms of different size and age.

Our findings challenge the traditional assumption that small firms inherently extract more value from knowledge spillovers. Medium and large firms can benefit from knowledge collaboration for innovation as much as small firms, provided they strategically select knowledge partners and choose the intensity of collaboration. This shifts the emphasis from firm size alone to the strategic configuration of knowledge sourcing, expanding both the knowledge spillover theory of entrepreneurship and the open innovation literature. We reflect on a more nuanced and inclusive understanding of how firms can engage in knowledge collaboration to generate spillovers more effectively, regardless of their size and age.

6.1. Limitations and future research

While our study benefits from rich micro-level datasets on business registry and innovation, its anonymized structure limits contextual insights into the breadth of collaboration within each type of knowledge partner as well as the ability to match other micro-level data—for example, on finance or taxes—to see the confounding effects. In terms of sampling, the data are an unbalanced panel because each firm may appear in the data between one and six waves, as it is not a repeated but rotated randomized sample. Limiting the dataset to panel data only may improve the estimation efficiency if the sample is treated for panel election bias. Future research may use firm panel data to explore the switching effects in knowledge collaboration or (and) the persistence of knowledge collaboration within the same type of knowledge partner over time. In addition, a change in the depth of collaboration by estimating the effect of persisting at the same level of collaboration intensity over several time periods may shed more light on the temporal effects of knowledge spillovers and the role that persistence of intensity of knowledge collaboration can play over time. Experimenting with time-lagged knowledge spillover could extend our research.

From a methodological standpoint, our multi-model and multi-sample estimation across firm age and size demonstrates the heterogeneous effects of knowledge spillover of innovation with diminishing marginal returns that depend on the source of knowledge spillover, intensity of collaboration, and the final innovation outcome. A multi-level approach could be applied in future research when examining the effects of specific regional characteristics, such as the level of economic development, innovation ecosystem maturity and dynamics, and quality of institutions. Future research could also investigate the effect of specific industry characteristics beyond competition controls, such as market structures, shrinking and growing industries, labor mobility, and industry openness.

CRediT authorship contribution statement

David B. Audretsch: Writing – review & editing, Writing – original draft, Supervision, Investigation, Conceptualization. **Maksim Belitski:** Writing – original draft, Software, Resources, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

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

Appendix A

Table A1
Data description by industry, region, year of survey and firm size.

Industry	Obs.	%	Region	Obs.	%
1 – Mining and Quarrying	231	0.66	North East	2060	5.85
2 - Manufacturing basic	2029	5.76	North West	3195	9.07
3 - High-tech manufacturing	6275	17.81	Yorkshire and Humber	2936	8.34
4 – Utility	780	2.21	East Midlands	2809	7.97
5 – Construction	3464	9.83	West Midlands	3070	8.72

(*continued on next page*)

Table A1 (*continued*)

Industry	Obs.	%	Region	Obs.	%
6 - Wholesale, retail trade	5270	14.96	Eastern England	3134	8.90
7 - Transport, storage	2017	5.72	London	3650	10.36
8 - Hotels and restaurants	1983	5.62	South East	3827	10.87
9 – ICT	2329	6.61	South West	3011	8.55
10 - Financial intermediation	1220	3.46	Wales	2270	6.44
11 - Real estate and other business activities	4654	13.21	Scotland	2804	7.96
12 - Public admin, defense	3682	10.45	Northern Ireland	2457	6.98
13 – Education	531	1.50	Total	35,223	100.00
16 - Other community, social activity	758	2.15			
Total	35,223	100.00			

Survey year	Obs.	%	Firm size	Obs.	%
UKIS4 (2005)	6625	18.80	Micro and small (2–49 FTEs)	19,688	55.90
UKIS5 (2007)	7511	21.32	Medium (50–99 FTEs)	7383	20.96
UKIS6 (2009)	7578	21.51	Medium large (100–249 FTEs)	7771	22.06
UKIS7 (2011)	5713	16.21	Large (250 and more)	381	1.08
UKIS8 (2013)	3881	11.01	Total	35,223	100.00
UKIS9 (2015)	3915	11.12			
Total	35,223	100.00			

Source: Office for National Statistics. (2022). *UK Innovation Survey, 1994–2020: Secure Access*. [data collection]. *8th Edition.* UK Data Service. SN: 6699, DOI: doi: https://doi.org/10.5255/UKDA-SN-6699-8 (hereinafter UKIS- UK Innovation survey).
Office for National Statistics. (2021). *Business Structure Database, 1997–2021: Secure Access*. [data collection]. *14th Edition.* UK Data Service. SN: 6697, DOI: doi: https://doi.org/10.5255/UKDA-SN-6697-14 (hereinafter BSD- Business Structure Database).
Office for National Statistics. (2023). *Business Expenditure on Research and Development, 1995–2021: Secure Access*. [data collection]. *12th Edition.* UK Data Service. SN: 6690, DOI: doi:https://doi.org/10.5255/UKDA-SN-6690-12 (hereinafter BERD – Business Expenditure on research and development)

Appendix B. Sample description

Table B1
Description of variables.

