Evaluating internal and external knowledge sources in firm innovation and productivity: an industry perspective

R&D MANAGEMENT

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Both internal knowledge – investment in internal R&D and information and communication technologies (ICT) as well as external knowledge – knowledge spillovers and active collaboration with partners are rapidly fostering firm productivity and innovation. In this study, we investigate the role of internal and external knowledge in firm productivity and innovation. In addition, we test interactions between investment in R&D and ICT as well as between knowledge spillovers and knowledge collaboration in their association to firm innovation and productivity. We use a recombinant innovation approach and four samples for firms in manufacturing, creative, ICT and science, and professional services industries during 2002–2014 and for pre-and post-crisis periods to perform our analysis. In addition to innovation and productivity, we also examine the role of internal and external knowledge as a conduit to the development of innovation internally and the co-creation of innovation with external partners. Our results lead to managerial and policy implications.

1. Introduction

Productivity and innovation have been part of the research and policy agenda for decades (Chiesa and Piccaluga, 2000; Leyden and Link, 2015; Di Minin et al., 2021), with a number of policy responses in the United States and Europe. Among areas of emphasis was the investment in R&D, advanced technology and software (Enkel et al., 2009), as well as the importance of pursuing an open innovation strategy to understand 'why' and 'how' acquiring external knowledge is necessary to compete (Antonelli and Colombelli, 2017; Casprini et al., 2017; Audretsch and Belitski, 2020a). Altogether productivity, innovation and investment in R&D and technology have been areas of relative underperformance in many European countries (Griffith et al., 2006; Hall et al., 2013; Li et al., 2016) and in Europe vis-à-vis the USA (Van Ark et al., 2003; Bloom et al., 2012).

Failures to invest in ICT and R&D are often thought to be due to management weakness (Belitski and Liversage, 2019), inability to create knowledge internally (Miotti and Sachwald, 2003; Powell et al., 2005;

Antonelli and Colombelli, 2015), or a lack of distinctive capabilities (Casprini et al., 2017).

Both theoretical and empirical evidence suggest that investment in internal knowledge along with access to external knowledge (Cohen and Levinthal, 1989; Hall et al., 2009; Antonelli and Colombelli, 2017; Roper et al., 2017) can facilitate innovation and productivity with the most recent research confirming it (Bustinza et al., 2019; Demircioglu et al., 2019). One of the main challenges, however, is how to optimally integrate investment in R&D and ICT as well as knowledge across different collaboration partners and *via* knowledge spillovers (Chen et al., 2018; Link and Scott, 2019). This is to fully leverage the potential of knowledge generation and transfer (Griliches, 1979; Nelson, 1982; Veugelers, 1997; Nooteboom, 2000).

In this study, we depart from the notion of the recombinant knowledge generation process (Antonelli and Colombelli, 2015), highlighting the role of internal and external knowledge for innovation and productivity. We discuss the well-known Crépon–Duguet–Mairesse (CDM) model of R&D, innovation, and productivity (Crépon et al., 1998; Griffith et al., 2006; Hall et al., 2009, 2013), but explain why a different approach should be taken to analyze decision-making process as a simultaneous process. Building on the extant open innovation literature that discusses the role of R&D investments and potential knowledge spillovers (Sofka and Grimpe, 2010; Denicolai et al., 2016; Roper et al., 2017), this study aims to examine the role of ICT and R&D investment as innovation inputs (Hall et al., 2013), as well as external knowledge sources such as open collaboration for innovation (Gassmann et al., 2010; Van Beers and Zand, 2014) and knowledge spillovers (Bloom et al., 2019; Audretsch and Belitski, 2020b) for productivity and innovation. We use data across four industries in the UK during 2002–2014: manufacturing, information and communication technologies (ICT), creative and scientific and professional services to test our research hypotheses.

This study expands the prior research by investigating how a simultaneous increase in investment in internal knowledge (Hall et al., 2013; Belitski, 2019) and external knowledge inputs (Gassmann et al., 2010; Casprini et al., 2017; Link et al., 2019; Link and Scott, 2019) results in more productivity and innovation, in addition to changes in the propensity to create new products in-house and co-create innovation with external partners.

Our contribution is both theoretical and methodological. First, we analyze how changes in internal and external knowledge affect firm innovation and productivity across four major UK industries. It is one of the few studies in the field (Antonelli and Colombelli, 2017) that analyzes the two dimensions in a simultaneous model setting.

Second, our methodological contribution is in applying a holistic analysis to examine the firm-level relationships between four outcomes of innovation: co-creation of new products with external partners, in-house development of innovation, innovation sales, and productivity. This is to bypass some of the measurement difficulties and the issues of endogeneity when dealing with innovation inputs and outputs (Arora et al., 2016) by estimating equations for productivity, knowledge transfer, and innovation sequentially (Hall et al., 2009, 2013; Giovannetti and Piga, 2017) while still correcting for endogeneity and selectivity in firm R&D and ICT investment. Our novel approach draws on the prior research on innovation and productivity (Griffith et al., 2006; Audretsch and Belitski, 2020b) as well as sheds light on the role of recombinant knowledge approach, e.g., external and internal knowledge in the knowledge generation function and innovation (Antonelli and Colombelli, 2015, 2017).

The results answer our research question: ‘How investment in a firm’s own R&D and ICT in addition to knowledge collaboration and spillovers affect firm innovation and productivity?’ across four distinctive industries and pre-and post-crisis periods.

Section 2 reviews the micro-foundations on the use of ICT, R&D, and external knowledge sources. This is followed by Section 3 with the model, data, and estimation results in Section 4. Section 5 discusses and concludes.

2. Investment in knowledge, productivity and innovation: a micro perspective

2.1. Recombinant approach to firm innovation and productivity

Due to limited resources available for innovation in every given firm, the recombination approach to explain firm innovation and productivity has gained popularity where both external knowledge (e.g., active knowledge collaboration and spillovers) and internal knowledge (e.g., R&D and ICT expenditure) are assumed to be complements to innovation (Antonelli and Colombelli, 2017). In fact, Antonelli (1999) argues that the new knowledge is a result of a portfolio of various existing knowledge such as learning, R&D, search for technology, an external collaboration that enables various channels for knowledge acquisition and adoption recently tested for the UK innovators in the empirical studies of Giovannetti and Piga (2017) and Belitski et al. (2020).

Investment in internal knowledge such as R&D as well as the acquisition of external knowledge (Conte and Vivarelli, 2005) affect all key innovative outputs with the external knowledge, which is an important boundary condition and an indispensable input to internal knowledge for new knowledge generation in a firm. By using the recombinant knowledge approach (Antonelli and Colombelli, 2015, 2017) we can develop the framework of productivity-innovation analysis and accommodate the key role of investment in knowledge as a key knowledge input.

However, the recombinant approach may not only relate to the interaction between external sources of knowledge and the firm's own R&D (Denicolai et al., 2016) but to the interactions within internal and external knowledge inputs. For example, the recombinant approach assumes that new ideas are generated by means of the recombination of existing ideas, for example, internal knowledge creation *via* R&D and investing in ICT under the constraint of diminishing returns to scale in performing the R&D activities (Roper et al., 2017). Similarly, the generation of new knowledge stems from the active external knowledge collaborations with suppliers, customers, universities, and competitors (Kobarg et al., 2019), in addition to sourcing knowledge *via* spillovers from other firms and industries. Innovation spurs from an ongoing recombinant process that consists of the reorganization of internal (R&D and ICT) and external knowledge configurations (knowledge collaboration with external partners and knowledge spillovers).

2.2. *Innovation and internal knowledge inputs*

Investment in ICT and R&D is a major source of relative competitive advantage for firms (Cohen and Levinthal, 1989; Hall et al., 2009, 2013; Antonelli and Colombelli, 2017; Khalil and Belitski, 2020). Firms that invest in R&D and IT are likely to be more agile and capable of competing in dynamic markets (Straub and Watson, 2001). Investment in ICT and software affects a firm's ability to achieve growth and create and sustain a competitive advantage.

While the role of R&D investment in firm productivity and innovation has been widely discussed in the literature (Jaffe and Lerner, 2001; Kor and Mahoney, 2004; Cassiman and Valentini, 2016; Link and Maskin, 2016; Veugelers and Schneider, 2018), there is a paucity of knowledge about the simultaneous effect of investment in ICT and R&D (Griffith et al., 2006; Hall et al., 2013). Hall et al. (2013) studied the R&D and ICT investment at the firm level to assess their relative importance for firm innovation and firm productivity. The recent study for UK firms (Giovannetti and Piga, 2017) mainly focuses on knowledge networks and knowledge investment for firm productivity and innovation. Our motivation is to include both investments in R&D and ICT into one system of productivity-innovation is as follows. First, it is important to reconcile a more traditional view stating that 'ICT enables "organizational" investments, mainly business processes and new work practices,' generating new knowledge (Hall et al., 2013, p. 303). Second, investment in R&D and ICT lead to cost reductions and improving output, enabling the firm to increase its productivity.

Cohen and Levinthal (1989) discuss the two faces of R&D – knowledge creation and increasing the absorptive capacity to recognize external knowledge, which altogether will increase (a) innovation and (b) firm productivity (Veugelers, 1997). It is reasonable to assume that the argument for R&D in the digital age (Li et al., 2016) will equally hold for ICT investment affecting both the level of firm innovation and firm productivity. We hypothesize:

Hypothesis 1 Investment in R&D is positively associated with (a) firm innovation and (b) productivity.

