

The knowledge spillover of innovation

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The knowledge spillover of innovation

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Abstract

This study advances our understanding of knowledge spillover of innovation, putting a firm's own R&D investment and knowledge spillovers to a competitive test. We use three matched databases of 15,430 firms in the United Kingdom (UK) during the period 2002–2014 in order to demonstrate that knowledge spillovers emanating from R&D investment within and between industries have different effects on innovation compared to imitation and that the ability to access spillover is conditional on the firm's own investment in R&D. This study furthers our understanding in two different ways. Firstly, it supports the two faces of the R&D story. Second, it demonstrates that the relationship between knowledge spillover and firm innovation depends on the firm's own investment in R&D and reveals the positive effects of knowledge transfer as well as factors limiting the use of spillovers such as industry competition, transaction costs, and eventually innovation type.

JEL classification: D83, L26, O32, O36

1. Introduction

Following the early contributions made by Marshall (1920), Weber (1929), Dosi (1982), Dosi *et al.* (1990), Romer (1986), Jacobs (1970), Porter (1990), and Acs *et al.* (1994a, 1994b), economic geographers, industrial economists, and innovation scholars have studied how regional intra-industry (specialization) and inter-industry (diversification) spillovers can best contribute to boosting firm performance (Carlino and Kerr, 2015; Lee *et al.*, 2015). A number of studies have re-stated the role of localized knowledge spillovers in increasing innovation, including Jaffe (1986), Breschi and Lissoni (2001), Cassiman and Veugelers (2002), Boschma (2005), Coombs *et al.* (2009), and Qian (2014).

However, it may be that the literature has been asking the wrong question—whether is regional specialization or, alternatively, diversification that matters for firm innovation? (Beaudry and Schiffauerova, 2009; Enkel and Heil, 2014). This question locks the answer into an unequivocal dichotomy—either one or the other (or possibly neither). While the answer to this question has been emphatically positive (Caragliu *et al.*, 2016), the dichotomous nature of the question may mask a more nuanced relationship. Perhaps the more relevant and compelling questions is not which one but rather under which conditions regional specialization is more conducive to firm innovation and under which conditions diversification is more conducive to innovation. Thus, *how, when, and which types of knowledge spillover matter for different innovation types remains*

unclear (Alexy *et al.*, 2013; Roper *et al.*, 2013, 2017; Cappelli *et al.*, 2014; Battke *et al.*, 2016; Denicolai *et al.*, 2016) as innovation activity differs between local, technological, and knowledge contexts (Rosenthal and Strange, 2003; Coombs *et al.*, 2009; Buzard and Carlino, 2013; Dosi and Tranchero, 2021). We define firm innovation as a firm's ability to create new market products as fundamental changes in the firms' products, processes, technologies, and organizational structures and methods. This requires investment in knowledge and R&D (Cohen and Levinthal, 1990) as well as a further experimentation with knowledge (Teece, 2010). We define specialization (localized intra-industry) and diversification (localized inter-industry) spillovers as non-pecuniary externalities (Breschi and Lissoni, 2001), which arise from the fact that firms in a region and industry cannot fully appropriate the new knowledge they create, and this knowledge spills over to other firms.

This argument has been overwhelmingly supported by the knowledge externalities and competition literature (Bloom *et al.*, 2013), the open innovation literature (Chesbrough, 2003, 2006; West *et al.*, 2014; Tucci *et al.*, 2016), and the innovation and industry change literature (Lakemond *et al.*, 2016). The regional innovation literature revealed the role of physical proximity (Audretsch and Feldman, 1996) and technological and sectoral proximity (Dumais *et al.*, 2002; Boschma, 2005) as facilitators of knowledge spillovers in cities and regions (Glaeser, 1999; Audretsch and Lehmann, 2005). The core idea is that the flow of tacit knowledge is made easier when the probability of face-to-face contact is increased by physical proximity. This effect leads to positive spillovers for firms co-located in the area (Jaffe, 1986).

Because the literature examining the relationship between a variety of different knowledge spillovers and innovation activities is still in its exploratory stages (Bloom *et al.*, 2013; Cappelli *et al.*, 2014; Audretsch and Belitski, 2020a), this study responds to numerous calls in the regional innovation (Boschma, 2005; Carlino and Kerr, 2015; Caragliu *et al.*, 2016) and open innovation literature (West *et al.*, 2014; Roper *et al.*, 2017; Kobarg *et al.*, 2019) to employ a variety of knowledge search strategies using innovation survey data to explain how new products and services can be developed and introduced to market.

A number of different mechanisms could be involved in this, such as the complementarities between a firm's own R&D investment and knowledge externalities (Cohen and Levinthal, 1989) in the form of knowledge collaborations and spillovers (Powell *et al.*, 1996; Leiponen and Helfat, 2010; Cassiman and Valentini, 2016; Belitski, 2019). This study therefore aims to further examine the mechanisms that define the relationship between intra- and inter-industry spillovers and two types of firm innovation (Glückler, 2013; Cappelli *et al.*, 2014). A number of recent studies (Denicolai *et al.*, 2014, 2016; Roper *et al.*, 2017; Kobarg *et al.*, 2019) have partly unpacked this relationship, pointing to the role of a firm's own R&D investment and the non-linear relationship between various sources of external knowledge sourcing and innovation. However, there is still a paucity of knowledge on the mechanisms that determine the spillover–innovation relationship and how changes in knowledge spillovers and a firm's own R&D investment affect the innovation choice between new product creation (innovation) or imitation.

To test this relationship, we use the novel dataset created by matching the UK Innovation Survey (UKIS), the Annual Business Registry and the Business Enterprise Research and Development Survey during 2002–2014 (19,510 observations for 15,430 firms located in 80 industries and 175 Geo regions). Finally, to verify the robustness of our results, we offer several alternative robustness checks.

This study contributes to the regional innovation and industrial change literature in two important ways. First, we extend the discussion on channels of Marshall (1920), Jacobs (1970), and Porter (1990) externalities by theoretically debating and empirically testing how the extent of the localized intra- and inter-industry spillovers change a firm's propensity to innovate and imitate depending on the firm's own R&D investment.

Second, we put a firm's own investment in R&D and knowledge spillovers to a competitive test, connecting the choice for R&D and availability of knowledge spillovers to a decision on what type of innovation to undertake—imitation or innovation. In doing so, we explain the shape of the relationship between intra- and inter-industry knowledge spillovers and two innovation types, emanating from the positive knowledge transfer effect (Marshall, 1920; Roper *et al.*, 2013, 2017), the negative (competition) effect (Porter, 1990; Bloom *et al.*, 2013; Giarratana and Mariani,

2014; Qian, 2014), and the transaction cost effect (Mansfield *et al.*, 1981; Alexy *et al.*, 2013; Audretsch and Belitski, 2020b).

Our findings suggest that firms should carefully consider whether they will innovate or imitate, as the outcome will depend on the level of knowledge spillover (high–low), investment in internal R&D and other knowledge, and the type of knowledge spillover (intra- or inter-industry). By considering this complex relationship, we found that a firm’s absorptive capacity (Munari *et al.*, 2012; Enkel and Heil, 2014) will positively moderate the knowledge spillover of innovation at first, but once a certain threshold is reached, the positive relationship between knowledge spillovers and firm innovation becomes negative. While spillovers initially have an overwhelmingly positive effect on innovation, we also found that a continuous increase in the availability of knowledge spillover as an externality may lead to uncontrolled knowledge flows (Teece, 1986), and further reduction in benefits from spillovers, as under high knowledge spillovers, no firm has an incentive to further invest in R&D or increase innovation. The effects are strong for both imitation and innovation. We find an inverted U-shaped relationship for the knowledge spillover innovation and empirically demonstrate that high levels of spillovers disincentivize R&D investment. We also find a similar effect for imitation propensity and explain why R&D investors and non-R&D investors converge in their propensity to innovate and imitate at the highest levels of spillovers.

Another important finding from this study is that the localized intra- and inter-industry spillovers may be driven by exogenous factors. However their effectiveness for a firm’s innovation is related to the firm’s own R&D intensity.

The remainder of the paper is set out as follows. The next section outlines the theoretical framework and formulates the main research hypotheses. Section 3 describes the data and sample, while offers an identification strategy. Section 5 describes our major empirical findings, while provides a series of robustness checks. Section 7 discusses our findings and offers policy implications, and concludes.

2. Conceptual framework

2.1 Three approaches to knowledge externalities

While there is wide agreement on the importance of knowledge externalities for innovation performance (Audretsch and Feldman, 1996; Coad *et al.*, 2016), the way in which such knowledge spills over is a controversial point. The literature on industrial and regional economics distinguishes three theoretical approaches to understanding how knowledge spills over. The first is the Marshall–Arrow–Romer (MAR) approach (Marshall, 1920; Arrow, 1962; Romer, 1986), which suggests that knowledge spillovers are more relevant and stronger for firms within the same industry (intra-industry spillovers) and region. The most relevant approach for our research question is Marshall’s (1920) view on localization economies, which implies that firms located in agglomerated regions that produce similar goods in the same industry enjoy easier knowledge transfers and skilled labor pooling. Consistent with this approach, other studies have pointed out that high intra-industry spillovers may constrain the innovation efforts of the best-performing firms, who might perceive spillovers to increase unintended knowledge outflows (Cassiman and Veugelers, 2002; Arora and Gambardella, 2010). Knowledge is usually organization- and people-embodied and consists of tacit elements that make it spatially clustered and persistent (Dosi and Tranchero, 2021).

A second approach is associated with the work of Jacobs (1970), who argued that knowledge arising from a variety of geographically proximate industries promotes innovation and productivity in the region. Most recently, Caragliu *et al.* (2016: 93) described agglomeration externalities in regions that are the focal points of innovation, “the place where co-locating firms enjoy the presence of other creative companies, active in different industries and cross-fertilizing ideas through formal and informal exchange[s] of information.”

The first and second approaches to knowledge spillovers agree on the relevance of knowledge localization and physical proximity between firms (Audretsch and Feldman, 1996; Rosenthal and Strange, 2003; Beaudry and Schiffauerova, 2009; Buzard and Carlino, 2013; Carlino and Kerr, 2015). Physical proximity is also relevant as a competition-enhancing factor.

In this regard, the third approach (Porter, 1990, 1998) argues that knowledge spillovers in specialized, geographically concentrated industries stimulate growth. It thus agrees with the MAR externalities while also stating that competition externalities promote growth and supporting Jacobs (1970). In this view, Porter's (1990) work focuses on the effects of intense competition on firm efficiency. The main root of competitive advantage is identified in this case as the continuous improvements in efficiency caused by the specialization of the market, where many firms manufacturing similar goods and concentrated in a region are competing (Porter externalities). Caragliu *et al.* (2016) found some slight (although highly significant) evidence of negative Porter externalities: regions characterized by lower degrees of competition, which tend to perform better than more diversified areas. The authors explain this by the decrease in the physical distance between competitors, which implies that competition increases as firms become physically and technologically closer while rents decline. The fear of knowledge outflows might overshadow the benefits of openness (Giarratana and Mariani, 2014) as the likelihood of losses from the imitation capabilities of competing firms increases.

