



Harnessing the science base: Results from a national programme using publicly-funded research centres to reshape firms' R&D

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ABSTRACT

Since 2000 and the launch of Science Foundation Ireland, Irish policymakers have been involved in a large-scale national science policy programme. Starting from a position with little pre-existing research infrastructure beyond its traditional higher education system, Ireland allocated significant public resources to rapidly develop an extensive research centres programme. These centres are designed to harness knowledge embedded in the national science base to impact firm-level Research and Development (R&D). Each research centre focuses on basic and applied research (as opposed to development), targeted at prioritised sectors of the economy. Using a novel panel dataset (2007–2017), our analysis provides the first evaluation of these research centres. Results indicate that research centre collaborations increase firm-level R&D, and, over time, re-orientate collaborating firms' R&D towards more applied research. We also consider how impacts vary depending on the firms' characteristics (size and sector), and research centre characteristics. Our findings demonstrate that Ireland's policy programme improved firms' R&D profile, and suggest key policy lessons for other economies who might consider adopting a similar strategy.

1. Introduction

Collaborating with key actors in the publicly-funded science base, such as universities, can be a catalyst for firm-level Research and Development (R&D), driving innovation and firm performance (Readman et al., 2018). However, firms and universities often have fundamental differences in their institutional logics and priorities (Hall, 2003). While firms tend to view new knowledge as a means of achieving competitive advantage, knowledge creation can be an end in itself for university academics (Dasgupta and David, 1994). Known as the 'two-worlds' paradox, this issue presents a potential barrier to successful firm-university collaborations (Hewitt-Dundas et al., 2019). This issue is a major concern for policymakers seeking a return on their investment in higher education, through harnessing the knowledge generated for innovation in the industrial base (OECD, 2011). As recently emphasised by Lenihan et al. (2019, p. 10), it is of paramount importance that any policy intervention involving scarce public resources "needs to demonstrate that its (potential) social value outweighs its opportunity costs".

In 2003, policymakers in Ireland launched a major new science policy funding initiative focused on a national research centres programme. This initiative was designed to bridge the gap between university-based knowledge and firm-level R&D (DBEI, 2014; SFI, 2018), so as to create a step change in Ireland's R&D landscape (Indecon, 2018; Technopolis, 2014). Through a new national science funding agency, Science Foundation Ireland¹ (SFI), the Irish government has to date allocated over €1 billion to establish and maintain a series of research centres based at Irish Higher Education Institutes (HEIs), which are designed to build research capacity within the higher education system. Each SFI research centre has a dual mandate to conduct world-leading basic and applied research, and enhance the economy through research collaborations with firms. While similar publicly-funded research centres exist in other economies (e.g. Fraunhofer in Germany), they typically emerge from several decades of targeted funding in R&D laboratories and human capital, which builds a large research infrastructure over time (Intarakumnerd and Goto, 2018). In contrast, starting from a position with little pre-existing research

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¹ For more information on the funding agency Science Foundation Ireland (SFI), see: <https://www.sfi.ie/about-us/about-sfi/>.

infrastructure beyond its traditional higher education system, Ireland allocated significant sums of public money to rapidly establish a national research centres programme. This paper provides the first evaluation of the impact of this novel, large-scale policy programme on firms' R&D profile. The results suggest policy lessons for other countries which, like Ireland in 2003, do not possess a well-developed research infrastructure, but want to develop their national science base and see an impact on firm-level R&D.

This study makes two significant contributions to the existing literature on public funding for R&D. First, previous studies on research collaboration have focused primarily on the impact collaboration has on the total scale of firms' R&D (for reviews, see Dimos and Pugh, 2016 and Zúñiga-Vicente et al., 2014). However, both Vanino et al. (2019) and Nilsen et al. (2020) have recently argued that distinguishing between research or more development-focused projects is crucial, but has not been explored in the literature to date. This distinction is critical as it has long been argued that, for firms, conducting basic and applied research (as opposed to development) is essential for building in-house scientific capabilities (Arora et al., 2018; Belderbos et al., 2016), which are a key source of competitive advantage (Durand et al., 2008; Gambardella, 1992). Therefore, our first contribution is to go beyond whether collaboration changes the total volume of firm-level R&D, and examine the type of R&D firms conduct. We focus on the differential effects of collaboration on basic research and applied research, the so-called 'R' in R&D (Czarnitzki et al., 2009).

Our second contribution focuses on examining whether the mechanisms underlying our hypothesised treatment effects vary depending on firm-specific characteristics, and/or the characteristics of the research centres with which firms collaborate. In terms of firm-specific characteristics, existing literature highlights the important role firm size and industrial sector can play in determining treatment effects (Dimos and Pugh, 2016). In terms of research centre-specific characteristics, Damiooli et al. (2021) highlight that the research domain of a collaboration partner (i.e. the field of research the partner focuses on; for example, biotechnology or software development) can play a significant role in driving heterogeneous treatment effects. As noted by Becker (2015), examining heterogeneous treatment effects is important because it can have significant implications for policy. A treatment effect may be identified in the general sample of firms, but not in a specific sub-group which policymakers may wish to target (Becker, 2015). However, such heterogeneity analyses are still rare; and, to our knowledge, no evidence is available in terms of firm-level basic and applied research. Therefore, we make a novel contribution to the literature by examining whether the mechanisms of transmission underpinning our hypothesised treatment effects vary depending on firm-specific and research centre-specific characteristics.

Our analysis is based on a new panel dataset, which merges administrative data on SFI research centre collaborations with detailed survey data on firms' R&D activities, from the Business Expenditure on Research and Development (BERD) survey, for the period 2007–2017. The final dataset is an unbalanced panel with 961 firms, resulting in 2,489 observations over five waves. The analysis investigates the impact of collaboration on firms': 1) in-house investment in R&D; 2) applied research; 3) basic research; 4) the share of applied research in firms' total in-house R&D; and, 5) the share of basic research in firms' total in-house R&D. While the first three outcome measures can be used to show changes in firms' R&D investment due to the collaboration, the latter two measures may indicate a more fundamental *re-orientation* towards basic and/or applied research as a result of the collaboration. However, it is critical to note that, if effective, it is likely that this form of multi-year research collaboration may take time to have an impact (Kaiser and Khun, 2012; Scandura, 2016). Therefore, the analysis examines the impact of research centre collaboration on firms' R&D intensity and composition in the 1–2, 3–4, and 5–6 year period after the start date of the collaboration. We then examine whether treatment effects vary depending on firm size and sector, and/or the research domain of the

research centre firms collaborate with.

