

# The Dynamic Contribution of Innovation Ecosystems to Schumpeterian Firms: A Multi-level Analysis

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## Suggested citation:

Audretsch, D. B., Belitski, M., & Guerrero, M. (2022). The dynamic contribution of innovation ecosystems to schumpeterian firms: A multi-level analysis. *Journal of Business Research*, 144, 975-986. <https://doi.org/10.1016/j.jbusres.2022.02.037>

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## **Abstract**

This study investigates how geographical proximity with innovation ecosystems' agents contribute to Schumpeterian firms' innovation performance. By adopting the knowledge spillover theory of entrepreneurship (KSTE) perspectives, we propose and test a conceptual model of innovation in Schumpeterian firms using a firm-level dataset that merged information from multiple sources of 3,074 observations during 2002-2014. Our results contribute to the literature by extending three academic discussions: (a) the achievement of Schumpeterian firms' innovation performance based on geographical approximation with innovation ecosystems' agents, (b) the role of absorptive capacity of Schumpeterian firms' in benefiting from external collaborations, and (c) the mechanism how policymakers can promote the improvement of knowledge-intensive capabilities in Schumpeterian firms. Our results have direct implications for innovators, regional and national policymakers.

## **Keywords:**

Innovation Ecosystems; Innovation, Schumpeterian Entrepreneurship; Knowledge Spillover Theory; United Kingdom

## **1. Introduction**

Firms are very different in terms of their growth ambition (Autio et al., 2014), their impact on the national economy (Acs et al., 2014, 2017), as well as their collaboration with stakeholders in the innovation ecosystems (Bogers et al., 2019). Only a small fraction of firms (Frenz and Ietto-Gillies, 2009; Autio et al., 2014; Laursen and Salter, 2014) follow a high-growth knowledge-intensive orientation. This small fraction of firms is the only one that appropriates the Schumpeterian view of entrepreneurship (Malerba and Orsenigo, 1996) that refers to high-growth and knowledge-intensive innovative firms (Schumpeter, 1934). Despite all the impressive progress made in the recent entrepreneurship and innovation literature in explaining both what drives Schumpeterian firms as well as the impact on regional entrepreneurial ecosystems (Mthanti and Ojah, 2017; Colombelli, Krafft and Quatraro, 2014), the case of Schumpeter's entrepreneurship and how best to achieve it remains noticeably absent.

A complementary academic debate has focused on source of innovation and the role of innovation ecosystems in facilitating entrepreneurship and economic growth (Adner, 2017; Bogers et al., 2017, 2019). Schumpeterian firms actively engage in knowledge collaboration with innovation ecosystems' agents across different geographical proximities, resulting what is known the knowledge spillover of entrepreneurship (Audretsch and Keilbach, 2007; Audretsch and Belitski, 2013). We draw on Beers and Zand (2014) and Roper et al. (2017) to define innovation ecosystems' agents as external knowledge partners (e.g. customers, suppliers, consultants, university, government, competitors) who co-create value jointly with a focal firm through knowledge creation and transfer.

Prior research has identified that it is geography of collaboration that limits the extent that entrepreneurs are able to benefit from knowledge co-creation with external partners (Boschma, 2005), while Feldman (1999) and Audretsch and Lehmann (2005) explicitly point on the nature of knowledge, that changes the way entrepreneurs consider the geographical locus of collaboration.

Despite the theoretical underpinning and importance of knowledge collaboration between Schumpeterian type firms and innovation ecosystems' agents (Cappelli et al., 2014; Acs et al., 2017; Roper et al., 2017), there is a paucity of knowledge about the role of geographical proximity and co-location with innovation ecosystem agents for play in innovation performance of Schumpeterian firms.

Using a firm-level data we link two distinctive datasets of UK Innovation survey and Business structure database resulting in 3,074 observations during 2002-2014, this paper aims to examine the extent of that geographical proximity in knowledge collaboration with innovation ecosystem agents (locally, nationally, globally) can affect innovation outcomes in Schumpeterian firms. We conclude that it is the nature of knowledge – tacit, the co-location

(region) and absorptive capacity (firm size) which determines the outcomes of the knowledge spillover entrepreneurship and determines innovation performance.

The paper makes two key contributions to the innovation and entrepreneurship literature. First, this paper explains and show that geography of innovation ecosystems shapes the innovation performance of Schumpeterian firms and in particular co-location between innovation ecosystem agents and Schumpeterian entrepreneur. Second, we demonstrated that absorptive capacity is a boundary condition of knowledge collaboration with innovation ecosystem agents across different geographical dimensions and size of firm.

The remainder of this paper is as follows. Section 2 briefly describes our theory development and the proposed conceptual model. Section 3 describes the methodological design, while the results are discussed in Section 4. Finally, Section 5 discusses and concludes with policy implications, limitations, and recommendations for future research.

## **2. Theoretical framework**

### **2.1. Schumpeterian firms' performance and geographical proximity to innovation ecosystems' agents**

Schumpeterian entrepreneurs' innovation-creating capabilities are associated with exploration and exploitation of new knowledge (Shane and Venkataraman, 2000). Typically, a Schumpeterian firm creates knowledge in-house by investing in internal R&D (Schamberger et al., 2013; Roper and Hewitt-Dundas, 2015; Beers and Zand, 2014), while it also engages in co-creating knowledge with external partners (Roper et al. 2017) as sources of knowledge.

The knowledge spillovers theory of entrepreneurship (KSTE) (Acs et al. 2009) explains the mechanism of knowledge flows between a Schumpeterian firm and

innovation ecosystems' agents and the outcomes of starting a business to commercialize new knowledge (Roper and Hewitt-Dundas, 2015; Acs et al., 2017). Based on The KSTE perspective, the geographical proximity between innovation ecosystems' agents and an entrepreneur is an important condition for knowledge spillovers (Storper and Venables, 2004; Audretsch and Belitski, 2020). Knowledge spillovers are higher when an entrepreneur and innovation ecosystem agents are collocated within the same ecosystem and in a close geographical proximity (Boschma, 2005; Nooteboom et al. 2007; Lahiri, 2010).

