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Subsidising innovation outside or within firms' existing knowledge bases: which is best for radical innovation?

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ABSTRACT

Public financial support for firm-level Research and Innovation (R&I) can generate important socio-economic returns. This is especially true if firms use this support to develop radical innovation, defined as new-to-market goods and services. However, radical innovation is risky, and prone to failure. Therefore, subsidising radical innovation can also generate sub-optimal socio-economic returns (i.e. policy failure). Understanding how public funding for R&I can be allocated in a way that encourages radical innovation, while avoiding policy failure is crucial. Our paper investigates whether public funding for R&I generates more radical innovation in firms seeking to exploit their existing knowledge base, versus firms seeking to innovate by engaging in knowledge areas that are new to them. We make this distinction using a novel approach, based on the knowledge challenges that firms face when innovating. By merging firm-level survey data with administrative data on public funding for R&I in Ireland, we find that subsidising firms seeking to engage in new knowledge areas, can result in more radical innovation and turnover from radical innovation, compared to firms seeking to exploit their existing knowledge base. These are critical insights from theoretical and policymaking perspectives, regarding the allocation of public funding for R&I.

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1. Introduction

Governments in many countries provide firms with public financial support for their research and innovation (R&I) activities (Link and Scott 2013; OECD 2023). Subsidising firm-level R&I can generate socio-economic returns, including improved economic performance, and high-quality employment (Cerulli et al. 2022; Choi and Lee 2023). Academics and policymakers increasingly recognise that such returns are more likely to arise when public financial support for R&I results in radical innovation in firms (Beck, Lopes-Bento, and Schenker-Wicki 2016; Laplane and Mazzucato 2020; OECD 2023). Radical innovation is defined as goods and services that are new to the market, such as products and services offering new solutions to users, that have not been available before (Choi and Lee 2023). Radical innovation can increase firms' turnover, since it often addresses new needs, with the potential to improve the innovator's performance in the market, whilst also generating

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important knowledge spillovers (Autio, Kanninen, and Gustafsson 2008; Beck, Lopes-Bento, and Schenker-Wicki 2016; Berrutti and Bianchi 2020). Despite its importance, there is only limited empirical evidence on how policymakers can successfully deliver R&I support in a way that translates into radical innovation in firms (Berrutti and Bianchi 2020; Mina et al. 2021). This is a critical knowledge gap that prevails in the literature concerned with ensuring a more impactful allocation of public funding for R&I. As articulated by Criscuolo et al. (2022, 3) 'best practices for designing and modulating R&D incentives continue to be an open question'.

Public support for R&I can serve various policy goals, and policymakers face several policy options when allocating this support to firms (Okamuro and Nishimura 2015; Pereira and Suárez 2018). For example, policymakers have to decide whether to target the support at specific technologies (e.g. renewable energies), specific types of firms (e.g. start-ups, SMEs), and/or certain types of R&D activities (e.g. R&I within firms, industry-academic collaborations). In this paper, we analyse one key policy option that policymakers typically face, when allocating public financial support for R&I to firms. That is, whether to focus support on: (1) Firms seeking to innovate by exploiting their existing knowledge base; or (2) Firms seeking to innovate by engaging in knowledge areas that are new to them.

Our focus on the above groups of firms is important, in the context of using public financial support for R&I to generate more radical innovation. On the one hand, focusing support on firms seeking to engage in new knowledge areas can enable such firms to generate new knowledge and innovate radically (Mina et al. 2021; Yang, Chou, and Chiu 2014). This, in turn, can result in firms opening new markets and/or developing new business models (Colombo et al. 2017; Radicic 2021). However, focusing support on such firms is risky and likely to result in failed innovation projects (D'Este, Amara, and Olmos-Peñuela 2016). Therefore, it can lead to so-called 'policy failure', which refers to the misallocation of public funding resulting in sub-optimal (or no) socio-economic returns (Haapanen, Lenihan, and Mariani 2014; Kärnä et al. 2022). On the other hand, focussing support on firms seeking to exploit their existing knowledge base can clearly reduce such risks, but the innovation activities of these firms may be less likely to be radical, resulting in lower levels of socio-economic returns (Berrutti and Bianchi 2020; Colombo et al. 2017). There is also a risk of deadweight spending effects, as such firms may use public financial support to carry out R&I activities that they would have carried out anyway (Lenihan 2004; Mina et al. 2021; Pereira and Suárez 2018). Investigating whether public financial support for R&I results in radical innovation when focused on these two groups of firms is thus vital, as it can usefully inform a more impactful allocation of public financial support for R&I (Berrutti and Bianchi 2020; Cerulli et al. 2022; Fiorentin, Pereira, and Suarez 2019).

To identify the above two groups of firms, we use a new approach, based on information regarding the knowledge challenges that firms can face when innovating (Coad, Pellegrino, and Savona 2016; D'Este et al. 2012; Zahler, Goya, and Caamaño 2022). Firms seeking to engage in new knowledge areas will need to generate and/or absorb new knowledge (Hewitt-Dundas, Gkypali, and Roper 2019; Yang, Chou, and Chiu 2014). In doing so, they are likely to face knowledge challenges related to a lack of knowledge about the technologies and markets they aim to enter, as these are new to them (Keupp and Gassmann 2013; Lee, Wu, and Pao 2014). Several studies support this, by outlining that firms are likely to face such knowledge challenges as they become more innovative and reach their knowledge frontiers (Coad, Pellegrino, and Savona 2016; D'Este et al. 2012; Hölzl and Janger 2014; Radicic 2021; Santiago et al. 2017). Based on this, we identify firms facing a lack of information on technologies and markets for their desired R&I activities, as firms seeking to innovate by engaging in knowledge areas that are new to them. Firms that do not experience such knowledge challenges are considered to innovate by exploiting their existing knowledge base. Using these definitions, we analyse whether public financial support for R&I results in a higher probability of radical innovation, if allocated to the former or the latter group of firms. We measure whether firms innovate radically in binary form (Perez-Alaniz et al. 2023). Moreover, to maximise socio-economic returns, radical innovation needs to generate economic benefits to firms (Cowling 2016; Nilsen, Raknerud, and Iancu

2020). Therefore, we also analyse the percentage of turnover that the two groups of firms generate from radical innovation, as a result of receiving public financial support for R&I. As outlined by Hewitt-Dundas, Gkypali, and Roper (2019, 1315), this is a standard measure of the 'initial market success of firms' NTM [new to-market] innovation activity', which is how we define radical innovation in the current paper.

Our paper makes a novel contribution to the literature concerned with a more impactful allocation of public financial support for R&I to firms. One body of previous studies has mainly focused on analysing the impact of public financial support for R&I when allocated to firms with limited innovative capacity (e.g. R&D starters), *vis-à-vis* more established innovative firms (Berrutti and Bianchi 2020; Nilsen, Raknerud, and Iancu 2020; Wanzenböck, Scherngell, and Fischer 2013). Another body of prior studies has analysed the impact of public R&D support on the 'Research' and 'Development' components of firm-level R&D (Beck, Lopes-Bento, and Schenker-Wicki 2016; Hottenrott, Lopes-Bento, and Veugelers 2017). Our study however, is related to previous studies concerned with whether R&D support encourages explorative innovation in firms, with explorative innovation defined as innovations that require firms to develop and absorb new knowledge (Gao et al. 2021; Lee, Wu, and Pao 2014). In this context, Gao et al. (2021, 2) specifically outline that 'whether public R&D subsidies trigger firms' exploratory innovation, and what the effects of different public subsidy programs are remain unclear in existing literature'. Our study thus plays a critical role in addressing this gap, and is to the best of our knowledge, the first to empirically analyse whether public financial support for R&I is more effective at generating radical innovation when targeted at: (1) Firms seeking to exploit their existing knowledge base, or; (2) Firms seeking to engage in new knowledge areas. From a policy perspective, Mina et al. (2021, 3) note that public financial support for R&I needs to be allocated with 'a greater degree of selectivity in order to address the funding gaps of firms with growth opportunities'. The insights of our paper can thus usefully contribute to this key knowledge and policy challenge.

Our empirical analysis uses a novel and detailed database with information on firms in Ireland. We combine two waves of the Innovation in Irish Enterprises Survey (IIE, 2008–2010 and 2014–2016), with administrative data on public financial R&I support from all of the main funding agencies in Ireland (i.e. Enterprise Ireland, IDA Ireland, and Science Foundation Ireland) and data on R&D tax credits (from Ireland's Revenue Commissioners).[1] Based on propensity score matching (Vanino, Roper, and Becker 2019), we build a matched sample of firms that received public financial support for R&I and firms which did not receive this support (i.e. treated and control firms). The control firms are statistically similar to the treated firms, on average, in terms of past innovation activities, knowledge challenges, and other firm-level characteristics (e.g. firm sizes and sectors). We then use the balanced sample to estimate innovation production functions (Nilsen, Raknerud, and Iancu 2020), using radical innovation as the output measure. The model includes a variable for public financial support for R&I, variables for the importance of knowledge challenges, and interaction terms for R&I support and knowledge challenges. This setting allows us to investigate whether treated firms that face knowledge challenges are more or less likely to produce radical innovation outputs, compared to treated firms not facing such challenges.

The remainder of the paper is organised as follows. Section 2 discusses the conceptual framework that guides our research. Section 3 presents the data and the empirical approach. Section 4 discusses our main findings. Section 5 concludes with some implications for innovation policy and suggested avenues for future research.

2. Conceptual framework

2.1. Public financial support and radical innovation

Public financial support for research and innovation (R&I) primarly focuses on addressing market failures resulting from knowledge spillovers (Arrow 1962; Choi and Lee 2023). Since knowledge

spillovers limit the appropriation of returns from R&I investment, the returns of many R&I activities may be too low for firms to justify investing in them (Hall et al. 2016). Because of this, firms may refrain from investing in R&I activities, limiting the generation of new knowledge (Link and Scott 2013). Subsidising firm-level R&I can enable firms to perform additional R&I activities, create new knowledge spillovers, and improve innovation and productivity (Autio and Rannikko 2016; Mina et al. 2021).

Given the importance of public financial support for R&I in driving firm-level R&D, policymakers typically face a critical decision when allocating such support to firms. On the one hand, they want to maximise the socio-economic returns of public investments (Haapanen, Lenihan, and Mariani 2014; Mina et al. 2021). In the case of public financial support for R&I, this is most likely to occur when the support stimulates radical innovation in firms, which entails offering solutions that have not been available to users before (Choi and Lee 2023; Dean, Zhang, and Xiao 2020). Radical innovation can enable firms to gain new customers, enter new markets and achieve growth (Choi and Lee 2023; Dean, Zhang, and Xiao 2020; Hewitt-Dundas, Gkypali, and Roper 2019). Moreover, radical innovation is most likely to maximise knowledge spillovers (Autio and Rannikko 2016; Colombo et al. 2017). A key reason for this is that, in developing radical innovation, firms will likely engage in generating and absorbing new knowledge, by engaging in explorative R&I activities (Colombo et al. 2017; Gao et al. 2021; Lee, Wu, and Pao 2014).