Hypothesis 2 Investment in ICT is positively associated with (a) firm innovation and (b) productivity.

There is a lack of research on how the investment in R&D will affect firm innovation and productivity if the firm simultaneously increases other investments in knowledge (Cassiman and Valentini, 2016), and investments in ICT (Li et al., 2016). Black and Lynch (2001) focus on the interaction between ICT, human capital, and organizational innovation, while Hall et al. (2013) focus on the interaction between investment in ICT and R&D. It is an important omission, as it is the intensity of knowledge investment that matters, rather than how much you invest in R&D. By looking at intensity of investment in ICT and R&D one may better understand the returns to such investments and compare firms of different size and age (Coad et al., 2016).

A potentially relevant theory/model addressing alignment between investment in R&D and information system strategy is strategic alignment theory used in information system literature (Coltman et al., 2015) and recombinant innovation prospective (Antonelli and Colombelli, 2015). The extant empirical research supports this point and shows that strategic planning and alignment of business processes and ICT operations is unlikely to happen if ICT investment is not coordinated with R&D investment (Audretsch and Belitski, 2021). First, the notion of strategic alignment builds on the arguments (Hirschheim and Sabherwal, 2001) that investment in ICT in addition to general investment in knowledge, and in particular in digital technology and software, increases firm innovation and changes firm structures and capabilities. These capabilities are needed that support the successful realization of strategic decisions, leading to a higher productivity level. Second, alignment is a two-way process where R&D and ICT investment act as mutual drivers. Hence an increase in ICT (e.g., adoption of digital tools, buying out data, cloud, etc.) would also require a subsequent investment in R&D (e.g., training, skills development, workshops, and equipment) to increase the effectiveness of technology adoption and use. Third, strategic alignment of ICT and R&D within a firm further improves absorptive capacity (Cohen and Levinthal, 1989, 1990) to allow an increased pace of technology adoption (Khalil and Belitski, 2020) and continuous adaptation to change in external knowledge sources (Denicolai et al., 2016). We hypothesize:

> **Hypothesis 3** There is a positive interaction effect between investment in R&D and ICT on (a) firm innovation and (b) productivity.

2.3. *Innovation and external knowledge inputs*

While external knowledge is an important source of firm productivity and innovation (Gassmann et al., 2010; Casprini et al., 2017), the relationship between knowledge spillovers and active knowledge collaboration in their impact on innovation (Cassiman and Veugelers, 2002, 2006) and productivity (Giovannetti and Piga, 2017) is complex and understudied. Active knowledge collaboration with external partners and knowledge spillovers brings new knowledge to a firm that can further contribute to existing internal knowledge and become important knowledge inputs. What we know is that a probability of innovation and productivity increases with recombination of investment in internal knowledge (e.g., R&D, training, ICT) (Griliches, 1979; Hall et al., 2013; Belitski et al., 2020) as well as external knowledge such as knowledge collaboration and spillovers (Faems et al., 2005; Link et al., 2007; Antonelli and Colombelli, 2015).

Knowledge collaboration enables access to interorganizational knowledge (Faems et al., 2005), to distribute the costs of innovation between collaboration partners and increase productivity (Veugelers, 1997), and to reduce the product development stage as part of the innovation lifecycle (Hagedoorn, 1993). Knowledge collaboration with external partners increases competitiveness by integrating, modifying, and creating new combinations of resources (Cohen and Levinthal, 1989; Mowery et al., 1998; Miotti and Sachwald, 2003), becoming a conduit to firm innovation and productivity.

In addition to knowledge collaboration, where financial compensation is sought, knowledge spillovers can become useful input as a public good (Agarwal et al., 2010; Link and Scott, 2019). It increases the breadth of knowledge *via* conference participation, technology conference memberships, patent filing, and publications (Audretsch and Keilbach, 2008; Cassia et al., 2009). However, knowledge spillovers as a form of knowledge externality (Audretsch and Keilbach, 2008; Bloom et al., 2019) will not be accessed and utilized unless there is a clear, direct benefit from available knowledge.

Knowledge sourcing *via* external knowledge collaboration and access to knowledge spillovers (Audretsch and Feldman, 1996) will facilitate productivity and innovation *via* two distinctive channels: new product development internally based on available new knowledge *via* spillovers and co-creation of innovation in collaboration with external partners (Bogers et al., 2017). We hypothesize:

> **Hypothesis 4** Knowledge collaboration is associated with an increase in (a) firm innovation and (b) productivity.

> **Hypothesis 5** Knowledge spillovers are associated with an increase in (a) firm innovation and (b) productivity.

The wider and easier access to knowledge spillovers, the larger will be the amount of new knowledge generated by firms for a given level and composition of active knowledge collaboration with external partners (Van Beers and Zand, 2014; Antonelli and Colombelli, 2015). Following this logic, the role of external knowledge collaboration is dual for the firm's incentive to invest in such collaboration for innovation and productivity. First, knowledge collaboration increases a firm's absorptive capacity (Cohen and Levinthal, 1990), enabling recognition of tacit knowledge from different external partners and assimilating it *via* spillovers (Audretsch and Feldman, 1996; Cassiman and Veugelers, 2002). Second, knowledge collaboration eases learning within an organization and adapt knowledge spillovers to the firm's routines. Third, knowledge collaboration helps firms increase their economic value of knowledge spillovers by integrating and modifying external knowledge, including collaborating with external partners (Miotti and Sachwald, 2003; Bogers et al., 2017; Belitski, 2019; Kobarg et al., 2019).

Finally, an increase in knowledge collaboration with external partners when knowledge spillovers are high enables exploitation of exiting firm technology to a greater extent (Veugelers and Schneider, 2018) as well as unpacking a complexity of knowledge by increasing the speed of knowledge recognition, adoption, and commercialization. Antonelli (1999) described innovation as a recombinant process where existing knowledge is input to new knowledge generation and can be further accumulated (Griliches, 1979), increasing innovation and productivity. We hypothesize:

Hypothesis 6 There is a positive interaction effect between knowledge collaboration with external partners and knowledge spillovers on (a) firm innovation and (b) productivity.

3. Data and method

3.1. Data matching and sample description

To test our hypotheses, we used six pooled cross-sectional datasets Business Structure database known as Business Structure database (BSD) and the UK Innovation Survey (UKIS) over 2002–2014. First, we collected and matched six consecutive UKIS waves (UKIS 42002-04, UKIS 52004-06, UKIS 62006-08, UKIS 72008-10, UKIS 82010-12, and UKIS 92012-14) each conducted every second year by the Office of National Statistics (ONS), United Kingdom (UK). Second, we matched the BSD variables for years 2002, 2004, 2006, 2008, 2010, and 2012 to a correspondent CIS survey wave. The BSD data include information on firm legal status, ownership, export, turnover, employment, industry, and postcode. Having finalized the sample construction, we realized that the sample is very diverse, which raised the issue of its pullability. Analysis with the pulled sample and industry-based samples demonstrated significant differences in R square between the industry-specific and the entire samples. This would mean that the model is much better if applied to an industry rather than a set of industries. We, therefore, focused on four specific industries with the highest level of knowledge collaboration, knowledge spillovers, and investment in R&D compared to other industries such as retail and wholesale trade, real estate, public services, construction, utility, mining. Our first industry is manufacturing (3725 observations), which includes high, medium, and low-tech manufacturing (*SIC* 10 - *SIC* 33), excluding crafts (SIC32). Our second industry is ICT and services (*SIC* 58 - *SIC* 63) (889 observations), excluding publishing (*SIC* 58), film, TV, video, radio, and photography (*SIC* 59-60). Our third industry is scientific and professional services (*SIC* 69 - *SIC* 74) (1372 observations), ICT, excluding design, graphic and fashion (*SIC* 74), advertising and marketing (*SIC* 70), Architecture (*SIC* 71). Our fourth industry is the creative industry (515 observations) which includes music, performing and visual arts (*SIC* 59, 85, 90), museums, galleries and libraries (*SIC* 91), publishing (*SIC* 58), film, TV, video, radio, and photography (*SIC* 59-60), design: product, graphic and fashion design (*SIC* 74), advertising and marketing (*SIC* 70), architecture (*SIC* 71), crafts (*SIC* 32).

Most of the firms in our sample are from the South-East of England (12.0%), London (14.5%), the North-West (9.2%), and East England (8.7%). Firms from Wales (5.3%), Scotland (6.0%), and Northern Ireland (4.1%) are least represented. The geographical structure of firms does not change across four samples, waves, and firm size. Most of the observations for four industries were from the pre-crisis period (4,450 observations), while its only 2078 observations come from the post-crisis. The share of new product innovators (Colombelli et al., 2016) dropped significantly in the post-crisis period, resulting in the missing values for innovation.

3.2. Methodology

Crépon, Duguet, and Mairesse (CDM) (1998) approach provides the first econometric analysis of the knowledge generation function combined with a single framework's technology production function.

It was used to analyze the relationship between innovation and productivity and may take into account the role of knowledge and ICT in the innovation process (Hall et al., 2013).