Variable (source)	Definition
Dependent variables	
Product Innovation (UKIS)	Dependent variable: Binary variable equals one if a firm had turnover from goods and services that were new to the market during the past 3 years, zero otherwise.
New market entry (UKIS)	Dependent variable: Binary variable equals one if a firm introduced a new good or service to the market before competitors during the past 3 years, zero otherwise.
Explanatory variables	
Active spillover: Vertical collaboration (UKIS)	How important to this business's innovation activities was knowledge from suppliers (equipment, materials, services, software) (from 0 – not applicable to 3 – high) and customers (clients or end users) (from 0 – not applicable to 3 – high). The measure is a simple average of two ordinary variables, with the values varying between 0 and 3.
Active spillover: Horizontal collaboration (UKIS)	How important to this business's innovation activities was knowledge from competitors or other businesses in industry (from 0 – not applicable to 3 – high)
Active spillover: Consultant collaboration (UKIS)	How important to this business's innovation activities was knowledge from consultants, commercial labs, private R&D institutes (from 0 – not applicable to 3 – high)
Active spillover: University collaboration (UKIS)	How important to this business's innovation activities was knowledge from regional, national, and international universities or other higher education institutes (from 0 – not applicable to 3 – high).
Passive spillover: Conference and exhibitions (UKIS)	How important to this business's innovation activities was knowledge from conferences, trade fairs, exhibitions (0 – not applicable to 3 – high)
Passive spillover: Scientific journals (UKIS)	How important to this business's innovation activities was knowledge from scientific journals and trade/technical publications (0 – not applicable to 3 – high)
Passive spillover: Professional associations (UKIS)	How important to this business's innovation activities was knowledge from professional and industry associations (0 – not applicable to 3 – high)
Passive spillover: Technical standards (UKIS)	How important to this business's innovation activities was knowledge from technical, industry or service standards (0 – not applicable to 3 – high)
Firm characteristics for splitting the sample	
Start-ups (BSD)	Binary variable equals one if a firm is between zero and seven years since establishment (it had less than 50 full-time employees at the establishment which means a firm was not a part of an enterprise group), zero otherwise
Small-size firm (BSD)	Binary variable equals one if a firm is of small size, 2–49 FTEs, zero otherwise. All firms part of the enterprise group and having other business units >49 FTEs at the establishment period or in any year were considered medium or large firms.
Control variables	
Firm employment (BSD)	Number of full-time employees, in logarithms.
Firm age (BSD)	Age of a firm (years since the establishment), in logarithms.
R&D intensity (UKIS)	Expenditure on internal Research and Development (000 s) to total sales (000 s GBP).

(*continued on next page*)

Table B1 (*continued*)

Variable (source)	Definition
Digital intensity (UKIS)	Expenditure on acquisition of advanced machinery, equipment, hardware, and digital software for innovation (000 s) to total sales (000 s GBP).
Training intensity (UKIS)	Expenditure on training for innovative activities (000 s) to total sales (000 s GBP).
Human capital (UKIS)	The proportion of employees who hold a degree or higher qualification in science and engineering at BA/BSc, MA/PhD, PGCE levels.
Economic risks (UKIS)	How important were the following factors in constraining innovation activities (0–3): Excessive perceived economic risks from zero—not important to 3—very high.
Demand uncertainty (UKIS)	How important were the following factors in constraining innovation activities (0–3): Uncertain demand for innovative goods or services from zero—not important to 3—very high.
Process innovation (UKIS)	Binary variable equals one if a firm introduced any new or significantly improved processes for producing or supplying goods or services, zero otherwise. Process innovations are all new or significantly improved methods for the production or supply of goods or services, although new to the business, they do not need to be new to industry. This variable includes all process innovations, regardless of their origin.
Exporter (UKIS)	Binary variable equals one if a firm sells its products and services in foreign markets, zero otherwise.
Foreign (BSD)	Binary variable equals one if a firm has headquarters abroad, zero otherwise.
Herfindahl index (BSD)	Herfindahl index (sales) based on the sum of sales shares in a three-digit industry (SIC 2007) and the number of firms selling in the industry (0—perfect competition, 1—monopoly).
Intra-industry local knowledge (BERD)	Intra-industry local knowledge production capacity calculated using total internal R&D expenditure in GBP 000 by all firms by the 2-digit SIC 2007 within 128 UK city regions (by 2-letter postcode) in the same industry and normalized by country's total R&D expenditure for each 2-digit SIC industry and (by 2-letter postcode) within the same industry. The R&D expenditure of a firm itself is excluded from the calculation of intra-industry local knowledge production capacity. The indicator is standardized around a mean of zero.
Inter-industry local knowledge (BERD)	Intra-industry local knowledge production capacity calculated using calculated using total R&D expenditure in GPB 000 by all firms by the 2-digit SIC 2007 within 128 UK city regions (by 2-letter postcode) outside a firm's own industry and normalized by country's total R&D expenditure for each 2-digit SIC industry and (by 2-letter postcode) for industries outside firm's own industry. The indicator is standardized around a mean of zero.
Collaboration breadth (UKIS)	Number of types of external collaboration partners simultaneously engaged in collaboration with the firm from 0—firm does not collaborate on innovation with external partners to a maximum of eight partner types such as: suppliers and clients (1); competitors or other businesses in industry (2); consultants, commercial labs, and private R&D institutes (3); universities or other higher education institutes (4); conferences, trade fairs, and exhibitions (5); scientific journals and trade/technical publications (6); professional and industry associations (7), technical, industry, or service standards (8).

Source: UKIS—UK Innovation Survey; BSD—Business Structure Database; BERD—Business Expenditure on research and development.

Table B2
Summary statistics for variables used in this study for a full sample (35,223 obs.) as well as for startups vs. incumbent firms and small vs. medium and large firms.