Bathelt et al. (2004) highlights the conditions under this the argument breaks out of the simple 'tacit = local' versus 'codified = global' model of knowledge transfer, by describing the conditions under which firms can source tacit and codified knowledge both locally and globally. Authors argue that the co-existence of high levels of local buzz (collaborations) and many global pipeline connections provides a firm located in a cluster with "a string of particular advantages not available to outsiders" (Bathelt et al. 2004: 31).

In the case of Schumpeterian firms, one could expect that, despite the importance of collaboration with innovation ecosystem agents globally, for managers co-location within the external collaborators within the same region will increase tacit knowledge exchange and facilitate knowledge spillovers (Audretsch and Lehmann, 2005). Firstly, we expect knowledge transfers with regional and national partners to be more important for firms focused on local innovation ecosystems and customers markets, as well as those who rely on tacit knowledge transfers. Secondly, codified knowledge may become valuable only if it is applied with tacit knowledge in a local context (Maskell et al. 2004) and the exchange of tacit knowledge is limited when distance between partners increases (Audretsch and Feldman, 1996; Feldman, 1999). Thirdly, regional and national markets can be used as a test ground by SMEs for new products and services before scaling up internationally (Rugman and Verbeke, 2001), with more opportunities for the transmission of sticky, nonarticulated, tacit forms of knowledge

between firms located there in a country (Bathelt et al. 2004). Fourthly, the intensity in competition and level of intellectual protection varies across the geographical proximity – national or international (Nooteboom et al. 2007). It is easier and quicker to enforce intellectual property rights within national boundaries should there be any infringement of intellectual property (IP) and unauthorised leakage of knowledge to competitors. Fifthly, Schumpeterian firms rely on a speedy access to knowledge which is rapid within close geographical-proximity networks (Audretsch and Feldman, 1996; Crescenzi et al., 2016).

Finally, in developed countries it is likely that Schumpeterian firms may access global knowledge locally through industrial clusters (Asheim and Coenen, 2005) and presence of large multinationals (Rugman and Verbeke, 2001; Kenney and Patton, 2005; Iammarino and McCann, 2006). Based on these arguments, we hypothesize:

***H1: Schumpeterian firms will achieve higher innovation performance in collaboration with innovation ecosystems' agents in a close geographical proximity.***

## **2.2. Schumpeterian firms' size and greater innovation returns**

Firm size plays an important role in the relationship between knowledge collaboration and firm innovation (Kelley and Helper, 1999; Rogers, 2004) as it affects the level of absorptive capacity of external knowledge (Cohen and Levinthal, 1989). Small-sized Schumpeterian firms operate under higher resource constraints than their larger counterparts. Therefore, small-sized Schumpeterian firms are more likely to exploit collaboration within closer geographical proximity innovation ecosystems' agents because of the lower cost of external knowledge sources (Acs and Audretsch, 1990; Bughin and Jacques, 1994; Cohen and Klepper, 1996; Chesbrough et al. 2006; West et al. 2014).

The way knowledge spillover is appropriated and commercialized by Schumpeterian firms depends on the absorptive capacity (Ghio et al. 2015) as a critical factor that affects the process of transmitting knowledge spillover by Schumpeterian firms. The absorptive capacity theory of knowledge spill over entrepreneurship (Qian and Acs, 2013) clarifies how knowledge spillover may vary between firms. The absorptive capacity theory of knowledge spillover entrepreneurship argues that, the level of knowledge spillover depends not only on the speed of knowledge creation, but also on entrepreneurial absorptive capacity. Cohen and Levinthal (1990: 128), define absorptive capacity as "an ability to recognize the value of new information, assimilate it, and apply it to commercial ends" with Qian and Acs (2013: 191) extending this definition to "entrepreneur to understand new knowledge, recognize its value, and subsequently commercialize it by creating a firm". Smaller firms lack time and financial resources to support acquisition, assimilation, transformation and exploitation of new knowledge, therefore small Schumpeterian firms will be more likely to rely on local knowledge collaborations to compensate for the lack of absorptive capacity and will use spatial and cognitive proximity to innovate new products (Lahiri, 2010; Balland et al. 2015). Small size firms will build their innovation process relying on external knowledge they absorb naturally from the local markets, local suppliers, customers and universities.

Close geographical proximity to innovation ecosystems' agents becomes an efficient mechanism to leverage the lack of absorptive capacity and further diffuse knowledge at a low cost (Audretsch and Feldman, 1996). On the one hand, absorptive capacity involves the scientific knowledge the firm should have in order to understand what's new and recognize its market value. On the other hand, firm may rely on the market or accessible business knowledge with which the firm can use to innovate.

Typically, small-sized firms will rely on local knowledge sourcing, such as industrial clusters generating considerable knowledge spillovers to smaller firms (Audretsch and Belitski, 2017)..

For a small-sized Schumpeterian firm, knowledge spillovers are local where a firm would have a cognitive understanding and which can start from research laboratories, government programmes, universities, local customers, and suppliers (Audretsch and Vivarelli, 1996; Feldman and Kelley, 2006; de Massis et al., 2016). Unlike medium and large-sized firms, with higher absorptive capacity to recognize and assimilate knowledge spillovers (Cohen and Levinthal, 1990), small-sized Schumpeterian firms rely on technology and knowledge sourcing from local innovation ecosystems' agents (Cassiman and Veugelers, 2002) and within their regional ecosystems (O'Connor et al. 2018). Based on these arguments, we hypothesize:

***H2: The small-size Schumpeterian firms have higher benefits from collaboration with geographically close innovation ecosystem agents.***

### **3. Methodology**

#### **3.1. Sample**

We build a panel dataset merging the Business Structure Database (BSD), the Business Enterprise Research and Development survey (BERD), and the UK Innovation Survey (UKIS) from 2002 to 2014. First, we collected and matched six consecutive UKIS waves to BSD data. Each wave was conducted every second year by the Office of National Statistics (ONS) in the UK on behalf of the Department of Business Innovation and Skills (BIS).

The UKIS offers the most comprehensive data in terms of the range of enterprises surveyed. This dataset covers all manufacturing sectors and most private services, ICT, the creative sector (UK Standard Industrial Classification of Economic Activities), and micro,

small, medium, and large-sized firms. It includes direct measures of innovation performance, such as a share of new to market sales and a wide variety of factors influencing innovation.