The main shortcoming of the CDM approach is that it follows Griliches (1979) and overlooks external knowledge's role as a boundary condition for innovation and productivity (Conte and Vivarelli, 2005; Audretsch and Belitski, 2020b). The CDM approach is limited in assigning external knowledge search strategies and their interplay in the knowledge generation function (Antonelli and Colombelli, 2017).

In this study, we build a model with four productivity and innovation measures in a simultaneous decision-making process given some potential interdependence of four outcomes by estimating the seemingly unrelated regression equations (SURE) model, in which the individual equations are related to one another (Zellner, 1962). Model one represents a system of equations:

$$\begin{cases} Y_{prod\ (it)} = \beta_0 + \sum_{j=1}^{n} \beta_{11} x_{it} + \sum_{j=1}^{n} \beta_{12} z_{it} + \rho_{1c} + \rho_{1j} + \lambda_{1t} + u_{1(it)} \\ S_{(it)} = \beta_0 + \sum_{j=1}^{n} \beta_{21} x_{it} + \sum_{j=1}^{n} \beta_{22} z_{it} + \rho_{2c} + \rho_{2j} + \lambda_{2t} + u_{2(it)} \\ H_{(it)} = \beta_0 + \sum_{j=1}^{n} \beta_{31} x_{it} + \sum_{j=1}^{n} \beta_{32} z_{it} + \rho_{3c} + \rho_{3j} + \lambda_{3t} + u_{3(it)} \\ C_{(it)} = \beta_0 + \sum_{j=1}^{n} \beta_{41} x_{it} + \sum_{j=1}^{n} \beta_{42} z_{it} + \rho_{4c} + \rho_{4j} + \lambda_{4t} + u_{4(it)} \end{cases} \tag{1}$$

where $Y_{prod(it)}$ is ith firm productivity (relative to the average in the industry) in time t. $S_{(it)}$ is commercialization of innovation measured as share of new to market products of firm i at time t; $H_{(it)}$ is new to market products created in-house by firm i in time t. $C_{(it)}$ is co-creation of new to market products with external partners by firm i in time t. x_{it} is a vector of our explanatory variables such as R&D and ICT investment, knowledge spillovers and collaboration for firm i at time t. z_{it} is a vector of control variables and error term is u_{it}. As in equation (1) we included three additional vectors for time, industry, and city-region controls (ρ_c, ρ_j, λ_t).

3.3. Variables

3.3.1. Dependent variables

For our empirical model, we used four dependent variables. Our first dependent variable is firm productivity. It is calculated as a difference between firm's labor productivity and the average labor productivity in the industry (three-digit *SIC* code industry). Our second dependent variable is innovative sales measured as a share of new to market product sales to total sales. This variable varies between zero – no innovation sales to 100% (Arora et al., 2016). A turnover-based measure enables us to integrate these innovations' highly variable commercial value (Negassi, 2004). Our third dependent variable equals one if new to market goods and services were developed mainly by the business or enterprise group, zero otherwise. This indicator represents in-house innovation, also known as 'Make' innovation strategy and knowledge process outsourcing through alliances (Mudambi and Tallman, 2010). Our fourth dependent variable equals one if a firm developed new to market goods and services with other businesses, zero otherwise. This variable represents the 'ally' innovation strategy (Jacobides and Billinger, 2006) and discussed in management literature in Veugelers and Schneider (2018).

3.3.2. Explanatory and control variables

Our main explanatory variables are an investment in R&D and ICT (internal knowledge) as well as knowledge spillovers and knowledge collaboration (external knowledge). Investment in R&D and ICT were used in prior research (Griffith et al., 2006; Hall et al., 2013) and are associated with firms' absorptive capacity (Cohen and Levinthal, 1990) such as specific skills, experiments, equipments, and advanced machinery (Powell et al., 2005; Li et al., 2016). We use R&D and ICT expenditure to sales ratio known as R&D and ICT intensity. We take a natural logarithm of one plus R&D and ICT intensity to account for non-linear effects of absorptive capacity on innovation and productivity found in the prior literature (Denicolai et al., 2016; Roper et al., 2017).

Incoming knowledge spillovers are calculated using Audretsch and Keilbach (2008) and Cassiman and Veugelers (2002, 2006) definition as the sum of scores (0 to 3) of how important to innovation activities was information obtained from external sources: conferences, trade fairs; professional and industry associations; technical, industry or service standards; scientific journals, trade/technical publication (rescaled between zero and one). These sources are available as an externality for a firm, either without financial compensation for access to knowledge or a greater amount of external resources that were obtained compared to the amount invested in accessing the spillover.

Explanatory variable knowledge collaboration varies between zero – no collaboration on knowledge with external partners to 4, which means knowledge collaboration within four geographical dimensions (regionally, nationally, in Europe and other world) (Balland et al., 2015).

We included several control variables to estimate (1) such as *'firm size'* measured as the number of employees (small, medium, and large) taken in logarithms as well as firm age (Roper et al., 2017). We control for the firm's absorptive capacity by controlling for a share of employees with the BSc degree and above (Cohen and Levinthal, 1989). We add the firm's '*Legal status*' as a binary variable for sole-proprietorship, on-for-profit, and partnership (including family businesses). We controlled for sales abroad and appropriability of innovation (Arora et al., 2016) and firm foreign ownership *(*Love et al., 2014).

Finally, we include industry city-region fixed effects. The list of all variables is in Table 1, with descriptive statistics by industry in Table 2. Variables used to calculate and rescale the knowledge spillover are presented in Table 3.

Table 1. Description of variables

Variable (source)	Definition
Productivity (BSD)	Difference between firm's labor productivity and average labor productivity (sales per employee) by 3 digit *SIC* industry using a full ample of firms from the Business registry by each year. Based on productivity variable percentile subsamples were created
Innovation sales (UKIS)	% of firm's total turnover from goods and services, that were new to the market (%)
In-house innovation (UKIS)	Binary variable = 1 if goods or services developed mainly by business or within enterprise group, zero otherwise
Co-creation innovation (UKIS)	Binary variable = 1 if goods or services developed by this business with other businesses or organizations, zero otherwise
Age (BSD)	Age of a firm (years since the establishment), in logs
Employment (BSD)	Number of full-time employees, in logarithms
Scientist (UKIS)	The proportion of employees that hold a degree or higher qualification in science and engineering at BA/BSc, MA/PhD, PGCE levels
Exporter (UKIS)	Binary variable = 1 if a firm sells its products in foreign markets, 0 otherwise
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
Herfindahl Index (BSD)	Herfindahl Index calculated using concentration in employment by 2 *SIC* digit industry
Foreign (BSD)	Binary variable = 1 if a firm has headquarters abroad, 0 otherwise
Subsidiaries (BSD)	Number of firm's subsidiaries and local units, in logarithms
Appropriability (UKIS)	Sum of scores of the effectiveness of the following methods for protecting new products and processes: secrecy, complexity of goods and services, lead time advantages, patenting, design, copyright, trademarks, lead, complexity, secrecy (rescaled between zero and one)
R&D (UKIS/BSD)	Internal R&D expenditure to sales ratio in logs
ICT (UKIS/BSD)	Advanced equipment and ICT expenditure to sales ratio in logs
Collaboration (UKIS)	Collaboration on innovation with external partners (enterprise group, suppliers; clients or customers; competitors; consultants, commercial labs, private R&D institutes; universities; government and public research institutes) across 4 geographical dimensions. This variable changes from 0 – no collaboration; 1 collaboration with all partners regionally; 2 – regionally and nationally; 3 – regionally, nationally and in Europe, 4 – collaboration within the country, in Europe and with other world
Spillover (UKIS)	Knowledge spillover calculated as a sum of scores (0 to 3) of how important to innovation activities was information from: conferences, trade fairs; professional and industry associations; technical, industry or service standards; scientific journals, trade/technical publication (rescaled between zero and one)

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

4. Results

4.1. Industry perspective

We estimated model (1) for four relatively homogeneous industries. Table 4 provides the manufacturing and ICT industry results and Table 5 for creative and scientific industries. Our results related to the hypotheses are introduced in the following sequence. We started by testing the effect of R&D on firm innovation (H1a) and productivity (H1b) estimated by the coefficient. We then moved to evaluate the impact of ICT on innovation and productivity (H2a and H2b) with the coefficient followed by the interaction coefficient for R&D and ICT to test our H3a and H3b. We followed by estimating the effect of knowledge collaboration on innovation, testing our (H4a) and productivity (H4b), estimating the coefficient and H5a and H5b on the effect of knowledge spillover. Finally, we included an interaction term of knowledge collaboration and spillovers to test H6a and H6b.