Sample	Full sample = 35,223 obs.				Startups (0–7 years old) =6559 obs.		Incumbents (8 and more years old) = 28,664obs		Small firms (2–49 FTEs) = 19,688 obs.		Medium and large firms (50+ FTEs) = 15,535 obs.	
Variables and source	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Product Innovation (UKIS)	0.33	0.47	0.00	1.00	0.36	0.48	0.33	0.47	0.31	0.46	0.36	0.48
New market entry (UKIS)	0.17	0.38	0.00	1.00	0.18	0.39	0.17	0.37	0.16	0.37	0.19	0.39
Vertical collaboration (UKIS)	1.2	1.15	0.00	3.00	1.18	1.15	1.20	1.15	1.13	1.15	1.28	1.15
Horizontal collaboration (UKIS)	1.04	1.09	0.00	3.00	1.07	1.10	1.04	1.09	0.95	1.07	1.15	1.10
Consultant collaboration (UKIS)	0.58	0.85	0.00	3.00	0.59	0.88	0.57	0.85	0.50	0.82	0.67	0.89
University collaboration (UKIS)	0.38	0.72	0.00	3.00	0.38	0.74	0.38	0.72	0.34	0.70	0.44	0.75
Conference and exhibitions (UKIS)	0.76	0.95	0.00	3.00	0.76	0.96	0.77	0.95	0.69	0.94	0.85	0.96
Scientific journals (UKIS)	0.68	0.88	0.00	3.00	0.67	0.90	0.68	0.88	0.63	0.87	0.75	0.89
Professional associations (UKIS)	0.79	0.96	0.00	3.00	0.79	0.97	0.79	0.95	0.71	0.94	0.89	0.97
Technical standards (UKIS)	0.84	1.02	0.00	3.00	0.82	1.03	0.84	1.02	0.74	0.99	0.97	1.05
Firm employment (BSD)	3.91	1.72	0.00	12.34	2.84	1.35	4.15	1.70	2.75	0.70	5.37	1.49
Firm age (BSD)	2.65	0.81	0.00	3.99	1.28	0.61	2.97	0.44	2.47	0.88	2.88	0.64
R&D intensity (UKIS)	0.01	0.05	0.00	0.67	0.02	0.08	0.01	0.04	0.01	0.06	0.01	0.04
Digital intensity (UKIS)	0.02	0.08	0.00	0.70	0.04	0.13	0.02	0.07	0.03	0.10	0.01	0.06
Training intensity (UKIS)	0.09	0.19	0.00	0.61	0.13	0.23	0.08	0.17	0.11	0.21	0.07	0.16
Human capital (UKIS)	6.63	16.51	0.00	100	9.06	20.46	6.08	15.41	7.01	17.87	6.16	14.59
Economic risks (UKIS)	0.99	1.11	0.00	3.00	0.96	1.11	1.01	1.11	0.96	1.12	1.05	1.09
Demand uncertainty (UKIS)	0.84	0.99	0.00	3.00	0.81	0.98	0.85	0.99	0.79	0.99	0.91	0.99
Process innovation (UKIS)	0.21	0.41	0.00	1.00	0.22	0.42	0.21	0.41	0.19	0.39	0.24	0.43
Exporter (UKIS)	0.34	0.47	0.00	1.00	0.27	0.44	0.36	0.48	0.29	0.45	0.42	0.49
Foreign (BSD)	0.42	0.49	0.00	1.00	0.20	0.40	0.47	0.50	0.18	0.39	0.72	0.45
Herfindahl index (BSD)	0.08	0.1	0.01	0.86	0.09	0.11	0.08	0.09	0.08	0.09	0.08	0.10
Intra-industry local knowledge (BERD)	0.11	0.17	0.00	1.00	0.11	0.18	0.11	0.17	0.10	0.16	0.12	0.18
Inter-industry local knowledge (BERD)	0.08	0.09	0.00	0.49	0.09	0.09	0.08	0.09	0.08	0.09	0.09	0.09
Collaboration breadth (UKIS)	3.62	3.26	0.00	8.00	3.57	3.23	3.64	3.27	3.3	3.18	4.04	3.32

Source: UKIS—UK Innovation Survey; BSD—Business Structure Database; BERD—Business Expenditure on research and development.

Table B3
Correlation matrix for all firms in a sample (35,223 obs.)