The BSD also offers information on the year of establishment, ownership, employment, and industry. Likewise, the BERD offers additional information on R&D expenditure in-house and buying R&D from innovation ecosystems' agents. We matched each correspondent UKIS survey wave with the BSD data for each UKIS period's initial year. Our match resulted in 3,074 observation, which complies with Schumpeterian selection criteria (Schumpeter, 1934; Colombelli et al., 2016) such as up to seven years since establishment, filing a patent, introducing a new product or process, investing in any form of R&D, collaborate on knowledge with external innovation ecosystems' agents, introducing new products to market. The criteria are characterized by 'creative destruction' with technological ease of entry and new firms' major role in innovative activities (Malerba and Orsenigo, 1996). All missing values and non-applicable answers were labelled as missing and not included in our sample. Table 1 illustrates the sample distribution by industry and the UK region where the firm is located.

--- Insert Table 1 here ---

### **3.2. Dependent and explanatory variables**

Our dependent variable (innovation performance) is sales of new-to-market products, the percentage of a firm's total sales serves as a proxy for radical product innovation taken from UKIS. This proxy of product innovation was used in previous studies on innovation in firms (Kleinknecht et al., 2002; Santamaría et al., 2009; Frenz and Ietto-Gillies, 2009; Roper et al., 2008; Leiponen and Helfat, 2010) and within the UK Innovation survey (Laursen and Salter, 2006, 2014). The use of this variable comes from Schumpeter's use of language (i.e., his identification of this activity as disruptive, while Kirzner (1973, 1999) has maintained that this

entrepreneurial activity is the possibility of winning pure profit. The average firm's sales of new-to-market products in our sample is 4.03%, with a standard deviation of 14.5 percent.

The role of geographical proximity is captured through collaboration as a proxy for knowledge spillover for innovation. We created four new explanatory variables from the UKIS named collaboration proximity: "UK regional," "UK national," "Europe," and "other countries" (Cappelli et al., 2014; Balland et al., 2015). These binary variables take value one if the firm collaborates on innovation with at least three interdependent actors within innovation ecosystems (e.g., businesses within enterprise groups, suppliers, clients or customers, competitors, consultants, commercial labs, universities, governments), and zero otherwise (Adner, 2017; Bogers et al., 2017, 2019). Most importantly, these variables capture external exposure to knowledge collaboration (Faems et al., 2005; Cassiman and Veugelers, 2006; Laursen and Salter, 2014). Each collaboration is viewed across four geographical dimensions: regional, national, Europe, and other countries. A similar indicator was also used in earlier studies related to the measurement of collaboration proximity (Boschma, 2005; Boschma and Frenken, 2010). The full list of explanatory and control variables used in this study is in Table 2.

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### **3.3. Control variables**

We have included several control variables related to firm characteristics, year, industry (2 SIC digits), the survey wave, and the UK region fixed effects. We use a binary variable, which indicates whether or not a firm's innovation activity faces the following "*constraints on innovation*": the perceived direct innovation costs and risks are high, there is a lack of qualified personnel and a lack of information on markets and market domination by established firms. Firms that report greater constraints are exposed to a higher level of competition, which may

affect both the propensity to innovate and the innovation performance (Miotti and Sachwald, 2003; Nooteboom et al., 2007; Schamberger et al., 2013; Beers and Zand, 2014). A Schumpeterian firm will remain entrepreneurial to the extent that individuals can engage in entrepreneurial behaviour and decision-making (Hornsby et al. 2013). Operationalized with the Corporate Entrepreneurship strategy, “*entrepreneurial climate*” is measured as new methods of organising work responsibilities and decision-making.

A firm that aims to improve innovation performance is also likely to experiment with new collaboration models. Evidence that was creating new collaboration methods with external innovation ecosystems’ agents plays a role in transmitting knowledge and innovation (Colombelli and Quatraro, 2018). We use a binary variable “*Process innovation external*” as new methods of organising external relationships with other firms or public institutions and another binary variable for “*exploration activity*” of a firm (March, 1991; Schamberger et al. 2013). Additionally, we use a binary variable, which indicates whether or not a firm introduces process innovation in-house “*Process innovation internal.*” Process innovation relates to all-new or significantly improved methods, although new to the firm, does not need to be new to the industry.

We control for a “*firm size*” measured as the number of employees (small, medium, and large), firm age measured as a log of firm age, thereby capturing potential decreasing marginal returns to firm age (Kelley and Helper, 1999). We control for the firm’s absorptive capacity by controlling for “*scientists*” – a share of employees with the BS degree and above, which is also used as a proxy for general human capital (Zahra and George, 2002). General human capital refers to employees’ knowledge and skills obtained through formal education and professional experience (Criaco et al. 2014), which is applicable to various innovation activities. We add a firm’s “*Legal status*” as a binary variable for sole-proprietorship, on-for-profit, and partnership (including family businesses) with limited company liability as a reference category. We also

control for sales abroad as a measure of internationalisation with a binary variable for “*Exporter*” (Rugman and Verbeke, 2001; Narula, 2004) and firm foreign ownership with a binary variable for “*Foreign firm.*”

We included “*in-house R&D expenditure*” in logarithms to capture the firm’s absorptive capacity as well as “*design intensity*” measured as all forms of design expenditure (£) to the total sales (£) and “*training intensity*” measured as all forms of training activities to create new knowledge and innovate (£) to the total sales (£). Also, we included external R&D expenditure in logarithms as a control for buying external creative knowledge. It is important to distinguish between buying knowledge and knowledge externalities (knowledge spillovers, collaboration, flows) where no financial compensation is involved (Battke et al., 2016). Finally, we include 70 industry fixed effects (SIC code 2 digits) (mining and quarrying as the reference category) and 12 regional fixed effects (North-East region of the UK as the reference category) in the regression.