Our econometric analysis combines propensity score matching (PSM) with a Difference-in-Differences (DiD) estimator, henceforth referred to as PSM-DiD. While the initial PSM ensures that collaborating firms are matched with an appropriate control group, the subsequent DiD accounts for possible omitted variable bias by using the panel structure of our rich dataset. Szücs (2018), and Dai and Wang (2019) highlight that PSM-DiD enables a superior estimation of treatment effects, relative to the more common approach of relying on either PSM or DiD alone. Our findings demonstrate that collaborating with SFI research centres leads firms to increase their overall in-house R&D intensity, and that the magnitude of this impact increases over time. In addition, collaborating firms significantly increase the proportion of applied research in their overall in-house R&D, but it takes 3–4 years for this impact to materialise. Finally, firm size and sector play key roles in determining the strength of these identified treatment effects.

The remainder of the paper is organised as follows. Section 2 reviews the literature on the role of research collaborations in firms' R&D, and formulates hypotheses. Section 3 describes the data and econometric method. Section 4 presents and discusses the results of the analysis, while Section 5 summarises the key results and discusses implications for policy.

2. Theory and hypotheses

The type of publicly-funded research centres programme examined in this study has two primary functions. Firstly, it provides an environment which fosters scientific activities, including conducting research (in Science Technology Engineering and Mathematics [STEM] research areas), publishing academic papers and training researchers (Intarakummerd and Goto, 2018). Secondly, these research centres are designed to enhance the economy by linking firms with the publicly-funded science base (OECD, 2011), thus facilitating the commercial exploitation of discoveries and enhancing innovation (Fleming et al., 2019; Watzinger and Schnitzer, 2019).

There is a broad consensus amongst academics and policymakers that the allocation of public funding to support private firms' R&D projects is socially desirable (Becker, 2015). Indeed, all Organisation for Economic Co-operation and Development (OECD) member countries spend significant amounts of public money on programmes intended to stimulate firms' R&D and innovation activities (OECD, 2011). Government R&D programmes have generally been designed to support commercial R&D projects that have significant social benefits (Zúñiga-Vicente et al., 2014). However, such R&D projects are risky, often have very long time horizons, and may have inadequate expected private returns to incentivise firm-level investment in the absence of public funding (Clausen, 2009). This can lead to lower private R&D investment than is desirable for society (Salter and Martin, 2001).

Nelson's (1959) study was amongst the first, in an extensive cannon of studies, which argued that the social value of firm-level R&D is higher than the private value. This literature suggests that, in particular, the research components of R&D projects (i.e. basic research and applied research) often yield unexpected results, and the knowledge generated may be of little value to the firm which makes the initial investment (Zúñiga-Vicente et al., 2014). Furthermore, even if the knowledge from a firm's R&D is of value, the firm may struggle to prevent others from exploiting the generated knowledge due to knowledge spillovers (Czarnitzki et al., 2011). Additionally, factors such as the time lag from research to a marketable product may discourage firm-level investment in research (Hall et al., 1986). These and other such related considerations underpin the classical market failure rationale for policy intervention to subsidise private firms' R&D activities (Haapanen et al., 2014), with a greater emphasis placed on supporting basic and applied research as opposed to development (Clausen, 2009).

Incentivising and facilitating collaborations with the publicly-funded science base represents a key type of policy intervention in this regard

(Intarakumnerd and Goto, 2018). In general, most forms of public funding for R&D are effective at stimulating firm-level R&D (Becker, 2015). However, as suggested by Zúñiga-Vicente et al. (2014), the impact public R&D funding has on the research components of R&D (i.e. basic research and applied research) remains largely un-addressed within the literature.

2.1. Impact of research centre collaborations on firm-level R&D

Collaborations with actors such as universities within the national science base can influence firm-level R&D via three main mechanisms. Firstly, the science base can act as a source of knowledge, which firms can use as a direct input into their innovation processes through knowledge spillovers (Yusuf, 2008). Secondly, collaborating with research centres on R&D projects can help build firms in-house research capabilities (Belderbos et al., 2016). Finally, many actors within the science base are nodes in global information networks, and collaborations provide firms with an entry point to these networks (Dasgupta and David, 1994; Rosenberg, 1989; Salter and Martin, 2001). However, the impacts of collaboration may differ depending on the type of organisation with which a firm collaborates (Feller et al., 2002; Readman et al., 2018).

The literature regarding collaboration between the science base and firms, centres on the production of knowledge by universities, and the transmission and use of knowledge spillovers by firms within a knowledge production function framework (Acs et al., 1992; Griliches, 1979; Griliches and Pakes, 1984; Jaffe, 1986 & 1989). Knowledge is said to spill over when the organisation that uses knowledge, is distinct from the organisation which produced the knowledge in the first place (Czarnitzki et al., 2007). Studies on innovation systems highlight the fundamental role interactions between diverse economic actors (e.g. firms, universities, government agencies) play in the production, diffusion, and use of knowledge (Chaminade et al., 2012). This literature positions the firm as the key actor within the innovation system, responsible for translating knowledge spillovers into innovations.

Explaining how firms benefit from knowledge spillovers from the science base depends on understanding the distinction between tacit and codified knowledge (Lundvall et al., 1988). Codified knowledge refers to knowledge that is transmittable in formal, systematic language (e.g. scientific methods). In contrast, tacit knowledge is highly personal and context-dependant, and is usually generated and transmitted through problem-solving interactions and other shared experiences. In this way, tacit knowledge cannot be easily acquired via the market and is difficult to communicate, other than through frequent and often intensive personal interactions. Such interactions are particularly important for knowledge flows when firms require a process of learning by *doing*, along with *using and interacting* (Chaminade et al., 2012) such as occurs with firm-university linkages.

There are many strategic options available to firms in terms of how they source knowledge and engage in R&D (Miotti and Sachwald, 2003). Firms must decide on the most efficient way to augment their technological capabilities, either through in-house efforts or external knowledge sourcing, especially within the framework of collaborative research projects (Lopez-Vega et al., 2016). Firms engage in collaborative research projects with academic partners because it allows for the utilisation of external resources for their own purposes in a direct and systemic way (Czarnitzki et al., 2007). Becker and Dietz (2004) summarise the benefits of collaborative research projects as follows: 1) joint financing of R&D; 2) reduction of uncertainty; 3) cost savings; and, 4) realising economies of scale and scope. However, research collaboration is also hampered by a number of transaction costs, which means that it is only an effective R&D strategy if the trade-off between costs and benefits is expected to be positive (Bruneel et al., 2010).