On the other hand, policymakers also need to avoid public financial support being provided for R&I activities that are likely to fail (Cerulli et al. 2022; Haapanen, Lenihan, and Mariani 2014; Kärnä et al. 2022). As Haapanen, Lenihan, and Mariani (2014) and Kärnä et al. (2022) note, this is important so as to avoid 'policy failure', which refers to the misallocation of public financial support for R&I resulting in sub-optimal (or no) socio-economic returns. Supporting radical R&I activities in firms can result in policy failure, because generating and successfully implementing radical innovation is challenging (D'Este, Amara, and Olmos-Peñuela 2016; Radas and Božić 2009). As noted earlier, this is because firms need to generate new knowledge, and/or combine different types of existing knowledge to come up with new solutions and/or technologies (Colombo et al. 2017; Gibbert and Scranton 2009; Radas and Božić 2009). Firms may also need to convince users to adopt these new solutions and/or technologies, and/or create new markets for them (Colombo et al. 2017; Jugend et al. 2020; McDermott and O'Connor 2002; Perez-Alaniz et al. 2023).

To minimise the above risks, policymakers may focus public financial support for R&I on firms that are capable of successfully developing and implementing radical innovation (Hottenrott, Lopes-Bento, and Veugelers 2017; Mina et al. 2021). There are two groups of firms that fulfil this policy requirement. The first group comprises firms that have well-developed knowledge stocks, and that seek to innovate based on technologies and competencies already available to them (Kapoor and Adner 2012; Roy and Sarkar 2016). As such firms exploit their existing knowledge base, targeting support at this group of firms is likely to result in high levels of innovation outputs. However, it can also result in low levels of additionality, since these firms are likely to achieve high levels of innovation output, regardless of public financial support for R&I (Berrutti and Bianchi 2020; Wanzenböck, Scherngell, and Fischer 2013). This, in turn, can lead to policy failure due to deadweight spending effects (Haapanen, Lenihan, and Mariani 2014; Mina et al. 2021).

To avoid low additionality, policymakers may focus on supporting a second group of firms. This group comprises firms seeking to innovate by engaging in knowledge areas that are new to them (Lee, Wu, and Pao 2014; Roy and Sarkar 2016). Targeting support at this group of firms can potentially generate high additionality, especially in terms of radical innovation. This is because the support can enable such firms to carry out R&I activities that they would not carry out (or carry out to a lesser extent) without support (Beck, Lopes-Bento, and Schenker-Wicki 2016; Hewitt-Dundas, Gkypali, and Roper 2019; Lee 2011). However, such firms may not have all of the necessary knowledge and technology to successfully achieve their desired radical innovation projects. Therefore, some risk of project failure remains, especially if the firms are unable to obtain all the necessary knowledge to go beyond their existing technological frontiers (Colombo et al. 2017; Gibbert and Scranton 2009).

Gao et al. (2021) demonstrate that firms with a large existing stock of technological knowledge, are less likely to expand their innovation efforts towards new fields of technology. Yet, government subsidies can encourage such firms to step into new fields of technology.

Allocating public financial support for R&I to the above two groups of firms, in view of realising more radical innovation, presents a challenge for policymakers. They need to strike a balance between the likelihood of the support resulting in radical innovation, while at the same time minimising the likelihood of policy failure. In this context, whether to target public financial support for R&I at firms seeking to engage in new knowledge areas, or at firms that exploit their existing knowledge base, remains the focus of academic and policy debates (Berrutti and Bianchi 2020; Fiorentin, Pereira, and Suarez 2019; OECD 2023).

2.2. Public financial support and knowledge challenges

As noted earlier (Section 2.1), allocating public financial support for R&I to drive radical innovation is risky. This is because radical innovation (i.e. goods and services that are new-to-market by offering new solutions to users) typically requires firms to generate new knowledge, and combine this new knoweldge with existing knowledge, in order to go beyond existing technological frontiers (Colombo et al. 2017; Gibbert and Scranton 2009). Firms can usually follow two different avenues to do this. The first avenue is to rely on their existing knowledge and established links to external knowledge sources. Radical innovation is based on exploiting these knowledge sources in a way that shifts the technological frontier within a given field of technology (Antonelli, Orsatti, and Pialli 2023; D'Este, Amara, and Olmos-Peñuela 2016). Moreover, firms can use their existing in-depth knowledge about markets and customer requirements to develop new ways to address existing user needs, or to identify new user needs (Colombo et al. 2017). A second avenue through which firms can achieve radical innovation is by engaging in knowledge areas and markets that are new to them (Antonelli and Fusillo 2023; Hottenrott, Lopes-Bento, and Veugelers 2017). This strategy is likely to require more effort by firms when generating, absorbing and recombining knowledge, compared to exploiting their existing knowledge base. However, when compared to the first avenue, the second one has the potential to result in more novel and impactful radical innovations (Colombo et al. 2017; Inauen and Schenker-Wicki 2012; McDermott and O'Connor 2002).

Regarding both of the above avenues, firms will need to perform internal R&D in addition to identifying and absorbing relevant external knowledge (Roper and Hewitt-Dundas 2015). The key difference between these two avenues is that firms seeking to exploit their existing knowledge base will likely face fewer knowledge challenges, compared to firms seeking to innovate by engaging in new knowledge areas and markets. Therefore, the extent to which public financial support for R&I translates into radical innovation in such firms depends on the firms' abilities to overcome knowledge challenges (Colombo et al. 2017; Inauen and Schenker-Wicki 2012; Radicic 2021).

A key knowledge challenge that firms are most likely to face when engaging in new knowledge areas is a lack of information on technologies and markets. As D'Este et al. (2012), Keupp and Gassmann (2013) and Zahler, Goya, and Caamaño (2022) have stressed, firms are likely to face a lack of information on technologies and markets in two key instances along their innovation paths. The first instance pertains to situations where firms have low levels of R&I knowledge and experience. In this context, a lack of information of technologies and markets can result in firms stopping R&I activities, or refraining from conducting such activities. The second instance, which is the focus of the current paper, is when innovative firms seek to expand their knowledge frontiers (D'Este et al. 2012; Keupp and Gassmann 2013; Zahler, Goya, and Caamaño 2022). In this latter case, a lack of information on technologies and markets does not deter firms from innovating. Instead, it reveals the level of firms' R&I efforts (D'Este et al. 2012; Coad, Pellegrino, and Savona 2016; Zahler, Goya, and Caamaño 2022). More specifically, it can indicate that such firms are seeking to generate innovations that require them to extend beyond their existing knowledge base.

Public financial support for R&I can result in radical innovation in both types of firms as presented above. In the case of firms seeking to innovate by exploiting their existing knowledge base, the support can enable such firms to conduct R&I activities faster, at a larger scale, or with a larger scope (Roper and Hewitt-Dundas 2015). This, in turn, can help such firms to achieve a higher level of novelty, and to bring their innovations to the market faster, and/or to address a larger group of potential users. As a result, public financial support for R&I can enable these firms to improve their radical innovation outcomes (Beck, Lopes-Bento, and Schenker-Wicki 2016). In the case of firms engaging in knowledge areas that are new to them, public financial support for R&I can help them to overcome their lack of information on technologies and markets. This can take place by providing firms with the financial means to engage in new thematic areas, or to find new sources of external knowledge (Gao et al. 2021; Hottenrott and Lopes-Bento 2014; Hottenrott, Lopes-Bento, and Veugelers 2017; Lee 2011). If successful, these R&I activities can result in radical innovation, with the potential to disrupt markets and gain commercial success.

Considering the above, in the current paper we seek to understand whether public financial support for R&I is more impactful, in terms of radical innovation outcomes, when focused on: (1) Firms seeking to exploit their existing knowledge base; and (2) Firms seeking to engage in new knowledge areas. We achieve this by focusing on firms that face and do not face, knowledge challenges relating to a lack of information on technologies and markets for their desired R&I activities. The key research question we address in this paper is: *Is public financial support for R&I more likely to result in radical innovation, when allocated to firms that face or do not face, knowledge challenges?* The next sub-section discusses the data, and the empirical approach used to address this question.

3. Data and empirical approach

3.1. Data

Our analysis uses a novel dataset with information on the knowledge challenges and research and innovation (R&I) activities of firms that responded to both the 2010 and the 2016 waves of the Innovation in Irish Enterprises survey (IIE, which is the Irish contribution to the European Union's Community Innovation Survey [CIS]). The IIE is a biennial survey focused on the R&I activities of firms with at least 10 employees.[2] The 2010 IIE survey wave dataset includes information on 3,245 firms for the period 2008 to 2010. The 2016 IIE survey wave dataset includes information on 2,576 firms for the period 2014 to 2016. We specifically focus on the 2010 and 2016 IIE survey waves, because they include questions on the challenges that firms face when innovating (i.e. the questions on challenges to innovation were not included in the 2012 and 2014 IIE survey waves). Moreover, a total of 1,296 firms in the 2010 survey dataset (approximately 40 percent of the firms) also feature in the 2016 survey dataset. Therefore, the 2010 and 2016 IIE survey waves are ideal given the focus of the current paper.

Despite the above, it should be acknowledged that, focusing on firms that responded to both the 2010 and the 2016 waves of the Innovation in Irish Enterprises survey can affect the external validity of our analysis. This occurs if the resulting sample is systematically different to the full sample of IIE survey firms. Appendix A presents the results of a representativeness test, which compares our effective sample with the full 2010 IIE survey wave sample. As Appendix A shows, our effective sample maintains the key characteristics of the full IIE survey sample, in terms of the percentage of firms being Irish owned, firms that are part of an enterprise group, firm-sizes and sector compositions. Some differences can also be observed. For example, 29 percent of firms in the full 2010 IIE survey sample introduced innovations during the 2008–2010 period. This figure is approximately 35 percent in our effective sample. Moreover, approximately 17 percent of firms in the full 2010 IIE sample introduced radical innovations, while this is approximately 21 percent in our effective sample. Despite this, we do not find statistically significant differences between the level of turnover that firms generated from radical innovation, between the firms in the two samples. This suggests,

that our effective sample remains representative of the full sample of firms, as included in the 2010 IIE survey wave.

The above survey data are merged with detailed administrative data on public financial support instruments for R&I from the three main funding agencies for R&I in Ireland, covering the period between the two IIE survey waves (i.e. 2011–2014).[3] More specifically, we merge firms that received public financial support for R&I during 2011 to 2014, with the sample frame of firms in the 2010 IIE survey wave. The three main funding agencies are: (1) Enterprise Ireland (EI); (2) the Industrial Development Agency Ireland (IDA Ireland), and (3) Science Foundation Ireland (SFI). These are the main agencies responsible for allocating financial support for R&I activities to firms in Ireland (Lenihan et al. 2024a). EI provides a range of policy supports for Irish-owned firms from start-up to maturity, with a particular focus on innovation and exporting activities (Enterprise Ireland 2023). IDA Ireland mainly focuses on attracting and supporting investments into Ireland, by foreign-owned multinational corporations (IDA 2023). We only consider financial support instruments that focus on firm-level R&I. SFI primarily funds scientific research in higher education institutions. However, SFI funded institutions can also provide cutting edge knowledge to firms through co-funded collaborative research projects (SFI 2023). Our data include information on firms that have engaged in R&I collaborations with SFI's research centres. Finally, information on R&D tax credits from Ireland's Revenue Commissioners, which oversees all tax-related matters in Ireland, are also merged.[4] Appendix B lists all of the types of public financial support instruments considered.