The major debate in all three approaches focuses on the mechanisms of knowledge spillover and their ability to enhance firm productivity and innovation (Griliches, 1992; Kugler, 2006; Hall *et al.*, 2013). These mechanisms may include observation of the actions and behavior of competitors, reverse engineering, labor mobility, inter-personal networks, trade publications and professional associations, supply chain interactions, and the codification of knowledge (Maliranta *et al.*, 2009). For example, an increase in a firm's R&D intensity will enable the company to gain access to and assimilate complex external knowledge (Denicolai *et al.*, 2014, 2016).

The heterogeneous effects of external knowledge can be predicted by the source of external knowledge, including "free inputs" via spillover and knowledge collaboration with various economic agents. This differentiation is of particular interest, and it is important to distinguish between the sources of external knowledge such as knowledge spillovers and knowledge from competitors, customers, suppliers and research institutions via direct collaboration (Audretsch *et al.*, 2021).

2.2 Knowledge spillovers and new-to-market product development

Economic activity has long been concentrated within clusters because of the three types of externalities. Power and Lundmark (2004) demonstrated that the clusterization of knowledge yields an increasing mobility of ideas exchange and returns to scale. This was also supported by Carlino and Kerr (2015), who demonstrated that innovation activity is spatially concentrated. For all industries, the localization effects of being near similar businesses decay rapidly with distance within cities—"the positive localization effect from being within one mile of another company in one's own industry is at least 10 times greater than the positive effect realized when locating two to five miles away" (Carlino and Kerr, 2015: 363). This effect is consistent for the manufacturing, software and fabricated metal and machinery industries (Rosenthal and Strange, 2003). While research on the geographical concentration of complementary firms is often called "old wine in new bottles," a more recent concept of innovation ecosystems (Breschi and Lissoni, 2001) and open innovation (Tucci *et al.*, 2016; Heaton *et al.*, 2019) has also confirmed that firm's co-location matters.

Current research on the relationship between knowledge externalities and firm's innovation is divided into two main strands.

Firstly, a more critical approach builds on the open innovation literature and the attempts to better understand the conditions under which localized knowledge is most effective and focused on strategies for searching and sourcing external knowledge (Giarratana and Mariani, 2014; Denicolai *et al.*, 2016). While the field has grown significantly since the work of Chesbrough (2006), relatively few studies have examined the conditions needed for knowledge spillovers to facilitate firm innovation. Drawing on Marshall (1920) and Jacobs (1970) externalities, Robertson *et al.* (2012) argue that the emerging literature on open innovation (Chesbrough, 2006) has failed to adequately acknowledge the challenges involved in applying external knowledge. Firms with the capacities of collecting, sorting and analyzing knowledge from both internal and external sources could ensure that new technology is suitable for the firm's own purposes

and to ensure external technology can be used in existing processes and products. The critical conceptual distinction in the open innovation literature proposes that knowledge spillovers under firm's own R&D investment can be transformed into inflows of knowledge.

The second approach builds on the regional innovation literature and examines the impact of Marshallian, Jacobean and Porter externalities on firm innovation. This method has the closest connection to the knowledge spillover literature (Audretsch and Feldman, 1996; Glaeser, 1999; Maliranta *et al.*, 2009; Carlino and Kerr, 2015). The work of Boschma (2005) introduced evolutionary economic geography by claiming that while geographical proximity per se is neither a necessary nor sufficient condition for learning to take place, it does facilitate interactive learning, most likely by strengthening the other dimensions of proximity, such as technological proximity. While the regional innovation literature considers the role of specialization and diversification spillovers for firms as “Manna from Heaven” (Audretsch and Keilbach, 2007)—a God's eye policy view of creating economic growth (Boschma, 2005)—they are a “mixed bag” for specific firms within the innovation ecosystem (Dahlander and Gann, 2010; West *et al.*, 2014).

The open innovation literature makes further arguments (Roper *et al.*, 2017) regarding the market “stealing” effect of competition. The authors argue that firms co-located in areas with their innovation partners and competitors may lose out if other firms can observe and source original knowledge and therefore find it cheaper and easier to create new products. This suggests the potential for negative (competition) externalities in regions where specialization spillovers are high, which might therefore make it difficult for a focal firm to increase its investment in R&D (Tucci *et al.*, 2016) due to the essentially unmanageable nature of spillovers and their incomplete excludability (Kugler, 2006).

Both positive knowledge transfers (Marshall, 1920; Jacobs, 1970) and the negative (competition) effects (Bloom *et al.*, 2013) of knowledge localization are based on the assumption that knowledge that has been made available in the industry may be used by other firms within the industry if they have the absorptive capacity. The positive and negative effects emanating from localized competition and knowledge externalities are thus conditional on a firm's absorptive capacity (Cohen and Levinthal, 1990) and the degree of competition and imitation capabilities between innovators within the industry (Giarratana and Mariani, 2014). As Roper *et al.* (2017: 46) write, “The negative competition effects of openness might be even greater in the case of knowledge spillovers” than knowledge collaboration.

On the one hand, knowledge spillovers encourage increasing specialization by allowing firms to reduce the cost of experimentation (Boschma, 2005). If they decide to innovate, firms can externally source the resources they require to innovate (Carlino and Kerr, 2015). More timely access to industry-relevant knowledge spillovers and investment in internal R&D is associated with an increase in new product creation and the ability to introduce new-to-market products first. On the other hand, as the competition effect increases and more firms take risks and invest in R&D internally, the spatial concentration of intra-industry spillovers increases. It then becomes more difficult for firms to manage knowledge inflows and outflows (Roper *et al.*, 2017), and internal investment in R&D can be easily dissipated within the industry and become common knowledge (Alexy *et al.*, 2013; Denicolai *et al.*, 2016).

Combining the positive effects of localized knowledge spillovers with the negative competition effects within industries (Battke *et al.*, 2016), we hypothesize with regard to both the positive and negative slopes of the relationship between intra-industry (specialization) spillovers and firm innovation:

H1a: There is an inverted U-shape relationship between intra-industry knowledge spillovers and innovation (positive knowledge transfer and negative competition effects) conditional on a firm's own investment in R&D.

Enkel and Heil (2014) make the important distinction between a firm's ability to identify and value “distant” knowledge on the one hand and its knowledge base on the other. Griliches (1992) found that using “distant” knowledge is an effective way to produce innovative new products that are different from competitors, maximizing the positive effects of knowledge externalities and minimizing negative competition effects (Giarratana and Mariani, 2014; Qian, 2014).

Building on the open innovation literature that indicates inter-industry spillovers decrease per-unit costs (Bernstein, 1988) through the cross-fertilization of knowledge among value chain participants, we outline three mechanisms through which inter-industry spillovers will increase firm innovation.

Firstly, inter-industry spillovers are characterized by knowledge complementarity, faster integration (Lafontaine and Slade, 2007), and a locus of coherent knowledge combinations (Foros, 2004). Knowledge from technologically distant sectors creates a greater knowledge pool that results in more radical ideas and increasingly novel combinations of knowledge for the industry (Gilsing *et al.*, 2008; Cappelli *et al.*, 2014).

Secondly, inter-industry spillovers do not trigger negative competition effects as firms do not compete for the same customers. On the contrary, inter-industry knowledge brings technological interdependencies and learning externalities for firms (Dosi and Tranchero, 2021).

Thirdly, inter-industry spillovers offer tried-and-tested knowledge related to inputs and can be readily integrated into existing products with a degree of novelty to an industry, increasing the speed of new product development. Although firms may be more selective when collaborating between industries, on average they form knowledge combinations and matches more quickly. While the mechanisms and returns to knowledge spillovers remain more uncertain between industries than within an industry, direct interactions between workers (Carlino and Kerr, 2015) as well as intermediate supply and demand for inputs between different industries (Giovannetti and Piga, 2017) enhance inter-industry knowledge spillovers. As with specialization spillovers, firm investment in R&D is important to access, recognize, and experiment with new knowledge combinations that are unfamiliar to an industry (Gesing *et al.*, 2015; Denicolai *et al.*, 2016). Firms need to be able to recognize a set of design possibilities and engage with users of innovation if they wish to begin innovating (Baldwin *et al.*, 2006; Pisano and Teece, 2007).

Transaction cost theory can be used to outline the limitations of inter-industry knowledge spillovers, which may have a negative effect on firm innovation. Recent research by Audretsch and Belitski (2020b) and Saura *et al.* (2022) theorizes that there are greater limits to open innovation between industries and across different knowledge-intensive sectors. As new inter-industry knowledge combinations are often unfamiliar (cognitively and technologically distant), firm partners will incur coordination costs when monitoring, controlling, and managing knowledge spillovers (Camacho, 1991). Transaction cost theory can be employed by assuming that the open innovation management structures between firms and industries have to be applied that best fit a particular knowledge spillover mechanism. Due to differences in absorptive capacity across firms, there is an additional cost of monitoring, controlling, and managing knowledge spillovers, and the cost increases with the heterogeneity between industries (Vural *et al.*, 2013). Inter-industry differences in knowledge creation, coding, and transfer will thus lead to differences in transaction costs between firms with different levels of absorptive capacity. Transaction costs limit the use of absorptive capacity in the recognition and appropriation of inter-industry knowledge spillovers. The transaction costs of knowledge transfers are likely to be higher for firms with higher absorptive capacities (Kobarg *et al.*, 2019; Audretsch and Belitski, 2022) leading to diminishing returns from knowledge spillovers. We therefore hypothesize:

H1b: There is an inverted U-shape relationship between inter-industry knowledge spillovers and innovation (positive knowledge transfer and negative transaction cost effects) conditional on a firm's own investment in R&D.

2.3 Knowledge spillovers and new to firm product development

Interactive knowledge collaborations, such as R&D partnerships, network linkages, or other knowledge transfer agreements (West and Bogers, 2014), as well as knowledge spillovers, help firms to develop new-to-the-world knowledge (Roper *et al.*, 2017). However, they may increase a set of innovation risks, for example, by increasing intra-industry competition for new knowledge (Battke *et al.*, 2016), raising commercial, technology, managerial, and imitation risks (Astebro and Michela, 2005; Giarratana and Mariani, 2014) as well as transaction costs when new knowledge is unfamiliar and complex (Audretsch and Belitski, 2022). In order to reduce innovation risks, a firm may choose to reduce or even stop its R&D investment instead of creating a product

that is new to the firm but already exists in the market (imitation). Although it is well known that knowledge spillovers both stimulate innovation and induce imitation (Cappelli *et al.*, 2014), research into this has been scarce. Some studies have argued that a firm's ability to create such products relates to the incremental improvement of existing products, processes, technologies, organizational structures, and methods and requires less radical knowledge, which can be directly implemented via spillovers within and between industries (Breschi and Lissoni, 2001; Forés and Camisón, 2016). In doing so, a firm adopts intra- and inter-industry knowledge spillovers to exploit its existing market position via imitation (Glückler, 2013; Cappelli *et al.*, 2014). If a firm is unable or unwilling to invest in internal R&D, the firm could adopt imitation as its innovation strategy because using knowledge developed by others via spillovers will naturally be cheaper than investing in own R&D. As a consequence, firms with little or no R&D investment see imitation as a mechanism of lowering knowledge and other transaction costs in order to outcompete rivals. Prior research has argued that a reduction in R&D combined with an increasing availability of knowledge spillovers will positively affect the incentives to imitate (Cappelli *et al.*, 2014).