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1.Product Innovation	1.00																							
2.New market entry	0.64	1.00																						
3.Vertical collaboration	0.42	0.30	1.00																					
4.Horizontal collaboration	0.41	0.29	0.68	1.00																				
5.Consultant collaboration	0.35	0.29	0.54	0.56	1.00																			
6.University collaboration	0.31	0.29	0.42	0.49	0.60	1.00																		
7.Conference and exhibitions	0.37	0.31	0.53	0.54	0.50	0.50	1.00																	
8.Scientific journals	0.33	0.27	0.57	0.65	0.54	0.68	0.60	1.00																
9.Professional associations	0.33	0.29	0.56	0.63	0.50	0.64	0.68	0.68	1.00															
10.Technical standards	0.31	0.27	0.62	0.60	0.54	0.71	0.60	0.68	0.76	1.00														
11.Firm employment	0.05	0.04	0.06	0.11	0.03	0.10	0.07	0.07	0.07	0.09	1.00													
12.Firm age	−0.03	−0.05	−0.03	−0.12	−0.04	−0.11	−0.07	−0.07	−0.11	−0.11	0.34	1.00												
13. R&D intensity	0.18	0.20	0.10	0.22	0.12	0.12	0.12	0.14	0.11	0.14	−0.06	−0.10	1.00											
14.Digital intensity	0.12	0.10	0.18	0.19	0.12	0.12	0.13	0.11	0.12	0.13	−0.12	−0.12	0.23	1.00										
15.Training intensity	0.33	0.30	0.30	0.41	0.23	0.29	0.26	0.23	0.25	0.29	−0.11	−0.12	0.16	0.27	1.00									
16.Human capital	0.21	0.22	0.20	0.27	0.20	0.23	0.20	0.23	0.19	0.23	−0.05	−0.09	0.41	0.12	0.19	1.00								
17.Economic risks	0.23	0.25	0.23	0.34	0.26	0.34	0.34	0.35	0.23	0.29	−0.06	−0.11	0.09	0.09	0.18	0.14	1.00							
18.Demand uncertainty	0.29	0.30	0.32	0.37	0.34	0.32	0.35	0.35	0.35	0.35	−0.03	0.01	0.11	0.07	0.16	0.15	0.60	1.00						
19.Process innovation	0.45	0.35	0.39	0.41	0.33	0.28	0.29	0.32	0.29	0.32	0.11	0.12	0.12	0.16	0.24	0.15	0.23	0.21	1.00					
20.Exporter	0.37	0.28	0.30	0.37	0.27	0.26	0.27	0.27	0.29	0.27	0.09	0.05	0.17	0.05	0.07	0.25	0.21	0.23	0.21	1.00				
21.Foreign	0.06	0.06	0.09	0.10	0.09	0.09	0.11	0.10	0.09	0.11	0.53	0.23	0.01	−0.05	−0.06	0.02	0.04	0.05	0.06	0.17	1.00			
22.Herfindahl index	0.03	0.03	−0.01	0.03	0.03	0.05	0.09	0.03	0.05	0.09	−0.01	0.04	0.04	0.03	0.05	0.09	0.01	−0.01	0.04	−0.01	0.04	1.00		
23.Intra-industry local knowledge	0.01	0.01	0.00	0.01	0.00	0.06	0.01	0.01	0.04	0.04	−0.01	0.00	0.04	−0.01	−0.01	0.04	−0.01	−0.01	0.01	0.04	0.06	0.04	1.00	
24.Inter-industry local knowledge	0.00	0.00	−0.01	0.01	0.00	0.02	−0.03	0.00	0.00	−0.03	0.00	−0.01	0.01	−0.01	−0.01	0.01	−0.01	−0.01	−0.01	−0.01	0.02	0.02	0.10	1.00
25.Collaboration breadth	0.46	0.35	0.67	0.67	0.69	0.69	0.69	0.69	0.70	0.68	0.11	0.02	0.17	0.15	0.32	0.26	0.43	0.42	0.38	0.34	0.12	0.01	0.01	0.01

Source: UKIS—UK Innovation Survey; BSD—Business Structure Database; BERD—Business Expenditure on research and development.

Appendix C. Regression results

Table C1
Logistic regression results for startups (0–7 years old firms) and small firms (2–49 employees). Dependent variables: Product (service) innovation and new market entry. Results reported in odd-ratios.

Firm type	Startups (0–7 years since establishment)										Small-sized firms (2–49 FTEs)	
Dependent variable	Product (service) innovation									New market entry	Product (service) innovation	New market entry
Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Vertical collaboration	1.679***								1.714***	1.404*	1.263**	1.215*
	(0.246)								(0.286)	(0.263)	(0.127)	(0.140)
Vertical collaboration squared	0.929*								0.893**	0.941	0.985	0.978
	(0.038)								(0.041)	(0.048)	(0.027)	(0.031)
Horizontal collaboration		1.447**							1.541**	1.312*	1.669***	1.572***
		(0.198)							(0.251)	(0.236)	(0.161)	(0.171)
Horizontal collaboration squared		0.940							0.915*	0.917*	0.888***	0.875***
		(0.037)							(0.043)	(0.046)	(0.024)	(0.027)

(*continued on next page*)

Table C1 (*continued*)