As Appendix B presents, a total of 221 firms received public financial support for R&I in our working sample, from 2011 to 2014. Based on our administrative data however, a total of 1,848 firms received public financial support for R&I during this period (which is the population of treated firms). Therefore, Appendix C presents the results of a comparison between the firms in our working sample, with the population of treated firms. Appendix C shows that there is some variation in the composition of the working sample in terms of firm-sizes and industrial sectors which are not covered by the IIE survey dataset (e.g. Arts and Entertainment). Besides this, our sample of treated firms mirrors the composition of the full population of treated firms very closely. This indicates that our effective sample maintains the key characteristics of the population of treated firms.

Our final dataset comprises 1,296 firms featured in two repeated cross-sections of the IIE survey, meaning that we observe these firms during the periods 2010 to 2012 and 2014 to 2016. From these, 221 firms received public financial support for R&I, during the period 2011 to 2014.

3.2. Definition of key variables

Our analysis focuses on the extent to which public financial support for R&I results in radical innovation, when allocated to firms seeking to innovate by engaging in knowledge areas that are new to them, or to firms seeking to exploit their existing knowledge base. We measure radical innovation in two ways. In a similar way to Hewitt-Dundas, Gkypali, and Roper (2019) and Perez-Alaniz et al. (2023), our first measure is a binary variable, taking the value of 1 if firms introduce goods or services that are new to the market, otherwise the value is 0. A good or service is new to the market if no other firms have offered the same or a similar good or service in their respective market. New to the market comprises new solutions for users, often addressing needs that have not been fully addressed by existing goods and services in the market. For our second measure, we use the percentage of total turnover that firms obtain from radical innovation (Beck, Lopes-Bento, and Schenker-Wicki 2016; Hewitt-Dundas, Gkypali, and Roper 2019). Using this second measure is important, as the socio-economic returns of financial support for R&I may only be fully realised if firms generate economic benefits from their radical innovations (Colombo et al. 2017).

Data on both of the above measures of radical innovation are collected by the IIE survey, following the guidelines of the *Oslo Manual* (OECD and Eurostat 2018). Firms are first asked whether they have introduced new or improved goods or services (i.e. innovations), during a three-year reference period (e.g. in the case of the 2016 wave, for the period 2014 to 2016). Firms that answer yes to this

question, are then asked if the goods or services introduced were new to the firm (i.e. the product and/or service is new to the firm, but similar goods and services already existed in the market), or new to the market (i.e. no similar good or service was available at the time the firm introduced the innovation to the market). We obtain our first measure of radical innovation from this latter question. Finally, firms reporting new to the market products and services are asked to report the share of sales obtained from these product and service innovations, which is our second measure of radical innovation.

To measure the receipt of public financial support for R&I, we construct a binary variable that takes the value of 1 if firms receive public financial support for R&I. Otherwise, the value is 0. Using an aggregated measure of public financial support for R&I is common in the literature (Berrutti and Bianchi 2020; Czarnitzki and Lopes-Bento 2014; Hottenrott, Lopes-Bento, and Veugelers 2017). As discussed in Section 3.1, some of the public financial support instruments considered are not directly allocated to firms, but the funding is provided to Research Centres at Higher Education Institutions (e.g. SFI funded collaborations). However, as Scandura (2016), Vanino, Roper, and Becker (2019) and Mulligan et al. (2022) demonstrate, firms benefit financially from such instruments, as they lower the cost of access to external knowledge.

In terms of firms' knowledge challenges, we obtain this information from specific questions in the 2010 IIE survey wave, regarding the factors hampering firms' R&I activities. This is in line with a plethora of previous studies on this topic (see for example, D'Este et al. 2012; Pellegrino and Savona 2017; Perez-Alaniz et al. 2025). The specific question used asks firms whether their R&I activities were affected by several hampering factors, which are presented in a list. The list includes a total of eleven hampering factors. Firms evaluate the importance of each of these hampering factors, by using a four-point scale (high, medium, low, not relevant). Appendix D shows the framing of the specific questions used. Our key variable of interest 'Knowledge Challenge (*KC*)' specifically pertains to a lack of information on technology and a lack of information on markets. As noted in Section 2.2, this is because firms that seek to innovate by entering knowledge areas that are new to them, are highly likely to face these challenges. The questionnaire includes these challenges as two separate items, as outlined in Appendix D (i.e. a lack of information on technology and a lack of information on markets). In our analysis, they are operationalised as one variable (i.e. lack of information on technologies and markets) due to a high correlation between the two individual challenges (i.e. correlation coefficient = 0.87).[5]

Using the combined variable pertaining to a lack of information on technologies and markets, as explained above, we generate four new variables. The first variable *Knowledge Challenge (KC)* equals 1 if firms experience these knowledge challenges at any level of importance (i.e. high, medium or low levels), otherwise 0. We use this variable as our main headline variable. The remaining three variables (KC_1, KC_2, KC_3) do the same as above, but now consider the different levels of importance that firms attach to their knowledge challenges. More specifically, KC_3 takes the value 1 if a firm reported facing a lack of information on technologies and markets at a high level of importance; otherwise 0. KC_2 and KC_1 do the same for medium and low levels of importance, respectively.

The above variables are in line with a cannon of earlier studies focused on analysing the drivers and impact of obtacles to innovation in firms (see, for example, Iammarino, Sanna-Randaccio, and Savona 2009; Pellegrino 2018; Pellegrino and Savona 2017; Perez-Alaniz et al. 2025). As outlined in these previous studies, the importance that firms attach to their obstacles can indicate the extent to which they seek to expand their R&D and innovation portfolios. As an illustrative example, D'Este et al. (2012) show that, as firms become more innovative and engage in more novel R&D projects, they are more likely to experience financial and knowedge challenges at a high level of importance. Based on this, we consider the level of importance that firms attach to their knowledge challenges, as an indication of the extent to which such firms seek to expand their knowledge base when innovating. Table 1 shows the distribution of the four Knowledge Challenge (*KC*) variables, differentiated by whether firms received and did not receive public financial support for R&I.

Table 1. Challenges to R&I variables, and their distribution in the matched sample.

Knowledge challenges	Treatment = 0	Treatment = 1	Total
Lack of information technologies and markets = 0	109	174	283
Lack of information technologies and markets = 1	59	138	197
Total	**168**	**312**	**480**
Lack of information technologies and markets low = 1	92	85	177
Lack of information technologies and markets medium = 1	69	62	131
Lack of information technologies and markets high = 1	27	29	56
Total	**188**	**176**	**364**

3.3. Empirical approach

Evaluating whether public financial support for R&I results in radical innovation in firms necessitates considering the well-known issue of endogeneity due to selection bias (Hottenrott and Lopes-Bento 2014; Lenihan et al. 2024b; Nilsen, Raknerud, and Iancu 2020). Ideally, such an evaluation would compare the radical innovation activities of firms that received public financial support for R&I (i.e. treated firms), with a counterfactual scenario where the same firms had not received such support. As observing this counterfactual scenario is not possible, this needs to be estimated using firms that do not receive public financial support for R&I (Imai, Kim, and Wang 2021; Lenihan and Hart 2004). However, firms self-select into receiving public financial support for R&I. Moreover, some public financial support for R&I instruments are competitive in nature (e.g. R&D grants and funding for Academic-Industry collaborations), and programme managers may prefer firms with a strong innovative track record (Hünermund and Czarnitzki 2019; Nilsen, Raknerud, and Iancu 2020; Vanino, Roper, and Becker 2019). Other public financial support for R&I instruments such as R&D tax credits may be available to all firms, but focus on specific R&D activities which are deemed desirable for society (Lenihan et al. 2024a). Ultimately, this means that firms receiving public financial support for R&I can be intrinsically different from firms that do not receive such support.

Considering the above, we construct a counterfactual of untreated firms, that had similar probabilities of being supported as treated firms at the point of treatment. We do this based on a set of observable covariates (Iacus, King, and Porro 2012; Imai, Kim, and Wang 2021; Imbens and Rubin 2015). We achieve this by using a propensity-score matching (PSM) approach, in a similar way to studies such as Czarnitzki and Lopes-Bento (2013), Vanino, Roper, and Becker (2019), Lenihan et al. (2024a) and Perez-Alaniz et al. (2025). The PSM approach relies on the conditional independence assumption, where treatment and outcome are assumed to be statistically independent for firms with the same set of observable characteristics (Rubin 2001). Therefore, assuming that the matching process is performed correctly, any differences in outcome between treated and control firms after an intervention and/or treatment, can be typically attributed to the intervention and/or treatment. It is important to note that matching on the propensity of receiving treatment (based on observable covariates) does not completely solve the issue of endogeneity, but this is an issue which cannot be directly tested (Imai, Kim, and Wang 2021; Imbens and Rubin 2015). However, Lenihan, McGuirk, and Murphy (2019, 6) note that establishing causal relationships depends on 'a mix of empirical findings, past literature and logical argument'. Moreover, numerous studies have highlighted the suitability of using PSM to evaluate the impact of public financial support for R&I on firm-level outcomes (see, for example: Nilsen, Raknerud, and Iancu 2020; Petrin and Radicic 2023; Vanino, Roper, and Becker 2019).

It should also be acknowledged, that matching on the propensity scores can present some disadvantages, *vis-à-vis* newer matching approaches. From several matching approaches that are gaining prominence in the literature, Coarsened Exact Matching (CEM) has proven especially useful for treatment effect estimations (Guy et al. 2021; Iacus, King, and Porro 2012; Ripollone et al. 2020). A key defining feature of the CEM approach is that the matching is carried out directly on the (coarsened) variables measuring firms' characteristics. As noted by Iacus, King, and Porro (2012), matching on the variables (as opposed to matching on the propensity scores) typically

results in superior matches, in comparison to PSM. King and Nielsen (2019) provide a detailed account of this process. As they note, PSM can at best approximate a randomised exercise by achieving covariate balance at the mean. Beyond this point, using PSM to refine the matching process can in fact increase imbalance. This takes place by PSM pruning observations which are similar to treated firms in terms of the covariates used, but not in terms of the propensity scores. In contrast to this, CEM can approximate full block randomisation, which means that covariate balance is achieved at a more granular level (i.e. each treated firm is balanced with a control firm). A drawback of the CEM approach is that, given the increased level of precision being imposed on the matching process, this process typically yields fewer matches, in comparison to matching approaches based on PSM (Guy et al. 2021; King and Nielsen 2019). Considering the number of treated firms (i.e. 221 firms) in our working sample, this issue was central to our decision to employ PSM, by adopting a two-step approach, as follows:

In the first step, we estimate the determinants of receiving public financial support for R&I with Equation (1):

$$PS_{i,t} = \alpha + \beta_X X'_{i,t-1} + u_{i,t} \quad (1)$$

Where $PS_{i,t}$ denotes whether firm *i* receives public financial support for R&I in the period 2011 to 2014, and X is a vector of variables that measure firms' key characteristics affecting their probability to obtain support in 2010 (as discussed in Section 3.4). The terms α and *u* represent the intercept and the error term, respectively, while β are our parameters of interest. We estimate Equation (1) with a probit regression model. Appendix E presents the results of this estimation, which we use to derive the propensity scores used in our PSM routine.