The majority of empirical studies have focused on firms' collaborations with universities, showing that collaborating firms often have increased R&D and innovation performance (Giannopoulou et al.,

2019). While universities can be a key source of knowledge for firms, R&D collaboration is far from the only (or primary) function of the higher education system (Hewitt-Dundas et al., 2019). In an attempt to directly foster firm-level R&D in key sectors, policymakers in many countries fund research centres that are mandated to conduct basic and applied research *and* enhance industry through research collaborations (OECD, 2011). While both research centres and university collaborations function through similar mechanisms to impact firms' R&D, they also differ in certain ways. For example, Hall (2003) highlights the key barriers to successful research collaborations between firms and universities, centring on essential differences in institutional logics and priorities in the 'two-worlds' of academia and business. Similarly, Hewitt-Dundas et al. (2019, p. 1311) note that R&D and innovation are primarily a "means to an end" for firms, in terms of enhancing business performance, while for universities knowledge creation is an important goal in and of itself. On this basis, it may be argued that publicly-funded research centres with a dual mandate to conduct scientific research and engage in research collaborations with firms may help to overcome the 'two-worlds' paradox (Intarakumnerd and Goto, 2018). The above literature and underpinning mechanisms suggests our first hypothesis:

Hypothesis 1a: Collaborating with publicly-funded research centres will increase firms' in-house R&D investment.

2.2. The research components of R&D

Much of the empirical literature treats firms' R&D investment as a single activity (Zúñiga-Vicente et al., 2014). However, it is widely agreed that basic and applied research differ significantly from experimental development, in both their nature and influence on firm-level innovation (Arora et al., 2018). Conducting basic and applied research can foster a specific form of scientific absorptive capacity (Belderbos et al., 2016), and thus improve firms' competitive advantage (Durand et al., 2008). Firms often seek academic collaborators who can provide access to leading-edge and specialist knowledge, reduce the complexity, and share the costs and risks associated with basic and applied research (Butler, 2008; Fey and Birkinshaw, 2005). However, a wide spectrum of possible academic collaborators exist, differing significantly in terms of the specific knowledge they possess, and their willingness to transfer that knowledge to industry partners (Damioli et al., 2021). These differences suggest that the type of academic collaborator a firm selects to partner with, will fundamentally depend on the type of research project they seek to engage in, and on their own in-house R&D capabilities (Miotti and Sachwald, 2003).

In light of the above, publicly-funded research centres at the leading-edge of academic science can be a unique and vital source of highly specific knowledge for firms (Intarakumnerd and Goto, 2018). However, collaborating with this type of research-intensive academic partner can also be challenging, as it requires firms to build up new capabilities (Hewitt-Dundas, 2012), specifically those around basic and applied research (Link and Scott, 2019). In this way, successful collaboration with leading-edge research centres often leads to the production of new knowledge (OECD, 2011), which can be far removed from the firm's pre-collaboration knowledge base (Becker and Dietz, 2004). As such, this type of collaboration brings a high potential for research breakthroughs (Lopez-Vega et al., 2016) and radical innovation (Beck et al., 2016; Szücs, 2018). Therefore, it can be argued that a specific form of experiential learning may take place in collaborations between academic partners (with a focus on basic and applied research), and firms with significant pre-existing R&D capacity, who have made the strategic choice to invest in basic and/or applied research. Such collaboration partners share a high degree of cognitive proximity, either in a common scientific domain or a common understanding of scientific findings across domains. This means that any collaboration can begin at an advanced stage (Boschma, 2005), and progress quickly, as firms internalise complex knowledge spillovers through advanced pre-collaboration capabilities (Czarnitzki et al., 2007).

Publicly-funded research centres with a dual mandate to collaborate with firms and engage in basic and applied research projects have, arguably, two specific advantages over other academic collaboration partners in terms of catalysing firm-level basic and applied research. First, the creation of new knowledge requires frontier-edge research, which is likely to require high academic quality and research intensity of the academic partner (Cassiman et al., 2018). Even in comparison to the most research-intensive universities, specific publicly-funded research centres tend to be the world leaders in narrowly defined academic fields (Feller et al., 2002; Intarakumnerd and Goto, 2018; Yusuf, 2008). This makes research centres an ideal collaboration partner for helping firms to engage in basic and applied research. Second, the innovations emanating from investment in basic and applied research may produce more significant economic gains than other types of R&D (Coad et al., 2020; Fleming, 2001). Publicly-funded research centres with a dual mandate, have specific institutional set-ups designed to ensure that commercial and academic incentives are aligned (OECD, 2011). As such, they are well placed to incentivise and enable firms to engage in basic and/or applied research (Hall, 2003; Intarakumnerd and Goto, 2018). Therefore, building on Hypothesis 1a, we examine whether research centre collaborations increase firm-level basic and/or applied research investment, by testing the following hypotheses:

Hypothesis 1b: Collaborating with publicly-funded research centres will increase firms' investments in applied research.

Hypothesis 1c: Collaborating with publicly-funded research centres will increase firms' investments in basic research.

2.3. The research-orientation of firms' R&D

Even if research centre collaborations drive additional firm-level investment in basic and applied research, this project-specific expenditure may not change the proportion of basic and applied research in firms' overall in-house R&D. The allocation of in-house financial resources to more explorative forms of research improves firms' absorptive capacity (Cassiman et al., 2018). However, Coad et al. (2020) note that investments in basic and applied research require relatively long periods of time to generate commercially valuable knowledge. As such, the potentially negligible short-term impact of investment in basic and applied research on firm-level innovation and performance could diminish firms' incentives for investment in these activities (Cassiman et al., 2018). Within this context, Link and Scott (2019) highlight that actors within the publicly-funded science base can play a key role in transferring new knowledge to firms, thus reducing the need for firms to bear the full cost and risk of such investments. Therefore, dual-mandate research centres may be ideally placed to increase the proportion of firms' R&D devoted to basic and/or applied research, over the longer-term.

Cunningham et al. (2016) highlight that it may take relatively little time for some of the intended consequences of public funding for R&D to materialise, such as commencing new R&D projects and additional R&D investment. However, more fundamental behavioural changes can take significant time to materialise (Kaiser and Kuhn, 2012). Given the associated risk and cost, increasing the proportion of in-house R&D investment devoted to basic and applied research may be considered as a fundamental change in firms' investment behaviour (Clausen, 2009; Rosenberg, 1989; Salter and Martin, 2001; Zúñiga-Vicente et al., 2014). In addition, building up the firm-level capabilities necessary to fully engage in basic and applied research, as well as the trust necessary to collaborate effectively on such costly and high-risk projects, can take a significant amount of time (Arora et al., 2018; Belderbos et al., 2016). Therefore, if research centre collaborations re-orientate firms' R&D investment towards more basic and/or applied research, it may take time for this impact to materialise.