### **3.4. Model specification**

We estimate innovation production function (Pakes and Griliches, 1984) in which external knowledge collaboration, investment in knowledge, and other firm-level characteristics become inputs, and product innovation is an output using a mixed-effects generalised linear model (Luke, 2004; Goldstein, 2011). The regression is multi-level and includes firm-level characteristics, survey wave, and one of 128 city-regions in the United Kingdom (UK), where a firm is located. The model contains both fixed and random effects. Fixed effects are directly estimated, in addition to being indirectly estimated by covariances of random intercepts and slopes (Rabe-Hesketh et al., 2000). Innovation production function was estimated using a generalised linear mixed-effect model with the dependent variable  $y_{ijk}$  and the independent variable  $x_{ijk}$  such that:

$$y_{ijk} = \beta_0 + \beta_1 x_{ijk} + \beta_2 \tau_{ijk} + \varepsilon_{ijk} \quad (1)$$

where  $i$  is the firm level-1,  $j$  is the region level-2, and  $k$  serves to index the wave survey level-3. The dependent variable  $y_{ijk}$  represent product innovation for firm  $i$  in region  $j$  and taken from the wave  $k$ . The explanatory variables, which were previously described, are presented by  $x_{ijk}$ . Other control variables which represent firm-specific characteristics described in Table 1 are presented by  $\tau_{ijk}$ , this also includes industry 2 digit SIC fixed-effects. Finally,  $\varepsilon_{ijk}$  is an error term that consists of three components in the hierarchical model:

$$\varepsilon_{ijk} = \gamma_i + \mu_j + t_k + v_{ijk} \quad (2)$$

Where  $\gamma_i$  represents the omitted variables that vary across firms but not over regions and waves,  $\mu_{ij}$  denotes the omitted variables that vary over regions but are constant across firms and waves,  $t_k$  represents omitted variables which vary across waves but not across firms and regions, while finally  $v_{ijk}$  is the error term. The presence of more than one residual term makes the standard multivariate model, such as a fixed-effects specification, inapplicable. A generalised maximum likelihood (GML) procedure should therefore be used, which is estimated using maximum likelihood with the truncated distribution of  $y_{ijk}$ . The co-variation between firm innovation performance sharing the same regional and time externalities can be expressed by the intra-class correlation in this model (Goldstein, 2011). With this, the between-regions variance contributes to firm innovation performance in addition to the variance between firms.

#### 4. Empirical results

Table 3 reports the estimated mixed effect (multi-level) generalised linear model (GLM), which measures firm, time, industry, and regional characteristics, which may affect innovation performance. We use four binary explanatory variables (specification 5, Table 3) to measure the joint effect of all collaboration innovation ecosystems' agents and geographical dimensions

on firm innovation. The coefficient of interest is positive and statistically significant with regional ( $\beta_r=0.48$ ,  $p<0.05$ ) and national innovation ecosystems' agents ( $\beta_n=0.52$ ,  $p<0.05$ ). This result is supporting H1 (Audretsch and Feldman, 1996; Iammarino and McCann, 2006). The size of the beta coefficients for the UK regional and UK national collaborators is within the same confidence interval. It means no significant difference between the returns to knowledge collaboration for national and regional innovation ecosystems' agents. There is no evidence of the relationship between international innovation ecosystems' agents and firm innovation.

--- Insert Table 3 here ---

The results reported in specifications 1-4, Table 3 illustrate positive and significant moderation coefficient of firm size and European innovation ecosystems' agents ( $\beta_E=0.83$ ,  $p<0.05$ ), which is different from H2. H2 is not supported as small-sized Schumpeterian firms; when engaging in external knowledge, collaboration with regional and national innovation ecosystems' agents will not experience higher innovation performance than firms of other sizes. Although knowledge collaboration with European and international innovation ecosystems' agents is important for Schumpeterian firms, the statistical effect is weaker than knowledge collaboration on firm innovation with regional and national innovation ecosystems' agents (spec. 5, Table 3). Other interesting results are related to the positive effect of in-house R&D investment on firm innovation ( $\beta_{R\&D}=0.25$ ,  $p<0.001$ ), while buying R&D and investment in design and training was not found to affect innovation directly (Table 3). Improvement in the external forms of collaboration ( $\beta_{ext}=0.23$ ,  $p<0.05$ ) as well as process innovation ( $\beta_{int}=0.88$ ,  $p<0.001$ ) are positively associated with product innovation. The entrepreneurial climate within a firm ( $\beta_{climate}=0.22$ ,  $p<0.01$ ) supports product innovation (Hornsby et al. 2013).

Schumpeterian firms in high tech sectors have higher innovative performance ( $\beta_{\text{Hightech}}=2.59-2.64, p<0.01$ ) compared to medium and low tech firms. Once we controlled for additional characteristics, Firm age and scientists were not associated with firm innovation, which means that Schumpeterian firms during the establishment stage are likely to produce as much innovation as firms 6-7 years after establishment. Changes in a share of employees with a college degree were not associated with innovation. Firms which perceive the cost of innovation as a significant obstacle have higher innovation performance ( $\beta_{\text{cost}}=0.43, p<0.001$ ) (Table 4). Exporters and foreign-owned firms have higher innovation performance than non-exporters ( $\beta_e=0.33, p<0.001$ ) and firms which are not foreign-owned ( $\beta_e=0.14, p<0.01$ ) (Frenz and Ietto-Gillies, 2009).

### **Post hoc analysis**

Post hoc analysis aims to check the robustness of the results. Using multi-level GLM estimation results in equation (1), we calculate product innovation's predictive values for small, medium, and large-sized Schumpeterian firms (Table 5). These firms are divided into two groups: those who do not collaborate on knowledge with external innovation ecosystems' agents and across regional, national, European, and international geographical dimensions. The predictive margins shown in Figure 1 demonstrate that Schumpeterian firms of all sizes benefit from knowledge collaboration with external innovation ecosystems' agents across all geographical dimensions, with the highest levels of product innovation achieved in collaboration with regional/national innovation ecosystems' agents, thereby supporting H1.