In line with Hottenrott and Lopes-Bento (2014) and Mina et al. (2021), we match treated firms with up to three control firms, by employing a nearest neighbour approach. To ensure that the matching is carried out correctly, we use a caliper of 0.2 points of the standard deviation of the propensity score (Austin 2011). Moreover, we only allow matches between firms of the same size-group (i.e. 1 = small, 2 = medium, and 3 = large-sized firms), and one-digit NACE Rev 2 Sections (Lenihan et al. 2024b; Vanino, Roper, and Becker 2019). For completeness, we also carry out this approach by following a 1:1 matching specification.

The second step consists of estimating the following innovation production function, using our matched sample:

$$RI_{i,t+1} = \alpha + \beta_X X'_{i,t-1} + \beta_{KC} KC_{i,t-1} + \beta_{PS} PS_{i,t} + \beta_{PSKC} PS_{i,t} * KC_{i,t-1} + u_{i,t+1} \quad (2)$$

In Equation (2), α is a constant, β are parameters to be estimated, and *u* is an error-term. As in Equation (1), X is a vector of control variables, which we discuss in Section 3.3. We include these variables to capture any remaining imbalance following the matching process. $PS_{i,t}$ represents whether a firm obtained public support for R&I in period *t*, while $KC_{i,t-1}$ represents whether a firm faced knowledge challenges, related to a lack of information on technologies and markets during the period before treatment (i.e. 2008 to 2010). Importantly, $PS_{i,t} * KC_{i,t-1}$ is an interaction term, measuring whether a firm that faced knowledge challenges related to a lack of information on technologies and markets during this period, received public financial support for R&I (PS) in the period 2011 to 2014. The key coefficient of interest is β_{PSKC}, which indicates whether public support for R&I results in significantly higher (lower) radical innovation outputs during the period 2014 to 2016, when provided to firms facing knowledge challenges (in 2008 to 2010). The coefficient is interpreted relative to the coefficient β_{PS}, which indicates the impact of public financial support for R&I, when provided to firms not facing knowledge challenges. As noted earlier, firms facing knowledge challenges are considered to be seeking to innovate by engaging in knowledge areas that are new to them. In turn, firms not facing such challenges, are considered to be firms seeking to innovate by exploiting their existing knowledge base.

As discussed in detail below (Section 3.3), we have two measures of radical innovation (*RI*). Therefore, we estimate Equation (2) using both a probit regression model (for a binary measure of *RI*) and

an ordinary least squares (OLS) regression (for a continuous measure of *RI*). When using our binary measure of radical innovation (*RI*), marginal effects of the interaction terms are calculated as the difference of the marginal effects between firms that received public financial support for R&I and faced knowledge challenges, and treated firms that did not face such challenges. That is, by holding all other control variables constant, we calculate the discrete change of the average marginal effects of treated firms, depending on whether they faced knowledge challenges. This is important because, as noted by Karaca-Mandic, Norton, and Dowd (2012), the marginal effects of interaction terms in non-linear models can be influenced by all other control variables in the model.

For completeness and robustness, we replicate our analysis based on a matched sample obtained using the coarsened exact matching approach. Moreover, we repeat our main analysis by adding new variables, which enables us to control for the specific years in which treated firms received public financial support for R&I. We do this to check for potential changes in the way such support was allocated to firms across the years. Finally, we carry out our main analysis by considering any form of innovation, and not only radical innovation (i.e. whether firms introduced new to the firm or new to the market innovations). As Section 4.2 presents, the findings obtained with these additional analyses support the results of our main analysis.

3.4. Matching and control variables

Our main analysis is carried out using our matched sample. To achieve this matched sample, we use the propensity scores estimated with Equation (1) in a probit regression model. In estimating Equation (1), we include the following variables:

(i) firm sizes, as measured by three binary variables according to firms' number of employees (i.e. small-sized, medium-sized, and large-sized firms)[6];
(ii) whether firms are Irish (domestic) or foreign-owned, in binary form;
(iii) whether firms are part of an enterprise group, in binary form;
(iv) whether firms are exporters, in binary form;
(v) a count variable (0 to 4) measuring the breadth of innovation partners. In line with Roper, Du, and Love (2008), we include links with clients, suppliers, other firms, and Higher Education Institutions (e.g. universities), as measures of forward, backward, horizontal, and public links, respectively;
(vi) a count variable measuring the number of types of innovation (product innovation, process innovation, service innovation, and organisational innovation) that firms performed (0 to 4) in 2010;
(vii) whether firms introduced radical innovation in 2010, in binary form;
(viii) a continuous variable measuring the percentage of turnover generated from radical innovation in 2010 (Beck, Lopes-Bento, and Schenker-Wicki 2016; Hewitt-Dundas, Gkypali, and Roper 2019); and
(ix) a set of binary variables measuring whether firms faced financial or non-financial challenges in 2010 (i.e. including a lack of information of technologies and markets), at low, medium, and high levels of importance (Zahler, Goya, and Caamaño 2022). Including these variables enables matching firms that experienced the same set of challenges, before firms received public financial support for R&I. To obtain these variables, we grouped each of the challenges that firms face, into three headline variables (i.e. financial, knowledge and market), as organised in Appendix D. For example, the variable *Financial* high equals 1 if a firm declares any of the factors hampering their R&I activities to be of high importance. In a similar way, *Financial Medium* equals 1 if a firm declares any of the factors under this financial category to be of medium importance. This is carried out in a mutually exclusive way, meaning that firms that have been assigned the value of 1 for *Financial High*, are not considered for *Financial Medium*. The same process is followed for *Financial Low*, and for the other items listed in Appendix D as knowledge and market factors (i.e. *Knowledge* and *Market*).

Finally, we include indicator variables for the industry a firm belongs to, based on one-digit NACE rev. 2 classes. Appendix F presents a correlation matrix between all of the variables used in our analysis.

Our main analysis is based on estimating the innovation production function presented in Equation (2). In this case, we use the same set of control variables as described above in the context of Equation (1). As our analysis is carried out by using the matched sample, our model enables us to capture the effect of public support for R&I by comparing firms' levels of innovation output in the outcome period (from 2014 to 2016). Therefore, any differences in the radical innovation outputs of treated and control firms can be interpreted as resulting from public support for R&I.

3.5. Descriptive statistics and balance tests

The top panel of Table 2 presents the descriptive statistics for the outcome variables (during the period 2014 to 2016), while the bottom panel does the same for the variables used in our matching approach (period from 2008 to 2010). In the top panel, the table shows that 40 percent of firms that received public financial support for R&I during 2011 to 2014 (i.e. treated firms) introduced radical innovations to the market during 2014 to 2016. However, this was only the case for approximately 21 percent of untreated firms. Moreover, treated firms generated, on average, 7.7 percent of their total turnover from radical innovation during 2014 to 2016, with untreated firms only generating an average of 2.2 percent of turnover form such innovations in the same period.

Focusing on the comparison between treated versus untreated firms in the period before treatment (i.e. 2008 to 2010), the bottom panel of Table 2 shows that treated firms outperformed untreated firms in terms of their probability to innovate radically, and the turnover generated from radical innovation. We also observe that a larger proportion of the sample of treated firms faced challenges to innovation during 2008 to 2010 at all levels of importance (i.e. low, medium, and high), in comparison to untreated firms. Our descriptive statistics thus support our decision

Table 2. Descriptive statistics by treated and untreated firms.

	Treated				Untreated				Standardised Difference	Standard
	Mean	SD	Min	Max	Mean	SD	Min	Max	(T − C)	error
Outcome variables (i.e. in 2016)										
Introduced Radical Innovation (1 = Yes)	0.476	0.492	0	1	0.212	0.412	0	1	0.752***	(0.070)
Turnover from Radical Innovation (% Turnover)	7.746	16.423	0	100	3.222	9.851	0	100	0.483***	(0.072)
Control variables (i.e. in 2010)										
Small-sized firm (< 50 employees)	0.484	0.500	0	1	0.674	0.468	0	1	−0.396***	(0.073)
Medium-sized firm (50 to 249 employees)	0.389	0.488	0	1	0.260	0.439	0	1	0.285***	(0.072)
Large-sized firm (250 or more employees)	0.126	0.333	0	1	0.065	0.246	0	1	0.232***	(0.073)
Irish owned (1 = Yes)	0.696	0.460	0	1	0.711	0.453	0	1	−0.032***	(0.074)
Enterprise group (1 = Yes)	0.154	0.490	0	1	0.167	0.467	0	1	−0.272***	(0.072)
Export (1 = Yes)	0.904	0.293	0	1	0.551	0.497	0	1	0.724***	(0.071)
Breadth of cooperation partners (0 to 4)	0.574	0.943	0	4	0.209	0.636	0	4	0.525***	(0.072)
Breadth of innovation (0 to 4)	2.445	1.808	0	4	1.355	1.599	0	4	0.646***	(0.071)
Introduced Radical Innovation in 2010	0.470	0.500	0	1	0.165	0.467	0	1	0.738***	(0.070)
Turnover from Radical Innovation 2010 (% Turnover)	9.977	19.685	0	100	3.542	9.251	0	100	0.618***	(0.071)
Knowledge challenges high (1 = Yes)	0.095	0.293	0	1	0.060	0.238	0	1	0.138**	(0.073)
Knowledge challenges medium (1 = Yes)	0.285	0.452	0	1	0.215	0.441	0	1	0.165**	(0.073)
Knowledge challenges low (1 = Yes)	0.506	0.501	0	1	0.324	0.468	0	1	0.380***	(0.073)
Financial challenges high (1 = Yes)	0.276	0.448	0	1	0.253	0.434	0	1	0.052	(0.073)
Financial challenges medium (1 = Yes)	0.520	0.500	0	1	0.325	0.468	0	1	0.405***	(0.071)
Financial challenges low (1 = Yes)	0.425	0.499	0	1	0.276	0.447	0	1	0.324***	(0.073)
Market challenges high (1 = Yes)	0.180	0.385	0	1	0.190	0.393	0	1	−0.024	(0.071)
Market challenges medium (1 = Yes)	0.438	0.497	0	1	0.312	0.463	0	1	0.267***	(0.070)
Market challenges low (1 = Yes)	0.285	0.452	0	1	0.279	0.448	0	1	0.201**	(0.073)

The Standardised Difference and Standard Errors reported are the outcome of a t-test between the standardised variables for treatment and control groups *** denotes significance at the 99% level, ** 95% level and * 90% level.

to use a matching approach, as a means of dealing with differences between treated and untreated firms at the time of treatment assignment. Appendices G and H show the standard tests for our 1:3 and 1:1 matching routines performed. Appendix I does the same for the matched sample of firms obtained with the CEM routine. The tables indicate, that the matching processes resulted in control groups of firms being statistically indistinguishable (on average), to the treated firms in the period 2010 to 2012.

4. Results and discussion

4.1. Main results

Table 3 presents the impact of public financial support for research and innovation (R&I) on firms' probabilities to innovate radically (in 2014 to 2016), for firms that faced and did not face knowledge challenges due to a lack of information on technologies and markets (in 2008 to 2010). In Column 1 and Column 2 of Table 3, the variable *Public Financial Support (PS)* presents the impact of public financial support for R&I on firms not facing knowledge challenges, when obtained with a 1:3 and 1:1 nearest neighbour matching approach, respectively. Here, we observe that public financial support for R&I has a positive and significant effect on such firms' probabilities to introduce radical innovation. This impact is between 13 and 18 percentage points ($p < 0.01$), depending on the matching specification used. The interaction variables *Support × Challenge (PS × KC)* in the same columns capture the impact of public financial support for R&I, when allocated to firms facing knowledge challenges due to a lack of information on technologies and markets. The insignificant coefficients indicate that public financial support has a similar effect on firms with and without knowledge challenges.