4.1.1. Manufacturing industry

First, we report the coefficients in specifications 1 and 2 (Table 4). Our H1a is supported with the positive

Table 2. Summary statistics across various samples

Variable (source)	Manufacturing sector = 3725 obs.		ICT = 889 obs.		Scientific and professional services = 1372 obs.		Creative industry = 515 obs.		Pre-crisis (2002–08) = 4450 obs.		Post-crisis (2008–14) = 2078 obs.	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Productivity (BSD)	19.37	80.28	15.50	79.05	3.82	71.68	5.27	82.32	6.59	82.13	0.51	86.50
Innovation sales (UKIS)	5.20	12.24	8.94	18.51	6.99	19.83	4.39	11.52	3.89	12.06	4.21	13.95
In-house innovation (UKIS)	0.43	0.50	0.47	0.50	0.27	0.45	0.45	0.49	0.28	0.45	0.18	0.38
Co-creation innovation (UKIS)	0.17	0.37	0.13	0.37	0.11	0.31	0.32	0.46	0.12	0.33	0.06	0.24
Age (BSD)	2.84	0.66	2.38	0.78	2.56	0.81	2.54	0.87	2.68	0.74	2.62	0.81
Employment (BSD)	4.16	1.43	3.75	1.40	3.63	1.26	4.02	1.45	4.04	1.48	3.44	1.11
Scientists (UKIS)	6.08	12.60	19.85	27.56	20.76	29.83	10.21	21.03	6.35	15.86	7.39	18.56
Exporter (UKIS)	0.63	0.48	0.51	0.50	0.42	0.49	0.30	0.46	0.36	0.48	0.29	0.46
Survival (BSD)	0.60	0.49	0.54	0.50	0.64	0.48	0.65	0.47	0.55	0.50	0.81	0.39
Herfindahl Index (BSD)	0.03	0.05	0.07	0.08	0.05	0.03	0.04	0.03	0.04	0.05	0.04	0.05
Foreign (BSD)	0.51	0.50	0.44	0.50	0.35	0.48	0.42	0.46	0.50	0.50	0.07	0.25
Subsidiaries (BSD)	0.97	0.77	0.74	0.75	0.78	0.68	0.78	0.80	1.01	0.92	0.73	0.61
Appropriability (UKIS)	0.13	0.19	0.13	0.17	0.10	0.17	0.10	0.13	0.09	0.16	0.06	0.15
R&D intensity (UKIS/BSD)	0.01	0.03	0.04	0.08	0.03	0.08	0.01	0.03	0.01	0.04	0.01	0.06
ICT intensity (UKIS/BSD)	0.02	0.04	0.02	0.06	0.02	0.05	0.01	0.03	0.01	0.04	0.01	0.04
Collaboration (UKIS)	0.74	1.24	0.73	1.17	0.67	1.18	0.39	0.91	0.43	0.97	0.66	1.05
Spillover (UKIS)	0.33	0.28	0.35	0.27	0.33	0.30	0.25	0.29	0.28	0.27	0.21	0.29

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

Table 3. Variables used to calculate incoming knowledge spillover and appropriability

	Variables used to calculate knowledge spillovers	Mean	SD
Associations (UKIS)	How important to innovation activities was information from: professional and industry associations (0 – not applicable to 3 – high)	0.95	0.99
Standards (UKIS)	How important to innovation activities was information from: technical, industry or service standards (0 – not applicable to 3 – high)	0.90	1.09
Conferences (UKIS)	How important to innovation activities was information from: conferences, trade fairs or exhibitions (0 – not applicable to 3 – high)	0.95	0.90
Publications (UKIS)	How important to innovation activities was information from: scientific journals and trade/technical publications (0 – not applicable to 3 – high)	0.70	0.85

	Variables used to calculate appropriability	Mean	SD
Patenting (UKIS)	How effective were patents as a method for maintaining or increasing the competitiveness of product and process innovations: patents (0 – not applicable to 3 – high)?	0.32	0.83
Design (UKIS)	How effective were design registrations as a method for maintaining or increasing the competitiveness of product and process innovations: patents (0 – not applicable to 3 – high)?	0.30	0.75
Copyright (UKIS)	How effective were copyrights as a method for maintaining or increasing the competitiveness of product and process innovations: patents (0 – not applicable to 3 – high)?	0.42	0.80
Trademarks (UKIS)	How effective were trademarks as a method for maintaining or increasing the competitiveness of product and process innovations: patents (0 – not applicable to 3 – high)?	0.37	0.78
Lead (UKIS)	How effective were lead time advantages as a method for maintaining or increasing the competitiveness of product and process innovations: patents (0 – not applicable to 3 – high)?	0.03	0.12
Complexity (UKIS)	How effective were complexity of goods or services as a method for maintaining or increasing the competitiveness of product and process innovations: patents (0 – not applicable to 3 – high)?	0.02	0.10
Secrecy (UKIS)	How effective were Secrecy (include non-disclosure agreements) as a method for maintaining or increasing the competitiveness of product and process innovations: patents (0 – not applicable to 3 – high)?	0.05	0.10

Source: *UK Innovation Survey, 1994–2016 and Business Structure Database, 1997–2017: Secure Access*. UK Data Service.

Table 4. SURE estimation of productivity – innovation for manufacturing and ICT industry

Dependent variable	Productivity	Innovation sales	In-house innovation	Co-creation innovation	Productivity	Innovation sales	In-house innovation	Co-creation innovation
Industry	Manufacturing *SIC* 10 - *SIC* 33 Number of obs. = 3725				ICT *SIC* 58 - *SIC* 63 Number of obs. = 889			
Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age	−8.86*** (1.90)	−1.19*** (0.30)	0.01 (0.01)	0.001 (0.00)	−9.27** (3.81)	−2.57*** (0.88)	0.01 (0.02)	−0.002 (0.01)
Employment	6.30*** (1.50)	−0.44** (0.19)	0.01 (0.01)	−0.001 (0.01)	1.01 (2.70)	−0.91 (0.62)	0.001 (0.01)	0.001 (0.01)
Scientist	0.41*** (0.11)	0.08*** (0.01)	0.01 (0.00)	−0.001 (0.01)	−0.10 (0.11)	0.12*** (0.02)	0.002** (0.00)	0.003 (0.00)
Exporter	6.57** (2.80)	1.50*** (0.43)	0.13*** (0.01)	0.04*** (0.01)	19.32*** (5.71)	−1.12 (1.30)	0.05 (0.03)	−0.01 (0.01)
Survival	1.58 (2.16)	−0.03 (0.39)	0.01 (0.00)	0.01 (0.00)	−2.51 (5.30)	−1.52 (1.20)	0.01 (0.01)	−0.03 (0.02)
Herfindahl Index	38.42 (26.01)	−4.19 (3.90)	−0.19 (0.14)	0.08 (0.12)	−186.37** (37.00)	−4.57 (8.50)	−0.45* (0.21)	0.07 (0.17)
Foreign	19.82*** (3.10)	−1.32*** (.47)	−0.01 (0.01)	0.01 (0.00)	14.82*** (6.72)	−2.40 (1.40)	−0.03 (0.03)	0.03 (0.02)
Subsidiaries	18.86*** (2.01)	0.14 (.31)	−0.01 (0.01)	0.01 (0.01)	13.41*** (5.01)	−0.81 (0.53)	0.01 (0.02)	0.05* (0.02)
Appropriability	18.62* (8.41)	6.36*** (1.22)	0.40*** (0.04)	0.06 (0.04)	−11.04 (18.00)	10.21** (4.14)	0.40*** (0.10)	0.11 (0.07)
R&D β_1 (H1a, H1b)	−177.10*** (47.00)	65.76*** (7.10)	1.92*** (0.26)	−0.39 (0.22)	−148.80** (51.01)	26.40*** (9.30)	1.53*** (0.23)	−0.53** (0.18)
ICT β_2 (H2a, H2b)	53.30 (29.02)	13.34*** (4.44)	0.46*** (0.16)	0.64*** (0.14)	1.76 (55.01)	42.06*** (13.01)	0.43 (0.32)	0.43 (0.24)
R&D × ICT β_3 (H3a, H3b)	−207.71 (368.04)	80.01 (56.22)	−9.72*** (2.14)	−0.22 (1.80)	284.20 (444.02)	35.09 (99.20)	−6.04*** (2.50)	1.50 (1.90)
Collaboration β_4 (H4a, H4b)	−4.41 (2.38)	1.74*** (0.35)	0.09*** (0.01)	0.09*** (0.01)	−4.70 (4.90)	2.17 (1.15)	0.07** (0.02)	0.07** (0.02)
Spillover β_5 (H5a, H5b)	−12.32** (6.01)	3.61*** (0.90)	0.41*** (0.03)	0.18*** (0.02)	1.49 (12.00)	0.52 (2.71)	0.25*** (0.06)	0.09* (0.05)

Table 4. (Continued)

Dependent variable	Productivity	Innovation sales	In-house innovation	Co-creation innovation	Productivity	Innovation sales	In-house innovation	Co-creation innovation
	Manufacturing *SIC* 10 - *SIC* 33				ICT *SIC* 58 - *SIC* 63			
Industry	Number of obs. = 3725				Number of obs. = 889			
Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Collaboration × Spillover β_6 (H6a, H6b)	12.20*** (4.10)	−1.23** (0.62)	−0.14*** (0.02)	−0.08*** (0.02)	6.08 (8.51)	0.01 (1.19)	−0.11** (0.04)	−0.03 (0.03)
Industry controls (2 digit *SIC*)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City –region controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	7.79 (11.02)	4.93** (1.70)	0.05 (0.06)	−0.05 (0.05)	10.79 (32.00)	−1.46 (7.50)	0.19 (0.18)	−0.12 (0.14)
R^2	0.21	0.34	0.31	0.16	0.21	0.18	0.31	0.24
Chi^2	805.25	905.25	1980.10	605.25	102.58	254.28	402.58	100.25
Breush-Pagan test for interdependence of the coefficient	342.20 (Prob < 0)				87.08 (Prob < 0)			

Note: Reference category for legal status is Company (limited liability company), industry (mining), city-region (Newcastle). Industry, year and city region controls are supressed to save space. Robust standard errors are in parenthesis. Robustness check for standard errors included their clustering by 2 digit *SIC*. The coefficients of the SURE regressions for binary variables are the marginal effect of the independent variable on the probability of dependent variables in each regression. For dummy variables, it is the effect of a discrete change from 0 to 1. Significance level: *P < .10; **P < .05, ***P < .01.
Breusch –Pagan test for independence chi2(6) = 905.0, P-value < .01.
Source: *UK Innovation Survey, 1994–2016 and Business Structure Database, 1997–2017: Secure Access*. UK Data Service.