--- Insert Figure 1 here ---

Table 4 illustrates the interaction coefficient between a collaboration innovation ecosystems' agents and firm size calculated from the estimation (1). Small firms compared to

medium and large-sized Schumpeterian firms are likely to benefit more by collaboration with European innovation ecosystems' agents than with other agents. For example, by engaging in collaboration with knowledge innovation ecosystems' agents in Europe, small Schumpeterian firms in the UK are likely to increase their new-to-market sales from 15.5 percent to 57.7 percent, which is by 42 percent. Medium and large Schumpeterian firms in the UK will increase their innovation sales from 17.4 to 45.3 percent, which is 14.4 percent less than the small firms' effect.

--- Insert Table 4 here ---

An ability of Schumpeterian firms to exploit external knowledge that is sufficiently diverse (European innovation ecosystems' agents) but is located within a similar institutional context (European Union) resolves the "proximity paradox" of innovation (Boschma and Frenken, 2010). Knowledge inflows from European innovation ecosystems' agents for small firms are likely to bring new ideas while providing a secure institutional environment for firms to resolve insolvency and protect co-created knowledge (Love et al. 2014). Both the UK and European collaborators are subject to European regulation and are more likely to disclose their know-how and collaborate on innovation as part of their market development (safe internationalization) strategy (Rugman and Verbeke, 2001).

As a robustness check for H2, we also estimated model (2) using logistic panel data estimation. We used the same dependent, independent, and control variables, but did not account for multi-level effects. The logistic regression results support mixed-effect GLM results with the predictive margins for product innovation, which are illustrated in Figure 2. It confirms the positive effect of knowledge collaboration for product innovation in Schumpeterian firms across all geographical dimensions. One may observe that the change in

predicted innovation levels is the highest for small firms that collaborate with European innovation ecosystems' agents.

--- Insert Figure 2 here ---

## **5. Discussion and Conclusion**

We propose and estimate a model to understand how geographical proximity with innovation ecosystems' agents contribute to innovation performance in Schumpeterian firms. We use the KSTE perspective within the evolving literature on innovative start-ups (Colombo et al., 2011; West et al., 2014; Colombelli et al., 2014; 2016) to answer our research question and examine the role that innovation ecosystem agents across different geographical dimensions play in innovation in Schumpeterian firms.

This study reveals that the geography of innovation works as a filter for the tacit knowledge (Audretsch and Lehmann, 2005). Firstly, we find that Schumpeterian firms, when engaging in external knowledge exchange with regional and national innovation ecosystems' agents, experience higher innovation sales than Schumpeterian firms that collaborate with international innovation ecosystems' agents (Audretsch and Feldman, 1996; Iammarino and McCann, 2006).

Important managerial and policy implication of this finding is that it does not make sense to think of multiple geographical proximities when knowledge collaboration, rather than how Schumpeterian firms should engage with across different collaboration partners.

Secondly, Schumpeterian firms of different sizes have a similar innovation performance level when collaborating with innovation ecosystems' agents, except knowledge collaboration with European innovation ecosystems' agents. Interestingly, that Schumpeterian firms may be exposed to a "temporary" geographical proximity when knowledge collaboration with

innovation ecosystems' agents (Torre, 2008) is limited in time. Our finding draws attention to managers on the importance of considering diverse types of proximities (cognitive, institutional, and geographical) when designing knowledge collaboration with innovation ecosystems' agents.

Based on Schumpeter (1934) and Colombelli et al. (2016), we propose/test a conceptual model using a firm-level dataset that merged information from multiple sources of information from 2002 to 2014. Our results contribute to the literature by extending three academic discussions: (a) the achievement of Schumpeterian firms' innovation performance based on geographical approximation with innovation ecosystems' agents (Boschma, 2005; Acs et al., 2017; Guerrero et al., 2020), (b) the influence of Schumpeterian firms' size on their absorptive capacity based on knowledge sourcing (Faems et al. 2005; Colombo et al. 2011;), and (c) the mechanism about how/why policymakers can promote the improvement of knowledge-intensive capabilities among entrepreneurship and innovation ecosystems' agents distributed across cities, regions, countries or abroad countries (Santamaria et al., 2009; Schamberger et al., 2013; Beers and Zand, 2014; Welter et al. 2017).

The main limitations are as follows. Firstly, due to the anonymous nature of the UK Innovation survey, no additional sources for information on external innovation ecosystems' agents could be added to the database, which could have been used to supplement the data. In particular, we cannot track the intensity/time of engagements between innovation ecosystems' agents. Cross country analysis could have provided more robust and generalizable results. Secondly, this research focuses specifically on the multi-dimension of innovation with the mixed effect model within one country. A cross-country study could be performed to measure differences in the institutional environment across countries and their link to Schumpeterian entrepreneurship (North, 1991; Stenholm

et al., 2013). Finally, this study cannot measure the amount of jointly undertaken research and development nor the application on perception-based efficiency measures of collaboration from low to high. Subsequent research will address these limitations and expand the qualitative and quantitative measurements for the degree of collaboration between a Schumpeterian firm and an external innovation ecosystems' agents.

Future research will distinguish the breadth, depth, and length of knowledge collaboration across different sizes of firms and proximity. Also, future research may focus on different returns to necessity vs. opportunity-driven knowledge collaborations in Schumpeterian firms. It is important to distinguish between knowledge collaboration, financial compensation for the knowledge transfer, and knowledge spillovers as a knowledge externality. The research calls for future papers to address knowledge sourcing and Schumpeterian firms in other countries in order to understand better how innovation happens, for example, in the US "start-ups," German "Mittelstadt" and British "Brittelstandt."

The following implications for innovation policy can be developed. Firstly, our findings confirm the importance of using both geographical and firm size perspective when studying innovation Schumpeterian firms. We found that 'European' collaboration with innovation ecosystems' agents enables small-sized Schumpeterian firms in the UK, which are not associated with multinational corporations and enterprise groups, to obtain competences and knowledge not available where they are located. The decision to relocate where specific competencies are present (for example, where agglomeration economies occur) could be costly in the UK, so small-sized firms substitute the "permanent" geographical proximity with forms of "temporary geographical proximity" (Torre and Rallet, 2005). It is a plausible explanation for small firms benefiting more from European innovation ecosystems' agents than medium and large-sized firms. "Temporary" geographical proximity allows Schumpeterian firms to

reach competencies not available or not affordable outside national boundaries (Torre and Rallet, 2005; Torre, 2008).