Firm type	Startups (0–7 years since establishment)										Small-sized firms (2–49 FTEs)	
Dependent variable	Product (service) innovation									New market entry	Product (service) innovation	New market entry
Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Consultant collaboration			1.091						1.139	1.142	1.256**	1.113
			(0.141)						(0.195)	(0.203)	(0.129)	(0.121)
Consultant collaboration squared			1.014						0.978	0.957	0.927**	0.981
			(0.045)						(0.055)	(0.054)	(0.031)	(0.03)
University collaboration				1.478**					1.647**	1.562**	1.784***	1.549***
				(0.231)					(0.322)	(0.305)	(0.210)	(0.18)
University collaboration squared				0.921					0.864**	0.945	0.856***	0.929*
				(0.051)					(0.057)	(0.061)	(0.034)	(0.037)
Conference and exhibitions					0.879				1.132	1.294	1.390***	1.395***
					(0.123)				(0.184)	(0.222)	(0.133)	(0.145)
Conference and exhibitions squared					1.097**				1.011**	1.000	0.966	0.976
					(0.051)				(0.057)	(0.252)	(0.029)	(0.031)
Scientific journals						0.799			1.156	1.100	0.819* (0.083)	0.836*
						(0.114)			(0.198)	(0.198)		(0.092)
Scientific journals squared						1.070			0.952	0.956	1.045	1.049
						(0.052)			(0.054)	(0.055)	(0.035)	(0.037)
Professional associations							0.452***		0.695**	0.882	0.709***	0.754**
							(0.067)		(0.121)	(0.162)	(0.072)	(0.083)
Professional associations squared							1.242***		1.087**	0.988	1.067**	1.030
							(0.058)		(0.061)	(0.057)	(0.034)	(0.031)
Technical standards								0.598***	0.915	0.854	1.035	0.989
								(0.085)	(0.154)	(0.152)	(0.103)	(0.107)
Technical standards squared								1.157***	1.034	1.035	0.979	0.985
								(0.051)	(0.053)	(0.055)	(0.031)	(0.032)
Firm employment	0.978	0.979	0.977	0.980	0.947**	0.941**	0.944**	0.941**	0.947**	0.933**	0.967	0.945
	(0.026)	(0.025)	(0.025)	(0.025)	(0.026)	(0.025)	(0.026)	(0.025)	(0.026)	(0.029)	(0.030)	(0.034)
Firm age	0.972	0.984	0.984	0.982	0.996	1.003	0.994	1.002	0.995	1.026	0.897***	0.941**
	(0.053)	(0.053)	(0.053)	(0.053)	(0.058)	(0.057)	(0.056)	(0.057)	(0.057)	(0.067)	(0.022)	(0.027)
R&D intensity	5.080***	4.351***	4.141***	4.089***	4.340***	4.133***	3.843**	3.967**	4.262**	6.546***	7.661***	14.802***
	(2.634)	(2.252)	(2.149)	(2.133)	(2.478)	(2.229)	(2.080)	(2.141)	(2.332)	(3.210)	(3.195)	(5.474)
Digital intensity	1.088	1.257	1.268	1.319	0.839	0.784	0.798	0.783	0.734	0.821	0.765	0.664**
	(0.267)	(0.308)	(0.311)	(0.323)	(0.228)	(0.204)	(0.208)	(0.204)	(0.193)	(0.212)	(0.153)	(0.137)
Training intensity	4.434***	4.622***	4.497***	4.576***	3.270***	3.219***	3.298***	3.241***	3.324***	2.010***	3.665***	2.515***
	(0.624)	(0.649)	(0.631)	(0.641)	(0.497)	(0.479)	(0.493)	(0.483)	(0.501)	(0.319)	(0.353)	(0.258)
Human capital	1.001	1.001	1.001	1.001	1.000	1.001	1.001	0.999	1.001	1.005***	1.003**	1.005***
	(0.317)	(0.317)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Economic risks	1.164***	1.165***	1.173***	1.171***	1.135***	1.147***	1.147***	1.143***	1.128***	1.170***	1.082***	1.088***
	(0.040)	(0.042)	(0.040)	(0.040)	(0.042)	(0.042)	(0.042)	(0.042)	(0.041)	(0.048)	(0.023)	(0.026)
Demand uncertainty	1.177***	1.179***	1.180***	1.183***	1.188***	1.193***	1.182***	1.194***	1.176***	1.208***	1.184***	1.191***
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.048)	(0.047)	(0.048)	(0.047)	(0.054)	(0.028)	(0.027)
Process innovation	5.260***	5.265***	5.268***	5.270***	5.273***	5.295***	5.220***	5.276***	5.149***	3.012***	4.346***	2.522***
	(0.448)	(0.450)	(0.451)	(0.452)	(0.453)	(0.436)	(0.429)	(0.433)	(0.428)	(0.246)	(0.214)	(0.125)
Exporter	2.091***	2.060***	2.071***	2.051***	2.015***	2.067***	2.034***	2.049***	1.989***	2.009***	2.049***	2.253***
	(0.153)	(0.150)	(0.150)	(0.150)	(0.159)	(0.158)	(0.156)	(0.157)	(0.155)	(0.167)	(0.119)	(0.111)
Foreign	1.171**	1.163*	1.163*	1.165*	1.143*	1.142	1.141	1.129	1.145	1.107**	1.136**	1.106**
	(0.081)	(0.102)	(0.102)	(0.102)	(0.106)	(0.106)	(0.105)	(0.104)	(0.106)	(0.105)	(0.060)	(0.067)
Herfindahl index	1.776*	1.773*	1.773*	1.717*	1.716*	1.481*	1.496	1.464*	1.532*	1.741**	0.993	0.840**
	(0.540)	(0.537)	(0.519)	(0.518)	(0.519)	(0.469)	(0.480)	(0.468)	(0.468)	(0.614)	(0.126)	(0.124)
Intra-industry local knowledge production capacity	1.062	1.081	1.079	1.086	1.060	1.024	1.026	1.013	1.013	0.590**	0.991	0.957
	(0.210)	(0.213)	(0.213)	(0.213)	(0.227)	(0.214)	(0.472)	(0.472)	(0.213)	(0.213)	(0.131)	(0.143)
Inter-industry local knowledge production capacity	0.527***	0.589**	0.573	0.574**	0.433	0.472	0.505	0.491	0.497	0.763	0.661	0.783
	(0.133)	(0.229)	(0.286)	(0.286)	(0.232)	(0.249)	(0.268)	(0.259)	(0.265)	(0.449)	(0.214)	(0.288)
Collaboration breadth	1.964***	2.121***	2.402***	2.517***	2.160***	2.211***	2.417***	2.317***	1.754***	1.739***	1.773***	1.678***
	(0.155)	(0.174)	(0.186)	(0.203)	(0.165)	(0.106)	(0.123)	(0.136)	(0.317)	(0.186)	(0.188)	(0.114)
Collaboration breadth squared	0.943***	0.937***	0.926***	0.919***	0.933***	0.935***	0.932***	0.933***	0.941***	0.941***	0.941***	0.951***
	(0.057)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.008)	(0.004)	(0.005)
Obs.	6559	6559	6559	6559	6559	6559	6559	6559	6559	6559	19,688	19,688
LR (chi2)	2215.5	2490.73	2479.23	2483.33	2772.22	2927.24	2955.74	2937.22	2998.42	1780.23	8406.68	4730.63
pseudo R2	0.29	0.29	0.29	0.29	0.33	0.34	0.34	0.34	0.35	0.28	0.36	0.27
log-likelihood	−3030.2	−3032.72	−3038.38	−3036.42	−2693.12	−2813.15	−2800.38	−2809.76	−2779.99	−2239.34	−8012.35	−6247.39

