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ARTIFICIAL INTELLIGENCE AND FIRM INNOVATION: THE RESOURCE-ALLOCATION PERSPECTIVE

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ARTIFICIAL INTELLIGENCE AND FIRM INNOVATION: THE RESOURCE-ALLOCATION PERSPECTIVE

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Extant research has established that firms increase absorptive capacity to engage in knowledge sourcing and technology adoption and to create knowledge internally to achieve two strategically important objectives: to become more innovative and commercialize innovation. We shift this conversation to a new direction by asking the question of how the adoption of Artificial Intelligence (AI) technology changes firm's choice on resource allocation and shapes innovation performance. Using novel data on 14,143 UK firms over 2004-2020 and the two-step procedure to deal with endogeneity in innovation function, we find an inverted U-shape relationship between internal and external resource allocation and firm innovation and AI reduces the cost of knowledge investment, when these costs are high. Taken together, these results call for a fundamental rethinking of the resource allocation mechanisms and strategies used for firm innovation.

Keywords: R&D; Artificial Intelligence; knowledge collaboration, resource allocation; strategy

INTRODUCTION

A number of key inputs are needed to generate innovative activity, most notably knowledge.

Emerging technologies open up new avenues for innovation and collaboration both within organizations and across different organizational boundaries. Firms, by benefiting from the introduction of new technologies, accelerate the processes of idea recombination and the development of product or process innovations (Bailey et al., 2022; Lanzolla et al., 2020).

The success of technological innovation depends on the availability of sufficient knowledge resources to support continuous discovery and knowledge creation. Innovators require both internal and external knowledge, engaging themselves in a process of continuous search for knowledge resources. Belderbos et al., (2004, 2006) extensively studied the topic of external knowledge sources and choosing. They found that collaborations with different knowledge sources are important conduits of firm performance and innovation. Knowledge emanating from the R&D and human capital of external firms spills over to generate innovative activity in partner organizations.

Much has changed since Belderbos et al., (2004, 2006) found that knowledge collaboration is a unique source of innovation. Gassmann et al.,(2010), Mudambi and Tallman (2010), Cassiman and Valentini (2016), Casprini, et al., (2017) and Maritan and Lee (2017) pointed out that allocation of resources within organizations and knowledge sourcing from external partners, including direct knowledge transfer and acquiring external knowledge such as R&D, impacts firm innovation outcomes. By choosing a knowledge allocation strategy, whether make, buy, or ally, a firm chooses the type of innovation outcomes it wants to produce. This is what finally determines the extent of knowledge commercialization in the market.

Research on open innovation (Belderbos et al., 2004; Chesbrough, 2006) predates the development of highly-advanced digital technologies, such as Artificial Intelligence (AI). Despite a massive and fundamental revolution in digital technology, along with a reduction in the cost of data collection and knowledge transfer using AI, the strategic management literature still is unable to clearly evaluate the benefits that AI technology brings to firm innovation and discover novel practices that necessitate theoretical examination and clarification (Benbya et al., 2020).

Currently, there is a shortage of in-depth empirical understanding regarding the integration of Artificial Intelligence within a firm. Existing research faces limitations as it focuses on a narrow range of empirical cases, neglecting broader organizational contexts and phenomena where AI intersects and enhances well-established practices with multiple business routines and practices. Therefore, the purpose of this paper is to advance our understanding of the resource perspective of the role that AI alongside other internal and external knowledge sources play in a firm's innovation. Our main research question is how and to what extent AI has impacted firm innovation and been able to complement other knowledge sources? By answering this question we can also test whether or not the adoption of AI by a firm serves as an important conduit to firm innovation (Chen et al., 2018; Haefner et al., 2021; Keding & Meissner, 2021; Link & Scott, 2019). If it does not do so, the strategic management of resources and technology in organizations will require fundamental rethinking.

Using novel data on 14,143 firms with 24,017 firm-year observations over 2004-2020 in the United Kingdom, matched from six Business Structure Databases (BSD), the UK Innovation Surveys (UKIS) and the Beauhurst databases, we put resource allocation at the forefront of strategic management and open innovation research by emphasizing the role of internal and external knowledge within a firm as a nonfinancial resource relevant to a firm's innovation strategy. Our study makes the following three contributions to open innovation and management literature. Firstly, our findings from this paper put forward a very different view of the strategic management of resources than currently exists in the extant literature. We argue that a firm's internal and external investment in R&D has a consistent inverted U-shape relationship with the firm's innovation, while firms that adopt AI positively moderate the non-linear relationship, reducing the cost of resources to firms (Williamson, 1979).In particular, those firms who adopt AI are able to increase their innovation performance when investment in R&D, both internally and externally, complements the firm's own knowledge investment. In addition, we find that the adoption of AI by firms may serve as a substitute for knowledge collaboration with several external partners (e.g., suppliers, universities).

Secondly, we suggest the need to rethink the role of absorptive capacity in a firm's innovation as the adoption of digital technologies such as AI, e.g., ChatGPT, OpenAI, is capable of reducing transaction costs (Williamson, 1979), thus extending the firm's ability to invest in absorptive capacity and source knowledge from external resources, including spillovers and R&D collaborations (Bernal et al., 2022). In doing so, we extend the focus of management literature to the role of interplay between internal and external resources and the effect that AI has on leveraging the cost of knowledge adoption and engaging in external collaborations. This comes with the understanding that traditional digital technologies and platforms have reduced the marginal cost of adding additional knowledge units to the firm's processes and that they can complement human skills and decision-making.

Thirdly, our paper demonstrates different components in the firm’s absorptive capacity, each of them having a very distinct effect on firm innovation. These three components of AI include investment in R&D, digital and information technology, and AI. This went unnoticed in the earliest work of strategic knowledge management (Lovallo et al., 2020; Wu et al., 2014) and innovation literature (Belderbos et al., 2004, 2006, 2015; Nelson, 1982; Nelson & Winter, 1982). This is because each type of absorptive capacity serves different objectives of innovation and knowledge sourcing. The paper is structured as follows. Section 2 discusses the literature and postulates the research hypothesis. Section 3 examines data and methods, while Section 4 discusses the main results and Section 5 discusses and concludes.

INVESTMENT IN KNOWLEDGE AND INNOVATION: A MICRO PERSPECTIVE

Resource -based view of firm innovation

The resources that each firm has at its disposal to perform innovation processes are limited. By virtue of this, the resources may affect the strategic decisions of managers to innovate, and also explain how firms innovate. Internal knowledge creation occurs through R&D and ICT investment and hiring of highly skilled labor (Roper et al., 2017). External knowledge occurs through buying R&D, knowledge spillovers and collaboration with external such as suppliers, competitors, customers, and universities (Kobarg et al., 2019). Unlike internal and external investment in R&D, managers are more in control of knowledge collaboration and may quickly intervene and correct the intensity and breadth of such external collaborations.

Innovation knowledge inputs and technology

Investment in internal knowledge is a major source of relative competitive advantage for firms(Cohen & Levinthal, 1989; Hall et al., 2009, 2013). Firms that invest in R&D and ICT are likely to be more agile and capable of competing in dynamic markets (Straub & Watson, 2001). Investment in ICT and software affects a firm’s ability to achieve growth and to create and sustain a competitive advantage through innovation. While the effect of internal R&D and ICT investments have been discussed as overwhelmingly positive in the extant literature (Cassiman & Valentini, 2016; Jaffe & Lerner, 2001; Kor & Mahoney, 2004; Veugelers & Schneider, 2018), investment in R&D and ICT has transaction and financial costs can result in a diminishing marginal return when R&D intensity is high (Griffith et al., 2006; Hall et al., 2013). Cohen & Levinthal (1989) discuss two reasons for this, which authors call faces of R&D. Firstly, increasing the absorptive capacity of a firm will help the company to recognize and absorb external knowledge flows for innovation. Secondly, internal resource allocation enhances internal knowledge and may result in more innovation and patenting (Veugelers, 1997). It is reasonable to assume that in the digital age (Li et al., 2016) resource allocation in both R&D and ICT is equally important for innovation.

Resource allocation is expected to positively affect firm performance (Teece, 2007). However, the prior research of Winter (2003), and more recently Saura et al. (2022), and Audretsch and Belitski (2022), note that attempting too much investment in knowledge and collaboration with external partners is not free and can lead to additional transaction and operational costs. These costs occur when the frequent disruption due to the coordination of resource allocation outweighs the value of the resources created and bought by the firm. In this vein, it can be argued that excessive internal R&D and ICT investment could negatively affect both types of firm performance. There are three key reasons for this.