Secondly, collaboration with European innovation ecosystems' agents on innovation is likely to be more efficient for innovative start-ups with substantial government support to be given to such collaboration. The collaboration may also include mentoring, access to European financial markets, and customers. The UK government policy should ensure that small and micro-Schumpeterian firms will access important European innovation ecosystems' agents if Brexit occurs. European governmental and non-governmental support agencies may develop a guideline for the transition period to ensure that European customers and suppliers working with micro and small-sized Schumpeterian firms in the UK are not affected by Brexit conditions.

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Table 1: Sector divisions (by SIC 2007) and geographical regions

Sector divisions	Total	%	Region	Total	%
Mining & Quarrying	22	0.72	North East	169	5.50
Manufacturing basic	106	3.45	North West	310	10.08
High-tech manufacturing	355	11.55	Yorkshire and Humber	237	7.71
Electricity, gas, and water supply	42	1.37	East Midlands	250	8.13
Construction	358	11.65	West Midlands	257	8.36
Wholesale, retail trade	350	11.39	Eastern England	279	9.08
Transport, storage	170	5.53	London	298	9.69
Hotels & restaurants	310	10.08	South East	344	11.19
ICT	268	8.72	South West	273	8.88
Financial intermediation	132	4.29	Wales	217	7.06
Real estate & other business activities	386	12.56	Scotland	222	7.22
Public admin, defense	514	16.72	Northern Ireland	218	7.09
Education	12	0.39			
Other community, social active	49	1.59			

Source: Office of National Statistics: BSD, BERD, and UKIS (2002-2014).

Table 2: Descriptive Statistics

Label		Description of variables	Mean	Std. Dev.	Min	Max
			Product innovation 3,074 obs.			
Innovation performance (DV)		% of the firm's total turnover from goods and services, new to the market (%)	4.031	14.52	0.00	100.00
Geographical proximity to innovation ecosystems' agents	UK Regional	Binary variable=1 if the firm co-operates on innovation with at least three out of seven external partners partner regionally (enterprise group, suppliers, customers, consultants, competitors, university, government)	0.084	0.278	0.00	1.00
	UK National	Binary variable=1 if the firm co-operates on innovation with at least three out of seven external partners partner nationally (enterprise group, suppliers, customers, consultants, competitors, university, government)	0.087	0.282	0.00	1.00
	European Countries	Binary variable=1 if the firm co-operates on innovation with at least three out of seven external partners partner in Europe (enterprise group, suppliers, customers, consultants, competitors, university, government)	0.031	0.174	0.00	1.00
	Other Countries	Binary variable=1 if the firm co-operates on innovation with at least three out of seven external partners partner in another world (enterprise group, suppliers, customers, consultants, competitors, university, government)	0.027	0.163	0.00	1.00
In-house R&D expenditure		Internal Research and Development expenditure (£), log	0.829	1.686	0.00	10.72
External R&D expenditure		External Research and Development expenditure (£), log	0.277	0.981	0.00	8.51
Design intensity		All forms of design expenditure (£) to total sales (£) ratio	0.024	0.351	0.00	0.33
Training intensity		Training for innovative activities expenditure (£) to total sales (£) ratio	0.037	0.624	0.00	0.30
Entrepreneurial climate		New methods of organising work responsibilities and decision making (a new system of employee responsibilities, teamwork, decentralisation, integration or de-integration education/ training)	0.209	0.406	0.00	1.00
Process innovation external		New methods of organising external relationships with other firms or public institutions	0.223	0.416	0.00	1.00
Process innovation internal		Binary variable=1 if the firm introduced any new or significantly improved processes for producing or supplying goods or services, zero otherwise.	0.209	0.407	0.00	1.00
Firm size	<i>Small</i>	Binary variable equal one if the number of FTEs is <50, zero otherwise	0.705	0.455	0.00	1.00
	<i>medium</i>	Binary variable equal one if the number of FTEs is between 50 and 249, zero otherwise	0.214	0.410	0.00	1.00
	<i>large</i>	Binary variable equal one if the number of FTEs is >=250, zero otherwise	0.079	0.270	0.00	1.00
Industry	<i>High-tech Manufacturing</i>	Binary variable equal one if firms belong to one of the following SIC 2007 (2 digits): 21, 26, 30, zero otherwise	0.002	0.047	0.00	1.00
	<i>Medium-tech Manufacturing</i>	Binary variable equal one if firms belong to one of the SIC 2007 (2 digits): 20, 22-27, 28, 29, 32, zero otherwise	0.047	0.212	0.00	1.00
	<i>Low-tech Manufacturing</i>	Binary variable equal one if firms belong to one of the SIC2007 (2 digits): 10-19, 31, zero otherwise	0.046	0.211	0.00	1.00
	<i>High-tech Services</i>	Binary variable equal one if firms belong to one of the SIC2007 (2 digits): 59, 60, 61, 62, 72 zero otherwise	0.090	0.286	0.00	1.00
Legal status	<i>Sole proprietor</i>	Binary variable=1 if the firm's legal status is Sole-proprietor, 0 otherwise	0.067	0.250	0.00	1.00
	<i>Partnership</i>	Binary variable=1 if the firm's legal status is a partnership, 0 otherwise	0.075	0.261	0.00	1.00
	<i>Non-for-profit body</i>	Binary variable=1 if the firm's legal status is <i>Non for profit</i> , 0 otherwise	0.009	0.096	0.00	1.00
Exploration		How important were the Increasing range of goods or services and Increasing market share in your decision to innovate in goods or services, processes?	0.803	0.397	0.00	1.00
Constraints on innovation	<i>Cost</i>	Binary variable equals one if the firm states excessive perceived economic risks, direct innovation costs too high, cost and availability of finance, zero otherwise	0.354	0.479	0.00	1.00
	<i>Knowledge</i>	Binary variable equals one if the firm state's lack of qualified personnel, lack of information on markets, lack of information on techs markets, zero otherwise	0.152	0.359	0.00	1.00
	<i>Incumbents</i>	Binary variable equals one if the firm state's market dominated by established firms, uncertain demand for goods or services, zero otherwise	0.192	0.394	0.00	1.00
Age of firm		Age of a firm (years since the establishment), log	1.277	0.606	0.00	1.94
Scientist, % of FTE		The proportion of employees that hold a degree or higher qualification in science and engineering	7.431	18.19	0.00	100.00
Exporter		Binary variable=1 if a firm sells its products in foreign markets, 0 otherwise	0.249	0.433	0.00	1.00
Foreign ownership		Binary variable=1 if a firm has headquarters abroad, 0 otherwise	0.145	0.230	0.00	1.00

Source Office of National Statistics: BSD, BERD, and UKIS (2002-2014). The number of observations 3,074.