Collaborations between firms and academic partners which occur over a longer time period can reduce both the orientation-related and transaction-related barriers that hinder collaboration (Bruneel et al.,

2010). Indeed, firms typically only establish new routines over an extended period, through a form of experiential learning when working with a science base collaboration partner (Hewitt-Dundas et al., 2019). Fang et al. (2011, p. 744) call this "relationship-specific memory", defined as the "stored knowledge of collective insights, beliefs, routines, procedures and policies accumulated from interactions" between collaboration partners. The intensive long-term nature of firm collaborations with research centres (Intarakumnerd and Goto, 2018) may thus cultivate relationship-specific memory. However, the development of this form of tacit knowledge varies along the life cycle of a research project, in that it is generally highest in its earliest phase (Broström, 2010). At later stages of a research project, firms are in a position to reap the full benefits of the collaboration (Broström, 2010). As such, long-term collaborations which involve frequent, planned meetings and intensive cooperation, should increase communication and coordination between partners (Feller et al., 2002). Therefore, the combination of a reduction in both orientation and transaction-related barriers to collaboration, and the intensive nature of the collaboration, suggest the following hypotheses:

Hypothesis 2a: The impact of collaborating with publicly-funded research centres on the share of applied research in firms' overall in-house R&D investments increases over time.

Hypothesis 2b: The impact of collaborating with publicly-funded research centres on the share of basic research in firms' overall in-house R&D investments increases over time.

2.4. Heterogeneous treatment effects

In a review of the literature concerning the impact of different types of public support for R&D on firm-level outcomes, Becker (2015) highlights that most previous studies examine the impact of such support on a general sample of firms. This assumes that the strength of the mechanisms of transmission driving any hypothesised treatment effects are homogenous across firms. However, as detailed by Vanino et al. (2019), different underlying firm-specific characteristics, such as size and sector, as well as the characteristics of the policy programme under examination, can strengthen or weaken mechanisms of transmission. Under the homogenous treatment effect assumption, the estimated coefficients reflect average effects within the overall sample. While average effects reveal important information, they do not provide any information about potential heterogeneous treatment effects (Vanino et al., 2019).

We turn first to heterogeneity based on firm size. Relative to large firms, several factors make Small and Medium-sized Enterprises (SMEs)² more susceptible to market failures. The financial constraints argument is more acute for SMEs (Czarnitzki and Delanote, 2015). Although well-developed financial markets reduce the negative impact of financial constraints to some extent, there is evidence that SMEs face greater difficulties in accessing R&D finance, relative to large firms (Czarnitzki et al., 2007). Collaboration with SFI research centres may help SMEs to overcome appropriability problems associated with R&D. However, given that SFI research centres do not provide any direct financial support to firms as part of the collaboration (e.g. through R&D grants), SMEs may face large financial constraints in committing R&D resources to the collaborative research project, relative to large firms. In contrast, a greater possibility of access to more abundant financial resources means that large firms are more likely to benefit from the internalisation of knowledge spillovers enabled by the research centre collaboration (Czarnitzki and Hottenrott, 2012). Therefore, it may be anticipated that SFI research centre collaborations will have a positive effect on SMEs'

² We use the standard Eurostat definition for firm size classifications based on number of employees, where SMEs have less than 250 employees and large firms have 250 or more employees; see: <https://ec.europa.eu/eurostat/web/structural-business-statistics/small-and-medium-sized-enterprises>.

R&D investment, but the effect will be more pronounced in large firms. This suggests the following hypothesis:

Hypothesis 3: The treatment effects of collaborating with publicly-funded research centres will be greater for large-sized firms.

The sector to which a firm belongs represents another important factor for understanding the differences in how collaboration may impact firms' R&D outcomes. Firms face sector-specific technological opportunities and appropriability challenges, which respectively 'push' and 'pull' their R&D activity (Hall et al., 2009). Consequently, firms adapt their R&D strategy to their sector-specific economic environment, by choosing the most effective combination of inputs and outputs (Czarnitzki and Delanote, 2015). In doing so, they distribute economic resources between formal R&D investment, technological change embodied in machinery and equipment, purchasing of external know-how, and licenses (González & Pazó, 2008). For instance, low-tech manufacturing³ and less knowledge intensive services sectors are characterized by lower technological opportunities, relative to high-tech manufacturing and knowledge intensive services (Czarnitzki and Thorwarth, 2012). Therefore, a preference for cost-cutting process innovation may lead to the acquisition of externally-developed technology having a dominant role in low-tech manufacturing and less knowledge intensive services sectors. Alternatively, formal in-house R&D investment is likely to play a larger role in high-tech manufacturing and knowledge intensive services sectors (González & Pazó, 2008). Hall et al. (2009) report different R&D effects for high-tech versus low-tech firms, while Doran and Jordan (2016) confirm the existence of such differences in a wide range of different industries. These factors suggest that collaboration with SFI research centres may be more effective at driving firm-level R&D in high-tech manufacturing and knowledge intensive services sectors, and motivate the need to examine sector-specific heterogeneous treatment effects. On this basis, we form the following hypothesis:

Hypothesis 4: The treatment effects of collaborating with publicly-funded research centres will be greater for firms in high-tech manufacturing and knowledge intensive services sectors.

Beyond firm-specific heterogeneity, examining heterogeneity across the research domains of the SFI research centres firms collaborate with also holds potential insights. DBEI (2014) note that SFI research centres can be broadly categorised into three research domains: 1) Information and Communications Technology (ICT); 2) Biosciences; and, 3) Underpinning Technology.⁴ In contrast to firm size and sector, the research domain of collaboration partners has received relatively little attention in previous studies. Therefore, any anticipated heterogeneous effects based on research domain are somewhat less clear (Häussler and Colyvas, 2011). However, the 2019 EU Industrial R&D Investment Scoreboard (European Commission 2020) highlights that R&D intensity is highly concentrated in the ICT sector. Luukkonen and Palmberg (2007) note that ICT is at a more advanced stage of development relative to biosciences, and thus R&D investments in ICT can reap a higher market return. Echoing this, a recent study from Stucki and Woerter (2019) suggests that greater economic returns come from R&D investments in ICT, followed closely by biosciences, with lower returns achieved in engineering-specific research domains. Stucki and Woerter (2019) argue that the premium associated with ICT is determined two factors. First, because ICT is more established than other research domains, it has a more comprehensive stock of existing knowledge with a proven track

³ We use the standard Eurostat definition for the technology level of a sector, categorising firms into high-tech manufacturing, low-tech manufacturing, knowledge intensive services, and less knowledge intensive services; see: https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf.

⁴ DBEI (2014) identified the Underpinning Technology research domain as consisting of SFI research centres which are engaged in activities such as nanotechnology, photonics, optics, geotechnologies, plasma processing, and data analytics.

record of achieving economic return. Second, producing new knowledge in research domains that are already characterised by significant pre-existing high-performing knowledge, leads to greater economic returns due to complementarity. Therefore, we formulate the following hypothesis:

Hypothesis 5: The treatment effects of collaborating with publicly-funded research centres will be greater for firms who collaborate with research centres in the ICT research domain.