However, there will be an essential challenge for firms who decide to use knowledge spillovers for imitation: while imitation is cheaper than performing own R&D, it is not costless (Mansfield *et al.*, 1981). As a consequence, the potential imitator firm will have lower overall costs when creating new products, and it may still incur significant costs developing the capabilities to recognize and imitate existing knowledge. This is particularly sensitive between industries where technological and cognitive proximity to knowledge is low (Nooteboom *et al.*, 2007; Balland *et al.*, 2015). As the level of knowledge spillover increases, more competences, costs, and time are required to access and engage with external knowledge, pushing a firm to consider an investment in R&D to recognize knowledge spillovers. An increase in the availability of knowledge spillovers with the diversity and complexity of knowledge will create a demand for more R&D investment and will increase the costs of accessing and processing knowledge (Mansfield *et al.*, 1981), affecting the initial incentive to use "free" external knowledge for imitation. This knowledge spillover-imitation dilemma will lead to an emergence of two groups of firms. The first group includes firms who are "pushed" into R&D investment to recognize and use external knowledge, leading to new knowledge combinations (Antonelli and Colombelli, 2017) and reducing the likelihood of imitation. The second group of firms will find performing internal R&D costly and unaffordable, and their engagement with knowledge spillovers will be limited due to the increasing transaction costs of knowledge sourcing (Mansfield *et al.*, 1981; Saura *et al.*, 2022). The higher the level of spillovers, the higher the opportunity costs of engagement with spillovers. Firms with a paucity of internal knowledge will not be willing to pursue spillovers due to a cost to recognize, access, modify, process, or implement new knowledge (Camacho, 1991; Kobarg *et al.*, 2019). However when knowledge spillover is a commonplace, the uniqueness and value of knowledge is dissipated, again affecting the willingness of the second group of firms to engage with knowledge spillovers. The spillover-imitation dilemma can be illustrated diagrammatically as a flat line in a relationship between knowledge spillovers and imitation.

Whatever the level of knowledge spillovers, firms who invest in R&D are reluctant to imitate other firms' products as it is able to enter the market before competitors.

When knowledge spillovers are low, firms who do not invest in R&D will be unable to access and use spillovers due to an increased cost of accessing spillovers. When the level of spillovers is high, information becomes common knowledge and firms who do and do not invest in R&D will not be willing to engage with spillovers for imitation due to a limited return to knowledge spillovers. All firms will be able to access spillovers, whether they invest in R&D or not (Audretsch and Keilbach, 2007); however, only R&D active firms will be able to make the most sense of the knowledge and be able to sufficiently modify it to avoid imitation and innovate new products. We thus expect that firms who invest in internal R&D are less likely to imitate as spillovers spread knowledge because their absorptive capacity allows them to recombine and engineer knowledge in order to create new-to-market products.

We hypothesize:

H2: Firm's own investment in R&D reduces the propensity of imitation at any level of intra- and inter-industry knowledge spillovers.

3. Data and sample

We tested our hypotheses using three datasets—the Business Registry (BSD), the Business Expenditure on Research and Development (BERD), and the UKIS (Office for National Statistics, 2017, 2018, 2019). Firstly, we collected and matched six cross-sectional biannual UKIS surveys during 2002–2014 conducted by the Office of National Statistics (ONS) in the UK. The UKIS includes direct measures of innovation inputs and outputs, influencing barriers to innovation, measurements on human capital, partner types, training activities, partner locations, collaboration networks, and other information related to our hypotheses.

Secondly, we used BSD and BERD data for the years 2002, 2004, 2006, 2008, 2010, and 2012. The data were matched to a correspondent UKIS survey wave for the initial year of the period. While we understand that UKIS surveys are conducted in the middle year of each wave (e.g. the 2002–2004 survey was done in 2003), we match BSD and BERD data to the first year of the period to enforce a causality. Data on firm's own R&D were also matched from the BERD survey following a similar 1-year lag procedure. The match rate between BSD and UKIS by firm indicator—year during 2002–2014—is 96.5% and the match rate for firm's R&D expenditure from BERD to UKIS is 76.4%, while the BERD-UKIS match for R&D spillovers is 100% as it was done by borough using data on 2-letter UK postcodes for Geo regions in both datasets (e.g. OX, CB, M, LB, LE, and RG).

Several firm-specific variables were taken from the BSD: firm age and ownership, employment, industry code, and location by postcode. Spillover mechanisms, such as R&D spent by borough and industry (SIC¹ 2-digit code), were calculated using BERD data on all available R&D expenditure and matched to the BSD-UKIS dataset. Calculation of knowledge spillovers following Rosenthal and Strange (2001) was carried out in our study at the level of UK boroughs as indicated via the two-letter postcodes. This allowed us to exploit patterns of industry co-location (Ellison *et al.*, 2010).

Although there are six cross-sectional surveys covering 10 years of data, we work with a sample of 19,510 observations across 15,430 firms with non-missing values for innovation outputs and our main explanatory and control variables. There is a small panel element of 1651 firms in a sample, which was observed at least twice over 2002–2014. To be included in a sample, all questions related to the variables of interest needed to be completed with no missing values. The BSD is essentially a population of all UK firms. For the list of variables included in this study and their definitions and sources, please refer to Table 1.

Our final sample includes 80 industries by 2-digit SIC 2007 across 175 Geo regions, which were used to calculate spillovers. For the distribution of firms across estimated and population samples with regard to regions and firm size within six survey years, please see Table 2A–2B.

4. Identification strategy

4.1 Dependent variable

Following in the footsteps of innovation researchers (Klingebiel and Rammer, 2014), we use two dependent variables to measure:

- i) firm propensity to introduce a new good or service to the market before their competitors can do so (product innovation), which can also be viewed as the “prime mover” of innovation (Dosi, 1982);
- ii) firm propensity to introduce a new good or service that was essentially the same as a good or service already available from competitors—imitation (Cappelli *et al.*, 2014).

1 Standard Industrial Classification.

Table 1. Descriptive statistics

Variable (source)	Definition	Mean	St.dev.
Product innovation (UKIS)	This business introduced a new good or service to the market before competitors = 1, zero otherwise. This variable can also be used to predict first mover advantage	0.50	0.51
Imitation (UKIS)	This business introduced a new good or service that was essentially the same as a good or service already available from competitors = 1, zero otherwise	0.63	0.48
Age (BSD)	Age of a firm (years since the establishment)	17.85	9.71
Employment (BSD)	Number of full-time employees, in logarithms	4.00	1.48
Exporter (UKIS)	Binary variable = 1 if a firm sells its products in foreign markets, 0 otherwise	0.35	0.48
Human capital (UKIS)	Percentage of full-time employees that received degree (BA/BSc, MA/PhD, PGCE, and above) in science or engineering subjects	7.87	17.82
Foreign (BSD)	Binary variable = 1 if firm is foreign-owned (headquarter abroad), zero otherwise	0.44	0.49
Survival (BSD)	Binary variable = 1 if a firm survived as an independent unit or as a part of a group until year 2017, 0 otherwise	0.58	0.49
Software (UKIS)	The amount of expenditure for purchasing advanced machinery, equipment, and software (000s) to total sales (000s pound sterling)	0.01	0.04
R&D intensity (BERD)	The amount of expenditure for internal Research and Development (000s), to total sales (000s pound sterling)	0.01	0.05
R&D intensity predicted (BERD)	Predicted values of R&D intensity $\widehat{\varphi}_{it}$ using Tobit estimation and exclusion criteria	-0.05	0.04
Predicted R&D i (BERD)	Binary variable = 1 if R&D intensity predicted is positive (fourth quartile, $\widehat{\varphi}_{it} > 0$), zero otherwise (1th–3 rd quartile)	0.13	0.34
Intra-industry knowledge spillover (BERD)	Intra-industry knowledge spillover by 2-digit SIC and 175 Geo regions calculated using R&D expenditure in £000s within firm sector at 2-digit SIC (excluding firm's expenditure) in the Geo region where a firm is located	0.16	0.22
Inter-industry knowledge spillover (BERD)	Inter-industry knowledge spillover by 2-digit SIC and 175 Geo regions calculated using R&D expenditure in £000s outside firm sector at the 2-digit SIC level in the Geo region where a firm is located	0.15	0.13
Intra-industry knowledge spillover standardized	Standardized around the mean values of intra-industry knowledge spillover by 2-digit SIC and 175 Geo regions	-0.12	0.84
Inter-industry knowledge spillover standardized	Standardized the mean values of inter-industry knowledge spillover by 2-digit SIC and 175 Geo regions	-0.09	0.95
Suppliers intensity	How important to business's innovation activities (from zero—not important to 3—highly important) was the extent of the interactions between the focal firm and its suppliers of equipment, materials, services or software	1.44	1.10
Customers intensity	How important to business's innovation activities (from zero—not important to 3—highly important) was the extent of the interactions between the focal firm and its clients or customers	1.68	1.20

(continued)

Table 1. (Continued)

Variable (source)	Definition	Mean	St.dev.
Coopetition intensity	How important to business's innovation activities (from zero—not important and not used to 1—low, 2—medium, and 3—highly important) was the extent of the interactions between the focal firm and its competitors in the industry	1.23	1.05
Consultants intensity	How important to business's innovation activities (from zero—not important to 3—highly important) was the extent of the interactions between the focal firm and consultants, commercial labs or private R&D institutes	0.67	0.87
University intensity	How important to business's innovation activities (from zero—not important to 3—highly important) was the extent of the interactions between the focal firm and universities or other higher education institutes	0.42	0.74
Government intensity	How Important to business's innovation activities (from zero—not important to 3—highly important) was the extent of the interactions between the focal firm and government or public research institutes	0.43	0.73
Exclusion restrictions used in selection equation (Heckman, 1979)			
Industry-region scientists	Inter-industry scientist by 3 digits SIC and 175 Geo regions is calculated using BERD data on the number of researchers employed by each firm. We summed up researchers employed by firms at 3 digits SIC and 175 Geo regions excluding firm's own full-time employees with BA/BSc, MA/PhD, PGCE, and above in science or engineering subjects. We used logarithmic transformation of the variable. The variable was matched to UKIS data by 3-digit SIC and 175 Geo.	4.07	1.99

Number of observations: 19,510. Source: [Office for National Statistics \(2017, 2018, 2019\)](#).

The mean of the product innovation is 0.50 with a standard deviation of 0.51, which means that half the firms in the sample introduced new-to-market innovations before their competitors. The mean of the imitation is 0.63 with a standard deviation of 0.48, which means that 63% of firms in the sample were able to create a product which already existed in the market but which was new to the firm (see [Table 1](#)). Although not without imperfections, such survey-based measures are generally better suited to measure firms' new product development than patent- or innovation sales-based indicators ([Leiponen and Helfat, 2010](#); [Gesing et al., 2015](#)). These variables are appealing to competition tensions in the market and in clusters, where knowledge spillovers intensify market competition in addition to bringing novel knowledge. We can also see that the share of firms who report innovation (imitation) behavior is considerably higher than the share of firms that report sales of new-to-market products.