First, allocating capital to intensify R&D and ICT investment internally will take capital away from other areas of investment (e.g., employment, infrastructure, e-presence, etc.) which could disrupt the firm's operations. The extent of such disruption, which has the potential to compromise the success of the "make innovation" strategy, grows as R&D investment increases and ICT and R&D intensity is prioritized over other inputs in innovation. Second, excessive allocation of capital to ICT and R&D will lead to deviation from the current innovation strategy, increasing the cost and price of innovation, and result in higher volatility of resources reducing the firm's competitive advantage (Sirmon & Hitt, 2009). A greater level of investment in R&D and ICT implies a significant upgrading of physical capital, which is associated with a greater turnover of human capital as employees would need to leave the organization as their knowledge is either now not applicable or obsolete in the new innovation context. Third, a higher level of internal R&D and ICT expenditure brings greater risks (Lovallo et al., 2020). This is because every additional expenditure on R&D adds novel ideas that may challenge and potentially substitute status quo projects, where company has been specialized. The critical mass of newly created knowledge will increase the opportunity costs of pursuing products and services where a firm has already reached a status quo, and lead to an increase in the firm's slack of old and existing projects. We hypothesize:

Hypothesis 1. Internal knowledge resource allocation through various components of firm's absorptive capacity has an inverted U-shape relationship with firm innovation.

Along with the allocation of internal knowledge, sourcing external knowledge can be an important strategy for innovation (Gassmann et al., 2010; Casprini et al., 2017). This is particularly the case when a firm's absorptive capacity to create new knowledge is low, or when the time to introduce innovation should be shortened. The allocation of resources to external R&D is an innovation strategy intended to uncover diverse and novel knowledge. However, research on the buy innovation strategy is limited (Audretsch & Belitski, 2023; Mudambi & Tallman, 2010). The allocation of resources to external knowledge sources makes it easier and faster to access the inputs needed to develop the innovation process (Chesbrough, 2003; Laursen & Salter, 2006). Openness to external knowledge allows firms to increase innovation productivity and reduce costs (Cassiman & Valentini, 2016; Chesbrough, 2003; Faems et al., 2005). The environmental context represents several sources of external knowledge, and access to this context enables firms to overcome the problems associated with increasing internal R&D costs (Chesbrough, 2003). Firms that become more permeable to the external environment, and thus rely on externally developed knowledge and new technologies, can generate new revenues and reduce the cost and time of internal R&D via new technology adoption.

Prior research has demonstrated that firms that are open to external knowledge can identify a large number of knowledge transfer opportunities (Cassiman & Valentini, 2016; Rothaermel & Deeds, 2006) and transfer them into new ideas and products. However, the buying knowledge strategy has limitations. Buying knowledge takes place within and between industries. The larger the technological differences between a supplier and a consumer of knowledge, the higher the transaction costs associated with understanding the value of the knowledge and adjusting it to firm’s specialization. The transaction and monitoring costs of accessing knowledge may increase with external knowledge sourcing. Further increases in the purchase of external R&D will raise the costs of adapting new knowledge and integrating it into the firm’s routines, processes and procedures. Additional management structures may be needed to supervise and oversee knowledge flows, to understand which units should participate, and the extent to which external partners need to be involved in adopting and commercializing innovation. The combination of the generally positive effects of external knowledge sourcing with the potential limits to continuous levels of resource allocation externally leads us to the following hypothesis:

Hypothesis 2. External knowledge resource allocation via buying knowledge has a non-linear relationship with firm innovation.

In addition to buying knowledge from external partners, resources could be allocated externally for knowledge collaboration. The strategic management literature emphasizes an overwhelmingly positive effect of knowledge collaboration on building strategic partnerships and alliances (Belenzon & Schankerman, 2015) as well as incentivizing firms to invest in knowledge internally (Cohen & Levinthal, 1990). Knowledge collaborations with different partners in addition to “make” and “buy” knowledge, increase the absorptive capacity of a firm (Audretsch et al., 2021; Cassiman & Veugelers, 2002). External knowledge collaboration eases learning within an organization and with external partners and enables faster recognition and creation of new knowledge. While there is no “free lunch” in business, the positive effects of external resource allocation via collaboration on knowledge for all partners is embedded into co-creation and the economic value of knowledge, and by understanding the way existing knowledge can be modified (Bogers et al., 2017, 2019).

Knowledge collaboration may enable access to the intellectual property of partners for learning and adopting of new technology (Bernal et al., 2022). Allocation of knowledge externally will help firms to develop, but also scale and speed up the transfer of new technologies, which requires a significant amount of risk-taking, trust and negotiation between the collaborating partners (Belitski et al., 2020; Hall et al., 2013). In particular, a cost-sharing between partners remains one of the key arguments for allying on innovation (Hagedoorn, 1993; Veugelers, 1997). This is because it reduces average costs per unit of production and creates new knowledge combinations (Antonelli & Colombelli, 2017; Nelson, 1982).We hypothesize:

Hypothesis 3. External knowledge resource allocation via engagement in R&D collaboration with external partners is positively associated with firm innovation.

Prior research has found a non-linear relationship between external and internal resource allocation and firm innovation. A substantial increase in external and internal resource allocation leads to diminishing and finally negative returns to such allocation. Firm managers have therefore looked closely at how they can continue to allocate resource for innovation (Aghion & Howitt, 1998) while also minimizing the negative effects of resource allocation related to transaction and operational costs.

These costs could be reduced if information processing was optimized and more managerial functions were automated and outsourced to machines (McNally & Schmidt, 2011; Van Riel et al., 2004). The business world has changed, as the digitization of business routines and processes has reached unprecedented levels in the US (Digitally Driven, 2020) and Europe (Digitally Driven, 2021). In particular, AI has been extensively used to process innovation inputs and recombine various information streams. This is intended to produce systemized information (Haefner et al., 2021; Keding, 2021) which could be used as knowledge for innovation. There are several mechanisms that could enable AI to reduce operational and transaction costs for a firm (Madhok, 2002; Williamson & Masten, 1995) and minimizing knowledge slack (Lovallo et al., 2020), thereby enhancing innovation outputs. First, the adoption of AI by firms rapidly changing the way information is processed and exchanged. The use of AI technology challenges traditional ways of knowledge organisation and management in firms. While AI does directly generate innovation, it is able to substantially reduce the operational and transaction costs of searching, collecting and processing knowledge within and outside an organization. AI changes firm resource allocation choices so that only those strategies on resource allocation that require human judgment will be communicated to managers.

Second, by processing a significant amount of information flows and applying a cognitive procession algorithm, AI is able to filter and make sense of information. It can create new information channels for managers, so that analysis can be faster and more clustered and systemized (Keding, 2021; Haefner et al., 2021). In addition to clustering and classifying data, AI algorithms can follow up managerial decisions and provide interactive feedback, thus reducing firm operational and monitoring costs.

Third, the matching algorithms allow AIs to match suppliers with customers, and to give advice on market choices and channels, thus economizing on market research costs and learning about customers. In addition, AIs could advise managers on which markets they should avoid. This would help firms to respond quickly and reduce managerial procedures of data analysis and sense-making, increasing their competitive advantage.

Fourth, by enabling cognitive analysis AI analyses and ranks managerial decisions on resource allocation by their level of uncertainty and risk, and in doing so reduces both the riskiness and cost of decision-making processes (Belhadi et al., 2021; Haefner et al., 2021; Paschen et al., 2020). Fifth, AI is a form of intelligent capability that increases the speed of the knowledge adoption and knowledge assimilation process; what Cohen and Levinthal (1990) would call a firm’s absorptive capacity (Paschen et al., 2020; Srivastava et al., 2015). In its engagement with external resources, AIs perform a function of a firm’s dynamic capability (Teece, 2007), and it is particularly useful in uncertain environments when firm management is physically limited (e.g., small high-growth firms) (Escribano et al., 2009). Sixth, AI reduces transaction costs when managerial teams are large, where decision-making, discussion and debate take a long time. Large boards may wish to adopt an AI as they are able to mimic the "complex cognitive functions usually associated with humans, such as reasoning, predicting, planning, and problem-solving" (Dixit et al., 2021, p. 346). In a growing repository of data, and an increasing pressure on boards of faster decision-making, AI could reduce the transaction costs associated with negotiation and debate. AIs could be helpful when deciding on internal or external resource allocation by simulating the outcomes of a particular decision (Sjödin et al., 2021).

Finally, the marginal costs of using AI are nil or very minimal, as this technology caters for various amounts of numerical data and learning algorithms as long as the cloud capacity enables the data analysis and storage. AI reduces the time between collecting, learning, processing and acting on data, reducing the possibility of disruption.

We also argue that AI will inevitably affect firms with very low and very high resource allocations. Firstly, for firms that do not invest in knowledge, AI may be used as an alternative smart resource for data collection and sense-making. Secondly, for firms at the resource possibility frontier, AI reduces the costs of knowledge management and decision-making (Keding, 2021; Haefner et al., 2021).

This argument leads us to the following hypothesis:

Hypothesis 4a. Internal knowledge resource allocation for firm innovation is enhanced by the adoption of AI.

Hypothesis 4b: External knowledge resource allocation via buying new knowledge for firm innovation is enhanced by the adoption of AI.

Hypothesis 4c: Collaborating on knowledge for firm innovation is enhanced by the adoption of AI.