Note: reference category for legal status is Company (limited liability company), industry (mining), region (Northeast of England); year (2022–2004). Robust standard errors are in parenthesis. The coefficients of the logistic regressions are the marginal effect of the independent variable on the propensity to innovate new products and services, ceteris paribus. For dummy variables, it is the effect of a discrete change from 0 to 1. Number of startups =5878. Number of small firms = 16,323 firms. Source: UKIS—UK Innovation Survey; BSD—Business Structure Database; BERD—Business Expenditure on research and development.

Table C2
Logistic regression results for incumbents (8 years old and above firms). Dependent variables: Product (service) innovation and new market entry. Results reported in odd-ratios.

Firm type	Incumbent firms (8+ years since establishment)										Medium and large-sized firms (50+ FTEs and more)	
Dependent variable	Product (service) innovation									New market entry	Product (service) innovation	New market entry
Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Vertical collaboration	1.336**								1.204**	1.337***	1.314**	1.533***
	(0.102)								(0.099)	(0.130)	(0.145)	(0.201)
Vertical collaboration squared	0.972								0.990	0.947**	0.957	0.911***
	(0.020)								(0.022)	(0.024)	(0.028)	(0.031)
Horizontal collaboration		1.551***							1.469***	1.334***	1.324**	1.123
		(0.109)							(0.114)	(0.119)	(0.137)	(0.133)
Horizontal collaboration squared		0.926***							0.928***	0.926***	0.961	0.975
		(0.019)							(0.020)	(0.023)	(0.027)	(0.031)
Consultant collaboration			1.188*						1.151*	1.036	1.089	1.028
			(0.078)						(0.092)	(0.089)	(0.112)	(0.114)
Consultant collaboration squared			0.959						0.951*	1.006	0.974	0.997
			(0.022)						(0.025)	(0.027)	(0.032)	(0.035)
University collaboration				1.598***					1.513***	1.401***	1.336**	1.346**
				(0.123)					(0.137)	(0.132)	(0.154)	(0.163)
University collaboration squared				0.882***					0.889***	0.951	0.913**	0.965
				(0.024)					(0.027)	(0.029)	(0.035)	(0.038)
Conference and exhibitions					1.015				1.135*	1.216**	0.878	1.050
					(0.066)				(0.088)	(0.104)	(0.090)	(0.120)
Conference and exhibitions squared					1.048**				1.016	1.001	1.079*	1.030
					(0.022)				(0.042)	(0.026)	(0.039)	(0.039)
Scientific journals						0.595***			0.797***	0.838*	0.917	0.959
						(0.041)			(0.065)	(0.075)	(0.099)	(0.114)
Scientific journals squared						1.162***			1.052*	1.042	1.011	0.990
						(0.027)			(0.029)	(0.030)	(0.037)	(0.038)
Professional associations							0.481***		0.689***	0.643***	0.696***	0.620***
							(0.034)		(0.056)	(0.058)	(0.076)	(0.075)
Professional associations squared							1.207***		1.075***	1.085***	1.077**	1.102***
							(0.026)		(0.028)	(0.030)	(0.037)	(0.041)
Technical standards								0.631***	0.895	0.925	0.792**	0.884
								(0.043)	(0.071)	(0.082)	(0.084)	(0.105)
Technical standards squared								1.138***	1.038	1.016	1.095***	1.042
								(0.023)	(0.022)	(0.026)	(0.034)	(0.033)
Firm employment	1.014	1.013	1.014	1.016	1.017	1.010	1.019*	1.017	1.016	1.022*	1.017	1.053**
	(0.012)	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.013)	(0.015)	(0.018)
Firm age	0.819***	0.831***	0.823***	0.820***	0.817***	0.824***	0.819***	0.821***	0.827***	0.861***	0.890***	0.913**
	(0.031)	(0.031)	(0.031)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.031)	(0.037)	(0.030)	(0.036)
R&D intensity	41.202**(19.906)	35.199**	36.137***	34.793***	34.493***	36.369***	30.623**	34.407**	30.776**	29.261**	29.306***	18.440***
		(16.835)	(17.345)	(16.684)	(16.529)	(17.473)	(14.619)	(16.429)	(14.774)	(11.504)	(18.958)	(9.748)
Digital intensity	0.670*	0.751*	0.753	0.770	0.752	0.758	0.733	0.754	0.672*	0.564**	0.436***	0.552*
	(0.149)	(0.167)	(0.167)	(0.170)	(0.167)	(0.168)	(0.163)	(0.167)	(0.150)	(0.136)	(0.137)	(0.186)
Training intensity	2.749***	2.837***	2.778***	2.777***	2.775***	2.759***	2.848***	2.829***	2.880***	2.345***	2.219***	1.985***
	(0.245)	(0.253)	(0.248)	(0.247)	(0.248)	(0.246)	(0.258)	(0.252)	(0.259)	(0.225)	(0.285)	(0.271)
Human capital	1.004***	1.005***	1.004***	1.004***	1.005***	1.004***	1.004***	1.004***	1.005***	1.006***	1.004***	1.006***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Economic risks	1.084***	1.083***	1.094***	1.095***	1.090***	1.092***	1.092***	1.092***	1.074***	1.089***	1.089***	1.122***
	(0.019)	(0.018)	(0.019)	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)	(0.022)	(0.025)	(0.030)
Demand uncertainty	1.200***	1.194***	1.201***	1.200***	1.197***	1.199***	1.191***	1.202***	1.191***	1.172***	1.189***	1.157***
	(0.022)	(0.022)	(0.024)	(0.022)	(0.023)	(0.022)	(0.022)	(0.022)	(0.022)	(0.025)	(0.030)	(0.033)
Process innovation	4.199***	4.421***	4.321***	4.392***	4.446***	4.373***	4.343***	4.386***	4.184***	2.692***	4.298***	2.931***
	(0.159)	(0.158)	(0.165)	(0.165)	(0.165)	(0.163)	(0.162)	(0.163)	(0.159)	(0.105)	(0.209)	(0.147)
Exporter	1.912***	1.916***	1.903***	1.887***	1.864***	1.906***	1.849***	1.896***	1.821***	2.178***	1.672***	2.047***
	(0.065)	(0.065)	(0.064)	(0.064)	(0.063)	(0.064)	(0.062)	(0.064)	(0.062)	(0.087)	(0.075)	(0.084)
Foreign	1.193***	1.192***	1.185***	1.179***	1.183***	1.187***	1.180***	1.190***	1.185***	1.150***	1.257***	1.346***
	(0.047)	(0.046)	(0.047)	(0.047)	(0.047)	(0.046)	(0.046)	(0.046)	(0.047)	(0.053)	(0.060)	(0.090)
Herfindahl index	0.879	0.838	0.878	1.847	0.878	0.847***	0.899***	0.837***	0.924**	0.677***	1.176*	0.985
	(0.128)	(0.147)	(0.147)	(0.374)	(0.139)	(0.077)	(0.073)	(0.072)	(0.162)	(0.140)	(0.249)	(0.146)
Intra-industry local	0.977	0.984	0.981	0.988	0.984	0.977	0.996	0.986	0.988	0.935	1.014	0.775*
	(0.099)	(0.100)	(0.100)	(0.099)	(0.099)	(0.098)	(0.092)	(0.091)	(0.100)	(0.110)	(0.131)	(0.151)