3. Methodology and data

A key issue when examining the impact of public R&D funding is selection bias. For instance, in our study, the observed difference between collaborating and non-collaborating firms could reflect the collaborating firms' higher pre-existing capabilities, rather than the influence of the research centre collaboration. To correct for this selection bias, we employ a PSM-DiD model.

3.1. PSM-DiD model

In a PSM analysis, firms that collaborate with research centres are termed 'treated', while firms that do not collaborate are classified as 'untreated'. PSM facilitates the creation of a control group of untreated firms that are statistically identical to treated firms, thus enabling an accurate analysis of treatment effects. Our first step in constructing an appropriate control group utilises Eq. (1):

$$E(a_{TT}) = E(R^T|C = 1, X = x) - E(R^U|C = 0, X = x) \quad (1)$$

In Eq. (1), a_{TT} represents the average treatment effect on treated firms; R^T is the outcome variable; $C = 1$ denotes that the firm collaborated with an SFI research centre; and R^U is the counterfactual potential outcome if the treated firm had not been treated ($C = 0$). While R^T is directly observable, R^U is unobservable and must be estimated. PSM models match treated firms that have a set of observable characteristics, X , with a control group of untreated firms that are statistically identical to the treated firm in all characteristics except for the treatment. These observable characteristics are condensed into an index known as the propensity score, which measures the probability of being treated given the relevant covariates. At a given value of the propensity score,⁵ the exposure to treatment should be random, and therefore both treated firms and the matched control group should, on average, be observationally identical. Therefore, any significant difference in R&D outcomes between treated and untreated firms after matching can be attributed to the treatment. Full details of the PSM matching process employed in this study can be found in Appendix A in Supplementary material.

PSM allows us to control for selection bias (i.e. selection into treatment), which is crucial in producing un-biased estimations. However, it should be noted that PSM only controls for observed heterogeneity amongst treated and untreated firms. If unobserved variables exist that determine both the probability of being treated and influence the outcome variable(s), this will bias the matching process. In light of this, we utilise a comprehensive set of covariates, which represent important determinants of whether a firm has collaborated with publicly-funded research centres, and whether this influences firms' R&D investment behaviour (see Appendix B in Supplementary material). However, even though our study has access to comprehensive data, a strong assumption underpinning the pure PSM methodology is that the model captures all firm characteristics that determine whether firms select into the treatment category, and any observed changes in the outcome variable.

⁵ To avoid so-called 'bad matches', the maximum propensity score distance between treated and untreated firms is set to 0.25 times the standard deviation of the propensity scores (Guerzoni & Raiteri, 2015). Further details on the matching analysis can be found in Appendix A in Supplementary material.

Therefore, we combine PSM with a DiD estimator to control for selection bias based on observables and, in addition, time-invariant firm-specific effects in the unobservables. The DiD requires panel data, and compares the change in the outcome variables for treated observations with the change in the outcome of the counterfactual observations. We run the DiD analysis on our matched sample. As such, PSM-DiD analysis combines the advantages of the PSM estimator with the advantages of the DiD estimator (Dai and Wang, 2019; Szücs, 2018). This ensures that the treatment group and the matched control group are chosen based on observables, while common trends and constant firm-specific unobserved factors are also controlled for.

As our dataset has multiple time periods, and firms can receive a treatment in any of these time periods, we estimated a so-called 'within' fixed effects DiD regression, which has recently been described in great detail by Czarnitzki (2020). Employing this method, we specify three key variables: 1) Treatment, defined as the years when a firm was collaborating with an SFI research centre; 2) Post-treatment, defined as the years directly after a firm concluded its SFI research centre collaboration; and, 3) Pre-treatment, which captures the years immediately prior to the start of a firm's collaboration with an SFI research centre. Here, the variable post-treatment ensures that firms which were previously in the treatment category, do not revert back to the untreated control group after the treatment period ends. The variable pre-treatment captures whether the common trend assumption is violated in the regression analysis. The common trend assumption states that both the treatment group and the control group would have evolved similarly in the absence of the policy programme. This assumption becomes credible because the common trend can be observed before firms select into the treatment. As is standard practice in studies which apply the PSM-DiD methodology (see e.g. Dai and Wang, 2019; Szücs, 2018), the post-matching DiD analysis is estimated using Ordinary Least Squares regression analysis, with heteroscedasticity robust standard errors.

3.2. Institutional background and model set-up

As alluded to earlier in Section 1, SFI invests in academic researchers and research teams who it judges most likely to generate new knowledge, leading-edge technologies and competitive enterprises in the STEM research fields (SFI, 2018). A key recommendation of the government report which led to the establishment of SFI in 2000, was that Ireland needed to become "a centre of excellence" in the biotechnology and ICT sectors (Technology Foresight Ireland, 1999, p. 7). The rationale for prioritising these sectors was that they were judged to represent the most promising areas for technology-based growth. SFI-funded research centres engage in long-term collaborations with firms that are focused on basic and applied research (SFI, 2018). Firms do not receive any direct financial incentive to collaborate with SFI research centres, and must contribute a minimum of 30 per cent of the costs associated with the research collaboration (SFI, 2018). Moreover, firms are required to make a distinct and verifiable "intellectual contribution" to all collaborations with SFI research centres (SFI, 2018, p. 2). As such, the main incentive for firms to collaborate with SFI research centres is *not* to gain public funding for R&D, but rather to work with leading academics, and access scientific knowledge (DBEI, 2014).

In terms of understanding how the SFI research centres programme works, it is crucial to note that each centre sets its own research agenda (SFI, 2018). Though SFI funds the research centres, each centre is independent in terms of choosing which projects it pursues, and which industry partners it collaborates with (SFI, 2009 & 2013). However, centres are consistently reviewed by SFI to ensure the quality of the academic research outputs, as well as to demonstrate significant engagement with industry (Indecon, 2018). Industry engagement has been fundamental to the SFI research centres' *raison d'être* since their inception (Technology Foresight Ireland, 1999; Indecon, 2008). This is chiefly evidenced by the share of costs borne by industry partners in

each research collaboration (Indecon, 2008 & 2018). In this way, although each research centre controls its own research agenda, it must be in constant, formal consultation with industry partners to agree a common agenda (SFI, 2009 & 2013 & 2017). Firms are included in each research collaboration by providing cash and in-kind resources to sustain the project, and research staff from industry partners work directly with the research centre on each collaborative project (Indecon, 2008 & 2018).