DATA AND METHOD

Data matching and sample description

To test our hypotheses, we used six pooled cross-sectional datasets: the Business Structure database known as the BSD), the UK Innovation Survey (UKIS) over 2004-2020, and the Beauhurst database.

First, we collected and matched eight consecutive UKIS waves (UKIS 4 2004-06, UKIS 5 2006-08, UKIS 6 2008-10, UKIS 7 2010-12, UKIS 8 2012-14, UKIS 9 2014-16, UKIS 10 2016-18, UKIS 11 2018-2020). Each wave was conducted every second year by the Office of National Statistics (ONS) in the UK. Second, we matched the BSD variables for the years 2005, 2007, 2009, 2011, 2013, 2015, 2017 and 2019 to the corresponding CIS survey wave. The BSD data includes information on firm legal status, ownership, exports, turnover, employment, industry and postcode. Third, we used the Beauhurst (2020) data archive to identify sectors where AI is used and matched it to BSD and UKIS data. Beauhurst collects firm-level data on high-growth firms in the U.K. using an artificial intelligence algorithm to download information using open sources and company reports.

We use 14,143 firms with 24,017 observations over 2004-2020, with 8,605 firms observed only 1 time during 2004-2020, 2949 firms observed 2 times, 1646 firms observed 3 times, 472 firms observed 4 times, 261 firms observed 5 times, 118 firms observed 6 times, 65 firms observed 7 times, and 27 firms observed 8 times (all UKIS waves) (see Appendix A1 for more details). Most of the firms in our sample were in the South-East of England (10.93%), London (9.67%), the North-West (9.33%) and East England (8.82%). Firms from Northern Ireland (7.73%), Wales (6.61%), and North-East (5.62%) are least represented. Most of the firms in our sample are from the other manufacturing (22.20%), wholesale and retail (15.98%), and professional and scientific (11.18%). The less-represented industries are education (0.42%) and real estate (1.81%). The majority of businesses (44.63%) are small firms with 10 to 49 full-time employees (FTEs), followed by large firms (250 FTEs and more) which constitute 17.93% of the sample, and medium-small firms (50-99 FTEs) with 14.48% of the sample. Medium-large (100-249 FTEs) firms constitute 10.77% of the sample, and 12.19% of the total are micro firms (1-9 FTEs).

Although there are eight surveys covering 2004-2020, after cleaning for the missing values of the variables of interest, as well as non-active and dormant firms, we were left with a total of 24,017 observations (out of 116,584). When controlling for missing values, we found substantial non-reported data on knowledge collaboration in particular. To be included in the sample, all questions related to the variables of interest needed to be completed with no missing values.

Variables and measures

Dependent variables

Our main dependent variable is innovation sales, which is calculated as a percentage of total turnover over the last three years from goods and services that are new to the market. While it varies between zero and one hundred percent, the average share of new to market products in our sample is 4.98 percent of sales for all firms. (De Leeuw et al., 2014) interpreted 'new products to the market' as an indicator of product innovation. Operationalizing the innovation variable is consistent with innovation studies in related contexts (Laursen & Salter, 2006; Roper et al., 2017; Kobarg et al., 2019).

Explanatory variables

Our first explanatory variable is AI, which is a binary variable equal to one when the firm adopts AI, equal to zero otherwise. We used a sectoral approach to construct the measure of AI adoption, using an external (non-self-reported) Beauhurst database to identify sectors by the 5-digit Standard Industrial Classification (SIC Code) where AI is adopted. Next, using the 5 -digit SIC codes from the Beauhurst database, we matched them to 5 -digit SIC sector in the UK Innovation survey (CIS).

In addition, two inclusion criteria were applied. First, all firms with $ICT^{*}_{it} > 0$ are included. We predicted ICT^{*}_{it} in equation (2b) as the latent variable for ICT intensity. ICT intensity includes expenditures on advanced equipment, ICT, software and hardware to total sales. Second, all firms with a predicted share of employees S_{it}^{*} >0 from equation (2c) are included. S_{it}^{*} is the latent variable which is predicted and that represents an expected proportion of employees who hold an undergraduate or postgraduate degree in science and engineering at BA / BSc, MA / PhD or PGCE level employed by a firm. All firms which complied with the first criteria – belongingness to the AI adoption 5 digit SIC 2007 sector, but with either S_{it}^{*} =*0* or ICT_{it}^{*}=0 was excluded from AI adopters.

Our second set of explanatory variables represents different dimensions of firms absorptive capacity and is operationalized as an investment in R&D and ICT, as well as a share of employees with science and engineering degrees (scientists). We use predicted values of internal and external R&D intensity (R_{itz}^{*})as well as ICT intensity ICT_{it}^{*} in equation (3). This approach helps us to deal with the two-way causality between innovation inputs and outputs (Griffith et al., 2006; Hall et al., 2013). We used the predicted share of scientists employed by a firm S_{it}^{*} in our equation (3). Our third set of variable includes binary variables for operationalizing the choice of partners in external knowledge collaboration (Roper et al., 2017; Van Beers & Zand, 2014). The binary variables represent six types of collaboration partners (Cassiman & Veugelers, 2002; Faems et al., 2005), such as the government, universities, consultants, competitors, customers, and suppliers. In order to account for potential diminishing returns from investment in knowledge (Kobarg et al. 2019; Audretsch & Belitski, 2023), we used the predicted values of R_{itz}^{*} and ICT_{it}^{*} and scientists in levels and a squared terms. For each external partner, firms indicated whether and with which partner type collaboration was conducted and to what extent, from zero –collaboration not used to 3 – highly important collaboration channel for innovation.

Control variables

We included several control variables to estimate (1), such as "employment" measured as the number of employees (small, medium, and large) taken in logarithms (Roper et al., 2017). We controlled for the appropriability of innovation (Arora et al., 2016), measured as the average of appropriability strategies used by firms (patents), and “foreign” as firm foreign ownership (Love et al., 2014). We add the firm’s “reporting units” as a variable to count the number of units reported. We considered whether firms were “start-ups” (0-7 years since establishment), “established” (8-15 years since establishment), “transitioned” (16-30 years since establishment) and “mature” (over 30 years since establishment). Finally, we include industry and region fixed effects. We refer the reader to Table 1 for a description of the variables and summary statistics, while Table 2 contains the correlations between the examined study variables.

Insert Table 1 about here

Insert Table 2 about here

Methodology

The econometric model we adopted caters for the role of AI in facilitating the allocation of external and internal resources for innovation output. A similar approach was introduced by Negassi (2004), Faems et al. (2005), Laursen and Salter (2006) to estimate a knowledge production function, and more recently by both Giovannetti and Piga (2017) and Kobarg et al. (2019).

The choice of model is often determined by the available data and the construction of the dependent variable. The issue is related to the characteristics of our dependent variable, which is double censored, as firms can have none or all sales from new to the market products. There are several different ways of estimating such models with censored dependent variables using parametric techniques (Cameron & Trivedi, 2005; Wooldridge & Econometrics, 2003). The main benefit of concentrating on the Tobit estimation is that it provides a finer understanding of the potential selection of firms that innovate and develop new products and those that do not. We note that the standard Tobit model is useful if the sample is randomly selected among the population (Office for National Statistics, 2021a, 2021b). Despite it has many advantages, Tobit models may lead to imprecise estimates when scholars are misguided in discerning the nature of the dependent variable, the difference between selection concerns and censored data, and the distribution of the residuals(Amore & Murtinu, 2021).

The underlying assumption of the method is that the disturbances are normally distributed and the same data generating process that determines the censoring is the same process that determines the outcome variable. Our dependent variable is censored at zero, which allows us to apply a standard Tobit estimation (Wooldridge & Econometrics, 2003):

$$I_{it} = \beta_0 + \beta_1 R_{itz} + \beta_2 ICT_{it} + \beta_3 K_{it} + \beta_4 \rho_{it} + \beta_5 R_{itz}\rho_{it} + \beta_6 ICT_{it}\rho_{it} + \beta_7 K_{it}\rho_{it} + \beta_8 X_{it} + u_{it} \qquad (1)$$

where I_{it} represents innovation sales for firm i that varies between zero and 100 at time t. The term R_{itz}in is the allocation of resources such as R&D intensity of type z – internal (make) and external (buy), the term ICT_{it} is the ICT intensity (make); and the term K_{it} is knowledge collaboration (ally) of firm i at time t; ρ_{it} is AI – a binary variable which equals one if firm i uses AI at time t, zero otherwise. X_{it} is a vector of control exogenous variables including year, industry and region fixed effects; u_{it} is the error term and is assumed to be identically and independently distributed with mean zero and constant variance σ^2.

Solving the issue of endogeneity

Modelling the relationship between internal and external knowledge and firm's innovation presents an interesting set of challenges. First, there is the issue of timing. A firm manager decides to invest in ICT and R&D internally may be affected by the precedent commitment to innovation and success of commercialization (Hall et al. 2013). We assume here that firms which are in the process of developing innovation simultaneously decide on the extent of investment in internal knowledge and how to access external knowledge from partners and which partners should be prioritized or both.