By using these variables, we moved away from emphasizing innovation intensity as the share of new products in total sales. This is because these figures can be significantly skewed by large and established firms, who have very few innovation sales as a share of their total sales, while the share of new-to-market product sales is high for young and micro-firms. Our definition of product innovation includes both goods and services and is therefore applicable to both the manufacturing and service sectors. Product innovation and imitation are not mutually exclusive, with firms engaging in both types of innovation and developing products that are both new to the firm and the market ([Forés and Camisón, 2016](#)). Firms report zero innovation in cases where no innovation projects were undertaken or completed within the 3-year period for one of the following reasons:

Table 2. A: Sample distribution by twelve ONS regions and survey waves. B: Sample distribution by firm size and survey waves

Description	Sample of the regressions						Total
	2005	2007	2009	2011	2013	2015	
A							
North East	830	93	85	61	<20	17	
North West	1341	129	117	174	32	23	
Yorkshire and The Humber	1179	110	133	126	<20	17	
East Midlands	1178	145	121	121	<20	23	
West Midlands	1285	146	122	143	21	19	
Eastern	1252	143	128	159	25	34	
London	1401	104	111	170	36	32	
South East	1543	162	157	203	48	45	
South West	1196	127	141	128	27	18	
Wales	975	106	97	74	<20	19	
Scotland	1115	116	122	104	<20	38	
Northern Ireland	1215	84	90	73	<20	22	
Total							19,510
B							
Micro and small 1–49	6380	513	558	912	184	178	
Medium 50–249	4098	362	389	404	61	105	
Large >249	4032	590	477	220	23	24	
Total							19,510

Office for National Statistics (2017, 2018, 2019).

the project was abandoned or seriously suspended; the project was seriously delayed with respect to initial planning; and the project required more than 3 years to be completed.

4.2 Explanatory variables

We followed [Jaffe \(1986\)](#), [Knott *et al.* \(2009\)](#), [Cassiman and Veugelers \(2002\)](#), and [Keller \(2002\)](#) in operationalizing *specialization (intra-industry) and diversification (inter-industry) spillovers* using the flow of knowledge from R&D expenditure by other firms as a mechanism of innovation using BERD data. These actions can enhance the development of new and improved goods, services, and processes as well as other creative work undertaken within businesses. Spillovers are industry-specific and we use a 2-digit SIC classification and 2-letter postcode for boroughs. Specialization spillovers include the within-industry “spillover pool” (other firms’ in-house R&D expenditure and external R&D expenditures of public or private research organizations within the same 2-digit SIC code). While calculating specialization spillovers, it is important to exclude the firm’s own R&D expenditure in order to avoid double-counting the firm’s own R&D expenditure in the industry.

We assume that all firms benefit from R&D expenditure by other firms in the industry within a region and thus weight all firms equally within the same 2-digit SIC code. However, trade flows within a sector may vary in intensity, and so we also use a weight that captures the extent by which sector i buys its inputs and sells its outputs (in terms of goods/services) within its own sector. The specialization spillover is calculated as

$$S_{ir} = w_{ii} (R_{ir} - R_f) / (R_{i_country}) \quad (1)$$

where subscript i indicates the origin of the spillover (e.g. a firm or an industry); R is a measure of knowledge stock usually proxied by R&D expenditure for each industry; and w_{ii} is an intra-industry weight. As far as distance measures are concerned, some authors use the same weight for firms inside the same space (industry or region). This implies $w_{ii} = 1$; R_f is the firm’s own expenditure on R&D; R_{ir} is the R&D expenditure in industry i and region r (by 2-letter postcode

equivalent to 175 Geo regions in the UK); and $R_{i_country}$ is the country R&D expenditure for industry i .

Our measure of diversification (inter-industry) spillovers assumes that a firm's benefit in industry i from other firms' innovation efforts in industries j is inversely related to its technological distance (Jaffe, 1986; Griliches, 1992) and that the magnitude of the externality depends on the intensity of trade flows between sectors j and i . To obtain a measure of trade intensity between sectors, we use data from the input–output matrix for the UK 2-digit and 3-digit SIC code sectors in the years 1999, 2002, 2004, 2006, 2008, and 2011.

Although diversification spillovers may vary significantly with respect to their contribution toward information exchange and innovation (Cappelli *et al.*, 2014), previous research has found that supply-driven spillovers affect long-run growth more than demand-side spillovers that cause short-run disturbances (Morrison Paul and Siegel, 1999). We assume that the intensity of firm i 's flow of vertical spillover corresponds to the weighted sum of the R&D expenditure in each industry i , where the weights are given by the share of purchases and sales of industry j from and to industry i , for $j \neq i$. Weights are derived from the Demand/Consumption tables (to capture the intermediate trade flows across sectors) prepared by the ONS and based on Keller (2002). I-O Tables describe the distribution of sales and purchases of interim inputs across all sectors for each industry. Weights for the diversification spillovers within the same region are used together.

$$S_{jr} = \sum_{j \neq i}^n w_{ij} (R_{jr} - R_{ir}) / (R_{j_country} - R_{i_country}) \quad (2)$$

where subscript j indicates the origin of spillover (e.g. a firm or another industry different from i); j varies from 1 to n , where n is the number of sectors. R is a measure of knowledge stock usually proxied by R&D expenditure for each industry (Bloom *et al.*, 2013); and w_{ij} is an inter-industry weight proportional to the inter-industry intermediate consumption (trade flows), which is derived from input–output matrix coefficients. R_{jr} —R&D expenditure in industry j in a region r (by 2-letter postcode equivalent to 175 Geo regions in the UK); R_{ir} —R&D expenditure in industry i in region r . $R_{j_country}$ —country R&D expenditure in industry j ; and $R_{i_country}$ —country R&D expenditure in industry i .

The matrix of weights represents the trade proximity between firm i and the source of externalities j in the other sector. Keller (2002) and Giovanetti and Piga's (2017) approach assumes that the more that industry i buys from and sells to industry j , the more it benefits from the knowledge embedded in the inputs and outputs as well as through cooperation between firm i and firm j , thinking which originated with Jaffe (1986). Specialization and diversification spillovers are normalized by the total amount of R&D expenditure in the economy for the reference years 1999, 2002, 2004, 2006, 2008, and 2011.

Our third explanatory variable is a firm's R&D intensity as a proxy for absorptive capacity (Cohen and Levinthal, 1990; Griffith *et al.*, 2003) calculated as internal R&D expenditure to sales. We assume a zero-depreciation rate for R&D so that the accumulation dynamics equal current expenditures (Griliches and Lichtenberg, 1984). We build on a two-stage Heckman (1979) type procedure to calculate the predicted values of R&D intensity at a firm level using the exclusion restriction—industry-region scientists variable described below in detail. We then create the binary variable “predicted R&D” which equals one if predicted R&D intensity is positive (fourth quartile), zero otherwise (1st–3rd quartile), to be used in the model. Each firm's R&D data and industry-region data on employment of researchers was matched from the BERD to UKIS with a 1-year lag using firm identifier for the industry-region.

5. Control variables

Several control variables were included in order to avoid the endogeneity and omitted variable bias problems.

Firm employment is proxied by the logarithm of full-time employment (Colombelli *et al.*, 2013) and firm age in years was also included (Haltiwanger *et al.*, 2013). Acs *et al.* (1994b) discuss the differences between larger and smaller firms in appropriation of knowledge externalities,

indicating the importance of firm size in this relationship. We use a binary variable, taking a value of 1 if the firm exports products and services and zero otherwise. Drawing on [Sun et al. \(2020\)](#), who researched the role of human capital for innovation, we measure human capital as the proportion of employees holding a degree or higher qualification (e.g. BA/BSc, MA/PhD, PGCE, and above) in science or engineering subjects. We follow [Guadalupe et al. \(2012\)](#) who studied the effect of foreign ownership on innovation and measure foreign ownership as a binary variable taking a value of 1 if the firm has a headquarters abroad (outside the UK, Isle of Man, Channel Islands), zero otherwise.

Firms use both non-interactive (knowledge spillovers) as well as active knowledge search strategies ([Glückler, 2013](#)) that involve purposeful decisions on whether or not to engage in knowledge collaboration ([Knockaert et al., 2014](#)) and with what type of external partners ([Van Beers and Zand, 2014](#); [Audretsch et al., 2021](#)). The extent to which a firm is expected to benefit from external knowledge collaboration may depend on market size, customer demands, complexity of products ([von Hippel, 1988](#); [Tether, 2002](#)), and available resources ([Leiponen and Helfat, 2010](#)). Knowledge collaboration is an important channel of knowledge transfer, and we included six controls for collaboration intensity across six main types of collaboration partner—suppliers, customers, consultants, competitors, universities, and government ([Kessler and Chakrabarti, 1996](#); [Cassiman and Veugelers, 2002](#)). We take values of 1 if the effectiveness of knowledge collaboration is low, 2 if medium, and 3 if high, zero otherwise. We do not include external collaboration within the enterprise group.

In addition, firms benefit from investment in software and technology for innovation ([Hall et al., 2013](#)). We included expenditure for purchasing advanced machinery, equipment, and software (in thousands) to total sales ratio as a measure of software and technology intensity. As we work with unbalanced panel data, we included a binary variable “survival,” which equals one if a firm survived until 2017 from BSD independently of the year of establishment, zero otherwise ([Colombelli et al., 2013](#)). In addition to our control variables, we used year of the innovation survey fixed effects (using 2002–2004 as a reference year), regional fixed effects (North East of England as a reference category), and industry (2-digit SIC 2007) fixed effects (using mining and agriculture as reference category).

6. Econometric model

Modeling the relationship between investment in internal R&D, knowledge spillovers, and firm innovation outcomes presents an interesting set of challenges, especially given the nature of the UKIS data available to us with significant cross-sectional elements. First, there is the issue of self-selection. We assume that firms that are developing new products or services decide whether to undertake R&D, and if they do, how much of the investment in R&D should be done, as a function of firm and industry characteristics. Second, there may be a reverse causality between innovation outcomes and investment in R&D, posing an endogeneity problem ([Ganotakis and Love, 2011](#); [Hall et al., 2013](#)).

The first issue can be treated using the Heckman-type model approach ([Heckman, 1979](#)). If the selection process is time constant, panel estimators are able to resolve this problem; however, in an unbalanced panel such as ours, this may not be the case. We apply the selection correction of the data following the [Heckman \(1979\)](#) procedure, starting with the first-stage selection equation and identifying the exclusion criteria to predict R&D intensity. The predicted values will be used in the second stage.

The reversed causality appears as firms may decide whether to invest in R&D conditional on the extent of innovation. In order to analyze the role that R&D intensity plays in innovation or imitation at the firm level, we correct for potential endogeneity using the exclusion criteria we applied in the first stage ([Heckman, 1979](#)), which serve as instruments for R&D intensity. Unlike the IV estimation, we do not replace R&D intensity in the second stage with the instrument; rather, we follow [Heckman's \(1979\)](#) procedure to predict R&D intensity using the exogenous exclusion criteria (ϱ_1) which is not correlated with the unobserved factors (u_i) from the second-stage model so that $\text{corr}(\varrho_{it}, u_{it}) = 0$ holds ([Wooldridge, 2009](#)).

7. First stage

Drawing on the Heckman (1979) procedure to correct sample selection bias related to R&D investment decision, we found an exclusion restriction to predict R&D in the first stage (Certo *et al.*, 2016).