SFI research centre collaborations with firms typically last for 4–6 years. It is likely that the impact of a collaboration in its fourth year on firm-level R&D will differ substantially from a collaboration in its first year (Feller et al., 2002; Intarakumnerd and Goto, 2018). To address these issues, our analysis examines the impact of SFI research centre collaborations on firm-level R&D in the 1–2 year period, 3–4 year period and 5–6 year period after the collaboration begins. This model set-up allows for an examination of the immediate impacts of commencing a collaboration with an SFI research centre on firms' R&D, as well as analysing how these impacts unfold over subsequent years. In our sample, some firms engage in more than one SFI research centre collaboration. Following a similar approach to that employed by Vanino et al. (2019) and Scandura (2016), the analysis focuses on the impact of a firm's first collaboration in this period. In addition, the analysis restricts the matching to firms that were treated in the same time period. For example, firms where the start date for their first SFI research centre collaboration was in the 2007–2008 period are matched with untreated firms (with a similar propensity score and from the same sector) from the same time period.

3.3. Firm-level data

Our analysis is based on merging five datasets. Firstly, we use the Business Expenditure on Research and Development (BERD) survey from the Irish Central Statistics Office (CSO). BERD provides information on firms' in-house R&D expenditure, as well as a breakdown of this expenditure figure into the proportion devoted to basic research, applied research, and experimental development. These measures form the key outcome variables for the analysis. BERD also provides a series of other R&D-related firm characteristics, which are used as control variables in the analysis (see Section 3.2.2 below, and Appendix B in Supplementary material, for a detailed description of the variables used). BERD is conducted every two years, providing data on firms for the years 2007, 2009, 2011, 2013, 2015 and 2017. Secondly, the study draws on the CSO's Business Demography Database (BDD) to provide information on firm size, sector, age and location, which are also used as control variables in the analysis. The final two survey datasets our study draws on are the CSO's Census of Industrial Production (CIP) and Annual Services Inquiry (ASI) survey datasets, which provide key information on firms' turnover, productivity, and exporting behaviour.

The BERD survey is merged with administrative data from SFI, which captures the start date and end date for all firm collaborations with SFI research centres⁶ from 2007 to 2014. This information is used to create the treatment variable used in the analysis, which is the start date and duration of the collaboration between a firm and an SFI-funded research centre. Given that BERD provides data for every two years, the annual SFI data is merged into two-year waves. Therefore, the treatment variable is defined as whether a firm commenced a collaboration with an SFI research centre in the last two years. Data on SFI research centre collaborations with firms was not available for 2015, 2016 or 2017. However, it is vitally important to examine the potential lagged impact of collaborating with an SFI research centre on firms' R&D investment

⁶ SFI research centres were initially introduced as the Centres for Science, Engineering and Technology (CSETs) programme in 2003. For full details of the evolution of this programme since its introduction, see DEBI (2012 & 2014) and <https://www.sfi.ie/funding/funding-calls/sfi-research-centres/>.

behaviour. Therefore, we include the years 2015 and 2017 from BERD in the analysis to facilitate capturing the lagged impact of SFI research centre collaborations for firms that commenced the collaboration prior to 2015.

The final merged dataset used for the analysis contains 2,489 observations, corresponding to 961 unique firms over the 10-year period. Within this sample, 75⁷ unique firms collaborated with SFI research centres (between 2007 and 2014).⁸ This number of firms represents approximately 36 per cent of the total number of firms that collaborated with SFI research centres during the period. The remaining firms which collaborated with an SFI research centre were not surveyed in BERD and, therefore, cannot be included in this analysis. A number of firms in BERD indicated that they did not have any in-house R&D expenditure in any year from 2007 to 2017. Including a sample of firms that never invested in R&D in any year may bias the calculation of the propensity score, and artificially inflate the impact of the treatment variable on firm-level R&D (Czarnitzki et al., 2011). Therefore, firms that did not invest in R&D in any of the years covered by the BERD survey are excluded from the analysis. No treated firms are excluded as a result of this process.

3.3.1. Outcome variables

Our study first examines firms' overall R&D intensity, before shifting our focus to basic and applied research. We measure R&D intensity as firms' in-house R&D divided by employment. However, it is important to note that R&D intensity is more commonly measured as R&D divided by turnover. The rationale for this decision is that we have detailed annual information on firms' employment from the BDD, but we must rely on an average measure of firms' turnover from the CIP/ASI.⁹ The analysis also uses two further sub-divisions of R&D intensity, firms' in-house R&D expenditure on applied research and basic research, divided by total employment. The natural log of these variables is computed due to a non-normal distribution, which is common with measures of firm-level R&D (Czarnitzki et al., 2011). The final two outcome variables employed in the analysis are used to demonstrate whether a more fundamental re-orientation to applied research and basic research has taken place. These variables capture the share of applied research, and basic research in firms' overall in-house R&D expenditure. All variables used in our analysis are defined in Table 1.¹⁰

3.3.2. Control variables

To ensure the robustness of our analysis, we control for a comprehensive set of factors which previous studies have found are important in determining firms' R&D (defined in Table 1). We control for whether firms had a dedicated R&D unit (Feller et al., 2002), whether firms engaged in joint research partnerships with other firms (Hewitt-Dundas

⁷ Two firms are excluded from the analysis because they do not fulfil the strict common support conditions detailed in Appendix B in Supplementary material to ensure a reliable matching process.

⁸ Appendix C in Supplementary material provides details on the representativeness of the BERD survey relative to the population of R&D active firms in Ireland, as well as the representativeness of our merged sample of treated firms relative to the full population of treated firms.

⁹ The ASI/CIP surveys and the BERD survey have different sampling frames. As such, not all firms surveyed in BERD are also surveyed in ASI/CIP. Of those firms that are present in both ASI/CIP and BERD, they are not always surveyed in the same year. To ensure that we retain a sufficient sample size after the merge, we take the average of firms' turnover over the five years prior to treatment for which they were surveyed. This approach is similar to that applied by Lucking et al. (2019). Notwithstanding this, we perform a robustness test with R&D divided by average turnover for the past five years. We do this to ensure that our results are not sensitive to changes in how we define our outcome variable (for further details, see Section 4.1).

¹⁰ Summary statistics for all variables used in our analysis are presented in Appendix Table B1 in Supplementary material.

Table 1
Definition and variables used in the analysis.