Second, there may be a reverse causality relationship between innovation and investment in R&D and ICT (Hall et al. 2009; 2013; Giovannetti & Piga, 2017), as well as investment in human capital by hiring staff with science and technological, engineering background and qualifications (Audretsch et al. 2021). The nature of the unbalanced panel data in our sample may also create the bias for potential simultaneity of effects. The two-way causality is driven by the fact that more innovative firms may opt for internal R&D as this may, for example, increase their absorptive capacity in a long-term. In his study we aim to address this issue by using the technique that predicts the investment in internal and external R&D, ICT and employment of scientists by using the instruments. This does not fully solve the problem of simultaneity of decision-making induced by permanent unobservable differences in innovative inputs and outputs, but it does mitigate any bias arising from transitory effects.

Our model introduced in this section focuses on the roles that innovation inputs (e.g. investment in internal R&D and buying R&D, ICT and a share of employees with science and engineering degrees) may affect the probability of introducing innovation across all survey waves. The similar sequential approach to predict the production function was by Crépon, Duguet and Mairesse (1998) and Audretsch and Belitski (2021) to estimate the triangular relationship between investment in knowledge and innovation type in their effect on firm productivity. The main benefit of concentrating on this sequential approach is that it demonstrates that the channels between innovation inputs and outputs penetrate through the production system.

The first set of equations (first stage) of the model describes whether a firm undertakes internal and external R&D, ICT and the share of employees with science and engineering degrees employed by a firm. In the model, a firm must decide whether to do internal and external R&D, invest in ICT and how many scientists to employ. This statement of the problem is modelled with a standard sample selection model. The external and internal R&D, ICT and employment of scientists given the firm's characteristics.

$$R_{itz} = \begin{cases} R^{*}_{itz} = \beta x_{it} + \mu_{it} \ if \ R\&D > 0 \\ 0 \qquad if \ R\&D = 0 \end{cases} \tag{2a}$$

where $R^{*}_{itz}$is the unobserved latent variable corresponding to the firm's investment in R&D of type z, which means either internal R&D spending or buying R&D from external sources, and x_i is a set of determinants of the R&D (internal or external) expenditure intensity of type z – which can be internal R&D or external R&D. We measure intensity of R&D as the logarithm of internal (external) R&D expenditure to sales. We assume the error terms in equation (2a) are bivariate normal with zero mean and constant variance. Our R_{itz} is the level of R&D intensity of type z (internal, external) of a firm i at time t derived from equation (2a).

$$ICT_{it} = \begin{cases} ICT^{*}_{it} = \beta x_{i} + \mu_{i} \ if \ ICT > 0 \\ 0 \qquad if \ ICT = 0 \end{cases} \tag{2b}$$

where $ICT_{it}^{*}$is the unobserved latent variable corresponding to the firm's ICT intensity, that is measured as the ratio of ICT expenditure to sales; and x_i is a set of determinants of the investment in ICT to sales. ICT_{it} is the level of ICT intensity of a firm i at time t derived from equation (2b). We assume the error terms in equation (2b) are bivariate normal with zero mean and constant variance.

$$S_{it}=\begin{cases} S_{it}^{*}=\beta x_{it}+\mu_{it} & if\ share\ of\ employees\ with\ science\ degree\ >0 \\ 0 & if\ share\ of\ employees\ with\ science\ degree\ =0 \end{cases} \qquad (2c)$$

where $S_{it}^{*}$is the unobserved latent variable corresponding to the share of employees with science and engineering degrees employed by a firm, and x_i is a set of determinants of the share of employees with science and engineering degrees (scientists) in total number of full-time employees. We assume the error terms in equation (2c) are bivariate normal with zero mean and constant variance. Our S_{it} is the share of employees with science and engineering degrees of a firm i at time t derived from equation (2c).

The first stage procedure is grounded in the idea that many firms do informal R&D and invest in ICT, hire scientists, including non-full-time employees such as part-time or hourly contract paid employees and as consultants. It could be the case that scientists are in the process of being hired. These employees can not be reported and the investment in ICT and R&D cannot be registered in accounting books. Firms may also not be able to perceive the effectiveness of interaction with external stakeholders who invest in R&D and share their information technologies and digital tools, including open access ICT platforms available for firms to engage in open innovation (Digitally Driven, 2021). The first stage of the model fills the values of internal and external R&D intensity, ICT intensity and a share of employees with science and engineering degrees with what might have been expected given their size, age, legal status, export orientation, ownership type, industry, market competition and other firm specific characteristics drawing on the model of Griffith, et al. (2006). The fitted value of internal and external R&D intensity, ICT intensity and share of scientists will be included at the second stage, tackling the issue of endogeneity. For firms that actually report R&D and ICT expenditure and the share of scientists is a form of instrumental variable estimation of the innovation equations. This procedure helps to correct for the simultaneity that might be present due to the fact that innovation is measured over the past two years, whereas R&D and ICT are frequently same year measures. The results of the estimation of equations (2a-2c) are reported in Table A2 (Appendix A).

The variables included in the first stage (X_{it}), but excluded from the second stage, such as Herfindahl index, Business practices, Decision-making and External relationships operate as instruments for the (possibly endogenous) innovation input variables in the innovation equation (see Table A2).

We rewrite the equation (1) with the predicted values from equations (2a-2c). The equation (3) uses these predicted values to explain the level of innovation as a function of internal and external R&D intensity, ICT intensity and share of scientists R&D intensity, as well as controlling for the type of knowledge collaboration drawing on van Beers and Zand (2014) and Audretsch et al. (2021). Other important firm characteristics include firm age, size, innovation constraints, use of AI, industry/region characteristics and other. We estimate an innovation production function using a multivariate Tobit model. As additional covariates, this stage includes a set of control variables also used in stage one. The model in the second stage includes three separate equations which estimate the predicted values of internal and external R&D intensity, ICT intensity and a share of employees with science and engineering degrees

$$I_{it} = \beta_0 + \beta_1 R^*_{itz} + \beta_2 ICT^*_{it} + \beta_3 K_{it} + \beta_4 \rho_{it} + \beta_5 R^*_{it}\rho_{it} + \beta_6 ICT^*_{it}\rho_{it} + \beta_7 K_{it}\rho_{it} + \beta_8 X_{it} + u_{ijt} \quad (3)$$

where I_{it} represents innovation sales of firm i at time t. The term R^*_{it} in Eq. (3) is the latent variable for the internal R&D expenditure of firm i at time t of type z – internal and external R&D; ICT^*_{itk} in Eq. (2) is the latent variable the for ICT intensity, and K_{it} is the binary variables for knowledge collaboration with six types of external partners of firm i at time t. $R^*_{itz}\rho_{it}$ is an interaction between R^*_{itz} of type z and adoption of AI by firm i in time t. $ICT^*_{itz}\rho_{it}$ is an interaction between ICT^*_{itz} and adoption of AI by firm i in time t.

$K_{it}\rho_{it}$ is an interaction between the type of knowledge collaboration with external partner K_{it} by firm i in time t and adoption of AI (ρ_{it}). X_{it} collects all the remaining covariates of firm i at time t, including control variables, year, region and industry (2 digit SIC) controls. u_{ijt} is the error term and is assumed to be identically and independently distributed with mean zero and constant variance σ^2.

RESULTS

Table 3 shows the regressions estimates of the models using innovation sales as the dependent variable. In Model 2 we tested our H1, confirming that the internal knowledge allocation (make knowledge strategy) is positively associated with firm innovation; however, an increase in internal resource allocation leads to diminishing marginal returns, and finally a negative relationship. The level coefficient for both internal R&D (0.015, p<0.01) and ICT intensity (0.007, p<0.01) are positive and significant, while their quadratic terms are negative and significant (internal R&D is -0.001 (p<0.01) and ICT is -0.001 (p<0.01)) (Model 6, Table 3). We tested firms that follow a buying knowledge strategy, supporting H2 which states that external resource allocation via buying knowledge has a non-linear relationship with firm innovation. The first-order coefficient of the external R&D variable is positive and significant (0.074, $p<0.01$), while the second-order coefficient is negative and significant (-0.004, $p<0.01$) (Model 4, Table 3).

Considering different forms of external collaboration, we tested our Hypothesis 3 in Model 4. We support H3 by confirming that there is a positive effect of knowledge collaboration on firm innovation. This is because the coefficients of collaboration with suppliers (0.026, $p<0.01$), customers (0.077, $p<0.01$), consultants (0.013, $p<0.01$) and universities (0.033, $p<0.01$) are positive and significant. Interestingly, the collaborations with competitors and governments are not statistically significant for firm innovation. Knowledge is difficult to substitute and copy because it is subject to complexity and firm-specific characteristics (Lippman & Rumelt, 1982).