Table 5. SURE estimation of productivity – creative industries and scientific and professional services industry

Dependent variable	Productivity	Innovation sales	In-house innovation	Co-creation innovation	Productivity	Innovation sales	In-house innovation	Co-creation innovation
	Creative industries (*SIC* 58–60, 70, 71, 74, 85, 90)				Scientific and professional services *SIC* 69 - *SIC* 74			
Industry	Number of obs. = 515				Number of obs. = 1372			
Specification	(1)	(2)	(3)	(4)	(9)	(10)	(11)	(12)
Age	10.0***	−0.75	0.05	0.02	−0.80	−2.77***	0.003	0.001
	(4.90)	(0.80)	(0.05)	(0.02)	(2.80)	(0.55)	(0.02)	(0.02)
Employment	−11.30***	−0.21	0.05	−0.01	−3.05	−0.87	0.02**	−0.001
	(3.50)	(0.18)	(0.04)	(0.11)	(1.90)	(0.45)	(0.01)	(0.00)
Scientist	−0.95	0.05***	−0.09	−0.01	−0.19**	0.03	0.01	−0.002
	(0.51)	(0.01)	(0.10)	(0.11)	(0.07)	(0.02)	(0.00)	(0.01)
Exporter	14.15	1.79	0.20***	0.04	13.04***	1.22	0.10***	0.01
	(8.90)	(0.83)	(0.01)	(0.06)	(4.40)	(1.24)	(0.02)	(0.01)
Survival	5.58	−0.11	−0.05	−0.08**	4.98	−0.59	0.01	−0.01
	(4.16)	(0.99)	(0.04)	(0.01)	(4.15)	(0.85)	(0.00)	(0.00)
Herfindahl Index	120.42	−6.32	85.25	0.09	3.93	−27.02	−0.43	0.05
	(106.01)	(4.02)	(5.14)	(0.11)	(80.51)	(18.10)	(0.33)	(0.34)
Foreign	38. 2***	3.83***	−0.01	0.05	14.90***	−0.60	−0.03	0.01
	(20.10)	(1.47)	(0.02)	(0.04)	(5.01)	(1.12)	(0.02)	(0.00)
Subsidiaries	29.56***	0.95	−0.01	0.08	19.21***	1.36	−0.05**	0.01
	(4.01)	(.81)	(0.02)	(0.08)	(3.90)	(0.90)	(0.02)	(0.01)
Appropriability	63.52*	17.50***	0.26***	−0.31***	7.81	25.24***	0.53***	0.07
	(20.41)	(5.22)	(0.10)	(0.05)	(15.05)	(1.40)	(0.07)	(0.06)
R&D β_1 (H1a, H1b)	−228.10	104.46***	1.76***	−3.19	−91.11***	88.35***	0.52***	0.26
	(180.00)	(21.10)	(0.56)	(1.22)	(37.01)	(8.63)	(0.20)	(0.16)
ICT β_2 (H2a, H2b)	−153.10	3.59***	0.88***	0.12	85.21	−11.17	0.42	0.40
	(99.02)	(1.44)	(0.36)	(0.15)	(59.00)	(14.00)	(0.31)	(0.25)
R&D × ICT β_3 (H3a, H3b)	42.71	−43.01**	−4.30	0.24**	−0.50	−32.02	−2.32*	−2.12*
	(15.54)	(16.22)	(3.14)	(0.10)	(12.52)	(52.01)	(1.19)	(1.01)
Collaboration β_4 (H4a, H4b)	−4.41	0.62	0.29***	0.31***	0.01	0.92**	0.09***	0.03**
	(2.38)	(0.55)	(0.08)	(0.11)	(2.40)	(0.08)	(0.02)	(0.01)
Spillover β_5 (H5a, H5b)	5.02	2.36	0.86***	0.96***	16.91**	−3.89**	0.24***	0.18***
	(4.01)	(2.90)	(0.15)	(0.42)	(8.00)	(1.90)	(0.04)	(0.03)
Collaboration × Spillover β_6 (H6a, H6b)	22.21	4.84	−0.51***	−0.44***	1.06	3.05*	−0.10***	0.01
	(15.10)	(1.62)	(0.09)	(0.12)	(0.90)	(1.50)	(0.03)	(0.02)

Table 5. (Continued)

Dependent variable	Productivity	Innovation sales	In-house innovation	Co-creation innovation	Productivity	Innovation sales	In-house innovation	Co-creation innovation
	Creative industries (*SIC* 58–60, 70, 71, 74, 85, 90)				Scientific and professional services *SIC* 69 - *SIC* 74			
Industry	Number of obs. = 515				Number of obs. = 1372			
Specification	(1)	(2)	(3)	(4)	(9)	(10)	(11)	(12)
Industry controls (2 digit *SIC*)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City –region controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	–11.79 (19.52)	2.83 (2.65)	0.04 (0.09)	0.05 (0.15)	4.94 (15.02)	6.72 (3.50)	–0.01 (0.14)	–0.04 (0.10)
R^2	0.28	0.34	0.58	0.32	0.10	0.39	0.37	0.17
Chi^2	134.20	179.23	483.65	169.21	156.21	804.25	914.25	291.20
Breush-Pagan test for interdependence of the coefficient	145.20 (Prob < 0)				77.30 (Prob < 0)			

Note: Reference category for legal status is Company (limited liability company), industry (mining), city-region (Newcastle). Industry, year, and city region controls are supressed to save space. Robust standard errors are in parenthesis. Robustness check for standard errors included their clustering by 2 digit *SIC*. The coefficients of the SURE regressions for binary variables are the marginal effect of the independent variable on the probability of dependent variables in each regression. For dummy variables, it is the effect of a discrete change from 0 to 1. Significance level: *$P < .10$; **$P < .05$, ***$P < .01$. Breusch –Pagan test for independence chi2(6) = 905.0, P-value < .01.
Source: *UK Innovation Survey, 1994–2016 and Business Structure Database, 1997–2017: Secure Access*. UK Data Service.

effect of R&D on innovation (65.76, $P<.01$), extending prior findings of Hall et al. (2013), who found the positive link between R&D investment and product innovation in manufacturing. Our H1b is not supported as the effect of R&D intensity on productivity remains negative (−177.10, $P<.01$) and significant. An increase in ICT intensity ratio by 1% increases innovation sales on average by 13.34 ($P<.01$), supporting H2a. An increase in ICT intensity ratio does not change firm productivity, with H2b not supported (53.30, $P>.10$). The interaction coefficient of R&D and ICT is insignificant, not supporting H3a and H3b.

An increase in knowledge collaboration is positively associated with innovation sales (1.74, $P<.01$), supporting H4a, but it is not associated with firm productivity, not supporting H4b. Our finding expand Antonelli and Colombelli (2017), Audretsch and Belitski (2020b), and Denicolai et al. (2016) as we found that an increase in knowledge spillover is associated with positive changes in firm innovation (3.61, $P<.05$), supporting H5a, while the effect on productivity is negative (−12.32, $P<.05$), not supporting H5b. This finding means that there could be involuntary knowledge outflows when the level of spillovers is high (Cassiman and Veugelers, 2002; Hottenrott et al., 2017). Interestingly, our findings for the manufacturing sector demonstrate that knowledge collaboration and knowledge spillovers are substitutes for firm innovation, with the coefficient being negative (−1.23, $P<.05$), not supporting H6a. On the contrary, a combination of spillovers and collaboration increases firm productivity with the positive interaction coefficient (12.20, $P<.05$) supporting H6b.

4.1.2. *ICT industry*

The results for the ICT sector support our H1a with the positive association between a firm's investment in R&D and innovation (26.40, $P<.01$). In contrast, the effect of investment in R&D on productivity is negative (−148.80, $P<.01$), not supporting H1b. This finding expands Hall et al. (2013) for industries beyond manufacturing. An increase in ICT intensity ratio by 1% increases innovation sales on average by 42.06 ($P<.01$), supporting H2a, but does not affect productivity, not supporting H2b. In the ICT sector, the impact on innovation and productivity of combining R&D and ICT investment is not statistically significant, not supporting H3a and H3b. The result echoes the one for the manufacturing. Our interpretation is that firms in the ICT sector may have costs of R&D already, including the costs of ICT. The most surprising result is that ICT firms mainly use internal knowledge when innovating, while they are not dependent on external knowledge inflows, with the coefficients not statistically significant. Our H4a and H4b as well as H5a and H5b are not supported (specification 5-6, Table 4). As expected, the interaction coefficient between knowledge spillovers and collaboration is positive but not statistically significant (spec 5-6, Table 4), not supporting H6a and H6b. Our main takeaway is that investment in internal knowledge in the ICT sector is associated with innovation but is not associated with increased firm productivity. A simultaneous increase in external knowledge (spillover and collaboration) and internal knowledge (R&D and ICT investment) neither leads to an increase in innovation nor to an increase in productivity.