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Table C2 (*continued*)

Firm type	Incumbent firms (8+ years since establishment)										Medium and large-sized firms (50+ FTEs and more)	
Dependent variable	Product (service) innovation									New market entry	Product (service) innovation	New market entry
Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
knowledge production capacity												
Inter-industry local knowledge production capacity	0.579** (0.146)	0.571** (0.144)	0.578** (0.146)	0.587** (0.148)	0.585** (0.147)	0.565** (0.143)	0.580** (0.147)	0.569** (0.143)	0.560** (0.143)	0.531** (0.155)	0.436*** (0.142)	0.445** (0.167)
Collaboration breadth	1.723*** (0.052)	1.715*** (0.044)	1.963*** (0.044)	2.070*** (0.045)	1.929*** (0.045)	2.026*** (0.046)	2.162*** (0.052)	2.076*** (0.050)	1.773*** (0.088)	1.648*** (0.096)	1.760*** (0.109)	1.680*** (0.122)
Collaboration breadth squared	0.956*** (0.003)	0.956*** (0.003)	0.945*** (0.003)	0.936*** (0.003)	0.946*** (0.002)	0.949*** (0.002)	0.945*** (0.002)	0.945*** (0.002)	0.950*** (0.003)	0.961*** (0.004)	0.954*** (0.004)	0.962*** (0.006)
Obs.	28,664	28,664	28,664	28,664	28,664	28,664	28,664	28,664	28,664	28,664	15,535	15,535
LR (chi2)	11,198.9	11,206.03	11,224.03	11,257.33	11,167.11	11,172.31	11,235.11	11,260.22	11,462.33	6794.23	6027.98	3836.18
pseudo R2	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.32	0.27	0.29	0.26
log-likelihood	−12,547.1	−12,543.5	−12,543.5	−12,566.2	−12,563.1	−12,560.5	−12,528.9	−12,566.4	−12,415.1	−9554.17	−7156.72	−5533.3

Note: reference category for legal status is Company (limited liability company), industry (mining), region (Northeast of England); year (2022–2004). Robust standard errors are in parenthesis. The coefficients of the logistic regressions are the marginal effect of the independent variable on the propensity to innovate new products and services, ceteris paribus. For dummy variables, it is the effect of a discrete change from 0 to 1. Number of incumbents =21,807 firms. Number of medium/large firms = 11,362 firms.

Source: UKIS—UK Innovation Survey; BSD—Business Structure Database; BERD—Business Expenditure on research and development.

Appendix D

Table D1

Logistic regression and interaction effects of firm age and size. Dependent variables: Product (service) innovation, and new-to-market entry.