Columns 3 and 4 of Table 3 reveal that the results change significantly, when the importance that firms attach to their knowledge challenges is considered. In these columns, we observe that public financial support for R&I results in firms without knowledge challenges, being between 13 and 19 percentage points more likely to innovate radically ($p < 0.01$). This is in comparison to untreated firms. However, when public support is allocated to firms for which a lack of information on technologies and markets is of high importance, as captured by the variable *Support × Challenge High* ($PS \times KC_3$), the impact of such support is substantially higher (approximately 27 percentage points higher). This is in comparison to the impact of the support on firms not facing knowledge challenges ($P < 0.01$). Moreover, in the case of the one-to-one matching specification in Column 4, we find significant

Table 3. Knowledge challenges influencing how public financial support for R&I drives radical innovation in firms.

Dependent variable: Introduction of radical innovation(1 = yes) in Average Marginal Effects (dy/dx)				
	(1)	(2)	(3)	(4)
Public Financial Support (*PS*)	0.132*** (0.040)	0.189*** (0.025)	0.138*** (0.044)	0.194*** (0.022)
Knowledge Challenge (*KC*)	0.047 (0.063)	0.057 (0.056)		
Support × Challenge ($PS \times KC$)	0.035 (0.110)	0.109 (0.072)		
Knowledge Challenge Low (KC_1)			−0.059 (0.054)	−0.058 (0.066)
Knowledge Challenge Med. (KC_2)			0.045 (0.036)	0.041 (0.089)
Knowledge Challenge High (KC_3)			−0.043* (.025)	−0.015 (0.062)
Support × Challenge Low ($PS \times KC_1$)			−0.061 (0.061)	−0.251** (0.017)
Support × Challenge Med. ($PS \times KC_2$)			−0.036 (0.082)	−0.063*** (0.016)
Support × Challenge High ($PS \times KC_3$)			0.281*** (0.024)	0.272*** (0.043)
Control	Yes	Yes	Yes	Yes
Observations	480	370	480	370
Matching approach	3-Neighbours	One-to-one	3-Neighbours	One-to-one

Notes: Treatment effects are obtained with a probit regression analysis, and are presented as Average Marginal Effects, which are calculated as the discrete change of the Treatment variable between firms facing and not facing challenges. *** denotes significance at the 99% level, ** 95% level and * 90% level. Column 1 and Column 2 refer to the difference between Treatment and Control groups using a counterfactual comprising the nearest 3 neighbours for each treated firm. Column 2 and Column 4 presents the results obtained with a one-to-one matching routine. This explains the difference in number of observations relative to the other columns in the table.

negative effects for the variables *Support × Challenge Low (PS × KC_1)* and *Support × Challenge Med. (PS × KC_2)*. This suggests that public support for R&I can be less effective at increasing firms' probabilities of generating radical innovations, when allocated to firms with some knowledge challenges (i.e. at low and medium levels of importance). Again, this is in comparison to the impact that the support has on firms not facing knowledge challenges.

Table 4 presents the impact of public financial support for R&I on the percentage of turnover that firms generate from radical innovation. Columns 1 and 2 show that public financial support for R&I increases radical innovation turnover in firms without knowledge challenges. These firms, on average, generate between 1.9 and 2.3 percentage points more turnover from radical innovation (as percentage of total turnover) than untreated firms ($p < 0.01$), depending on the model specification used. The insignificant effect for our interaction variable *Support × Challenge (PS × KC)* indicates that the effect of public financial support does not differ between firms with and without, knowledge challenges. This is consistent with our findings from Table 3. Also consistent with Table 3, we find a significant positive effect for the interaction term *Support × Challenge High (PS × KC_3)* in Columns 3 and 4. This suggests that supporting firms that experience knowledge challenges at high levels of importance results in a higher percentage of turnover from radical innovation. The magnitude of the effect is substantial, at around 9 percentage points more, than treated firms not experiencing such challenges (total impact is between 11 and 13 percentage points).

Unlike the case of Table 3, we do not find a significant negative effect for the variable *Support × Challenge Low (PS × KC_1)* in Table 4. This means that treated firms facing knowledge challenges at low levels of importance generate a similar percentage of turnover from radical innovation, as treated firms not experiencing knowledge challenges. However, our results from Column 4 of Table 4 support the results in Table 3 for the variable *Support × Challenge Med. (PS × KC_2)*, which is negative and significant ($p < 0.01$). This indicates that public financial support for R&I can result in a lower percentage of turnover from radical innovation, when targeted at firms facing knowledge challenges at medium levels of importance. This is when compared to treated firms not facing knowledge challenges. The magnitude of the coefficient is also larger than the coefficient for the variable *Public Financial Support (PS)*, suggesting that the support may not result in more radical innovation turnover in these firms.

Based on the above, our combined findings indicate that, on average, public financial support for R&I has similar impacts on the radical innovation activities of the two groups of firms considered. These findings concur with Beck, Lopes-Bento, and Schenker-Wicki (2016), in the sense that public financial support for R&I can result in firms generating radical innovation, and additional turnover

Table 4. The impact of public financial support for R&I and knowledge challenges on turnover from radical innovation.

Dependent variable: Ln of total turnover from radical innovation				
	(1)	(2)	(3)	(4)
Public Financial Support (PS)	1.916*** (0.740)	2.271*** (0.107)	2.150*** (0.964)	1.986*** (0.737)
Knowledge Challenge (*KC*)	1.538 (3.594)	1.724 (0.111)		
Support × Challenge (*PS × KC*)	−0.675 (2.513)	−2.680 (2.880)		
Knowledge Challenge Low (KC_1)			−0.308 (2.830)	1.000 (4.097)
Knowledge Challenge Med. (KC_2)			−2.818 (1.902)	3.233 (3.583)
Knowledge Challenge High (KC_3)			−1.754 (1.879)	−3.132 (3.763)
Support × Challenge Low ($PS \times KC_1$)			−2.183 (2.666)	−3.193 (4.200)
Support × Challenge Med. ($PS \times KC_2$)			−1.781 (1.460)	−2.229*** (0.783)
Support × Challenge High. ($PS \times KC_3$)			9.137*** (3.376)	9.089*** (3.076)
Control	Yes	Yes	Yes	Yes
Observations	488	315	488	315
Matching approach	3-Neighbours	One-to-one	3-Neighbours	One-to-one

Notes: Treatment effects are obtained with regression analysis estimated with Ordinary Least Squares (OLS). *** denotes significance at the 99% level, ** 95% level and * 90% level. Column 1 and Column 2 refer to the difference between Treatment and Control groups using a counterfactual comprising the nearest 3 neighbours for each treated firm. Column 2 and Column 4 presents the results obtained with a one-to-one matching routine. This explains the difference in number of observations relative to the other columns in the table.

from radical innovation. Moreover, our findings support those of Lee, Wu, and Pao (2014) who propose that the increasing availability of firm-level financial resources (in our case due to public financial support for R&I) can drive firms to generate new knowledge and radical innovation. We extend the insights of these previous studies by showing that, on average, public financial support for R&I results in similar levels of radical innovation, when targeted at firms seeking to innovate outside or within their existing knowledge base.

Importantly, however, our findings reveal key additional insights, when the importance that firms attach to their knowledge challenges is considered. As discussed in Section 3.2, we conceptualise the importance that innovative firms attach to their knowledge challenges to indicate the extent to which firms seek to expand their knowledge frontiers. This is in line with a plethora of studies focused on the challenges that firms face when innovating (see, for example, D'Este et al. 2012; Keupp and Gassmann 2013; Zahler, Goya, and Caamaño 2022). Our results highlight the importance of not only considering whether firms seek to engage in new knowledge areas, but also considering the extent to which firms intend to do this.

In this context, we find that targeting public financial support for R&I at firms facing knowledge challenges at low or medium levels of importance, can lead to sub-optimal socio-economic returns (i.e. policy failure). This is because such firms are less likely to translate public financial support for R&I into more radical innovation outcomes, in comparison to treated firms without knowledge challenges. It is possible that firms facing knowledge challenges at a low or medium level of importance may only make small incremental efforts to go beyond their existing knowledge base, which do not result in radical innovation (Lee, Wu, and Pao 2014; Zahler, Goya, and Caamaño 2022). An alternative explanation relates to such firms using public funding to carry out explorative research activities, which may not necessarily focus on developing specific products and services (Mina et al. 2021; Wanzenböck, Scherngell, and Fischer 2013).

Our findings also highlight that allocating public financial support for R&I to firms facing knowledge challenges at a high level of importance, is much more likely to result in radical innovation, and higher levels of turnover from radical innovation. This is in comparison to treated firms that do not face knowledge challenges. Based on our conceptualisation of knowledge challenges, this means that public financial support for R&I is most impactful, in terms of radical innovation outcomes, when targeted at firms seeking to significantly extent their knowledge frontiers. This concurs with Yang, Chou, and Chiu (2014), who propose that radical innovation requires firms to 'unlearn' existing ways of innovating, and develop new ones. It is also consistent with some studies that outline firms' innovative strategies as key determinants of the impact that public financial support for R&I has on firms (Gao et al. 2021; Nilsen, Raknerud, and Iancu 2020; Wanzenböck, Scherngell, and Fischer 2013).

Finally, our findings elucidate that public financial support for R&I can help firms engaging in new knowledge, to overcome knowledge challenges and innovate radically. This in turn, lends support to studies highlighting the impacts that public financial support for R&I can have on improving organisational learning and R&I capabilities in firms (Clarysse, Wright, and Mustar 2009; Perez-Alaniz et al. 2025; Wanzenböck, Scherngell, and Fischer 2013).

4.2. Robustness tests and additional analyses

In this section, we present additional analyses which we carried out to test the robustness of our main findings. We specifically focus on replicating the analysis as presented in Table 3. This is because the results of Table 3 focus on the impact that public financial support for R&I has on the probability of firms introducing radical innovations to the market, which is the central focus of this paper.

Our first robustness test is to estimate Equation (2), by using a matched sample obtained with a coarsened exact matching (CEM) approach. As discussed in Section 3.2, matching treated and untreated firms based on propensity scores carries a risk of introducing bias in the matched sample. This is because the propensity scores do not fully account for the firm-level characteristics

as contained in the matching covariates. CEM avoids this issue, by matching directly on the observable covariates. However, given the additional matching restrictions imposed on the data, this process typically results in fewer matches, in comparison to PSM (Guy et al. 2021; Iacus, King, and Porro 2012; King and Nielsen 2019). This is the case in the context of our paper. As Appendix I highlights, the CEM approach results in a highly balanced sample of treated and control firms. Yet, only 191 out of 221 treated firms are matched. The results emanating from estimating Equation (2) on the balanced sample using CEM are presented in Column 1 of Table 5. As the table shows, public financial support for R&I results in an increase of approximately 13 percentage points on the probability of firms introducing radical innovations to the market ($p < 0.01$). This is in comparison to untreated firms. This probability increases by approximately 24 percentage points, when the support is allocated to firms experiencing knowledge obstacles at a high level of importance ($p < 0.01$). These results fully support the findings from our main approach.