In Models 3 and 5 we introduced the effect of the adoption of AI technology as a moderator in order to demonstrate that AI enhances the allocation of internal/external resources for firm innovation. Considering internal R&D and ICT, their first-order coefficients of interaction with AI are both significant but negative, -0.012 and -0.008 respectively. Meanwhile the second-order coefficients are both positive and significant (0.001, $p<0.01$ and 0.001, $p<0.10$). This confirms our H4a, which states that AI positively moderates the internal allocation of knowledge for firm innovation. Our H4b argues that AI positively moderates the external allocation of knowledge via buying R&D for firm innovation and is supported as the first order interaction coefficient between AI and external R&D is positive and significant (0.085, $p<0.01$), while it becomes negative and significant for the quadric term (-0.004, $p<0.01$). Our H4c assumes AI positively moderate the effect of knowledge collaboration on firm innovation and is not supported as the interaction coefficients between AI and various types of knowledge partners (Model 5) are insignificant, except for suppliers which is negative (-0.039, $p<0.01$). This is intriguing, as a demonstrates that by adopting AI a firm may substitute information that it receives within their upstream supply chain. Model 6 tests all the hypothesis simultaneously, confirming the results described above.

Several important findings can be derived from the control variables. For example, the firm growth stage is an important determinant of firm innovation, with the effect of start-ups (0.060, $p<0.01$) and established (0.024, $p<0.05$) (Model 6, Table 3) firms being significantly larger for firm innovation than transitioned and mature firms, expanding what we know from Coad, Segarra, and Teruel, (2016) human capital is also important for firm innovation, as we are able to quantify the extent to which the employment of scientists with engineering and other technical degrees contributes to firm innovation. We found an increase of scientists by 1 percent is associated with 0.1 additional sales growth from new products. Finally, an increase in appropriability increases firm innovation (0.147, $p<0.01$) expanding on Hall's et al. (2013) findings on the role of appropriating the results of knowledge creation.

Insert Table 3 about here

Post hoc analysis

In order to reflect how changes in internal and external resource allocation affect firm innovation in firms which have adopted AI and those who have not, we use predictive margins based on the results calculated in Model 6 (Table 3). We used the 'margins' command in Stata 17 to compute the standard errors of the means and predict our dependent variable. The margins plot was used afterward as it gives a good view of the shape of the relationship between our explanatory and dependent variables (Williams, 2012). We interpret our findings and conclusions related to our hypotheses to help readers identify the size of the impact. Figure 1 shows the change in the expected value of innovation sales for firms that invest in internal R&D and when firms use AI technology and when they do not. The shape of the curve is non-linear, as hypothesized in our H1 for firms that invest in R&D but do not adopt AI, with a strong negative effect after 42 percent of sales are allocated to internal R&D. Firms that adopt AI achieve higher predicted values of innovation sales and continue to produce positive marginal returns to investment in internal R&D, supporting H4a. At the same level of internal R&D intensity, firms that adopt AI achieve greater innovation. Interestingly, firms that do not invest in internal R&D are still better off in terms of innovation sales if they adopt AI. Figure 2 plots predictive margins for investment in ICT and adoption of AI for firm innovation, using the estimation results from model 6 (Table 3). We do not find that adoption of AI changes the shape of the relationship between internal resource allocation in ICT and the adoption of AI.

Figure 3 plots predictive margins for investment in external R&D for firm innovation between firms who adopt AI and those which do not. On the other hand, if one observes the curve shape that relates external R&D intensity with innovation sales, one can see that the allocation of resources to external R&D and the adoption of AI increases innovation sales. The relationship between the allocation of resources to external R&D and firm innovation is an inverted-U shape, and an increase in external R&D to a high level (at least 5 percent of sales to external R&D) will lead to a reduction in firm innovation. This finding expands the work of Lovallo et al. (2020) by demonstrating that the inverted-U shaped relationship is in fact true for both internal and external R&D for firm innovation, and that it holds for firms that do not use advanced digital technologies such as AI. For firms that adopt AI, the negative effect of the R&D slope is leveraged, and in fact firms continue to maintain a certain level of innovation at high levels of R&D external investment.

Insert Figure 1 about here

Insert Figure 2 about here

Insert Figure 3 about here

The predictive margins of knowledge collaboration with different external partners on firm innovation are shown in Figure 4. For low or no collaboration with suppliers, the benefit obtained by firms using AI is greater than those which do not use AI. This is due to the potential substitution effect between the adoption of AI and collaboration with suppliers. Our H4c is not supported as we find that AI adopters and non-adopters have the same level of innovation sales when intensity of collaboration with suppliers is high (see Fig. 4a). The substitution effect is also found for collaboration with universities, as firms that adopt AI but do not collaborate with universities are able to achieve the same level of innovation sales as firms who do not adopt AI and have high intensity of collaboration with universities, not supporting H4c (Fig. 4e).

Those firms that use AI and increase their intensity of collaboration with customers (Fig. 4b) and consultants (Fig. 4d) have on average higher innovation sales than firms who do not adopt AI but also increase collaboration with consultants and customers. While AI adoption is important for innovation performance, it does not moderate the knowledge collaboration effect and does not support our H4c. Firms that adopt AI and collaborate with competitors (Fig. 4c) and local and national governments (Fig. 4f) do not benefit by such collaboration; in fact, it reduces the returns from using AI. AI does not help to increase innovation when firms collaborate with competitors or (and) government. The effects of adopting AI may in fact dissipate if firms start to collaborate with competitors, due to knowledge leakage and appropriability issues (Cassiman & Veugelers, 2002). The mechanisms are different for collaboration with government, as government collaboration usually engages firms in public projects and grants. The adoption of AI may add to the opportunity costs of implementing large public projects, deviating from firm strategy and reallocating resources, adding to Lovallo et al. (2020) on the potential negative effects of resource reallocation.

Insert Figure 4 about here

DISCUSSION

Theoretical Developments

Most of the existing literature focuses on a binary choice between R&D (Cohen & Levinthal, 1989, 1990; Miotti & Sachwald, 2003) and open knowledge collaboration as two sources of innovation (Bogers et al., 2017; 2019). Our research builds on this by demonstrating the vital role of internal and external knowledge that can be used to innovate in a recombinant manner (Nelson, 1982; Nelson & Winter, 1982; Antonelli & Colombelli, 2017). This study considers that innovation inputs contain both internal (R&D and ICT) and new external (R&D and collaboration with external partners) knowledge (van Beers & Zand, 2014; Antonelli & Colombelli, 2017; Audretsch et al., 2021). An important aspect of AI technology is that it is now increasingly woven into a wide range of practices and relationships. In fact, as this study shows, AI is not to be regarded as a technology in its own right but should be considered and studied in relation to existing collaborative processes. This study re-examines the extent to which AI adoption moderates the relationship between a firm’s resources and innovation. Several studies have dealt with potential moderators of efficiency in resource allocation. For example, higher levels of managerial ownership (Scharfstein & Stein, 2000), as well as a higher correlation between business units (Rajan et al., 2000; Villalonga, 2004) and technological competencies (Song et al., 2007), have all been found to be positively correlated with allocative efficiency (Kuppuswamy & Villalonga, 2016). If these moderators have a similar impact on resource allocation, the moderating role of the latest technologies will be an interesting topic to investigate.

Our major findings systematize the results from testing our research hypotheses, and Figures 1 to 4 illustrate the post hoc consideration of the marginal effects of resource allocation and adoption of AI on firm innovation. We visualize non-financial resource allocation is a stable characteristic of firms rather than just a response to environmental contingencies. Our analysis involved financial and non-financial resource allocation, demonstrating that internal resource allocation can be complemented through the adoption of AI technology. We also highlight that firms who choose to invest in both R&D and ICT (Hall et al., 2013) and use AI (Trocin et al., 2021) increase innovation. Furthermore, our results confirm the evidence offered in the literature (Lovallo et al., 2020) on the inverted U-shaped relationship between internal and external resource allocation (using R&D) and firm innovation. We thus provide empirical data consistent with conjecture about the trade-off between benefits and costs when firms exercise their capabilities (Winter, 2003). We demonstrated that this U-shaped relationship could be changed thanks to the moderating effect of AI technology; the use of AI reduces the costs of knowledge management and decision-making (Keding, 2021; Haefner et al., 2021).

Furthermore, our study illustrates how the intersection between knowledge obtained through collaboration and the use of AI technology affects the way firms innovate and achieve results, expanding on the previous literature on innovation (Giovannetti & Piga, 2017; Griffith et al., 2006; Sofka & Grimpe, 2010). This study broadens our understanding of why the recombination of internal and external knowledge sources results in innovation when adequately supported. We discuss theories that facilitate or hinder innovation, highlighting the positive ways (financial and non-financial) investment in knowledge affects innovation (Kor & Mahoney, 2004; Griffith et al., 2006; Hall et al., 2013; Link & Maskin, 2016), and significantly expand existing knowledge on collaboration with external partners. Previous research aimed to better understand the unique nature of the interdependence between internal and external knowledge (Audretsch & Belitski, 2020). This study provides a detailed representation of the external partners with whom firms collaborate. It also goes on to describe the effects of collaborations between firms and suppliers, customers, competitors, consultants, universities and governments, and discusses their impact on innovation.