Our literature review suggests that scholars typically conflate exclusion restrictions in Heckman models with instruments in two-stage least squares, as highlighted by Certo *et al.* (2016). First, Angrist (2001) defines exclusion restrictions as exogenous variables that predict whether or not an observation appears in a sample. Second, instruments differ from exclusion restrictions in that instruments substitute for the endogenous variable in a second-stage estimation. In contrast, we incorporate exclusion restrictions to compute the predicted values of R&D intensity $\widehat{\varphi}_i$ that is included in the second-stage estimation to predict innovation outcomes (Angrist, 2001; Bushway *et al.*, 2007).

Equation (3) describes whether a firm undertakes R&D, and if so then how much as a function of firm and industry characteristics. A firm must decide whether to do R&D and then choose the R&D investment intensity. The R&D intensity variable in the innovation equations was computed as the expected R&D intensity given the firm's characteristics.

$$R_{it} = \begin{cases} R_{it}^* = \beta x_{it} + \mu_{it} & \text{if } R\&D = 1 \\ 0 & \text{if } R\&D = 0 \end{cases} \quad (3)$$

where R_{it}^* is the unobserved latent variable corresponding to the firm's investment in R&D, and x_i is a set of determinants of the R&D (Rogers, 2004). We measure expenditure intensity as the R&D-to-sales ratio. We assume the error terms in equation (2) are bivariate normal with zero mean and constant variance.

The first-stage procedure is grounded in the idea that many firms do informal R&D but do not report their spending separately to the statistical agency performing the survey. The first stage of the model fills in their R&D values with what might have been expected given the firm's size and age as well as exogenous industry-regional distribution of full-time employees with university and above degrees in science and engineering.

The industry-region scientists variable, which we used as an exclusion criteria ϱ_1 in equation (3), was calculated using BERD data on the number of researchers employed by each firm. We summed up researchers employed by firms at 3-digit SIC and 175 Geo regions, excluding each firm's own full-time employees with BA/BSc, MA/PhD, PGCE, and above in science or engineering subjects. We used logarithmic transformation of the variable. Industry-region scientists influence the probability of reporting R&D investment and ability to perform R&D but do not influence the ultimate dependent variable (firm innovation and imitation).

There is no consensus regarding the assessment of the appropriateness of exclusion restrictions (Certo *et al.*, 2016). Ganotakis and Love (2011) suggest determining exclusion restrictions on the basis of theoretical rather than statistical grounds. Nevertheless, Bushway *et al.* (2007) proposed evaluating the strength of exclusion restrictions by examining the predicted and factual values of $\widehat{\varphi}_{it}$. When the exclusion restrictions are poor in a model (or do not exist at all), the predicted values $\widehat{\varphi}_{it}$ will correlate too highly with φ_{it} thus introducing multicollinearity problems in the second stage of the model.

We estimate eq. (3) using tobit, as our dependent variable is left censored with 65% of firms in our sample reporting nil investment in internal R&D. We also use probit to estimate the Heckman (1979) model first stage as a robustness check. The results of the first-stage selection equation are reported in Table 3.

Both spec. 1 (Tobit estimation) and spec. 2 (probit estimation) clearly show that exclusion restriction ϱ_1 strongly and positively predict the R&D intensity even after controlling for industry, time, and Geo region fixed effects. The distribution of original φ_{it} and predicted $\widehat{\varphi}_{it}$ values of R&D intensity is illustrated in Figure 1.

Table 3. Predicting the levels of R&D intensity using tobit and logistic regressions (odds ratios reported)

Specification	(1)	(2)
DV	R&D intensity	R&D intensity
Estimation method	Tobit	Logit (odds ratios)
Age	-0.010 ^{***} (0.00)	0.896 ^{***} (0.01)
Employment	0.001 (0.00)	1.112 [*] (0.01)
Industry-region scientists	0.010 ^{***} (0.00)	1.148 ^{***} (0.01)
Time fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Geo region fixed effects	Yes	Yes
Constant	-0.075 ^{***} (0.01)	-1.491 ^{***} (0.123)
Number of obs.	19 510	19,510
LR Chi square	3138.91	3131.83
Left censored	12 057	
Log-likelihood	2228.18	-11,532.11
Pseudo-R ²		0.14

Reference category for industry (mining) and year (2002–2004). Robust standard errors are in parenthesis. Significance level:

*P < 0.05;

**P < 0.01;

***P < 0.001. Source: Office for National Statistics (2017, 2018, 2019).

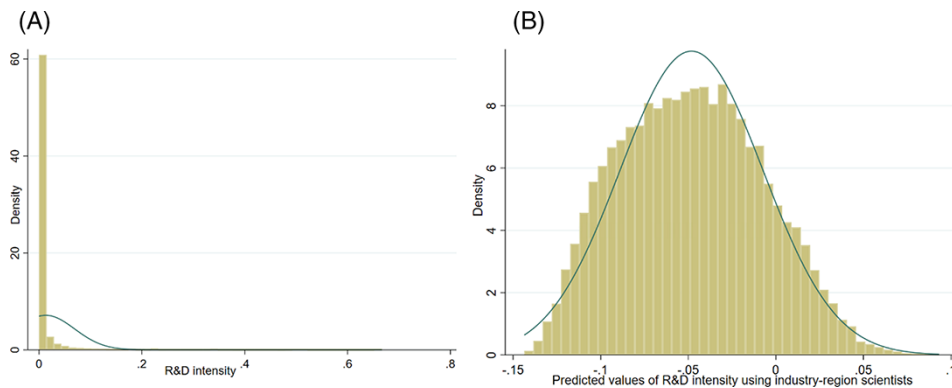


Figure 1. The distribution of original φ_{it} (left) and predicted $\widehat{\varphi}_{it}$ (right) values of R&D intensity predicted by applying the Heckman procedure first stage (1979)

8. Second stage

We are interested in estimating two models for new product creation (innovation) and new-to-firm products (imitation) using a multivariate logistic regression analysis (Wooldridge, 2009).

The second stage equation is

$$Prob(y_{it} = 1) = \beta_0 + \beta_i x_{it} + \lambda_1 S_{irt-1} + \lambda_2 S_{jrt-1} + \omega_r + \rho_j + a_t + u_{it} \tag{4}$$

Equation (4) is the logistic cumulative distribution function. S_{jrt-1} and S_{irt-1} are explanatory variables of intra- S_{ir} and inter-industry S_{jr} knowledge spillover in $t-1$ calculated by industry/region, while x_{it} is a vector of the firm’s characteristics, which includes the predicted values of R&D intensity $\widehat{\varphi}_{it}$ at time t for firm i , u_{it} is an error term for firm i at time t . S_{jrt-1} and S_{irt-1} are exogenous vectors and not correlated with u_{it} , while β_i may be correlated with u_{it} (Wooldridge, 2009: 517). Vectors ω_r, ρ_j, a_t are Geo region, industry, and time fixed effects.

In the first stage, we “purged” R&D intensity $\widehat{\varphi}_{it}$ of its correlation with u_{it} before estimating (4). As a measure of R&D intensity we use a binary variable “predicted R&D” which equals

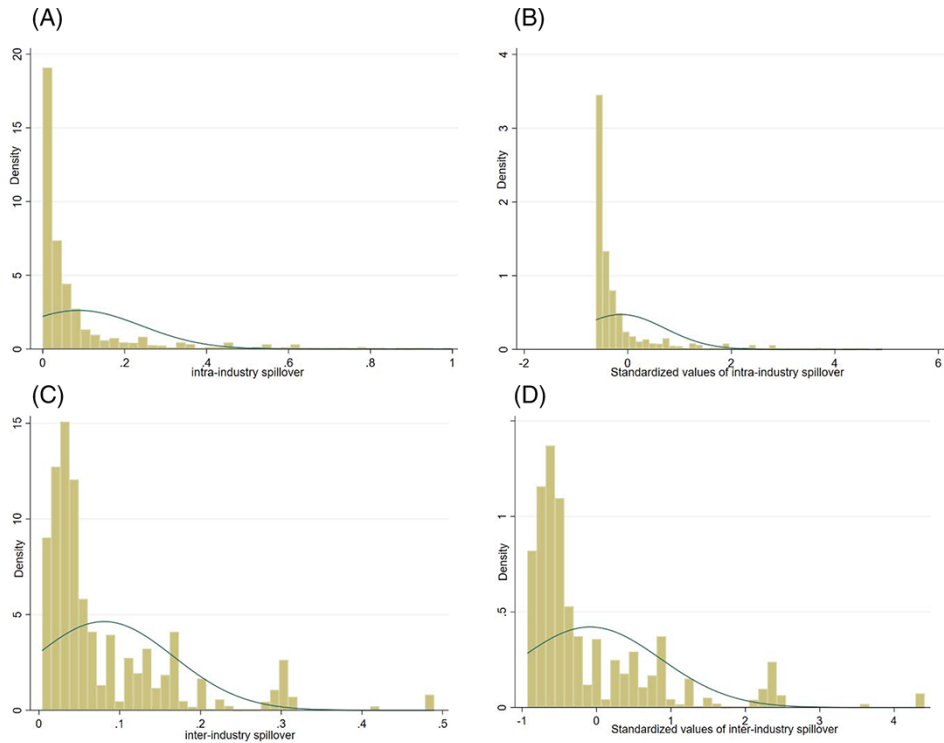


Figure 2. Non-standardized values of intra- and inter-industry knowledge spillovers (left) and standardized values used in the second-stage estimation (right)

one if $\widehat{\varphi}_{it} > 0$ (fourth quartile of predicted values of R&D intensity) from equation (3), zero otherwise.

We started exploring the multicollinearity of the variables by examining the variance inflation factors (VIFs) for all variables, finding each less than 5, while the VIFs for intra- and inter-industry knowledge spillovers are 9 and 11, respectively. To address it, we standardized the values of the intra- and inter-industry knowledge spillovers, enabling us to reduce the VIF in the estimated model (4) down to 3.95 and 4.52, respectively. Figure 2 illustrates the distribution of standardized and non-standardized values of intra- and inter-industry knowledge spillovers in our sample.

In addition, we analyzed the correlation coefficients ensuring that no coefficients were greater than 0.70. We analyzed all the variables' histograms and found the errors were identically and independently distributed with constant variance. We addressed the variance structure on the right-hand side of the model by limiting the number of control variables to those that were found in the extant literature (Beaudry and Schiffauerova, 2009; Coombs *et al.*, 2009; Enkel and Heil, 2014; West and Bogers, 2014; Caragliu *et al.*, 2016; Roper *et al.*, 2017). We used the maximum number of observations excluding missing observations to test our hypotheses and treated all non-applicable, non-identified and other responses as missing values, and did not replace them with zeros (Wooldridge, 2009).

Having estimated (4) for innovation and imitation, we saved u_{it} to provide the evidence of the second condition for the exclusion restriction to hold: ρ_1 to be uncorrelated with u_i $\text{corr}(\rho_1, u_{it}) = 0$ (Wooldridge, 2009). We estimate equation (5), where the dependent variable is u_i from equation (4) is regressed on the exogenous exclusion criteria (industry-region scientists) (ρ_1) from equation (3) controlling for the type of spillover (intra or inter-industry), firm age, size and time, industry and region fixed effects as in Hall *et al.* (2013).

$$u_{it} = \beta_0 + \beta_i z_{it} + \rho_1 \rho_1 + \rho_2 \rho_2 + \rho_3 \rho_3 + \epsilon_{it} \quad (5)$$

where u_{it} is error from equation (4). Variables z_{it} are control variables such as firm age, firm employment, industry, Geo region, and time fixed effects, and ϵ_{it} is an error term.