Our second robustness test is to replicate our main analysis, but now controlling for the years in which treated firms received public financial support for R&I. More specifically, this additional analysis extends Equation (2), by including a binary variable that equals 1 if the firms were treated during the years 2013 or 2014, and 0 if the firms were treated from 2011 to 2012. We expect this analysis to control for potential changes in the way the support was allocated to firms across the years. As Column 2 of Table 5 shows, including this additional control variable reduces the magnitude of the coefficient for the variable *Public Financial Support (PS)*. The latter measures the impact of public financial support for R&I, on the probability of firms introducing radical innovations to the market. This may indicate that the years in which firms were treated play an important role in determining the firm-level impacts of the support, especially in terms of driving radical innovation in firms. As shown by Spescha and Woerter (2019) and Hud and Rammer (2015), one reason for this may relate to differences in the business climate affecting the propensity of users to adopt radical innovations. Despite this, the results obtained from this additional analysis closely mirror the findings as presented in Table 3, thus supporting the robustness of our main analysis.

Table 5. Robustness tests and additional analyses.

	Introduction of radical innovation (1 = yes) (1)	Introduction of radical innovation (1 = yes) (2)	Introduction of innovation (1 = yes) (3)
Public Financial Support (PS)	0.139*** (0.051)	0.085** (0.032)	0.163*** (0.034)
Knowledge Challenge Low (KC_1)	0.027 (0.700)	−0.051* (0.030)	0.041*** (0.015)
Knowledge Challenge Med. (KC_2)	0.105 (0.134)	0.063 (0.039)	0.169*** (0.040)
Knowledge Challenge High (KC_3)	−0.110 (0.083)	−0.084** (0.033)	−0.086 (0.095)
Support × Challenge Low ($PS \times KC_1$)	−0.130* (0.078)	−0.132* (0.075)	0.184 (0.129)
Support × Challenge Med. ($PS \times KC_2$)	−0.086 (0.183)	−0.086 (0.056)	−0.115*** (0.035)
Support × Challenge High. ($PS \times KC_3$)	0.254*** (0.104)	0.235*** (0.030)	0.351*** (0.092)
Treated Year 2013–2014	No	0.094*** (0.020)	No
Control	Yes	Yes	Yes
Observations	1,074	488	487
Matching approach	CEM	3-Neighbours	3-Neighbours

Notes: Treatment effects are obtained with a probit regression analysis, and are presented as Average Marginal Effects, which are calculated as the discrete change of the Treatment variable between firms facing and not facing challenges. *** denotes significance at the 99% level, ** 95% level and * 90% level. Column 1 presents the difference between Treatment and Control groups using a counterfactual of firms composed by using the Coarsened Exact Matching (CEM) approach, and using CEM weights in the probit model. Column 2 uses a counterfactual of firms obtained using the nearest 3 neighbours for each treated firm. The dependent variable in this Column 2 measures whether firms introduced goods and services that are new to the firm or new to the market, as opposed to focusing only on good and services that are new to the market. The dummy variable Treated Year 2013–2014 equals 1 if firms received public financial support for R&I during the years 2013 and 2014, and 0 otherwise. This means that the base categogy for this variable comprises firms that received public financial support for R&I during the years 2011 and 2012. Column 3 replicates our main analysis (using the nearest 3 neighbours for each treated firm), but the model now controls for whether firms were treated during 2011 to 2012 (base), or 2013 to 2014. This results in the variable *Public Financial Support (PS)* now capturing the impact of public financial support for R&I on firms that received treatment before 2013 only.

Our final robustness test is to carry out our main analysis, but now considering any form of product innovation, and not only radical innovation. To achieve this, we replace our measure of radical innovation, with a measure of innovation which considers whether firms introduced new to the firm or new to the market goods and services. We do this to explore whether our findings also apply to other forms of product and service innovation, besides radical forms. In this context, it is important to note that based on our data, approximately 70 percent of firms introduced some form of product innovation to the market. The results of this additional analysis are presented in Column 3 of Table 5. Again, despite some expected changes in the magnitudes of the coefficients, the results are very much in line with our main findings. Based on this, we conclude that our robustness tests and additional analyses support the findings obtained with our main approach.

5. Conclusions and implications for policy

In this paper, we have addressed a critical knowledge gap that prevails in the literature regarding the allocation of public financial support for Research and Innovation (R&I) to firms. We achieved this by analysing how policymakers may successfully target public support for R&I to stimulate radical innovation in firms (Cerulli et al. 2022; Laplane and Mazzucato 2020; Mina et al. 2021; OECD 2023). This is important, because radical innovation is best placed for translating such public support for R&I into high socio-economic returns (Berrutti and Bianchi 2020; Colombo et al. 2017). However, radical innovation is risky, and public financial support for R&I can result in sub-optimal or no returns (i.e. policy failure), if firms fail to bring their radical innovations to the market, and/or fail to benefit from introducing radical innovations to the market (Haapanen, Lenihan, and Mariani 2014). Despite this, the question of how policymakers can best allocate public financial support for R&I in a way that drives more radical innovation in firms, while avoiding policy failure, remains unanswered (Berrutti and Bianchi 2020; OECD 2023).

Our paper directly addresses this question, by investigating whether public financial support for R&I results in more radical innovation when focused on two distinct groups of firms. These are: (1) Firms seeking to innovate by exploiting their existing knowledge base, and; (2) Firms seeking to engage in knowledge areas that are new to them. To identify these firms, we used a novel approach, focused on a key knowledge challenge that firms are most likely to face when seeking to engage in knowledge areas that are new to them. That is, a lack of information on technologies and markets.

Using matched administrative and survey data on firms in Ireland, we find that supporting firms experiencing knowledge challenges (at a high level of importance) results in a higher probability of radical innovation, and is associated with a higher percentage of turnover from radical innovation. This is in comparison to firms not facing such challenges. For firms facing knowledge challenges at low levels of importance, we find that public financial support for R&I has a lower impact on firms' probabilities to develop radical innovation (versus when targeted at firms not facing knowledge challenges). However, we do not find that government support affects the percentage of turnover that firms generate from radical innovation. Moreover, we find some evidence suggesting that public financial support for R&I becomes less effective, in terms of firms' probabilities to innovate radically and generate turnover from such innovations, when targeted at firms experiencing knowledge challenges at a medium level of importance. This is in comparison to supporting firms without knowledge challenges. Therefore, our findings highlight that, in the context of public financial support for R&I driving radical innovation in firms, the issue is not simply whether firms engage in knowledge areas, but the extent to which they do so.

Our paper contributes to the literature in several ways. First, we provide empirical evidence on the effectiveness of public financial support for R&I in firms that seek to innovate by exploiting their existing knowledge base, or by enterning knowledge areas that are new to them. This is an issue that has rarely been addressed in the literature until now. Our results indicate that firms' knowledge strategies, in terms of whether they seek to engage in new knowledge areas, play a key role in

determining the impact that public financial support for R&I has on firms. Hence, such strategies should be considered, when allocating public financial support for R&I to firms, and when evaluating the impact that such support has on firms.

Our specific focus in the current paper on radical innovation is important, because 'although the effect of public R&D subsidies on private R&D has been examined extensively, we know little about the quality of technologies that private firms produced using public R&D subsidies' (Choi and Lee 2023, 3). In a similar vein, our focus on the potential risks of policy failure associated with the allocation of public financial support is important. As Kärnä et al. (2022, 1037) have noted, previous studies focused on the allocation of public financial support for R&I 'have often been lacking considerations to the risks of political failures, meaning that policies fail to achieve their stated goals in a systematic manner'. Finally, our paper enhances our understanding regarding the extent to which public financial support for R&I enables firms to overcome key challenges affecting their R&I activities. This is with a view to stimulating radical innovation in firms. In this vein, our paper offers important insights which extend earlier studies focused on using public financial support for R&I to improve organisational learning and R&I capabilities in firms (Clarysse, Wright, and Mustar 2009; Fiorentin, Pereira, and Suarez 2019; Nilsen, Raknerud, and Iancu 2020; Wanzenböck, Scherngell, and Fischer 2013).

From a policy perspective, our results provide evidence which can usefully inform a more effective allocation of public financial resources for R&I. As discussed earlier, policymakers typically need to focus support on R&I projects that can maximise socio-economic returns. At the same time, they also need to avoid a misallocation of supports to R&I projects that are likely to fail, and/or result in low levels of additionality (Haapanen, Lenihan, and Mariani 2014; Mina et al. 2021). Our findings suggest, that allocating public financial support for R&I to firms seeking to innovate by engaging in knowledge areas that are new to them, can result in more radical innovation. Yet, this may only occur when firms are ambitious, in terms of advancing into new knowledge areas. These findings suggest that more attention might usefully be paid by policymakers at project appraisal stage when deciding what types of firms might be best to support in terms of public financial support for R&I, so as to ensure the greatest socio-economic returns. This may entail considering detailed information on the R&I activities of the applicant firms, as opposed to only focusing on the R&I projects that firms propose for funding. This is with a view to gathering a more comprehensive understanding of firms' R&I efforts and trajectories.

Related to the above, is the debate of whether public financial support for R&I should be allocated to firms by following a 'picking the winners' or 'aiding the poor' strategy (Autio and Rannikko 2016; Fiorentin, Pereira, and Suarez 2019). Mina et al. (2021) note in the context of the EC Horizon 2020 SME R&D policy instrument, that this support is mainly attracting already highly innovative firms. Based on this, the authors discuss potential issues of deadweight spending effects that may arise from supporting such firms. Several studies also discuss similar issues affecting the allocation of R&D subsidies in other country settings (e.g. Fiorentin, Pereira, and Suarez 2019; Nilsen, Raknerud, and Iancu 2020). More specifically, some studies in this vein highlight that public financial support for R&I, can be highly effective at encouraging firms to engage in R&D for the first time, rather than driving additional R&D in already highly R&D intensive firms (e.g. Huergo and Moreno 2017; Nilsen, Raknerud, and Iancu 2020). The impact of public financial support for R&I on firms' R&D investments is beyond the remit of the current paper. Yet, our findings suggest that radical innovation is most likely to occur, when public financial support for R&I targets highly innovative firms seeking to expand their knowledge frontier. This may indicate that in the specific context of driving radical innovation, 'picking the winners' could indeed be more effective than 'aiding the poor'.

There are some limitations pertaining to our paper, which could represent new avenues for future research. Our analysis is based on two repeated cross-sections of the Innovation in Irish Enterprises (IIE) survey, pertaining to the periods 2008–2010 and 2014–2016. This means that our data do not permit observing the firms in our sample during the period from 2011 to 2013, leading to an issue of time discontinuity. Moreover, the data structure prevents an analysis of whether treated

and untreated firms followed a similar trend in the outcome variable, prior to treated firms receiving public support for R&I (i.e. the common trend assumption). Future studies might usefully replicate our analysis (assuming the availability of panel datasets), to avoid the issue of data discontinuity and ensure common trends. Added to this, our effective sample largely maintains the representativeness of the sample of firms responding to the IIE survey, and the population of firms that received public financial support for R&I. Despite this, the firms in our working sample exhibited higher levels of R&D and innovation. It would be insightful for future studies to replicate our analysis, by using larger and more representative samples. Our empirical approach was also based on a matched sample of treated and control firms. Matching approaches have been widely used by previous studies to address issues of endogeneity due to selection bias. Yet, it is now widely recognised that they do not provide a wholly comprehensive solution for endogeneity problems. Future studies with access to more detailed datasets may be able to use more robust quasi-experimental methods, such as regression discontinuity designs.