Implications for Policymakers

Our results have policy implications that would be difficult to ascertain without considering the interdependencies between innovation and the role of different resource allocation strategies. We extended Nelson and Winter's (1982) prior research on resource recombination and Antonelli and Colombelli's (2017) more recent study on the role of recombinant innovation with internal and external knowledge. The ability of scholars to explain the causality of firm innovation has been limited and the recombination of resources opens a new way of thinking about resource allocation strategies for firm innovation.

We theoretically discussed and empirically examined the likelihood of engaging in internal knowledge creation via resource allocation and the co-creation of innovation with external partners, as well as explaining the dynamics of innovation. Policymakers may wish to use our findings when designing programs to stimulate the complementarity of investments in ICT, R&D and external collaboration. This will aid them in reducing the transactional costs of collaboration (Bustinza et al., 2019; Camacho, 1991) and overcoming limits to innovation (Saura et al., 2022).

Implications for Managers

Our managerial implications are as follows. First, managers need to be aware that AI can be used to support knowledge collaboration with external partners for product innovation. Second, our results demonstrated the joint significance of the interaction between internal R&D and AI technology. This may demonstrate to managers the importance of investment in R&D alongside adopting AI. Third, managers relying on external knowledge collaboration may want to diversify the knowledge collaboration to access skills and enhance inter-organizational abilities (Faems et al., 2005) that can complement new technological tools, such as AI, in the implementation of innovation.

Fourth, while the innovation process is highly complex, risky and costly, the innovative solutions to be developed by managers may require the in-house development or external sourcing of the specific skills (Desouza et al., 2020; Sjödin et al., 2021). Fifth, managers may want to foster engagement with suppliers and customers first-hand, as we found these two types of partners add most value to innovation.

Finally, policymakers who aim to support businesses with the allocation of external and internal knowledge inputs can focus on supporting specific forms of knowledge collaboration (e.g. suppliers, customers), and on saving time and reducing unnecessary coordination, management and engagement costs (Saura et al., 2022). Policymakers may want to allocate resources to validate new 'blue ocean' ideas and need to implement incentives for firms wishing to undertake this innovation effort.

Limitations and Future Research

One limitation of this study is that the data is unbalanced, meaning that not every firm takes part in the innovation survey every year. Future research needs to better understand how to use unbalanced data for innovation to robustly examine firm resource allocation and how managerial choices are made over time. Future research may explore a multi-level modeling of the phenomenon by including regional.

CONCLUSION

Resource allocation is a fundamental element of a firm's strategic management. Despite its significant importance, this topic is remarkably under-researched. Moreover, studies dealing with resource allocation do not properly address new and emerging technologies such as AI, nor do they study how these technologies interact with non-financial resources such as the internal and external allocation of knowledge. This paper aims to bring resource allocation to the forefront of strategic management research with an emphasis on the allocation of non-financial resources.

The findings of this study suggest a fundamental rethinking of the imperative of resource allocation for firm innovation is required. In particular, the role of the adoption of AI and the recombination of internal and external knowledge resources appears to be considerably more nuanced, as earlier studies in innovation have found (Antonelli & Colombelli, 2017; Paschen et al., 2020). This has shaped the current doctrine prevalent in the literature about investment in internal knowledge for innovation, which does, in fact, tend to have a non-linear relationship with firm innovation. However, internal and external knowledge investment is required alongside the adoption of AI if firms are to further increase their innovation performance. The use of AI facilitates resource allocation internally and externally even in the absence of knowledge sourcing from some types of external partners, and at high levels of R&D investment when the costs to maintain knowledge are high.

The findings of this paper call for a fundamental rethinking about the primacy of resource allocation for innovation and are in line with the actual digitization of managerial processes. It may be that, thanks to the advancement in AI, reliance on such technologies will become a primarily innovation strategy in the next generation of firms.

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Table 1. Description of variables

Variable (source)	Definition	Mean	ST.dev	Min	Max
Innovation sales	Percentage of total turnover over the last three years from goods and services that are new to the market. It varies between zero and one hundred percent.	0.05	0.14	0.00	1.00
AI (UKIS)	Binary variable=1 if firm adopts AI, zero otherwise. Firm is known to adopt AI if it belongs to a) one of the following sectors which adopts AI (SIC2007 3 digit 182; 261; 262; 263; 264; 279; 283; 289; 293; 322; 325; 329; 351; 465; 512; 522; 582; 591; 592; 612; 631; 639; 642; 643; 649; 651; 702; 711; 712; 721; 731; 741; 742; 743; 774; 801;803; 823; 856; 869; 900; 960); b) has advanced equipment, ICT, soft and hardware expenditure >0 and c) the proportion of employees that hold a degree or higher qualification in science and engineering at BA / BSc, MA / PhD, PGCE> 0	0.08	0.27	0.00	1.00
Internal R&D intensity (UKIS/BSD)	Internal R&D expenditure to sales ratio in logs	1.43	6.59	0.00	66.00
ICT intensity (UKIS/BSD)	Advanced equipment, ICT, soft and hardware expenditure to sales ratio in logs	1.49	4.73	0.00	40.00
External R&D intensity (UKIS/BSD)	External R&D expenditure (buying R&D) to sales ratio in logs	0.16	0.90	0.00	9.00
Suppliers (UKIS)	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	1.56	1.10	0.00	1.00

Customers (UKIS)	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	1.82	1.17	0.00	1.00
Competitors (UKIS)	Important to business's innovation activities (from zero – not importance and not used to 1- low, 2- medium and 3 highly important) was the extent of the interactions between the focal firm and competitor in the industry	1.37	1.07	0.00	1.00
Consultants (UKIS)	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	0.78	0.92	0.00	1.00
Universities (UKIS)	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	0.53	0.81	0.00	1.00
Government (UKIS)	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	0.52	0.80	0.00	1.00
Startups (BSD)	Firms with age between 0 and 7 years since the establishment	0.15	0.36		
Established (BSD)	Firms with age between 8 and 15 years since the establishment	0.26	0.44	0.00	1.00
Transitioned (BSD)	Firms with age between 16 and 30 years since the establishment	0.34	0.48	0.00	1.00

Mature (BDS)	Firms that are more than 30 years since the establishment	0.24	0.39	0.00	1.00
Employment (UKIS)	Number of full-time employees, in logarithms	3.79	1.76	0.00	11.08
Scientists (UKIS)	The proportion of employees that hold a degree or higher qualification in science and engineering at BA / BSc, MA / PhD, PGCE levels	7.91	17.93	0.00	100.00
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).	0.20	0.31	0.00	1.00
Foreign (BSD)	Binary variable=1 if a firm has headquarters abroad, 0 otherwise	0.36	0.48	0.00	1.00
Reporting units (BSD)	Number of firm's subsidiaries and local units	1.62	4.06	0.00	112.00
Variables used as instruments to predict innovation inputs at the first stage					
Herfindahl Index	Herfindahl Index calculated using concentration in sales by 2 SIC digit industry. (BSD)	0.04	0.05	0.002	0.704
Business practices	Business strategy and practices: binary variable =1 if firm made major changes in new business practices for organizing procedures (i.e. supply chain management, business re-engineering, knowledge management, lean production, quality management etc, zero otherwise (CIS)	0.25	0.43	0.00	1.00
Decision-making	Business strategy and practices: binary variable =1 if firm made major changes in	0.23	0.42	0.00	1.00

	new methods of organizing work responsibilities and decision making (ie first use of a new system of employee responsibilities, team work, decentralization, integration or de-integration of departments, education/training systems etc) , zero otherwise (CIS)				
External relationships	Business strategy and practices: binary variable =1 if firm made major changes in new methods of organising external relationships with other firms or public institutions (ie first use of alliances, partnerships, outsourcing or sub-contracting etc) , zero otherwise (CIS)	0.28	0.45	0.00	1.00

Source: Office for National Statistics. (2021a). Department for Business, Innovation and Skills, Office for National Statistics, Northern Ireland. Department of Enterprise, Trade and Investment. (2021). *UK Innovation Survey, 1994-2021: Secure Access*. [data collection]. *6th Edition.* UK Data Service. SN: 6699, http://doi.org/10.5255/UKDA-SN-6699-6

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Further source: *UK Innovation Survey, 1994-2021 and Business Structure Database, 1997-2021: Secure Access*. UK Data Service.