4.1.3. *Creative industries*

We support H1a on the positive association between R&D on innovation (104.46, $P<.01$), while H1b is not supported (−228.10, $P>.10$) (spec. 1-2, Table 5). An increase in ICT intensity is positively associated with innovation (3.59, $P<.01$), supporting H2a, and is not associated with productivity, not supporting H2b. This finding expands prior works of Crépon et al. (1998), Griffith et al. (2006), Hall et al. (2013) as well as Audretsch and Belitski (2019) on how internal resources used to develop innovation strategies. Our results contrast prior research of Black and Lynch (2001) and Bresnahan et al. (2002) for the USA and further advance the understanding of ICT's role in productivity and innovation in various sectors.

Joint investment in R&D and ICT in creative industries does not increase innovation, not supporting H3a, while it reduces firm productivity (−43.01, $P<.05$) (spec. 1-2, Table 5), not supporting H3b. Due to resource limitations in creative industries (Khlystova et al., 2022), investment in R&D and ICT are often mutually exclusive, which means that a manager-owner decides whether to invest in R&D or ICT based on resource constraints. Our finding adds to Hall et al. (2013, p. 317), who found a similar effect for Italian firms with 'these two kinds of investment are very different from each other' regarding risk and uncertainty and technological change.

Knowledge in creative industries is a place and market-specific, limiting the role of external knowledge inputs. The direct effects of knowledge collaboration H4a (H4b) and knowledge spillovers H5a (H5b) on innovation and productivity are not significant. The interaction coefficient between two external sources of knowledge is not significant. Our H6a and H6b are not supported (spec. 1-2, Table 5).

4.1.4. *Scientific and professional services industry*

First, a firm's investment in R&D is positively associated with innovation (88.35, $P<.01$), supporting H1a, but not supporting H1b as the effect on productivity is negative (−91.11, $P<.01$). The result furthers

Table 6. Summary of hypotheses testing across four industries

Industry	Manufacturing		ICT		Creative		Scientific services	
Hypothesis A-Innovation B-Productivity	A	B	A	B	A	B	A	B
R&D β_1 (H1)	+	–	+	-	+	n.s.	+	–
ICT β_2(H2)	+	n.s.	+	n.s.	+	n.s.	n.s.	n.s.
R&D × ICT β_3 (H3)	n.s.	n.s.	n.s.	n.s.	n.s.	–	n.s.	n.s.
Collaboration β_4 (H4)	+	n.s.	n.s.	n.s.	n.s.	n.s.	+	n.s.
Spillover β_5 (H5)	+	-	n.s.	n.s.	n.s.	n.s.	–	+
Collaboration × Spillover β_6 (H6)	–	+	n.s.	n.s.	n.s.	n.s.	+	n.s.

Note: '+' the coefficient is positive; '–' the coefficient is negative; 'n.s.' the coefficient is insignificant.

prior research of Polder et al. (2009) that R&D drives innovation in the service sector in the Netherlands. It also does in the manufacturing and service sectors in the UK. An increase in ICT investment does not change innovation and productivity, not supporting H2a and H2b. Our H3a and H3b are not supported as both interaction coefficients for ICT and R&D are insignificant (spec. 5-6, Table 5), not.

In contrast to Miller et al. (2018) and Chiesa and Piccaluga (2000) for the scientific sector, we do not find any association between knowledge collaboration and firm innovation (H4a) and productivity (H4b) with both hypotheses not supported. Interestingly, the negative association between spillover and innovation in the industry (−3.89, $P<.05$) (spec. 6, Table 5) does not support H5a, while an increase in knowledge spillovers is positively associated with firm productivity (16.91, $P<.05$) (spec. 5, Table 5), supporting H5b. We argue that the negative effect on innovation results from a high level of imitation in scientific services if knowledge is sourced *via* spillovers as a positive externality (Audretsch and Keilbach, 2008). This could be leveraged, by increasing the degree of collaboration and knowledge spillovers, which reduces the negative effect for innovation from −3.89 ($P<.05$) to −0.84 (3.05–3.89 = −0.84, $P<.05$), hence supporting H6a. The combined effect of knowledge spillover and collaboration does not change productivity, not supporting H6b. The summary of hypothesis testing across four industries is illustrated in Table 6, that provides the 'big picture' of internal and external knowledge recombination for innovation and productivity.

4.2. *Pre- and post-crises analysis*

A comparative analysis of pre-crisis (spec. 1-4, Table 7) and post-crisis (spec. 5-8, Table 7) results demonstrates different patterns, in particular for recombination between internal and external knowledge as well as the direct association between investment in ICT and R&D and innovation and productivity.

All four dependent variables have different R&D and ICT intensity ratios across the two samples. An increase in 1% of R&D intensity ratio is negatively associated with productivity, reducing on average by 120.10 GBP per worker ($P<.01$), not supporting H1b in the pre-crisis period (spec. 1, Table 7). The negative association doubles in the post-crisis period with a negative 214.20 GBP (spec. 5, Table 7). An increase in R&D is associated with an increase in innovation sales on average by 62.89% in the pre-crisis period (spec. 1, Table 7) and by 76.19 % in the post-crisis period (spec. 5, Table 7). Our H1a is supported as R&D is positively associated with innovation in pre -and post-crisis periods. We explain it as R&D expenditure is a cost, and it requires hiring additional workers or may drag finances away from investment in sales and marketing, which immediately transfer into sales. There is also a higher opportunity cost of R&D, resulting in a significant reduction in productivity in the post-crisis period. This finding expands the works of Griffith et al. (2006) and Hall et al. (2009, 2013) on the role of R&D in productivity and innovation.

An increase in ICT investment reduces productivity by 72.81 GBP per worker ($P<.01$) in pre-crisis not supporting H2b. It is associated with, on average, 14.08 % increase in innovation ($P<.01$) (spec. 1-2, Table 7) (Bresnahan et al., 2002), supporting H2a. ICT does not contribute to innovation and productivity in the post-crisis period, not supporting H2a and H2b. H3a and H3b are supported, which means that increased R&D when investing in ICT increases innovation and productivity (Table 7).

Table 7. SURE estimation of productivity – innovation for pre-crisis (2002–2008) and post-crisis period (2008–2014)

Dependent variable	Productivity	Innovation sales	In-house innovation	Co-creation innovation	Productivity	Innovation sales	In-house innovation	Co-creation innovation
	Pre-crisis period (2002–2008)				Post crisis period (2008–2014)			
Industry	Number of obs. = 4450				Number of obs. = 2078			
Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age	0.85	−0.97***	−0.001	0.01	1.08	−1.52***	0.01	0.01
	(1.10)	(0.15)	(0.01)	(0.01)	(2.50)	(0.33)	(0.01)	(0.01)
Employment	3.56***	−0.29**	0.01*	−0.001	0.46	−0.23	−0.01	0.01
	(0.70)	(0.08)	(0.00)	(0.01)	(1.90)	(0.25)	(0.00)	(0.01)
Scientist	0.22***	0.07***	0.001**	−0.001	0.07	0.05***	0.001	−0.01
	(0.05)	(0.01)	(0.00)	(0.01)	(0.12)	(0.01)	(0.00)	(0.01)
Exporter	14.59***	1.03***	0.12***	0.02***	19.01***	−1.75***	0.09***	0.01
	(1.81)	(0.24)	(0.00)	(0.00)	(4.60)	(0.59)	(0.01)	(0.01)
Survival	−1.69	0.30	0.003	−0.01	−3.62	0.47	0.02*	−0.01
	(1.50)	(0.21)	(0.01)	(0.00)	(4.66)	(0.60)	(0.01)	(0.00)
Herfindahl Index	−33.22**	−0.77	−0.08	0.02	−42.52*	7.05	−0.08	0.10
	(16.01)	(2.21)	(0.07)	(0.06)	(25.51)	(4.20)	(0.12)	(0.08)
Foreign	21.21***	−0.94***	−0.01	−0.001	18.48**	0.23	−0.04	−0.01
	(1.80)	(0.25)	(0.01)	(0.01)	(7.30)	(0.94)	(0.02)	(0.01)
Subsidiaries	3.66***	0.21	−0.01**	0.01	−4.93	−0.03	−0.01	−0.01
	(1.10)	(0.15)	(0.00)	(0.01)	(3.74)	(.45)	(0.01)	(0.00)
Appropriability	12.59**	8.35***	0.46***	0.08***	0.84	29.02***	0.84***	0.10
	(5.61)	(0.66)	(0.02)	(0.02)	(2.87)	(3.60)	(0.10)	(0.07)
R&D β_1 (H1a, H1b)	−120.10***	62.89***	1.75***	−0.40***	−214.2 ***	76.19***	1.07***	−0.15
	(29.10)	(4.00)	(0.14)	(0.11)	(46.50)	(6.20)	(0.17)	(0.13)
ICT β_2 (H2a, H2b)	−72.81**	14.08***	0.62***	0.40***	57.28	6.71	0.46**	0.28**
	(20.05)	(2.74)	(0.09)	(0.07)	(52.15)	(6.85)	(0.20)	(0.14)
R&D × ICT β_3 (H3a, H3b)	25.98	11.78	−8.95***	0.54	29.85	−20.32	−3.13***	−0.30
	(210.18)	(29.10)	(0.97)	(0.78)	(135.58)	(36.60)	(1.12)	(0.79)
Collaboration β_4 (H4a, H4b)	−1.14	2.11***	0.10***	0.09***	2.71	0.47	0.09***	0.04***
	(1.87)	(0.25)	(0.00)	(0.00)	(3.69)	(0.46)	(0.01)	(0.00)
Spillover β_5 (H5a, H5b)	6.52*	1.84***	0.26***	0.16***	11.94	0.71	0.25***	0.09***
	(3.25)	(0.46)	(0.01)	(0.01)	(10.02)	(1.30)	(0.03)	(0.02)