Besides the above, due to sample size limitations (specifically regarding treated firms that face knowledge challenges), we were unable to analyse potential heterogeneous effects between different types of public financial support instruments for R&I. Following Busom, Corchuelo, and Martinez-Ros (2014), in the context of financial constraints, this is a limitation, as firms' knowledge challenges could also influence the type of public financial support for R&I that they seek. Further studies could address this limitation. Our focus on firms in Ireland can provide important insights for policymakers beyond the Irish case. It would be interesting therefore, for future research to replicate our analysis in other country-settings. Finally, it would be fruitful for future research to replicate our analysis in the context of the types of R&D activities that firms engage in, such as explorative versus exploitative forms of research (Gao et al. 2021; Lee, Wu, and Pao 2014), which our available data did not permit. This is important given that explorative research activities are widely denoted in the literature as important drivers of radical innovation. This, in turn, will further enhance an understanding of how firms manage to develop R&I knowledge capabilities and overcome their knowledge challenges. Despite these limitations, our paper offers important insights, which can usefully inform an understanding of the effectiveness of public financial support for R&I, when it comes to generating more radical innovation in firms.

Notes

1. SFI and the Irish Research Council (IRC) were amalgamated into a new national competitive research and innovation funding agency called Taighde Éireann – Research Ireland on August 1st 2024. For additional information on this see: https://www.researchireland.ie/about/.
2. Specifically, the IIE survey is a stratified random sample of enterprises with at least 10, and a maximum of 49, persons engaged, and a census of firms with at least 50 persons engaged. The survey only includes enterprises in the following NACE Rev 2 Sectors: 05-39, 46, 49-53, 58-63, 64-66, 71-73. For further details see: https://www.cso.ie/en/methods/scienceandtechnology/innovationinirishenterprisesformerlyknownascommunityinnovationsurvey.
3. To merge the administrative data with the IIE survey, we used a unique ID which is assigned to each individual firm by the Irish Central Statistics Office (CSO). The specific process of merging required an initial process of merging the administrative dataset with the Annual Business Survey of Economic Impact (ABSEI) survey, which is a representative survey of firms that have ever engaged with the three agencies from which we obtained the administrative data. Once the administrative data is merged with the ABSEI survey, the data were merged with the 2010 IIE survey. The comparison presented in Appendix C is based on all firms in our administrative dataset (i.e. the full population of firms that received public financial support for R&I).
4. R&D tax credits are available to all firms in Ireland. Firms can claim a 25% Tax Credit on the following R&D-related expenditure: systemic, investigative, or experimental activities, be in the field of science or technology, involve basic research, applied research, and/or experimental development, seek to make scientific or technological advancement, involve the resolution of scientific or technological uncertainty (Irish Revenue Commissioners 2024).
5. We repeated our analysis with each individual variable, yielding almost identical results, to when the two variables are grouped into one single variable. An advantage of grouping the variables is that it enables more observations in the categories pertaining to 'encounter/did not encounter' the challenge. Such an approach improves the precision of our findings.

6. The European Union recommendation 2003/361 defines small-sized firms as firms with less than 50 employees, medium-sized firms as firms with at least 50 and fewer than 249 employees, and large firms, as firms with at least 250 employees. The recommendation also classifies firms according to their turnover or balance sheet (see http://data.europa.eu/eli/reco/2003/361/oj), but the number of employees is the most commonly used classification (Eurostat 2022). Data for firms with fewer than 10 employees were not available to this study.

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Appendices

Appendix A: Comparison between full sample of firms in the Innovation in Irish Enterprises survey with the effective sub-sample used in the analysis

Variables	A. Innovation in Irish Enterprises Survey 2010 (n = 3,245) (%)	B. Effective Sample (n = 1,296) (%)	Difference (A-B) (%)	(Standard Error) (%)
Irish Owned firm (Yes = 1)	69.779	70.910	1.131	(1.639)
Small-sized firm (Yes = 1)	71.010	64.195	6.813***	(1.664)
Medium-size firm (Yes = 1)	22.370	28.240	−5.870***	(1.543)
Large-sized firm (Yes = 1)	6.618	7.561	0.942	(0.914)
Part of Enterprise Group (Yes = 1)	15.993	16.481	−0.488	(0.251)
Sector B (Mining and Quarrying)	0.820	1.080	−0.259	(0.343)
Sector C (Manufacturing)	33.606	37.268	−3.661	(2.170)
Sector D (Electricity, Gas, etc.)	0.461	0.231	0.230	(0.217)
Sector E (Water Supply, etc.)	2.052	1.851	0.200	(0.400)
Sector G (Wholesale and retail)	23.858	26.774	−2.916*	(1.552)
Sector H (Transport and Storage)	11.800	10.725	1.075	(1.138)
Sector J (Information and Comm.).	9.748	9.560	1.806	(1.059)
Sector K (Financial Services)	13.032	7.561	5.470***	(1.111)
Sector M (Scientific and Technical act.)	4.617	4.938	−0.320	(0.762)
Product Innovation (Yes = 1)	29.091	34.876	−5.784***	(−1.662)
Process Innovation (Yes = 1)	33.453	39.274	−5.821***	(−1.715)
Organisational Innovation (Yes = 1)	36.736	43.595	−6.858***	(−1.748)
Radical Innovation (Yes = 1)	17.393	21.759	−4.365***	(−1.408)
Turnover from Radical Innovation (%)	3.326	3.810	−0.483	(0.429)

Note**:** Table produced by the authors using data from the IIE survey. Column 4 presents the results of a t-test. ***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix B: Public financial support instruments for R&I used in the analysis

Instrument	Funding agency	Number of firms supported
Company R&D Support	IDA/EI	27
Innovation Vouchers	IDA/EI	21
Innovation Partnerships	IDA/EI	12
Technical Feasibility/RD&I Feasibility	IDA	8
Tech centre collaboration	IDA/EI	5
Technology Gateway	EI	8
Research Centre Award	SFI	5
R&D Tax Credits	Revenue Commissioners	135
Total		221

Appendix C: Representativeness of sample of treated firms

	Treated (full sample)		Treated (working sample)	
	Number	(Percentage)	Number	(Percentage)
Firm sizes				
Small-sized firm (Yes = 1)	1,181	63.91	100	45.25
Medium-size firm (Yes = 1)	273	14.77	71	32.13
Large-sized firm (Yes = 1)	394	21.32	50	22.62
Total	1,848	100	221	100

(*Continued*)

Continued.

	Treated (full sample)		Treated (working sample)	
	Number	(Percentage)	Number	(Percentage)
Sector (NACE 2 digit sectors)				
Sector A (Agriculture, forestry and fishing)	12	0.65	2	0.90
Sector B (Mining and Quarrying)	2	0.11	1	0.45
Sector C (Manufacturing)	908	49.13	155	70.14
Sector D (Electricity, Gas, etc.)	7	0.38	1	0.45
Sector E (Water Supply, etc.)	13	0.7	1	0.45
Sector F (Construction)	35	1.89	1	0.45
Sector G (Wholesale and retail)	18	0.97	1	0.45
Sector H (Transport and Storage)	4	0.22	1	0.45
Sector I (Accommodation, etc.)	4	0.22	1	0.45
Sector J (Information and Comm.).	644	34.85	41	18.55
Sector K (Financial Services)	46	2.49	5	2.26
Sector M (Scientific and Technical act.)	87	4.71	9	4.07
Sector N (Admin Support Services)	30	1.62	1	0.45
Sector P (Education)	16	0.87	0	0.00
Sector Q (Human Health and Social Work)	19	1.03	1	0.45
Sector R (Arts, Entertainment, etc.)	2	0.11	0	0.00
Sector S (Other Services Activities)	1	0.05	0	0.00
Total	1,848	100	221	100
Regions of Ireland (NUTS3)				
Border	180	9.74	22	9.95
Dublin	750	40.58	67	30.32
Mid-East	150	8.12	22	9.95
Mid-West	114	6.17	10	4.52
Midland	80	4.33	14	6.33
South-East	141	7.63	23	10.41
South-West	257	13.91	35	15.84
West	168	9.09	28	12.67
Total	1,840	100	221	100

Note: Table shows the structural characteristics of the full population of treated firms, as obtained from the administrative data on public financial support for R&I instruments used in this paper, and the sample of treated firms which are included in the analysis (i.e. the effective sample).

Appendix D: Questions pertaining to hampering factors to Innovation activities included in 2010 Innovation in Irish Enterprises (IIE) survey wave

Question 7.1 During the three years 2008 to 2010, how important were the following factors in preventing your enterprise from innovating or in hampering your innovation activities?

		High	Medium	Low	Not relevant
Cost Factors	Lack of funds within your enterprise or group	o	o	o	o
	Lack of finance from sources outside your enterprise	o	o	o	o
	Innovation costs too high	o	o	o	o
Knowledge Factors	Lack of qualified personnel	o	o	o	o
	Lack of information on technology	o	o	o	o
	Lack of information on markets	o	o	o	o
	Difficulty in finding cooperation partners for innovation	o	o	o	o
Market Factors	Market dominated by established enterprise	o	o	o	o
	Uncertain demand for innovative goods or service	o	o	o	o
Reasons not to innovate	No need due to prior innovations by your enterprise	o	o	o	o
	No need because of no demand for innovation	o	o	o	o

Appendix E: Probability of receiving public financial support for R&I (average marginal effects)

Independent Variables	Probability of Treatment (1 = Yes) dy/dx
Medium-sized firm (1 = Yes, 50 to 249 employees)	0.039 (0.025)
Large-sized firm (1 = Yes, 250 or more employees)	0.040 (0.039)
Irish owned (1 = Yes)	0.037 (0.023)
Enterprise group (1 = Yes)	0.006 (0.025)
Export (1 = Yes)	0.169*** (0.031)
Breadth of cooperation partners (0 to 4)	0.022* (0.013)
Breadth of Innovation (0 to 4)	0.001 (0.007)
Introduced Radical Innovation in 2010 (1 = Yes)	0.099*** (0.029)
Turnover from Radical Innovation in 2010 (% Turnover)	0.000 (0.000)
Knowledge challenges high (1 = Yes in 2010)	0.068* (0.039)
Knowledge challenges medium (1 = Yes in 2010)	−0.008 (0.025)
Knowledge challenges low (1 = Yes in 2010)	0.039 (0.024)
Financial challenges high (1 = Yes in 2010)	−0.005 (0.025)
Financial challenges medium (1 = Yes in 2010)	0.034 (0.023)
Financial challenges low (1 = Yes in 2010)	0.035 (0.024)
Market challenges high (1 = Yes in 2010)	−0.038 (0.029)
Market challenges medium (1 = Yes in 2010)	−0.018 (0.024)
Market challenges low (1 = Yes in 2010)	−0.015 (0.025)
Sector C (Manufacturing)	0.159*** (0.086)
Sector D (Electricity, Gas, etc.)	0.311 (0.204)
Sector E (Water supply, etc.)	0.054 (0.125)
Sector G (Wholesale and retail)	0.492 (0.627)
Sector H (Transport and storage)	−0.027 (0.086)
Sector J (Information and comm.).	0.102 (0.090)
Sector K (Financial services)	−0.041 (0.0.087)
Sector M (Scientific and technical act.)	0.052 (0.096)
Constant	−2.389*** (0.665)
Observations	1,296
Log Likelihood	−433.126
Lr chi^2 (25)	257.67***
Pseudo R^2	0.229