Table 2. Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
Innovation Sales	1																		
AI	0.171*	1																	
Internal R&D intensity	0.323*	0.261*	1																
ICT intensity	0.125*	0.134*	0.226*	1															
External R&D intensity	0.202*	0.153*	0.407*	0.166*	1														
Suppliers	0.166*	0.127*	0.085*	0.153*	0.089*	1													
Customers	0.196*	0.148*	0.124*	0.100*	0.092*	0.633*	1												
Competitors	0.167*	0.127*	0.110*	0.075*	0.081*	0.584*	0.714*	1											
Consultants	0.194*	0.159*	0.162*	0.083*	0.167*	0.483*	0.433*	0.500*	1										
Universities	0.203*	0.173*	0.207*	0.064*	0.142*	0.374*	0.354*	0.403*	0.584*	1									
Government	0.182*	0.159*	0.159*	0.055*	0.119*	0.382*	0.371*	0.438*	0.570*	0.713*	1								
Startups	0.105*	0.035*	0.064*	0.043*	0.053*	0.019*	0.008	0.018*	0.002	0.004	0.009	1							
Established	0.032*	0.055*	0.047*	0.006	0.026*	0.006	0.018*	0.004	0.005	0.001	0.007	0.252*	1						
Transitioned	0.044*	0.017*	0.039*	0.022*	0.031*	0.003	0.006	0.007	0.011	0.010	0.018*	0.301*	0.433*	1					
Employment	0.005	0.031*	0.011	0.001	0.003	0.208*	0.225*	0.224*	0.198*	0.139*	0.152*	0.181*	0.052*	0.037*	1				
Scientists	0.258*	0.445*	0.391*	0.072*	0.186*	0.123*	0.174*	0.156*	0.226*	0.294*	0.240*	0.056*	0.055*	0.032*	0.031*	1			
Appropriability	0.174*	0.111*	0.151*	0.032*	0.119*	0.323*	0.295*	0.367*	0.413*	0.412*	0.391*	0.018*	0.003	0.005	0.208*	0.197*	1		
Foreign	0.036	0.010	0.015*	0.037*	0.007	0.028*	0.047*	0.060*	0.060*	0.015*	0.031*	0.166*	0.007	0.043*	0.404*	0.041*	0.160*	1	
Reporting units	0.011	0.016*	0.006	0.012	0.002	0.027*	0.032*	0.033*	0.038*	0.035*	0.034*	0.064*	0.062*	0.048*	0.166*	0.017	0.044*	0.034	1

Table 3: Second stage Tobit estimation of the innovation function. Dependent variable: Innovation sales

Specification	(1)	(2)	(3)	(4)	(5)	(6)
AI	-0.005 (.02)	-0.006 (.02)	0.007 (.02)	0.029 (.02)	0.096** (.04)	0.120** (.06)
Internal R&D intensity (H1)		0.023*** (.00)	0.024*** (.00)			0.015*** (.00)
Internal R&D intensity squared (H1)		-0.001*** (.00)	-0.001*** (.00)			-0.001*** (.00)
ICT intensity (H1)		0.016*** (.00)	0.017*** (.00)			0.007*** (.00)
ICT intensity squared (H1)		-0.001*** (.00)	-0.001*** (.00)			-0.001*** (.00)
External R&D intensity (H2)				0.074*** (.00)	0.087*** (.00)	0.054*** (.00)
External R&D intensity squared (H2)				-0.004*** (.00)	-0.004*** (.00)	-0.003*** (.00)
Suppliers (H3)				0.26*** (.01)	0.27*** (.01)	0.19*** (.01)
Customers (H3)				0.77*** (.01)	0.74*** (.01)	0.69*** (.01)
Competitors (H3)				0.001 (0.02)	0.001 (0.02)	0.001 (0.02)
Consultants (H3)				0.13*** (.02)	0.11*** (.02)	0.10*** (.02)
Universities (H3)				0.33*** (.01)	0.37*** (.01)	0.32*** (.01)
Government (H3)				-0.002 (.01)	0.002 (.01)	0.001 (.01)
AI x Internal R&D intensity (H4a)		-0.012***				-0.006***

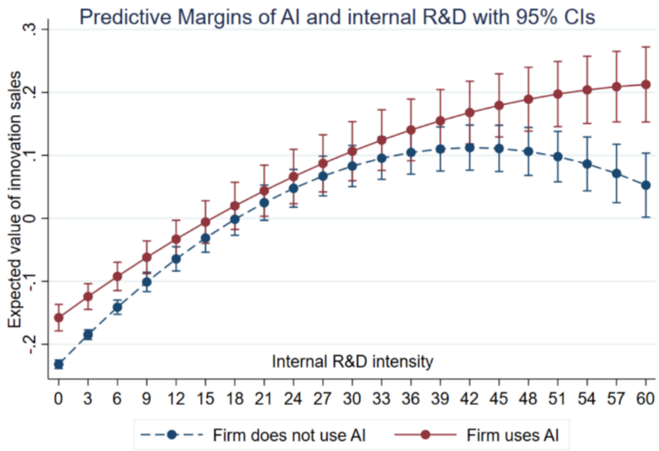
		(.00)				(.00)
AI x Internal R&D intensity squared (H4a)		0.001*** (.00)				0.001*** (.00)
AI x ICT intensity (H4a)		-0.008*** (.00)				-0.002 (.00)
AI x ICT intensity squared (H4a)		0.001*** (.00)				0.001 (.00)
AI x External R&D intensity (H4b)				0.085*** (.00)	0.098*** (.00)	0.066*** (.00)
AI x External R&D intensity squared (H4b)				-0.004*** (.00)	-0.007*** (.00)	-0.005*** (.00)
AI x Suppliers (H4c)					-0.039*** (.00)	-0.032*** (.00)
AI x Customers (H4c)					-0.002 (.01)	-0.002 (.01)
AI x Competitors (H4c)					-0.001 (.01)	-0.001 (.01)
AI x Consultants (H4c)					0.007 (.01)	0.005 (.01)
AI x Universities (H4c)					-0.005 (.01)	-0.018 (.01)
AI x Government (H4c)					-0.018 (.01)	-0.017 (.01)
Startups	0.064*** (.00)	0.064*** (.00)	0.058*** (.00)	0.058*** (.00)	0.057*** (.00)	0.060*** (.00)
Established	0.011*** (.00)	0.011*** (.00)	0.016*** (.00)	0.016*** (.00)	0.011*** (.00)	0.024*** (.00)
Transitioned	0.015*** (.00)	0.013 (.01)	0.012 (.01)	0.016 (.01)	0.011 (.01)	0.016 (.01)
Employment	0.016**	0.017**	0.017**	0.017**	0.065	0.061

	(.00)	(.00)	(.00)	(.00)	(.01)	(.01)
Scientists	0.003*** (.00)	0.003*** (.00)	0.002*** (.00)	0.002*** (.00)	0.003*** (.00)	0.002*** (.00)
Appropriability	0.250*** (.00)	0.229*** (.00)	0.225*** (.00)	0.201*** (.00)	0.150*** (.00)	0.147*** (.00)
Foreign	-0.073** (.00)	-0.066** (.00)	-0.063** (.00)	-0.049** (.00)	-0.048** (.00)	-0.043** (.00)
Reporting units	0.001 (.01)	0.002 (.01)	0.003 (.01)	0.002 (.01)	0.002 (.01)	0.002 (.01)
Constant	-0.35*** (.08)	-0.35*** (.08)	-0.36*** (.09)	-0.51*** (.07)	-0.51*** (.07)	-0.52*** (.05)
Region, time and industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Left-censored	17011	17011	17011	17011	17011	17011
Uncensored	7006	7006	7006	7006	7006	7006
Number of obs.	24017	24017	24017	24017	24017	24017
Chi2	3515.1	3539.9	5028.5	50.67.2	5370.2	5390.2

Note: reference category for legal status is industry (real estate), city-region (Newcastle), year (CIS wave) 2002-2004; growth stage (mature). Robust standard errors are in parenthesis. The coefficients of the Tobit regressions are the marginal effect of the independent variable on the dependent variables in each regression. Significance level: * $p<0.05$; ** $p<0.01$, *** $p<0.001$. Breusch –Pagan test for independence chi2(6) = 1,925.0, p-value<0.001

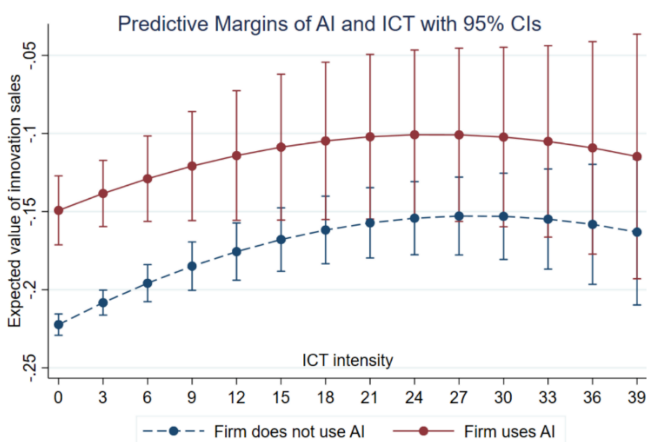
Source: Office for National Statistics. (2021a, 2021b).