Table 7. (Continued)

Dependent variable	Productivity	Innovation sales	In-house innovation	Co-creation innovation	Productivity	Innovation sales	In-house innovation	Co-creation innovation
	Pre-crisis period (2002–2008)				Post crisis period (2008–2014)			
Industry	Number of obs. = 4450				Number of obs. = 2078			
Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Collaboration × Spillover β_6 (H6a, H6b)	6.57**	−1.12***	−0.13***	−0.07***	0.41	1.24	−0.11***	0.01
	(3.20)	(0.44)	(0.01)	(0.01)	(6.80)	(0.88)	(0.02)	(0.00)
Industry controls (2 digit *SIC*)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City –region controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−32.55	3.98***	0.001	0.001	4.04	4.72***	0.001	0.001
	(3.80)	(0.52)	(0.03)	(0.05)	(10.81)	(1.32)	(0.02)	(0.05)
R^2	0.29	0.30	0.35	0.30	0.19	0.29	0.31	0.37
Chi^2	115.20	189.23	305.25	155.31	145.21	404.25	256.25	187.25
Breush-Pagan test for interdependence of the coefficient	255.10 (Prob < 0)				126.20 (Prob < 0)			

Note: Reference category for legal status is Company (limited liability company), city-region (Newcastle). Industry, year, and city region controls are supressed to save space. Robust standard errors are in parenthesis. Robustness check for standard errors included their clustering by 2 digit *SIC*. The coefficients of the SURE regressions for binary variables are the marginal effect of the independent variable on the probability of dependent variables in each regression. For dummy variables, it is the effect of a discrete change from 0 to 1. Significance level: *$P < .10$; **$P < .05$, ***$P < .01$. Breusch–Pagan test for independence chi2(6) = 685.02, P-value < .01.
Source: *UK Innovation Survey, 1994–2016 and Business Structure Database, 1997–2017: Secure Access*. UK Data Service.

An increase in knowledge collaboration, which refers to expanding to one geographical dimension, is associated with an increase in innovation sales by 2.11 %, supporting H4a in the pre-crisis period ($P < .01$), with the relationship dissipating in the post-crisis period. Our H4b on the relationship between knowledge collaboration and productivity is insignificant. Knowledge spillovers are associated with an increase in productivity (6.52, $P < .05$), supporting H5b, and to a greater extent in innovation (1.84, $P < .01$) (spec. 1-2, Table 7), supporting H5a. The effect dissipates in the post-crisis period of 2008–2014, where knowledge investment is significantly reduced, affecting spillovers. Our H5 and H5b are supported for the pre-crisis period and are not in the post-crisis period.

Finally, when spillovers are high, knowledge collaboration is negatively associated with innovation, not supporting H6a, and positively associated with productivity in -pre crises period, supporting H6b. The negative and significant interaction coefficient (−1.12, $P < .05$) demonstrates that managers choose between knowledge spillovers and collaboration. For example, firms that invest in knowledge spillovers may be able to source knowledge that does not require further engagement with external partners to reduce operational costs. Our results for post- and pre-crises are different as it is mainly investment in R&D which continues to be important, and the R&D premium doubles after crises.

5. Discussion and conclusion

This study uses the recombinant innovation approach and applies a holistic analysis where internal and external knowledge for productivity and innovation was put together in a competitive test. Our empirical evidence is based on using both industry and time perspectives in a large, unbalanced panel data sample of the UK firms in manufacturing, ICT, scientific service, and creative industries.

5.1. *Theoretical implications*

Building on the pervasive critique of research that discusses a binary choice between R&D (Cohen and Levinthal, 1989, 1990; Miotti and Sachwald, 2003) and open knowledge collaboration as two sources of innovation (Bogers et al., 2017), our study demonstrates the vital role of internal and external knowledge that can be used to innovate in a recombinant manner (Antonelli and Colombelli, 2015). This study considers that the innovation inputs contain both internal – investment in R&D and new technologies and external knowledge – a collaboration with external partners and knowledge spillovers (Van Beers and Zand, 2014; Antonelli and Colombelli, 2017; Audretsch et al., 2021). This study reexamines to what extent open knowledge collaboration and spillovers and investment in R&D and ICT are complementary for innovation, productivity, controlling for in-house and external innovation strategy. This empirical exercise which is done between sectors with different intensities of knowledge and across pre- and post-crisis period, may change our understanding of how knowledge sources are interlinked and their relevance for innovation outcomes across distinct industrial sectors. This means we need to expand the recombination theory of innovation (Antonelli, 1999) by overcoming an assumption that innovation is mainly R&D driven and that it is used to create new products and source external knowledge (Cohen and Levinthal, 1990; Denicolai et al., 2016). Unlike prior research that has focused on a firm's increase in *total* size (scale-ups) (Audretsch et al., 2021) and firm age (Coad et al., 2016) as well as the key firm characteristics to be able to absorb and recognize external knowledge (Un et al., 2010; Bustinza et al., 2019; Demircioglu et al., 2019) and generate knowledge internally (Casprini et al., 2017), this study introduces the complexity of knowledge inputs explaining how firms across four of the most innovative sectors – ICT, scientific and professional services, creative and manufacturing can innovate drawing on recombination of multiple knowledge inputs. Table 6 provides the systematization of the results from testing our research hypotheses and compares the results across four industrial sectors.

Thereby, we theoretically advance the examination of open innovation mechanisms combined with internal investment in knowledge and technology, but which has not yet been addressed in the scholarly discourse on the open innovation and recombination theory.

First, we demonstrate risks concerning lack of internal investment in absorptive capacity *via* R&D and ICT (Roper et al., 2017; Audretsch and Belitski, 2020b) in particular for manufacturing and ICT sectors, where internal knowledge investment drives innovation outcomes.

Second, we demonstrate that complementarities in R&D and ICT investment are limited and that firms who chose investments in both R&D and ICT are unable to increase their productivity and innovation, contrasting the prior research of Hall et al. (2013), who found that for Italian innovators, ICT and R&D investments are complementary. In fact, for creative industries in particular, the investment in R&D and ICT results in a reduction of firm productivity as adoption of new technologies may require additional competencies which are not available within most creative small firms and requires new recruits that may reduce firm productivity (Li et al., 2016).

Third, we found that the compound factors within external knowledge inputs compared to those within internal knowledge inputs have a more pronounced effect on innovation and productivity across all sectors. For example, increased knowledge collaboration between firms in industries with higher knowledge spillovers reduces innovation in manufacturing while increasing innovation in scientific services. There was no compound effects of internal knowledge inputs on innovation and productivity across sectors, except of a creative sector (Table 6).

Expanding upon the benefits and costs of external knowledge inputs for innovators (Enkel et al., 2009; Alassaf et al., 2020), firms in manufacturing may be most affected by the transaction and financial costs of knowledge collaboration with further access to knowledge spillovers resulting in negative externalities and reduction in innovation. As long as the depth and breadth of knowledge collaboration increases (Hsieh et al., 2018; Kobarg et al., 2019), accessing knowledge spillovers may no longer be critical for innovation or require an additional cost, particularly in manufacturing. In this case, firms that choose to pursue recombination of external knowledge inputs will incur additional costs and will face limits to knowledge collaboration (Audretsch and Belitski, 2020a).

Based on Jaffe (1989), Jaffe and Lerner (2001), and Balland et al. (2015), who stated that the innovation problems are usually complex and embrace many dimensions (e.g., technical, economical, cognitive, geographical, and social), both internal and external knowledge inputs will require a high task interdependence. It will increase the cost and trigger additional coordination efforts. Adopting knowledge collaboration and spillover for manufacturing, ICT, and creative sectors will require longer to proceed with idea development, experimentation, repetition, and implementation. The more complex are tasks (Alassaf et al., 2020), the more likely a firm will work at full resource capacity and will limit knowledge exploration and recombination. Firms in these sectors will require in-depth communication with external partners, increasing the limits to innovation (Salge et al., 2013; Saura et al., 2022). As a result, our negative coefficients demonstrate potential risks to autonomy and decision-making delays, increasing coordination and management costs.