Table 3: Mixed-effects GLM

Specification	(1)	(2)	(3)	(4)	(5)
Geographical proximity	Regional	National	Europe	World	Overall
Small firm (1-49 FTEs) (H2)	0.61* (.26)	0.66* (.26)	0.63* (.26)	0.67** (.26)	0.66** (.26)
small firm x UK Regional (H2)	0.49 (.30)				
small firm x UK National (H2)		-0.01 (.36)			
small firm x European countries			0.83* (.49)		
small firm x other countries				-0.35 (.67)	
Collaboration UK Regional (H1)	0.13 (.35)	0.48** (.2)	0.50** (.2)	0.48** (.2)	0.48** (.2)
Collaboration UK National (H1)	0.52* (.21)	0.52* (.32)	0.51** (.21)	0.52** (.21)	0.52** (.21)
Collaboration European countries	-0.27 (.36)	-0.33 (.36)	-0.88 (.54)	-0.34 (.36)	-0.33 (.36)
Collaboration Other World	0.28 (.37)	0.32 (.37)	0.28 (.37)	0.59 (.64)	0.32 (.36)
In-house R&D expenditure, log	0.25*** (.037)	0.25*** (.037)	0.25*** (.037)	0.25*** (.037)	0.25*** (.037)
External R&D expenditure, log	0.04 (.05)	0.04 (.05)	0.04 (.05)	0.04 (.05)	0.04 (.05)
Design intensity	0.46 (.32)	0.47 (.32)	0.45 (.31)	0.47 (.32)	0.47 (.32)
Training intensity	-0.09 (.18)	-0.09 (.17)	-0.09 (.18)	-0.09 (.17)	-0.09 (.17)
Entrepreneurial climate	0.22* (.14)	0.22* (.14)	0.22* (.14)	0.22* (.14)	0.22* (.14)
Process innovation external	0.24 (.14)	0.23* (.14)	0.23* (.14)	0.23* (.14)	0.23* (.14)
Process innovation internal	0.88*** (.13)	0.88*** (.13)	0.89*** (.13)	0.88*** (.13)	0.88*** (.13)
Medium firm (50-249 FTEs)	0.50* (.27)	0.49* (.27)	0.51* (.27)	0.48* (.27)	0.49* (.27)
High tech sector	2.64** (.97)	2.60** (.97)	2.59** (.97)	2.62** (.96)	2.60** (.97)
Medium-tech sector	0.50 (.41)	0.49 (.41)	0.48 (.41)	0.49 (.41)	0.49 (.41)
Low-tech sector	0.87 (.78)	0.90 (.78)	0.82 (.79)	0.91 (.78)	0.90 (.78)
High tech services	0.10 (.25)	0.09 (.25)	0.09 (.25)	0.10 (.25)	0.09 (.25)
Sole proprietor	-0.11 (.29)	-0.12 (.29)	-0.11 (.29)	-0.12 (.29)	-0.12 (.29)
Partnership	-0.48* (.29)	-0.49* (.29)	-0.48* (.29)	-0.49* (.29)	-0.49 (.29)
Non-profit making body	-0.69 (.73)	-0.73 (.73)	-0.74 (.73)	-0.73 (.73)	-0.73 (.73)
Exploration	2.52*** (.39)	2.52*** (.39)	2.53*** (.39)	2.52*** (.39)	2.52*** (.39)
Constrain innovation: cost	0.43*** (.13)	0.43*** (.13)	0.43*** (.13)	0.43*** (.13)	0.43*** (.13)
Constrain innovation: knowledge	0.02 (.17)	0.01 (.17)	0.02 (.17)	0.01 (.17)	0.01 (.17)
Constrain innovation: incumbents	-0.02 (.16)	-0.02 (.16)	-0.03 (.16)	-0.02 (.16)	-0.02 (.16)
Age of firm, logs	-0.01 (.09)	-0.01 (.09)	-0.01 (.09)	-0.01 (.09)	-0.01 (.09)
Scientists	0.01 (.00)	0.01 (.00)	0.01 (.00)	0.01 (.00)	0.01 (.00)
Exporter	0.33** (.13)	0.33** (.13)	0.32** (.13)	0.33** (.13)	0.30** (.13)
Foreign	0.14** (.04)	0.14** (.04)	0.14** (.04)	0.12** (.04)	0.15** (.04)
Mills ratio: innovation active bias	1.13*** (.29)	1.13*** (.29)	1.12*** (.29)	1.14*** (.29)	1.13*** (.29)
Mills ratio: protection bias	0.35*** (.11)	0.36*** (.11)	0.35*** (.11)	0.36*** (.11)	0.36** (.11)
Constant	-6.90*** (1.22)	-7.00*** (1.12)	-6.90*** (1.20)	-7.00*** (1.10)	-7.00*** (1.10)

variance (year)	0.19 (.21)	0.20 (.22)	0.20 (.23)	0.19 (.21)	0.20 (.22)
variance (year / region)	0.01 (.03)	0.01 (.03)	0.01 (.03)	0.01 (.03)	0.01 (.03)
number of fixed effect parameters	30	30	30	30	28
number of random effect parameters	2	2	2	2	2
Overall model chi2	411.1393	410.12	409.34	410.87	410.12
LR test vs. logistic model: chi2	17.80	17.96	18.09	17.75	18.01
log-likelihood	-988.67	-989.48	-988.54	-989.23	-989.50