Variable	Definition
<i>Outcome variables</i>	
In-house R&D intensity	Natural logarithm of firm's in-house R&D expenditure divided by number of employees.
Applied research intensity	Natural logarithm of firm's in-house R&D expenditure on applied research divided by number of employees.
Basic research intensity	Natural logarithm of firm's in-house R&D expenditure on basic research divided by number of employees.
Applied research share	Percentage of firm's total in-house R&D expenditure on applied research.
Basic research share	Percentage of firm's total in-house R&D expenditure on basic research.
<i>Treatment variable</i>	
SFI research centre collaboration	Binary variable equal to 1 if a firm began its first collaboration with an SFI research centre during the past two years; 0 otherwise.
<i>Control variables</i>	
R&D unit	Binary variable equal to 1 if a firm has a dedicated R&D unit; 0 otherwise.
Joint research projects	Binary variable equal to 1 if a firm engaged in joint research projects with other firms; 0 otherwise.
R&D outsourcing	Binary variable equal to 1 if a firm outsourced any R&D activities to other parties; 0 otherwise.
R&D subsidy	Binary variable equal to 1 if firm received an R&D grant, R&D tax credit or any other public R&D funding; 0 otherwise.
R&D employees	The percentage of firm's total employees engaged in R&D activities.
PhD employees	Natural logarithm of firm's PhD employees.
PhD recruitment	Binary variable equal to 1 if a firm indicates that it is either 'quite likely' or 'very likely' to recruit PhD qualified researchers in the next five years; 0 otherwise.
Turnover	Categorical variables: 0 = Lowest turnover quartile; 1 = Second turnover quartile; 2 = Third turnover quartile; 3 = Highest turnover quartile.
Productivity (GVA divided by employees)	Categorical variables: 0 = Lowest productivity quartile; 1 = Second productivity quartile; 2 = Third productivity quartile; 3 = Highest productivity quartile.
Exports	Categorical variables: 0 = Lowest export quartile; 1 = Second export quartile; 2 = Third export quartile; 3 = Highest export quartile.
Employees	Natural logarithm of firm's employees.
Age	Natural logarithm of firm's age.
Sector	Categorical variables representing 21 NACE sectors (defined in Appendix Table B2).
Region	Categorical variables: 0 = Northern and Western; 1 = Dublin; 2 = Eastern and Midland; 3 = Southern.

et al., 2019), and whether firms received any public funding for R&D in the past (Mulligan et al., 2019). In addition, we control for firms' intention to recruit PhD trained researchers over the next five-year period (Herrera and Nieto, 2015), as well as firms' current level of PhD employment (Barge-Gil et al. 2021). Furthermore, we control for past values of firms' overall R&D intensity, as well as the proportion of this overall figure devoted to basic research and applied research before the collaboration (Scandura, 2016). Beyond these R&D-specific factors, controlling for firms' business performance pre-treatment is essential in achieving a sound matching process (Vanino et al., 2019). Therefore, we control for firms' pre-treatment levels of turnover, productivity, and exporting. Finally, the analysis controls for firm size, sector, age, and regional location. Including these R&D-specific, and business performance-specific variables accounts for the fact that SFI research centres aim to cherry-pick the best and most capable firms for their research collaborations (as detailed in Section 3.2). Therefore, including a comprehensive set of control variables in the matching procedure

helps to ensure that treated firms are always matched with untreated firms with the same pre-treatment R&D, and business performance profile.

So as to be in a position to apply the PSM-DiD analysis, we first need to predict firms' probability of collaborating. Therefore, a probit model is estimated controlling for firm characteristics which may determine firms' selection into treatment. As can be seen in Appendix Table D1 in Supplementary material, the majority of the covariates are important drivers for the selection into the treatment.

4. Empirical results

This section presents and discusses the results from our PSM-DiD model.¹¹ We first discuss our results on the impact of collaboration on firms' overall in-house R&D, basic, and applied research. We then turn to our analysis of heterogeneous treatment effects.

4.1. Impact of publicly-funded research centre collaborations

Our DiD analysis on the matched sample is presented in Table 2. This shows the results of the analysis testing Hypothesis 1a, which states that collaborating with publicly-funded research centres will increase firms' in-house R&D investment.¹² The first row of Table 2 shows that treated firms experience a 51% growth in their R&D intensity over a 1–2 year period after they begin a research centre collaboration. This impact increases over time, with R&D intensity in treated firms being even greater than matched untreated firms 3–4 years and 5–6 years post-treatment respectively. This provides strong support for our first hypothesis.

Table 3 displays the results concerning Hypothesis 1b and 1c, which state that collaborating with publicly-funded research centres will increase firms' investments in applied research and basic research, respectively. A similar pattern is observed for applied research intensity as outlined in Table 2, with treated firms consistently possessing significantly higher applied research intensity relative to untreated firms. This provides support for Hypothesis 1b. However, we find little support for Hypothesis 1c, as we observe that treated firms and

Table 2
Impact of collaborating with SFI research centres on firm-level R&D intensity.

Variable	Impact 1–2 years after treatment	Impact 3–4 years after treatment	Impact 5–6 years after treatment
Treatment	0.510*** (0.021)	0.633*** (0.034)	0.784* (0.038)
Post-treatment	–0.012 (0.007)	–0.027 (0.009)	–0.009 (0.001)
Pre-treatment	0.023 (0.008)	0.047 (0.006)	0.014 (0.001)
Total observations	836	640	415
Treated firms	73	59	39
Matched untreated	219	177	117
R ²	0.241	0.203	0.189

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors in parentheses. Control variables defined in Table 1, as well as firm and year fixed effects are included in all models. The number of observations reduces as the time lag increases, because not all firms are observed in all time periods.

¹¹ The quality of the matching procedure is detailed in Appendix E in Supplementary material. To summarise, all necessary diagnostic tests are met for a robust analysis.

¹² As noted in Section 3.3.1, we use R&D divided by employees in our main analysis, and R&D divided by turnover as a robustness test. Results from this robustness test are presented in Appendix Table F1 in Supplementary material, and confirm the results from our main analysis.

Table 3
Impact of collaborating with SFI research centres on firm-level basic and applied research intensity.

Outcome variable: Applied research intensity			
Variable	Impact 1–2 years after treatment	Impact 3–4 years after treatment	Impact 5–6 years after treatment
Treatment	0.803*** (0.052)	0.933*** (0.061)	0.814* (0.055)
Post-treatment	–0.001 (0.009)	–0.012 (0.011)	–0.025 (0.007)
Pre-treatment	0.018 (0.011)	0.023 (0.008)	0.034 (0.027)
Total observations	836	640	415
Treated firms	73	59	39
Matched untreated	219	177	117
R ²	0.311	0.365	0.19
Outcome variable: Basic research intensity			
Variable	Impact 1–2 years after treatment	Impact 3–4 years after treatment	Impact 5–6 years after treatment
Treatment	–0.003 (0.002)	0.033*** (0.011)	0.144 (0.013)
Post-treatment	0.006 (0.017)	–0.024 (0.021)	–0.079 (0.015)
Pre-treatment	0.097 (0.073)	0.011 (0.012)	0.045 (0.062)
Total observations	836	640	415
Treated firms	73	59	39
Matched untreated	219	177	117
R ²	0.283	0.219	0.201

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors in parentheses. Control variables defined in Table 1, as well as firm and year fixed effects are included in all models. The number of observations reduces as the time lag increases, because not all firms are observed in all time periods.

untreated firms have identical basic research intensity 1–2 years and 5–6 years post treatment. The only significant result is in years 3–4 when we observe treated firms possessing higher levels of basic research intensity, relative to matched untreated firms.