For scientific services, the transaction cost of external knowledge will be relatively low as there are long-term practices of collaboration nationally and internationally, multi-tasking and self-coordination costs between researchers to monitor, control, and manage knowledge transfer (Camacho, 1991). Given lower transaction costs for collaboration and accessing spillovers, the open innovation management in the scientific sector is more likely to benefit from multiple sources of knowledge (Van Beers and Zand, 2014), reducing the transaction costs. Interestingly, for both scientific services and manufacturing, there is a positive direct effect of knowledge collaboration on innovation, unlike in the ICT and creative sectors. We argue that knowledge collaboration enables access to inter-organizational knowledge (Faems et al., 2005; Hsieh et al., 2018), which aims to distribute innovation costs between partners and speed up innovation. With a substantial cost of innovation in manufacturing, collaboration distributes such costs between partners, including different stages of value creation and supply chain (Cassiman and Veugelers, 2002; Cassiman and Valentini, 2016). For both manufacturing and scientific sectors, unlike the ICT and creative sectors, knowledge collaboration helps to reduce the product development stage as part of the innovation lifecycle (Hagedoorn, 1993; Bogers et al., 2017). In the ICT sector, the templates could be used to speed up IT product creation. In the creative sector, artists with more individualistic work, co-creation of knowledge may be limited. A combination of knowledge collaboration and spillovers with external partners increases productivity in manufacturing as it supports integrating, modifying, and creating new combinations of resources for new products (Cohen and Levinthal, 1989; Mowery et al., 1998; Miotti and Sachwald, 2003). The combination of external knowledge for scientific services will mainly affect innovation, as a short-term effect with an increase in firm productivity can be expected with a certain lag and not quickly.

We argue in this study that non-significant results for recombination of external knowledge for firms in ICT and creative industries (Table 6) can also be explained by relatively more fragile knowledge structure for protection, high risk of imitation and learning from these sectors, and limits to appropriate the knowledge created within these sectors. This could be the reason why investment in R&D and ICT in these sectors facilitates innovation to a greater extent than knowledge collaboration and spillovers, adding to Bloom et al. (2019) research on boundary conditions and risks for knowledge spillovers. Those firms in ICT and creative sectors who are aware of it and will undertake strategic (Hall et al., 2013) and legal knowledge protection measures, including sharing IP rights, licensing and other forms of IP collaboration (Hottenrott et al., 2017). Those firms in the ICT and creative sectors who are unable to apply strategic IP protection may either stop collaboration or use other channels of external knowledge sourcing.

Our study thus illustrates that knowledge collaboration and spillovers occur at the intersection of industry-level conditions in explaining how firms innovate and perform, extending prior research on innovation and productivity in R&D and innovation literature (Griffith et al., 2006; Sofka and Grimpe, 2010; Giovannetti and Piga, 2017). This study truly expands our understanding of why recombination of internal and external knowledge sources may not always result in innovation and productivity when we consider this recombination of within internal and external knowledge for innovation (Antonelli and Colombelli, 2015, 2017).

There are the following implications of this research that we would like to highlight. First, our theoretical implications further the view of Salge et al. (2013) and Saura et al. (2022) on the limitations to innovation furthering the recombinant knowledge hypothesis, where an investment in internal or external knowledge alone cannot fully explain innovation and productivity with the compound factors to be examined further (Antonelli, 1999). For example, by applying the theoretical lens on transaction costs, we explain why different industries show heterogeneity in benefits and costs of external knowledge across different innovation strategies. Second, we discuss theories that facilitate or impede firm innovation and productivity, emphasizing the positive impacts of knowledge investment on innovation (Kor and Mahoney, 2004; Griffith et al., 2006; Hall et al., 2013; Link and Maskin, 2016), and explore our unexpected findings across sectors which demonstrate negative and insignificant effects (Salge et al., 2013; Kobarg et al., 2019; Saura et al., 2022). Third, unlike prior research that aims to better understand the unique nature of the inter-dependence between internal and external knowledge (Audretsch and Belitski, 2020b), this study discusses the effect of compound factors of knowledge investment within a firm and knowledge engagement with external partners, including *via* spillovers for innovation and productivity. In addition to this, we discern compound internal and external factors related to firm's propensity to choose between co-creation innovation with external partners or in-house innovation. This empirical test became possible due to the application of the SURE methodological approach, which is different from the well-known Crépon–Duguet–Mairesse (CDM) model of R&D, innovation, and productivity (Crépon et al., 1998; Griffith et al., 2006) but explain why innovation and productivity should be analyzed as one simultaneous decision-making process controlling for in-house and co-creation of innovation decision-making.

5.2. Implications for policymakers

Our findings offer policy implications that would be difficult to ascertain without considering the interdependencies between productivity and innovation and their relationship with innovation strategies and the role of internal and external knowledge reconfigurations. We extended a seminal work of Antonelli and Colombelli (2017) on recombinant innovation with internal knowledge R&D and ICT (Hall et al., 2013) as well as external knowledge driving firm innovation and productivity. Scholarly ability to explain the causality of firm innovation and productivity was limited because a recombinant perspective within internal and external knowledge appears to be random, meaning that firms that rely on one innovation factor may not consider another one within the same origin. We theoretically debated and empirically examined the likelihood of engaging in knowledge creation in-house and co-creation of innovation with external partners in addition to explaining the dynamics of innovation and productivity Policymakers may want to use our findings to better design programs to stimulate complementarities in investment in ICT, R&D and external collaboration reducing transactional costs of collaboration (Camacho, 1991; Bustinza et al., 2019) and overcoming the limits to innovation (Saura et al., 2022).

5.3. Implications for managers

To our knowledge, very few studies have investigated R&D and ICT investments in their joint effect on innovation and productivity. This paper bridges the gap and acknowledges the existence of choice for firms between knowledge spillovers and knowledge collaboration due to potential transaction and coordination costs as well as between R&D and other in-house investments in knowledge. Managers in the creative, manufacturing, and scientific services industries need to be aware that exploring external knowledge collaboration and spillovers may reduce the co-creation of innovation and innovation in-house. Managers in the manufacturing industry may use a combination of external knowledge to increase their productivity, while this is limited for other industries. Interestingly, the returns to R&D are significantly higher during crises, and in relation to other investment in internal and external knowledge, guiding managerial choice for R&D. Investment in R&D and ICT significantly increase innovation performance and propensity to in-house innovation in creative industries, manufacturing, and ICT and investment in R&D in scientific and professional services industry increases the propensity for in-house innovation strategy.

By applying the recombinant innovation perspective to our analysis, further managerial implications can be developed. First and foremost, we show that knowledge collaboration and investment in R&D are both strong predictor of subsequent innovation performance. Policies targeted at facilitating knowledge collaboration are likely to be especially fruitful if they are directed at fostering an engagement within the supply chain and with customers. Policies targeted at knowledge spillovers appear better to incumbent firms. Second, when targeted based on a firm combination of external and internal knowledge inputs, policymakers may focus on specific forms of knowledge collaboration, thereby saving time and reducing unnecessary costs of coordination, management, and engagement. Another implication for the development of policy around factors that have a compound effect on innovation is fostering firms to experiment with new competitive areas or 'blue oceans' ideas within a unique source of internal and (or) external knowledge. This will allow managers to test ideas within limited time and scope and better focus on specific ad-hoc factors which may better work for their industry. Third, we demonstrated that by choosing R&D and ICT as an innovation input, a manager also chooses whether to support productivity or innovation, and the choice depends on the industry and the type of knowledge – external or internal or both. Finally, although we looked briefly at the role of absorptive capacity for innovation (Cohen and Levinthal, 1990), the compound findings for R&D and ICT investments differ across sectors. Managers may want to diversify investment in internal and external knowledge as we empirically evidenced the difference in the effect of R&D and ICT on innovation and productivity. R&D is more uncertain and leads to an increase in costs and intangible assets; however, the premium for innovation is higher compared to ICT investment. Former is more certain and less risky and allows lower marginal returns to innovation and productivity.

5.4. *Limitations and future research*

One of the limitations of this study is that data were collected using a survey that was limited to six time periods. In the UKIS, the sample is rotated, allowing only a small fraction of firms to get into the survey again. A balanced long-term longitudinal study with firm representation across industries, type of innovation, regions, firm size, and age will measure how internal and external knowledge investment change over time and their effect on innovation and productivity. Future research will focus on understanding the different combinations of knowledge and expand the industry perspective.

Another limitation is a reduction in observations in the final three waves of UKIS (2008–2014). The global financial crises likely impacted the availability and efficiency of internal and external resources and in particular, the willingness to collaborate and the availability for knowledge spillovers. We call for future research to examine the SURE model for firms that manage R&D during the crisis (Di Minin et al., 2021) and between developed and developing countries to tease out institutional effects in the relationship between internal and external knowledge, firm innovation and productivity.

Our empirical test has demonstrated that the use of the recombinant innovation approach may provide further insights into unpacking firm innovation strategy for 'make', 'buy' or 'ally' on innovation (Mudambi and Tallman, 2010; Bustinza et al., 2019). Our compound knowledge inputs within a firm – R&D and ICT investment and within external partner – knowledge spillovers and collaboration have a significant effect on changing the propensity of in-house innovation – 'buy' strategy; with no effect on the propensity to co-create new products with external partners – 'ally' strategy. This is a non-obvious finding which extends Jacobides and Billinger (2006) and Veugelers and Schneider (2018) prior research on designing the boundaries of the firm for 'make, buy or ally' innovation, demonstrating that recombination of knowledge sources has a pronounced effect on reducing the 'make', while is not affecting 'ally' strategy. Future research may use these findings as a springboard to further research and discussion on knowledge inter-relatedness and multi-dimensional recombination of knowledge and the choice of innovation strategy.

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Data availability statement

Data is the property of the UK Data Service, part of the UK data archive, and is available by licensing. Standard disclosure and data clearance procedures will apply.

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