Notes**:** Results of Probit model estimation are presented as average marginal effects (dy/dx). Robust standard error in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix F: Correlation matrix of variables used in the analysis

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1. Introduced Radical Innovation in 2016 (1 = Yes)	1.000																				
2. Turnover from Radical Innovation in 2016 (% Turnover)	0.571	1.000																			
3. Small-sized firm (< 50 employees)	−0.049	0.080	1.000																		
4. Medium-sized firm (50 to 249 employees)	−0.022	−0.087	−0.767	1.000																	
5. Large-sized firm (250 or more employees)	0.105	0.005	−0.382	−0.298	1.000																
6. Irish owned (1 = Yes)	0.008	0.037	0.276	−0.152	−0.191	1.000															
7. Enterprise group (1 = Yes)	−0.083	0.009	0.338	−0.144	−0.295	0.304	1.000														
8. Export (1 = Yes)	0.119	0.092	−0.103	0.056	0.073	−0.141	−0.161	1.000													
9. Breadth of cooperation partners (0 to 4)	0.236	0.082	−0.087	0.000	0.130	0.030	−0.078	0.149	1.000												
10. Breadth of innovation (0 to 4)	0.237	0.130	−0.117	0.071	0.071	−0.021	−0.026	0.214	0.395	1.000											
11. Introduced of Radical Innovation in 2010	0.278	0.208	−0.078	0.068	0.018	0.022	−0.034	0.147	0.224	0.545	1.000										
12 Turnover from Radical Innovation 2010 (% Turnover)	0.249	0.119	−0.125	0.086	0.061	0.033	−0.057	0.166	0.311	0.656	0.661	1.000									
13. Knowledge challenges high (1 = Yes)	−0.018	−0.037	0.093	−0.059	−0.053	0.101	−0.006	−0.059	0.033	0.064	0.004	0.057	1.000								
14. Knowledge challenges medium (1 = Yes)	0.132	0.150	0.073	−0.050	−0.036	0.080	0.053	0.062	0.107	0.134	0.095	0.167	0.091	1.000							
15. Knowledge challenges low (1 = Yes)	0.069	−0.001	0.000	0.024	−0.035	−0.050	−0.001	0.025	0.160	0.214	0.067	0.152	−0.139	−0.091	1.000						
16. Financial challenges high (1 = Yes)	0.033	0.033	0.162	−0.083	−0.120	0.121	0.157	−0.008	0.090	0.073	0.016	0.045	0.114	0.174	0.068	1.000					
17. Financial challenges medium (1 = Yes)	0.167	0.071	0.065	0.000	−0.097	−0.012	0.076	−0.005	0.166	0.224	0.147	0.210	0.086	0.268	0.237	0.202	1.000				
18. Financial challenges low (1 = Yes)	0.027	0.028	0.018	−0.008	−0.015	−0.053	−0.041	−0.004	0.042	0.040	−0.008	0.094	−0.121	0.109	0.277	−0.211	0.076	1.000			
19. Market challenges high (1 = Yes)	0.018	−0.023	0.075	−0.042	−0.051	0.140	−0.106	−0.106	0.063	−0.006	−0.003	0.018	0.144	0.100	0.041	0.289	0.135	−0.105	1.000		
20. Market challenges medium (1 = Yes)	0.066	0.061	0.030	−0.009	−0.031	0.093	0.035	0.035	0.127	0.190	0.089	0.204	0.107	0.255	0.165	0.174	0.268	0.179	0.000	1.000	
21. Market challenges low (1 = Yes)	0.034	0.021	0.066	−0.031	−0.053	−0.012	0.012	0.012	0.067	0.121	0.050	0.103	0.004	0.104	0.317	0.069	0.204	0.261	−0.182	−0.089	1.000

Appendix G: Balance check Stage 1 (Nearest 3 Neighbours)

Matching variables	Treated	Control	Difference (T − C)	*P*-Value (T − C)
Small-sized firm (1 = Yes, <50 employees)	0.487	0.436	0.051	0.294
Medium-sized firm (1 = Yes, 50 to 249 employees)	0.386	0.417	−0.031	0.527
Large-sized firm (1 = Yes, 250 or more employees)	0.125	0.146	−0.021	0.536
Irish owned (1 = Yes)	0.675	0.684	−0.009	0.844
Enterprise group (1 = Yes)	1.565	1.529	0.036	0.501
Export (1 = Yes)	0.893	0.922	−0.029	0.325
Breadth of cooperation partners (0 to 4)	0.532	0.555	−0.023	0.814
Breadth of Innovation (0 to 4)	2.442	2.373	0.067	0.676
Introduced Radical Innovation in 2010 (1 = Yes)	0.446	0.404	0.042	0.397
Turnover Radical Innovation in 2010 (% Turnover)	8.787	8.697	0.090	0.960
Knowledge challenges high (1 = Yes)	0.081	0.105	−0.024	0.404
Knowledge challenges medium (1 = Yes)	0.299	0.341	−0.042	0.308
Knowledge challenges low (1 = Yes)	0.492	0.466	0.026	0.603
Financial challenges high (1 = Yes)	0.284	0.285	−0.001	0.970
Financial challenges medium (1 = Yes)	0.522	0.496	0.026	0.604
Financial challenges low (1 = Yes)	0.406	0.444	−0.038	0.446
Market challenges high (1 = Yes)	0.187	0.175	0.012	0.761
Market challenges medium (1 = Yes)	0.441	0.463	−0.022	0.662
Market challenges low (1 = Yes)	0.373	0.367	0.003	0.446
Sector B (Mining and quarrying)	0.004	0.004	0.000	1.000
Sector C (Manufacturing)	0.680	0.680	0.000	1.000
Sector E (Water supply, etc.)	0.049	0.0049	0.000	1.000
Sector G (Wholesale and retail)	0.089	0.089	0.000	1.000
Sector J (Information and comm.).	0.154	0.154	0.000	1.000
Sector K (Financial services)	0.028	0.028	0.000	1.000
Sector M (Scientific and technical act.)	0.037	0.037	0.000	1.000
Rubin's B = 20.6. Mean Bias = 2.9; Median Bias = 3.5. R = 0.92				

Notes: *** Denotes significance at the 99% level, ** 95% level and * 90% level. The Rubin's B score represents the standardised difference of means of a linear index of the propensity score in treated and control firms. The Rubin's R is the ratio of treated to matched non-treated variances of the propensity score index. Values of below 25 for Rubin's B, and between 0.5 and 2 for Rubin's *R*, are usually accepted as indicating a sufficiently balanced sample, as per the guidelines of Rubin (2001).

Appendix H: Balance check Stage 1 (One to One Matching)

Matching Variables	Treated	Control	Difference (T − C)	*P*-Value (T − C)
Small-sized firm (1 = Yes, <50 employees)	0.497	0.502	−0.005	0.919
Medium-sized firm (1 = Yes, 50 to 249 employees)	0.409	0.393	0.016	0.756
Large-sized firm (1 = Yes, 250 or more employees)	0.093	0.103	−0.010	0.733
Irish owned (1 = Yes)	0.666	0.677	−0.011	0.827
Enterprise group (1 = Yes)	1.561	0.1545	1.4055	0.757
Export (1 = Yes)	0.888	0.904	−0.016	0.613
Breadth of cooperation partners (0 to 4)	0.554	0.486	0.064	0.524
Breadth of Innovation (0 to 4)	0.449	0.396	0.053	0.299
Introduced Radical Innovation in 2010 (1 = Yes)	0.450	0.398	0.052	0.304
Turnover Radical Innovation in 2010 (% Turnover)	9.492	8.921	0.571	0.437
Knowledge challenges high (1 = Yes)	0.444	0.412	0.032	0.534
Knowledge challenges medium (1 = Yes)	0.37	0.343	0.027	0.593
Knowledge challenges low (1 = Yes)	0.195	0.179	0.016	0.694
Financial challenges high (1 = Yes)	0.523	0.462	0.063	0.218
Financial challenges medium (1 = Yes)	0.412	0.475	−0.058	0.256
Financial challenges low (1 = Yes)	0.195	0.179	0.016	0.694
Market challenges high (1 = Yes)	0.444	0.412	0.032	0.534
Market challenges medium (1 = Yes)	0.376	0.343	0.027	0.256
Sector B (Mining and quarrying)	0.004	0.004	0.000	1.000
Sector C (Manufacturing)	0.680	0.680	0.000	1.000
Sector E (Water supply, etc.)	0.004	0.004	0.000	1.000
Sector G (Wholesale and retail)	0.890	0.089	0.000	1.000
Sector J (Information and comm.).	0.154	0.154	0.000	1.000

(*Continued*)

Continued.

Matching Variables	Treated	Control	Difference (T − C)	*P*-Value (T − C)
Sector K (Financial services)	0.028	0.028	0.000	1.000
Sector M (Scientific and technical act.)	0.037	0.037	0.000	1.000
Rubin's B = 23.1. Mean Bias = 3.9; Median Bias = 3.3. R = 0.98				

Notes: *** Denotes significance at the 99% level, ** 95% level and * 90% level. The Rubin's B score represents the standardised difference of means of a linear index of the propensity score in treated and control firms. The Rubin's R is the ratio of treated to matched non-treated variances of the propensity score index. Values of below 25 for Rubin's B, and between 0.5 and 2 for Rubin's R, are usually accepted as indicating a sufficiently balanced sample, as per the guidelines of Rubin (2001).

Appendix I: Balance check Stage 1 (Coarsened Exact Matching)

Matching Summary	Matched	Unmatched
Treated firms	191	30
Untreated firms	853	222
Multivariate L1 distance	0.106	
Strata:		
Number of strata	135	
Number of matched strata	55	

Univariate imbalance Variables	L1	Mean	Min	25%	50%	75%	Max
Small-sized firm (1 = Yes, < 50 employees)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Medium-sized firm (1 = Yes, 50 to 249 employees)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Large-sized firm (1 = Yes, 250 or more employees)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Irish owned (1 = Yes)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Enterprise group (1 = Yes)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Export (1 = Yes)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Introduced Radical Innovation in 2010 (1 = Yes)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Turnover Radical Innovation in 2010 (% Turnover)	0.042	0.010	0.000	0.000	0.000	0.000	0.000
Knowledge challenges high (1 = Yes)	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: CEM process carried out with Automatic Coarsening. Balancing statistics reported following Blackwell et al. (2010). Multivariate L1 distance is the k-dimensional relative frequencies between treated and control firms across the 55 matched strata. Perfect global balance is indicated by L1 = 0. The univariable L1 distance does the same for each of the variables used in the matching process.