Coefficients ρ_1 (Table A1) are not statistically significant, and we conclude that across for innovation models with intra- and inter-industry spillovers $\text{corr}(\rho_{it}, u_{it}) = 0$, thus ρ_1 is a valid instrument to be used in a selection model (3) to predict R&D intensity (ρ_{it}).

9. Empirical results

9.1 Hypotheses testing

Table 4 presents the results from the logistic panel data estimation with lagged explanatory variables (spillovers and absorptive capacities). We tested the hypothesized relationship between knowledge spillovers and innovation (specifications 1, 3, and 5) and imitation (specifications 2, 4, and 6), depending on the level of the firm's absorptive capacity proxied by the predicted values of R&D intensity. All coefficients are reported in odds ratios, which means if odds ratio is greater than one, there is a positive increase in the likelihood of innovation or imitation. In case the odds ratio is less than one, there is a reduction in the likelihood. We performed the likelihood-ratio test comparing the logistic model with ordinary linear square regression (specifications 1 and 2), advocating for logistic panel data estimation.

The effect of a firm's predicted R&D intensity on product innovation is significant and positive ($\beta = 1.741$, $P < 0.01$) (specification 1, Table 4), which means that the firms in the fourth quartile of predicted R&D intensity (positive values) are 1.74 times more likely to innovate new products than firms in the first, second, and third quartiles. In addition, these firms are 25.4% less likely ($\beta = 0.746$, $P < 0.01$) to imitate existing products (specification 2, Table 4). This finding is also supported once we control for the spillover effects and knowledge sourcing from external partners. Firms who invest in R&D are 1.81–1.89 times more likely to innovate ($\beta = 1.811$ – 1.890 , $P < 0.01$) (spec. 3 and 5, Table 4) and 27.8–28.1% less likely to imitate ($\beta = 0.719$ – 0.722 , $P < 0.01$) (spec. 4 and 6, Table 4). This adds to Leiponen and Helfat (2010), who linked internal resource allocation to firm performance. The direct effects of intra-industry spillover on innovation are statistically significant for level ($\beta = 1.087$, $P < 0.01$) and squared term ($\beta = 0.975$, $P < 0.01$), which empirically supports an inverted U-shaped relationship between intra-industry spillover and innovation (specification 3, Table 4).

Our findings further endogenous growth theory (Grossman and Helpman, 1991) where knowledge produced by a company increases productivity industry-wide (knowledge transfer effect), and the works of Marshall (1920) and Roper *et al.* (2013), (2017) on the benefits from within-industry knowledge externalities. We also find the limitations of the industry-wide knowledge spillover, which may lead to a reduced propensity of innovation (Bloom *et al.*, 2013; Qian, 2014). Our findings support H1a, as the interaction between investment in R&D and intra-industry spillover for innovation is statistically significant for level ($\beta = 1.040$, $P < 0.01$) and squared term ($\beta = 0.950$, $P < 0.01$) (specification 3, Table 4). This indicates the role of a firm's R&D (Tucci *et al.*, 2016) in recognizing and absorbing within-industry knowledge (Enkel and Heil, 2014).

Knowledge spillovers do not change the propensity for innovation in firms that do not invest in R&D. The negative effects of intra-industry knowledge spillovers on innovation for firms that do invest in R&D can be associated with an increase in the imitation capabilities of competitors within an industry (Giarratana and Mariani, 2014) as the knowledge spillovers increase. We find consistent results for the direct effect of inter-industry knowledge spillover on innovation, which is significant in levels ($\beta = 1.086$, $P < 0.01$) and a squared term ($\beta = 0.972$, $P < 0.01$), and for the interaction of R&D investment with the level ($\beta = 1.163$, $P < 0.01$), and a squared term ($\beta = 0.942$, $P < 0.01$) of inter-industry knowledge spillover (specification 5, Table 4), supporting H1b. The positive effects of spillovers are driven by a firm's ability to recognize and appropriate the "distant" external knowledge (Cohen and Levinthal, 1989; Dosi *et al.*, 2006) that brings new ideas from other industries. Inter-industry spillovers may lead to technological interdependencies and learning externalities (Dosi and Tranchero, 2021) and enable the creation of new-to-market products in other sectors.

Table 4. Results for logistic regression (odds ratios reported) for innovation and imitation

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Innovation	Imitation	Innovation	Imitation	Innovation	Imitation
Age	0.869*** (0.02)	1.001 (0.04)	0.865*** (0.02)	1.002 (0.03)	0.870*** (0.02)	1.000 (0.03)
Employment	1.034 (0.02)	0.968* (0.02)	1.034 (0.05)	0.965** (0.03)	1.033 (0.05)	0.968* (0.02)
Exporter	2.727*** (0.12)	1.002 (0.07)	2.720*** (0.13)	1.003 (0.03)	2.730*** (0.13)	1.005 (0.07)
Human capital	1.010** (0.00)	0.989** (0.00)	1.010 (0.00)	0.990*** (0.00)	1.010 (0.00)	0.989*** (0.00)
Foreign	1.157*** (0.06)	0.923 (0.07)	1.152*** (0.05)	0.925 (0.07)	1.154*** (0.06)	0.924 (0.07)
Survival	1.056 (0.06)	0.916 (0.05)	1.054 (0.04)	0.915 (0.05)	1.056 (0.04)	0.915 (0.05)
Software	3.057** (1.10)	2.255* (0.30)	3.094* (1.15)	2.075** (0.40)	3.150* (1.12)	2.177** (0.41)
Predicted R&D (high)	1.741*** (0.10)	0.746*** (0.05)	1.811*** (0.12)	0.719*** (0.06)	1.890*** (0.13)	0.722*** (0.06)
Intra-industry spillover β_1	1.254* (0.20)	1.468 (0.32)	1.087* (0.04)	1.091 (0.07)	1.091** (0.04)	1.048 (0.06)
Intra-industry spillover sqrd β_2	0.515** (0.05)	0.555 (0.35)	0.975* (0.18)	0.971 (0.02)	0.952 (0.04)	0.982 (0.02)
Inter-industry spillover β_3	1.012** (0.06)	7.037* (1.34)	1.238* (0.05)	1.149* (0.60)	1.086** (0.04)	1.160** (0.07)
Inter-industry spillover sqrd β_4	1.370(2.17)	0.095 (0.24)	0.958* (0.02)	0.980 (0.02)	0.972* (0.01)	0.960 (0.02)
Predicted R&D × intra-spillover			1.040* (0.10)	0.840 (0.11)		
Predicted R&D × intra-spillover sqrd			0.950** (0.04)	1.038 (0.05)		
Predicted R&D × inter-spillover					1.163** (0.05)	1.012 (0.10)
Predicted R&D × inter-spillover sqrd					0.942*** (0.02)	1.044 (0.05)
Suppliers intensity			1.188*** (0.03)	1.112*** (0.03)	1.190*** (0.03)	1.149*** (0.03)
Customers intensity			1.634*** (0.04)	1.024 (0.04)	1.640*** (0.04)	1.040 (0.03)
Cooperation intensity			0.910 (0.02)	1.254** (0.04)	0.919** (0.03)	1.245*** (0.04)
Consultants intensity			1.089*** (0.02)	0.975 (0.04)	1.096*** (0.03)	0.994 (0.04)
University intensity			1.272*** (0.01)	0.942 (0.04)	1.266*** (0.04)	0.935 (0.04)
Government intensity			1.048 (0.03)	0.944 (0.04)	1.038 (0.03)	0.932 (0.04)
Constant	0.052*** (0.02)	3.313*** (0.49)	0.034*** (0.00)	3.909*** (0.69)	0.038*** (0.02)	3.429*** (0.55)
Legal status controls	Yes	Yes	Yes	Yes	Yes	Yes
Time and Geo region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
LR Chi square	2810.21	1190.25	2882.25	1193.19	2891.16	1194.99
Log-likelihood	-6820.52	-3458.28	-6890.72	-3561.25	-6892.02	-3595.21
Pseudo-R ²	0.19	0.23	0.19	0.15	0.19	0.23
F-test of H0: $\beta_1 = \beta_2 = 0$ if $\widehat{\varphi}_{it} > 0$			4.11	1.55		
F-test of H0: $\beta_3 = \beta_4 = 0$ if $\widehat{\varphi}_{it} > 0$					4.48	2.37
F-test (Prob)			0.08	0.46	0.07	0.20

Number of observations – total sample: 19,510. Note: reference category for legal status is Company (limited liability company), industry (mining), and Geo region (York). Robust standard errors are in parenthesis. The coefficients of the regressions (1, 3, and 5) are the marginal effect of the independent variables on firm's propensity for new product creation, ceteris paribus. The coefficients of the regression (2, 4, and 6) are the marginal effect of the independent variables on firm's propensity to imitate products and services that are already introduced to market, ceteris paribus. For dummy variables, it is the effect of a discrete change from 0 to 1. Significance level:

** $P < 0.05$;

*** $P < 0.001$.

Office for National Statistics (2017, 2018, 2019).

The negative effects of inter-industry knowledge spillover on innovation for firms who invest in R&D is associated with an increase in the transaction costs for firms that recognize, modify, and adapt external knowledge within their organizational processes and routines (Saura *et al.*, 2022) and an increased cost of choice between a variety of knowledge, making some of it repetitive, obsolete, and unfamiliar (Audretsch and Belitski, 2020b). Our findings clearly demonstrate that in order to become receptive to intra- and inter-industry knowledge spillovers for innovation, firms must invest in internal R&D and build up their absorptive capacity (Alexy *et al.*, 2013). The concept of knowledge spillovers and absorptive capacity when applied together thus helps scholars better explain the role of R&D investment in innovation and a firm’s ability to learn from external knowledge (Cohen and Levinthal, 1989, 1990).

Independently to the level of intra- and inter-industry spillover, firms that do not invest in R&D will have lower propensity to innovate at any level of knowledge spillover. Both findings extend the later works of Denicolai *et al.* (2016), which argue that an excessive reliance on external knowledge may have a negative effect on firm innovation performance if not supported by prior investment in internal R&D. Our findings regarding H1a extend Alexy *et al.* (2013) by demonstrating that for firms who invest in R&D, an increase in spillovers may dissipate knowledge to competitors as well. This supports our H1bm, with both positive (knowledge transfer) and negative (transaction cost) effects of knowledge spillover on innovation conditional on investment in R&D. An increased inter-industry spillover reduces the coordination ability between firms and their external partners with an increase in heterogeneity of knowledge (Vural *et al.*, 2013) and increases search and implementation costs (Camacho, 1991). Figures 3A and 3C illustrate both effects diagrammatically. The non-linear relationship adds to what we know from Dosi *et al.* (2006), who denied the existence of a monotonically growing relationship between spillovers and innovation. It also adds to Kobarg *et al.* (2019) and Belitski and Mariani (2022), who focused on diminishing marginal returns to the breadth and depth of external knowledge sourcing via collaboration and spillovers for innovation.