Figure 1. Predicted margins of Internal R&D intensity and innovation output



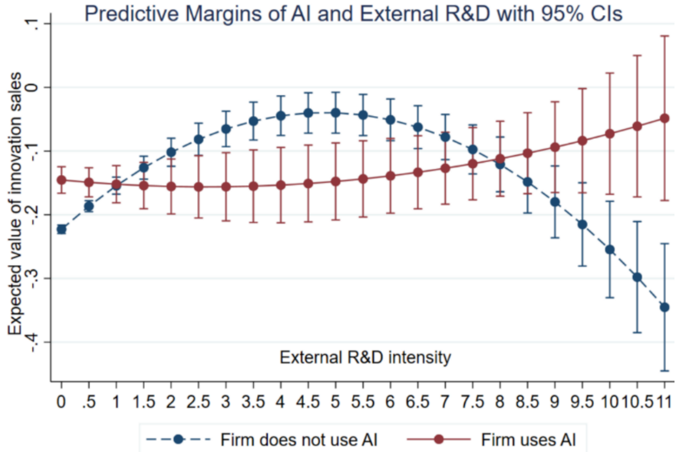
Source: Office for National Statistics. (2021a, 2021b).

Figure 2. Predicted margins of ICT intensity and innovation output



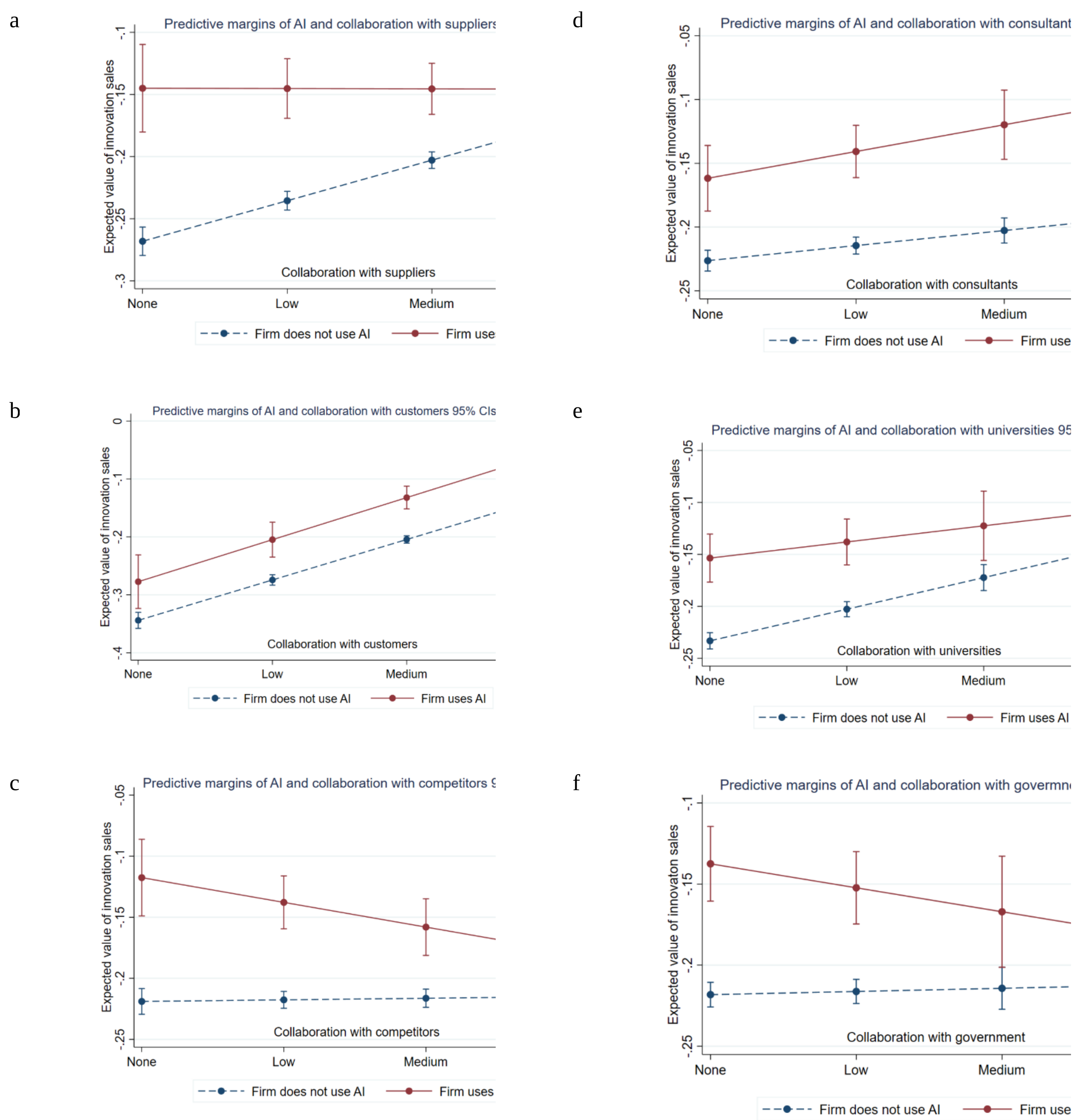
Source: Office for National Statistics. (2021a, 2021b).

Figure 3. Predicted margins of external R&D intensity and innovation output



Source: Office for National Statistics. (2021a, 2021b).

Figure 4: Predicted margins of collaboration with (a) – suppliers, (b) – customers, (c) – competitors, (d) – consultants; (e) – universities and (f) – government and innovation output



Source: Office for National Statistics. (2021a, 2021b).

Appendix A1: Sample distribution by industry (SIC 2007 ONS divisions), the UK regions and firm size

Industry distribution	Obs.	Share of obs.,%
Other manufacturing	5,332	22.20
High-tech manufacturing	818	3.41
Construction	2,296	9.56
Wholesale and retail trade	3,837	15.98
Transport	1,139	5.62
Accomodation and Food	1,334	5.55
ICT	1,776	7.39
Financial and Insurance	847	3.53
Real Estate	435	1.81
Professional and Scientific	2,686	11.18
Admin Services	2,370	9.87
Education	101	0.42
Other Services	836	3.48
Regional distribution	Obs.	Share of obs.,%
North East	1,349	5.62
North West	2,241	9.33
Yorkshire and the Humber	1,954	8.14

East Midlands	1,952	8.13
West Midlands	2,115	8.81
Estern	2,119	8.82
London	2,328	9.69
South East	2,625	10.93
South West	2,013	8.38
Wales	1,588	6.61
Scotland	1,876	7.81
Northern Ireland	1,857	7.73
Firm size distribution	Obs.	Share of obs.,%
Micro (<10 FTEs)	2,927	12.19
Small (10-49 FTEs)	10,719	44.63
Medium small (50-99 FTEs)	3,478	14.48
Medium large (100-249 FTEs)	2,587	10.77
Large (250+ FTEs)	4,306	17.93
Total	24,017	100

Source: Office for National Statistics. (2021a, 2021b).

Appendix A2: First stage estimates to predict internal and external knowledge inputs used for innovation. Estimation method – Tobit regression as the dependent variables are censored

Dependent variable	Share of scientists	ICT intensity	External R&D intensity	Internal R&D intensity

Specification	(1)	(2)	(3)	(8)
Startup	-0.04*** (.01)	-0.02** (.02)	-0.02** (.01)	-0.01*** (.00)
Established	0.06*** (.00)	0.11*** (.00)	0.13*** (.00)	0.01*** (.00)
Transitioned	0.15*** (.01)	0.19*** (.01)	0.17*** (.01)	0.01*** (.00)
Employment	0.09*** (.00)	0.02*** (.00)	0.05*** (.00)	0.01 (.00)
Appropriability	0.02 (.01)	0.04*** (.01)	0.04*** (.01)	0.01** (.00)
Foreign	0.05*** (.00)	-0.01 (.01)	-0.02 (.01)	0.01 (.01)
Reporting units	0.01 (.01)	0.01 (.01)	0.03* (.01)	0.01** (.00)
Exporter	0.26*** (.01)	0.07*** (.01)	0.19*** (.01)	0.03*** (.00)
Herfindahl Index	0.16 (0.14)	0.08 (0.13)	-0.24 (0.13)	0.01 (.01)
Business practices	0.13*** (.01)	0.06*** (.01)	0.09*** (.01)	0.01*** (.00)
Decision-making	0.13*** (.01)	0.13*** (.01)	0.15*** (.01)	0.01*** (.00)
External relationships	0.22*** (.01)	0.14*** (.01)	0.21*** (.01)	0.01*** (.01)
Constant	0.32*** (.08)	0.54*** (.08)	0.62*** (.09)	-0.09*** (.00)
Time, city and sector dummies	Yes	Yes	Yes	Yes
Number of obs.	24017	24017	24017	24017
log-likelihood	3789	2025	2801	4375

Chi2	4302	2181	2542	6217

Note: reference category for legal status is industry (real estate), city-region (Newcastle), year (CIS wave) 2002-2004; growth stage (mature). Robust standard errors are in parenthesis. The coefficients of the Tobit regressions are the marginal effect of the independent variable on the dependent variables in each regression. Significance level: * p<0.05; ** p<0.01, *** p<0.001. Source: Office for National Statistics. (2021a, 2021b).