Note: standard errors are in parenthesis. Reference category for firm size=large firm (250+ FTEs); The reference category for firm ownership status: public corporation. Industry (1 digit SIC) and year fixed effects are suppressed to save space. LR test vs. logistic model supports the use of a multi-level mixed-effects model. Significance level: \* p<0.05; \*\* p<0.01; \*\*\* p<0.001"

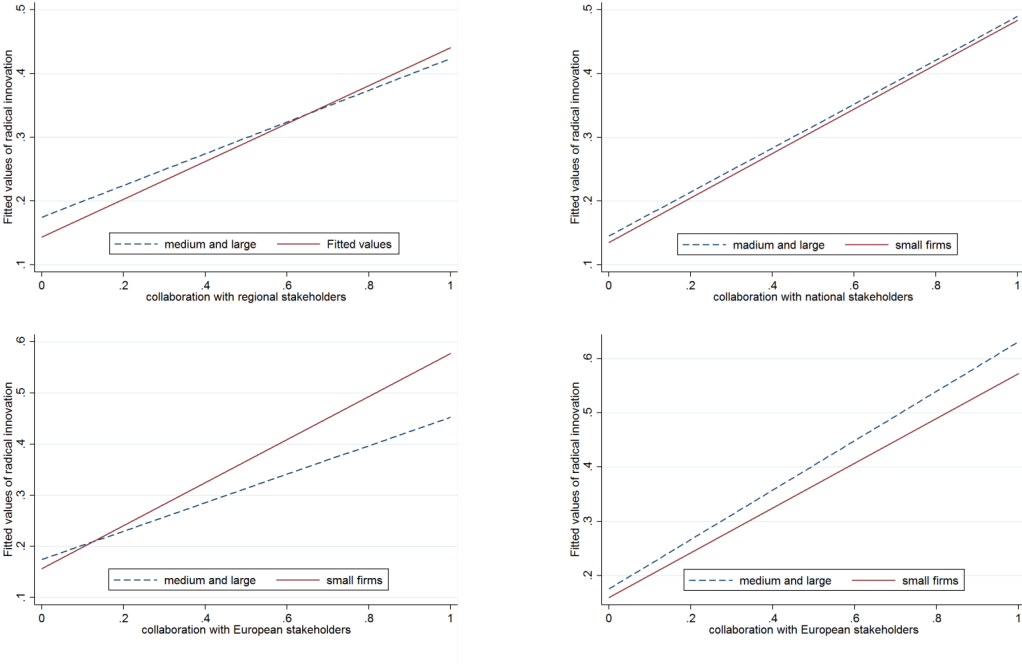
Source: The Office of National Statistics: BSD, BERD, and UKIS (2002-2014). The number of observations 3,074.

Table 4: Differences in product innovation between small and large Schumpeterian firms conditional on their collaboration partner (mixed-effect GLM)

Firm size	3,074 observations			
Regional-level			Total effect	Diff-in-diff
	No-collaboration	Collaboration		
Medium & large	0.175	0.424	0.249	0.045
Small	0.144	0.440	0.297	
National-level			Total effect	Diff-in-diff
	No-collaboration	Collaboration		
Medium & large	0.145	0.490	0.344	0.004
Small	0.135	0.484	0.348	
European-level			Total effect	Diff-in-diff
	No-collaboration	Collaboration		
Medium & large	0.174	0.453	0.278	0.142*
Small	0.157	0.577	0.420	
World-level			Total effect	Diff-in-diff
	No-collaboration	Collaboration		
Medium & large	0.176	0.631	0.455	-0.043
Small	0.160	0.572	0.413	

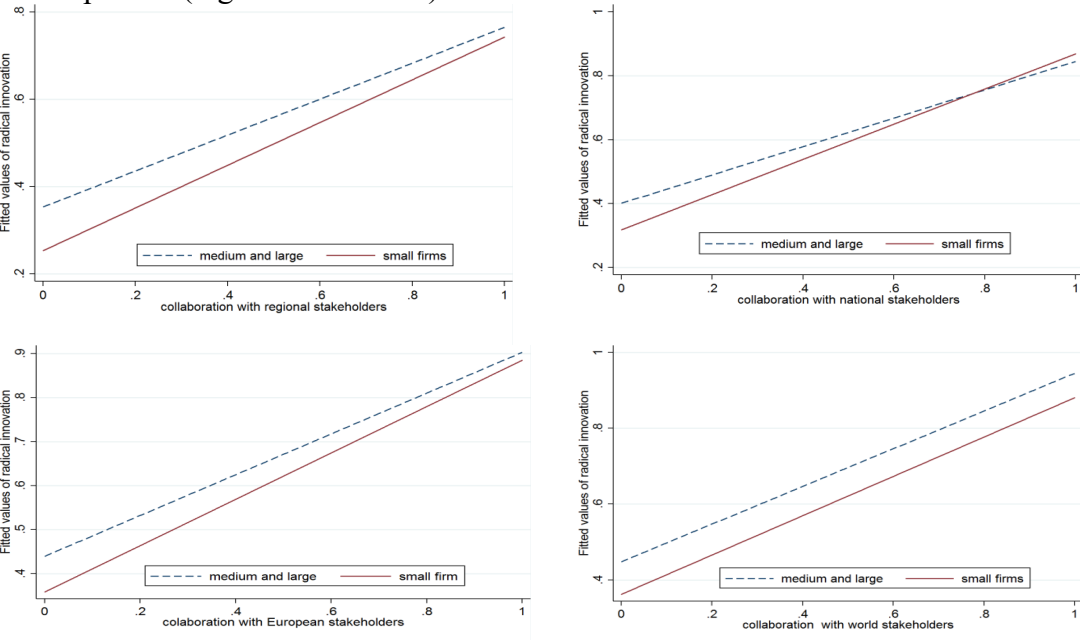
Source: Authors based on the Office of National Statistics: BSD, BERD, and UKIS (2002-2014).

Figure 1: Differences in product innovation conditional on knowledge conditional on their collaboration partner (mixed-effect GLM)



Source: Authors based on the Office of National Statistics: BSD, BERD, and UKIS (2002-2014).

Figure 2: Differences in product innovation conditional on knowledge conditional on their collaboration partner (logistic estimation)



Source: Authors based on the Office of National Statistics: BSD, BERD, and UKIS (2002-2014).