Variables	Product (service) innovation	New market entry	Variables	Product (service) innovation	New market entry
Specification	(1)	(2)	Specification	(3)	(4)
Vertical collaboration	1.262*** (0.074)	1.314*** (0.088)	Vertical collaboration	1.295*** (0.057)	1.159*** (0.059)
Vertical collaboration x Firm age	0.972* (0.020)	0.938** (0.023)	Vertical collaboration x Firm employment	0.975** (0.009)	0.990* (0.015)
Horizontal collaboration	1.166** (0.078)	1.001 (0.068)	Horizontal collaboration	1.127*** (0.051)	0.983 (0.051)
Horizontal collaboration x Firm age	1.002 (0.022)	1.012 (0.0255)	Horizontal collaboration x Firm employment	1.009 (0.010)	1.011 (0.012)
Consultant collaboration	0.934 (0.066)	0.871 (0.0663)	Consultant collaboration	0.976 (0.051)	0.996 (0.056)
Consultant collaboration x Firm age	1.035 (0.026)	1.072** (0.029)	Consultant collaboration x Firm employment	1.012 (0.011)	1.012 (0.02)
University collaboration	1.114 (0.090)	1.439*** (0.117)	University collaboration	1.145** (0.068)	1.247*** (0.075)
University collaboration x Firm age	1.008 (0.029)	0.952* (0.027)	University collaboration x Firm employment	0.998 (0.013)	1.002 (0.031)
Conference and exhibitions	1.051 (0.070)	1.205** (0.087)	Conference and exhibitions	1.371*** (0.070)	1.404*** (0.077)
Conference and exhibitions x Firm age	1.043 (0.025)	1.006 (0.026)	Conference and exhibitions x Firm employment	0.960*** (0.017)	0.964*** (0.012)
Scientific journals	0.929 (0.072)	0.867* (0.073)	Scientific journals	0.763*** (0.045)	0.858** (0.054)
Scientific journals x Firm age	0.994 (0.028)	1.036 (0.031)	Scientific journals x employment	1.047*** (0.014)	1.022** (0.015)
Professional associations	0.872* (0.068)	0.863* (0.074)	Professional associations	0.842*** (0.049)	0.738*** (0.047)
Professional associations x Firm age	0.985 (0.028)	0.976 (0.038)	Professional associations x Firm employment	0.999 (0.014)	1.024* (0.015)
Technical standards	1.002 (0.071)	0.855** (0.066)	Technical standards	0.959 (0.051)	0.899* (0.052)
Technical standards x Firm age	0.997 (0.025)	1.047 (0.029)	Technical standards x Firm employment	1.009 (0.012)	1.017 (0.013)
Firm employment	1.001 (0.010)	1.007 (0.012)	Firm employment	1.007 (0.015)	0.958* (0.024)
Firm age	0.876*** (0.029)	0.903** (0.043)	Firm age	0.884*** (0.017)	0.914*** (0.020)
R&D intensity	11.531*** (3.984)	16.336*** (4.928)	R&D intensity	11.420*** (3.944)	16.275*** (4.890)
Digital intensity	0.643*** (0.105)	0.626*** (0.103)	Digital intensity	0.652*** (0.105)	0.625*** (0.109)
Training intensity	3.087*** (0.237)	2.293*** (0.182)	Training intensity	3.102*** (0.239)	2.332*** (0.195)
Human capital	1.008*** (0.001)	1.002*** (0.009)	Human capital	1.003*** (0.001)	1.006*** (0.001)
Economic risks	1.088*** (0.017)	1.109*** (0.021)	Economic risks	1.089*** (0.017)	1.107*** (0.020)
Demand uncertainty	1.185*** (0.020)	1.175*** (0.020)	Demand uncertainty	1.184*** (0.020)	1.174*** (0.023)
Process innovation	4.328*** (0.149)	2.747*** (0.099)	Process innovation	4.321*** (0.149)	2.731*** (0.096)
Exporter	1.844*** (0.057)	2.135*** (0.075)	Exporter	1.840*** (0.057)	2.121*** (0.070)
Foreign	1.188*** (0.042)	1.150*** (0.042)	Foreign	1.192*** (0.043)	1.161*** (0.048)

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Table D1 (*continued*)

Variables	Product (service) innovation	New market entry	Variables	Product (service) innovation	New market entry
Specification	(1)	(2)	Specification	(3)	(4)
Herfindahl index	1.057 (0.161)	0.882 (0.151)	Herfindahl index	1.054 (0.161)	0.874 (0.151)
Intra-industry local knowledge	0.999 (0.091)	0.846 (0.084)	Intra-industry local knowledge	1.002 (0.091)	0.851 (0.090)
Inter-industry local knowledge	0.550*** (0.126)	0.576*** (0.154)	Inter-industry local knowledge	0.556** (0.127)	0.580** (0.151)
Collaboration breadth	1.779*** (0.045)	1.763*** (0.052)	Collaboration breadth	1.782*** (0.045)	1.777*** (0.056)
Collaboration breadth squared	0.950*** (0.002)	0.953*** (0.003)	Collaboration breadth squared	0.950*** (0.002)	0.953*** (0.003)
Obs.	35,223	35,223	Obs.	35,223	35,223
LR (chi2)	14,333.43	8486.77	LR (chi2)	14,352	8495.75
pseudo R2	0.36	0.29	pseudo R2	0.36	0.27
log-likelihood	−15,268.56	−11,843.29	log-likelihood	−15,257.12	−11,838.92

Note: reference category for industry (mining), region (Northeast England); year (2022–2004). Robust standard errors are in parentheses. The coefficients of the logistic regressions are the marginal effect of the independent variable on the propensity to innovate new products and services, ceteris paribus. For dummy variables, it is the effect of a discrete change from 0 to 1.

Data availability

The authors do not have permission to share data.

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