Our H2, which states that firm’s own investment in R&D reduces the propensity of imitation at any level of intra- and inter-industry knowledge spillovers, is partly supported, furthering our

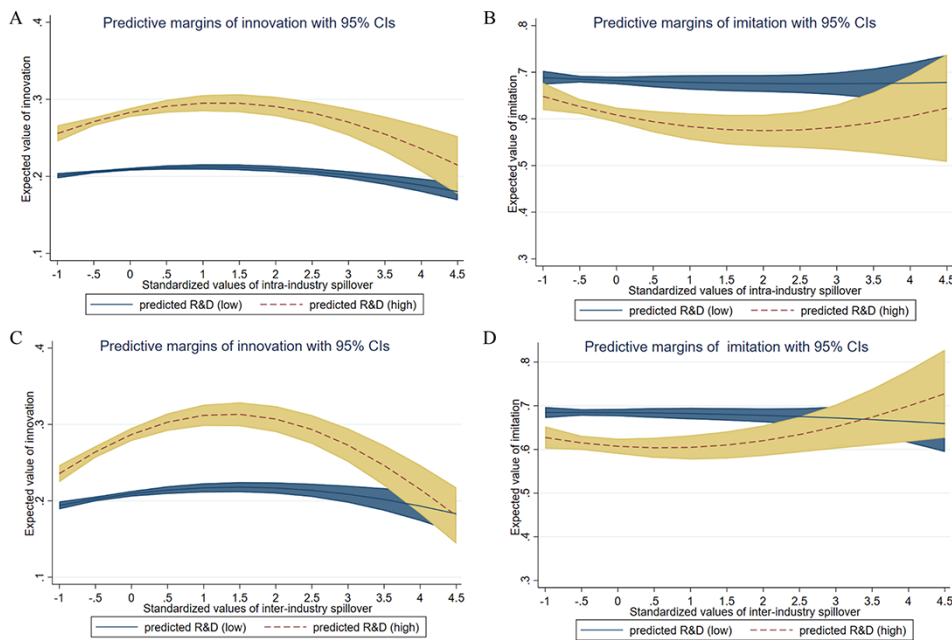


Figure 3. Predictive margins for intra and inter-industry spillovers for new product creation (innovation = 1A and 1C) and new-to-firm products (imitation = 1B and 1D)
 Source: Office for National Statistics (2017, 2018, 2019).

understanding of the spillover-imitation dilemma. First, an increase in intra-industry spillovers does not change imitation propensity for firms who invest in R&D and for non-R&D investing firms (specification 4, Table 4). Both the interaction coefficients of predicted R&D and intra-industry knowledge spillovers in levels ($\beta = 0.840$, $P > 0.10$) (spec. 4, Table 4) and squared term ($\beta = 1.038$, $P > 0.10$) are insignificant (spec. 4, Table 4). Second, the effect of inter-industry knowledge spillovers on imitation propensity is insignificant as well for firms who invest or do not in R&D, supporting H2. The interaction coefficients of predicted R&D and inter-industry knowledge spillovers in levels ($\beta = 1.012$, $P > 0.10$) (spec. 6, Table 4) and squared term ($\beta = 1.044$, $P > 0.10$) are insignificant (spec. 6, Table 4).

An increase in external knowledge via spillovers for firms who invest or do not in R&D is not associated with a subsequent change in the firm's propensity to imitate, extending Cappelli *et al.*'s (2014) discussion on the role of spillovers for incremental innovation. Spillover-imitation propensity does not change at any level of knowledge. We can observe two groups of firms in Figures 3B and 3D.

The first group of firms who invest in R&D will have the expertise and internal knowledge needed to invent new solutions and create new products via knowledge spillovers (Leiponen and Helfat, 2010). This group will aim to obtain first mover advantage rather than copy what already exists in the industry. Figures 3B and 3D illustrate that the propensity of imitation does not change with an increase in spillovers; rather, what changes is the choice of firms to invest in R&D.

The second group of firms who perceive knowledge spillovers as a substitute for R&D do not invest in R&D. These firms will realize that sourcing knowledge via spillovers comes at the cost of modifying and adapting external knowledge (Mansfield *et al.*, 1981). This constitutes the main limits of open innovation (Audretsch and Belitski, 2022; Saura *et al.*, 2022) and constrains undertaking innovation drawing on spillovers, pushing firms into imitation and increasing their imitation propensity. For example, accessing spillovers may require buying intellectual property (Chesbrough, 2003) or liaising with a specific type of external partner (Kessler and Chakrabarti, 1996; Beer and Zand, 2014) to better understand the nature of the knowledge and how it may be used (Leiponen and Helfat, 2010). Due to a cost to access spillovers, we find that the propensity to imitate for firms that do not invest in R&D is at least 10% greater than for firms who invest in R&D when knowledge spillovers increase within -1 to 3 (Figures 3B and 3D). This gap disappears at a high level of knowledge spillovers (3 to 4.5), which means that firms who invest or do not invest in R&D will have similar imitation propensities. When knowledge spillovers are high it may become a disincentive to engage in R&D for firms targeting innovation and imitation, which means all information will become common knowledge. The expected profits from spillovers can be dissipated due to high transparency and averaged exclusivity of external knowledge.

The confidence intervals for imitation and innovation for high levels of intra and inter-industry spillovers overlap for both R&D and non-R&D firms as knowledge spillovers become more accessible and knowledge more familiar and open. This effect calls for further research on knowledge appropriation and complexity when spillovers are high and how firm's R&D investment can be sustained.

While we cannot empirically test this, we argue that two different types of imitation are possible. One relies on knowledge spillovers and new-to-firm products and has a novel element, allowing firms to enter monopolistic-type competition. The other imitation type is based on knowledge available from competitors (Belitski and Mariani, 2022).

10. Other findings

In addition to knowledge spillovers, collaboration on knowledge with external partners is important for innovation and (or) imitation choice, and allows firms to better recognize and incorporate external knowledge from various partners via spillovers. Our results for the role of knowledge collaboration in innovation are both interesting and intriguing.

We find that firms who collaborate with suppliers on knowledge are 1.18–1.19 times ($\beta = 1.188$ – 1.190 , $P < 0.01$) (spec. 3 and 5, Table 4) more likely to innovate and 1.11–1.15 times ($\beta = 1.112$ – 1.149 , $P < 0.01$) (spec. 4 and 6, Table 4) more likely to imitate for every unit changed in collaboration intensity. Firms that collaborate with customers are 1.63–1.64 times

($=1.163-1.164$, $P < 0.01$) (spec. 3 and 5, [Table 4](#)) more likely to innovate for every unit changed in collaboration intensity. While these findings support prior research on spillovers from suppliers that may affect both firm imitation and performance ([Cappelli et al., 2014](#)), they do not support the findings on customers. Collaboration with customers aims at new product development and it is crucial when innovative products require further market adaptations ([von Hippel, 1988](#); [Tether, 2002](#)). Prior research has argued that spillovers from competitors should clearly lead to higher levels of imitation in the industry ([Cappelli et al., 2014](#)), with the results supported for imitation ($\beta = 1.245-1.254$, $P < 0.01$) (spec. 4 and 6, [Table 4](#)). This finding suggests that when competing firms collaborate on knowledge, even opening a “small window” of knowledge into competitors is sufficient to enable them to appropriate some of the knowledge. An increase in one unit of cooperation intensity reduces innovation propensity by 8–9% ($\beta = 0.910-0.919$, $P < 0.01$) (spec. 3 and 5, [Table 4](#)). Firms who collaborate with consultants are more likely to innovate ($\beta = 1.089-1.096$, $P < 0.01$) (spec. 3 and 5, [Table 4](#)), in addition to firms that collaborate on knowledge with universities ($\beta = 1.089-1.096$, $P < 0.01$) (spec. 3 and 5, [Table 4](#)). Firms who collaborate with consultants and universities on knowledge are as likely to imitate as firms who do not collaborate, with regression coefficients insignificant (spec. 4 and 6, [Table 4](#)). Finally, collaboration with government is not associated with imitation and innovation outcomes.

The baseline model (spec 1 and 2, [Table 4](#)) demonstrates several differences between other factors for innovation and imitation. First, larger firms are 3.2% less likely to imitate new products ($\beta = 0.968$, $P < 0.05$, spec. 2 [Table 4](#)), while firm size is not associated with innovation propensity, with coefficients insignificant in spec 1, 3, and 5 ([Table 4](#)) ([Colombelli et al., 2013](#)). Second, more mature firms are 13.1% less likely to innovate than younger firms ($\beta = 0.869$, $P < 0.01$, spec. 1 [Table 4](#)) ([Haltiwanger et al., 2013](#)). Third, investment in software and technology increases propensity to innovate by 3.05 times ($\beta = 3.057$, $P < 0.01$, spec. 1 [Table 4](#)) and imitate by 2.25 times ($=2.255$, $P < 0.01$, spec. 2 [Table 4](#)).

Investment in human capital, such as hiring employees with university degrees, increases the propensity to innovate ($\beta = 1.010$, $P < 0.01$, spec. 1, 3, and 5 [Table 4](#)) and decreases the propensity to imitate ($\beta = 0.989-0.990$, $P < 0.01$, spec. 2, 4, and 6 [Table 4](#)) ([Sun et al., 2020](#)). Foreign ownership increases the propensity to innovate between 15.4 and 15.7% ($\beta = 1.154-1.157$, $P < 0.01$, spec. 1, 3, and 5 [Table 4](#)), as firms that are foreign-owned are known to be more productive and technologically equipped ([Guadalupe et al., 2012](#)). In a similar vein, exporters are 2.72 times more likely to introduce new-to-market products than non-exporters ($\beta = 2.72$, $P < 0.01$) and 1.16 times more likely to imitate than non-exporters ($\beta = 1.160$, $P < 0.01$) (specifications 1 and 2, [Table 4](#)).

11. Robustness check

We performed several robustness checks. Firstly, we estimated the logistic regression with inter- and intra-industry knowledge spillovers only and then included other controls as well as time, regional, and industry fixed effects. The inclusion of firm characteristics and interactions only enabled us to observe the change in the significance of the predicted coefficients and decide on the size of a bias when spillovers and the other firm controls are estimated together. This was to respond to reviewer comments that the right-hand side of the model needed to be simplified by either creating indices that explain innovation performance or reducing the number of variables that explain it.

Secondly, we calculated knowledge spillovers at the 3-digit SIC level and by 175 Geo region and estimated [equation \(4\)](#) with the results of a range of confidence intervals, which remained the same as in [Table 4](#). The knowledge spillover effect's level of significance was lower than when estimated with knowledge spillover built using 2 digit SIC sectors. We explain this using the firm's high specialization within niche products and services, as a firm's niche specialization may lower its ability to keep up with new technologies from other industries ([Camagni, 1991](#)).

Thirdly, we ran logistic estimations with and without a bootstrap and clustered our standard errors by 2-digit industry SIC, correcting for heteroskedasticity across industries. The purpose of this was to check for potential bias in estimation due to autocorrelation in errors between firms when spillovers are calculated at 2-digit SIC 2007. Both estimations provided qualitatively

the same results on the direction of impact and the significance of the seven factors and control variables.

Fourthly, we used weights of the stratified sample provided by the ONS and calculated by industry as well as size of firm using the original UKIS sample. We compared the results of the estimation with the predicted coefficients between weighted and unweighted estimations, which followed the signs, significance, and confidence intervals.

Fifthly, we standardized R&D intensity and performed our estimation with it interacting R&D intensity standardized with intra- and inter-industry spillovers. The results did not change.

Finally, we point out that [Lind and Mehlum \(2010\)](#) argued that conventional means of testing nonlinearities, such as the *F*-test, are inadequate and proposed additional testing beyond the significance and signs of coefficients. In line with their approach, we calculated predictive margins to test for the inverted U-shape relationships and inflection points in our model (4) ([Figures 3A–3D](#)). We also performed the inverted U-shape test for nonlinearity of the interaction coefficients, supporting an inverted U shape for innovation (see [Table 4](#)).

12. Discussion

Building on the prior research on knowledge spillovers ([Jacobs, 1970](#); [Griliches, 1992](#); [Audretsch and Feldman, 1996](#)), this study has put the localized intra- and inter-industry spillovers as well as a firm's own investment in R&D to a competitive test. This allowed us to develop and test the knowledge spillover of innovation, concluding with the following arguments. Firstly, investment in R&D is an important boundary condition to recognize, access, modify, process, and implement knowledge spillovers ([Camacho, 1991](#); [Bloom et al., 2013](#)).

Secondly, knowledge spillovers are a primary source of entrepreneurship ([Audretsch and Feldman, 1996](#)), innovation ([Kugler, 2006](#); [Hall et al., 2013](#); [Denicolai et al., 2016](#)), and productivity ([Griliches, 1992](#)) and not imitation, which contrasts with the prior research of [Cappelli et al. \(2014\)](#) and [Kobarg et al. \(2019\)](#).

Thirdly, expanding prior research on specialization ([Marshall, 1920](#)) and diversification spillovers ([Jacobs, 1970](#); [Romer, 1986](#)) as a positive externality for firm innovation and performance ([Carlino and Kerr, 2015](#); [Lee et al., 2015](#)), we argue that the relationship between intra- and inter-industry knowledge spillovers and innovation is an inverted U shape, advancing prior research into the limits to open innovation ([Kobarg et al., 2019](#); [Audretsch and Belitski, 2020a](#); [Saura et al., 2022](#)). The negative side of the knowledge spillover–innovation relationship can be explained by within-industry competition effects (intra-industry) and transaction cost effects (intra- and inter-industry). The inverted U-shaped relationship only holds for firms who invest in R&D and other creative knowledge and is flat for firms who do not perform R&D.

Fourthly, accessing knowledge spillovers in addition to R&D may also involve buying intellectual property and engaging in collaborative R&D with external partners ([Chesbrough, 2003](#)). This interpretation of the inverted U-shaped relationship contrasts with the “mainstream” economic view of spillovers as a positive externality ([Marshall, 1920](#); [Jacobs, 1970](#); [Jaffe, 1986](#)). However, in the literature of industrial organizations ([Jirjahn and Kraft, 2011](#)), the external source of knowledge is typically not the result of an unintended leakage of knowledge; rather, a firm makes a strategic decision to access available spillovers.

Fifthly, building on this argument, the essential characteristics of knowledge spillovers (e.g. in-excludability, complexity, and tacitness) will incentivize innovators to use spillovers while disincentivizing imitators, extending [Jirjahn and Kraft's \(2011\)](#) argument on the role of spillovers in drastic and incremental innovation.

Sixthly, the knowledge spillover–imitation relationship comes in the form of a dilemma, which should be studied within two groups of firms: those who either start performing R&D to recognize and access knowledge spillovers, or stop investing in R&D due to an inability to access spillovers or because it is generally costly. The dilemma is that firms are either unable to access spillovers due to the paucity of internal knowledge investment and opt out of knowledge spillovers, or firms that are unwilling to imitate as investment in R&D enables new solutions and innovation. The spillover–imitation relationship uncovers the ability-willingness paradox

for firms that are able to use spillovers but unwilling to imitate or firms willing to use spillovers for imitation but unable to do so due to the paucity of knowledge.

Finally, when intra- and inter-industry spillovers are high it means they are not fully controlled (Teece, 1986). The Nash equilibrium under high levels of spillovers and high levels of innovation and imitation averages profits, as no firm has an incentive to further increase innovation (imitation) efforts to unilaterally increase their payoffs. As a result, the propensity of innovation and imitation converges at the highest level of spillovers for firms that invest and do not in R&D.

Our findings send a clear signal to managers who consider knowledge spillovers as a substitute for internal R&D for innovation and imitation. Firstly, we demonstrated that firms that do not invest in R&D are unable to benefit from intra- and inter-industry spillovers. Secondly, while investment in R&D increases the absorptive capacity of innovators, this is not the case for imitators. Thirdly, transaction costs when accessing spillovers are another concern for knowledge sourcing between industries when knowledge is more diverse, unfamiliar, and technologically distant (Nooteboom *et al.*, 2007). Finally, competition externalities and transaction costs related to spillovers can affect firm manager's decisions to (i) co-locate and invest in R&D and (ii) change their innovation strategies.

Policymakers and firm managers should be aware of the non-linear effects of spillovers for new product creation with a flipping point of 1.5 standard deviations above the mean for both intra- and inter-industry spillovers. This threshold of the knowledge spillover of innovation indicates that further increases in knowledge spillovers and investment in R&D will lead to a reduction in innovation propensity.

13. Conclusions

This study provided important insights into why innovators respond differently to changes in spillovers. In particular, the literature has focused on variations of firm-, industry-, and region-specific characteristics to explain why some firms choose (or not) to innovate. Contributing to the open innovation and knowledge spillover literature, this study demonstrated that this choice is not specialization vs. diversification, because both types of spillovers matter for innovation (Caragliu *et al.*, 2016) and that internal R&D investment is needed to create absorptive capacity (Cohen and Levinthal, 1990; Jansen *et al.*, 2005; Leiponen and Helfat, 2010) and to be able to benefit from knowledge spillovers. In contrast to Cohen and Levinthal (1989, 1990), we argue that investment in R&D cannot fully offset the negative effects of knowledge spillovers, and other mechanisms should be examined in subsequent research (e.g. appropriability incentives, intellectual property protection, cooperation and R&D subsidies).

This study creates the foundations for the theory of knowledge spillover innovation by integrating Marshallian and Jacobian knowledge externalities with Porter's (1990, 1998) competition externalities as well as Mansfield *et al.*'s (1981) and Chesbrough's (2003) costs of accessing external knowledge. As firms continue to invest in their own knowledge to access spillovers within and between industry (Cohen and Levinthal, 1990), knowledge created by incumbent firms within an industry will be easier to adapt to the firm's needs (Tether, 2002), whereas the competition effect may dissipate the benefits of investment in R&D under high spillovers (Bloom *et al.*, 2013).

In regions and industries where imitation and copying are common, innovators and investors may downgrade their expectations of post-innovation returns, reducing the incentive to invest in innovation inputs including investment in knowledge generating and sourcing activities. This in turn is likely to reduce the level of innovation in firms within those industries and regions, suggesting that the competition effect of knowledge spillovers may become overwhelmingly negative (Denicolai *et al.*, 2014, 2016; Roper *et al.*, 2017) or stronger for specific industries (Audretsch and Belitski, 2020b).

The role of the mechanisms of formal and informal knowledge appropriation need further analysis, as this may help to reduce transaction costs and increase both knowledge collaboration and spillovers (Breschi and Lissoni, 2001; Dosi *et al.*, 2006; Reitzig *et al.*, 2010). The downside of this, however, is a potential reduction in knowledge spillovers affecting the economy as a whole (Cappelli *et al.*, 2014). The knowledge spillover innovation theory therefore suggests that new

localized knowledge within and between industries is particularly relevant for innovation but not for imitation.

Given the diversity of knowledge sources, it is likely that firms will rely both on spillovers and knowledge collaboration with external partners, with the knowledge sourcing depending on the firm's own R&D. The benefits from intra- and inter-industry spillovers include increased innovation activity, whereas the type of collaboration partner defines both imitation and innovation propensity.

This finding further extends the stream of spillover research on the linearity and exclusivity of spillovers for innovation and productivity (Jacobs, 1970), with a refocus on the type of spillover, knowledge type and a subsequent choice of innovation or imitation.

This study has several limitations. Firstly, we built a repeat cross-sectional dataset (over 79% of observations were observed only once) that has a panel component. While this severely limited the research design, specifically the ability to get close to causal inferences, pooling the three distinct data sources together proved more inferences and controls and gave us a sense of what was being estimated.

Our second limitation is that our proxies for specialization (intra-) and diversification (inter-industry) spillovers have a correlation of 0.58. Future research could use alternative sectoral aggregation, for example, at 3- or 4-digit SIC codes with a more granulated approach to the measurement of industry spillovers and Geo regions as well as approximate schemes based on more in-depth information on relatedness and knowledge flows. For example, R&D collaboration agreements between firms within and between industries could be used as a proxy for the knowledge spillover emanating from knowledge collaboration.

Future research should aim to motivate scholars to experiment with panel data and measure spillovers with the extent of information received from external sources related and unrelated to the main product or service. These sources could include conferences and trade fairs; professional and industry associations; technical, industry, or service standards; and scientific journals and trade/technical publications as proxies for knowledge spillovers and their effects on innovation decision-making and strategy. Next, more research is needed on how combining external shocks (e.g. regulation, financial crises, and pandemic effects) with innovation and imitation and the degree spillovers affect the choice of innovation strategy. Finally, future research could focus on the mechanisms that converge propensity of innovation and imitation for R&D and non-R&D performers when intra- and inter-industry knowledge spillovers are high.

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Appendix A

Table A1. Second-stage post-estimation analysis: random effect (RE) estimation of model (5) using predicted residuals from equation (3) from second-stage estimation

Dependent variable	(1)	(2)	(3)	(4)
	Innovation residual $y_i - \hat{y}_i$ (equation 3)		Imitation residual $y_i - \hat{y}_i$ (equation 3)	
Equation with knowledge spillover	Intra-industry spillover	Intrr-industry spillover	Intra-industry spillover	Intrr-industry spillover
Industry-region scientists ρ_1	0.008 (0.01)	-0.002 (0.00)	-0.001 (0.01)	-0.002 (0.00)
Control variables				
Age	-0.007 (0.01)	-0.001 (0.01)	-0.006 (0.01)	-0.001 (0.01)
Employment	0.002 (0.00)	0.002 (0.00)	-0.003 (0.01)	0.002 (0.01)
Time, industry, and Geo region controls	Yes	Yes	Yes	Yes
Constant	-0.107 (0.09)	-0.312 (0.23)	-0.063 (0.10)	-0.311 (0.23)
Number of observations	19,510	19,510	19,510	19,510
Number of firms	15,430	15,430	15,430	15,430
Wald Chi ²	101.23	100.08	58.67	53.75
R ² within	0.003	0.002	0.005	0.002
R ² between	0.003	0.002	0.012	0.014
R ² overall	0.004	0.003	0.012	0.014
Sigma u	0.263	0.400	0.334	0.401
Sigma e	0.909	0.911	0.888	0.912

Note: Standard errors robust for heteroskedasticity are in parenthesis. Reference groups: survey wave (2002–2004). Industry (Mining). Significance level:

* $P < 0.05$;

** $P < 0.01$;

*** $P < 0.001$.

Coefficient ρ_1 (human capital) is weakly significant with imitation as dependent variable with inter-industry spillovers ($P = 0.09$) when innovation sales residuals are used as dependent variable. Number of observations 19,510. BSD—Business Register (2002–2014) and UKIS—UK Innovation Survey (2002–2014).