To examine whether collaborating with SFI research centres re-orientates firm-level R&D towards more basic and/or applied research, Table 4 presents the analysis of the impact of research centre collaboration on the proportion of applied research and basic research in firms' overall in-house R&D. In the initial period 1–2 years post treatment, there is no significant difference between the treated and untreated firms. However, we do observe significant differences 3–4 years and 5–6 years post treatment. This provides strong support for Hypothesis 2a, which states that firms that collaborate with research centres will increase the proportion of applied research in their overall in-house R&D intensity, but only after a time lag. However, a similar effect is not detected for the proportion of basic research undertaken by treated firms, given that the differences between treated and untreated firms in row five are not statistically significant. This indicates no support for Hypothesis 2b.

When considering these findings, it is vitally important to recall the nature of the policy programme under examination in our study: publicly-funded research centres which have a dual mandate to conduct basic and applied research, and engage in research collaborations with firms. As detailed previously (Section 3.2), the main incentive for firms to collaborate with SFI research centres is not to gain public funding for R&D, but rather to work with leading academics and research teams, and access scientific knowledge (DBEI, 2014). Therefore, it may be useful to consider our results in light of the findings presented by Scandura (2016) and Vanino et al. (2019) which focus on a similar form

Table 4
Impact of collaborating with SFI research centres on firm-level basic and applied research share.

Outcome variable: Applied research share			
Variable	Impact 1–2 years after treatment	Impact 3–4 years after treatment	Impact 5–6 years after treatment
Treatment	11.51 (0.327)	23.25*** (0.215)	26.31*** (0.562)
Post-treatment	–0.147 (0.912)	–0.152 (0.811)	–0.235 (0.757)
Pre-treatment	9.078 (0.193)	7.327 (0.186)	0.934 (0.217)
Total observations	836	640	415
Treated firms	73	59	39
Matched untreated	219	177	117
R ²	0.343	0.297	0.231
Outcome variable: Basic research share			
Variable	Impact 1–2 years after treatment	Impact 3–4 years after treatment	Impact 5–6 years after treatment
Treatment	–29.01 (0.716)	–3.17 (0.431)	–0.031 (0.352)
Post-treatment	–0.006 (0.086)	–0.009 (0.073)	–0.001 (0.091)
Pre-treatment	1.032 (0.175)	5.212 (0.231)	0.096 (0.274)
Total observations	836	640	415
Treated firms	73	59	39
Matched untreated	219	177	117
R ²	0.217	0.209	0.198

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors in parentheses. Control variables defined in Table 1, as well as firm and year fixed effects are included in all models. The number of observations reduces as the time lag increases, because not all firms are observed in all time periods.

of collaboration. Both of these studies focus on firm-university collaborations funded by the UK's Engineering and Physical Sciences Research Council (EPSRC). In these collaborations, firms do not receive direct EPSRC funding, and often make significant financial contributions to the funded project. The incentive for firms to collaborate is to gain knowledge and work on specific projects with academic experts.¹³ Scandura (2016) finds that such collaborations drive an increase in firm-level R&D intensity and R&D employment. Building on this work, Vanino et al. (2019) examine the wider firm-performance benefits of collaborative EPSRC projects. Results from this study indicate that participation in collaborative projects increases firms' employment and turnover growth. These findings suggest that the additional R&D stimulated by collaborations of this nature lead to forms of innovation that provide firms with a competitive edge (Vanino et al., 2019). This form of highly R&D-intensive innovation requires a significant scientific input (Clausen, 2009), often necessitating effective collaboration with the science base (Hewitt-Dundas et al., 2019). Our analysis demonstrates that collaborating with SFI research centres not only drives firm-level R&D, but also re-orientates firms' R&D investment towards more applied research, and thus builds scientific capacity. In the context of the previous studies noted above, our findings suggest that dual-mandate research centres can be an effective policy instrument for reshaping firm-level R&D.

¹³ For further information on EPSRC-funded collaborations, see: <https://epsrc.ukri.org/innovation/business/opportunities/>.

4.2. Analysis of heterogeneous treatment effects

Our analysis of heterogeneous treatment effects focuses first on large firms versus SMEs, before examining treatment effects in four sectoral aggregations (high-tech manufacturing, low-tech manufacturing, knowledge intensive services, and less knowledge intensive services). In the final set of heterogeneity tests, we examine differences amongst SFI research centres, by sub-dividing the research centres into their respective research domains. We examine each of these potential sources of variation using interaction terms, which capture the impact of SFI research centre collaboration in each of the specific sub-sets defined above (e.g. large firms versus SMEs). This empirical set-up enables us to investigate whether the mechanisms underpinning each hypothesised treatment effect vary in strength depending on firm-specific and research centre-specific heterogeneity.

Turning first to firm size, Table 5 examines the impact of firm collaborations with SFI research centres on large-sized firms and SMEs. The results in this table examine Hypothesis 3, which stated that the mechanisms of transmission underpinning our hypothesised treatment effects would be greater in large-size firms. Table 5 shows that, in general, treated large firms have an 18% higher R&D intensity than SMEs (given by the coefficient on 'Large'). Treated SMEs have a 32% increase in their R&D intensity, relative to untreated SMEs. Large firms have a 54% increase in their R&D intensity relative to untreated firms (the sum of the coefficients on 'Treatment' and 'Treatment * Large'). Therefore, the effect of collaborating is positive and significant for both SMEs and large firms, but the effect is greater for large firms (32% versus 54%). This treatment effect increases over time, for both large firms and SMEs. In terms of the mechanisms of transmission, these results verify our findings for Hypothesis 1a discussed above, and lend support to Hypothesis 3. As such, they indicate that firms with greater absorptive capacity and financial resources, benefit the most from SFI research centre collaborations in terms of R&D intensity.

Table 6 examines Hypothesis 3 further, by investigating whether firm-size plays a role in the mechanisms underpinning the impact of SFI research centre collaboration on firms' applied and basic research intensity. Applied research intensity appears to follow a similar path to firms' overall R&D intensity found in Table 5. However, turning to the results presented in Table 7, focusing on the share of basic and/or applied research in firms' overall R&D, a new pattern emerges. 3–4 years after a collaboration begins, SMEs experience a 34% increase in

Table 5

Impact of collaborating with SFI research centres on firm-level R&D intensity, heterogeneity analysis for firm size.

Variable	Impact 1–2 years after treatment	Impact 3–4 years after treatment	Impact 5–6 years after treatment
Treatment	0.32*** (0.081)	0.39*** (0.067)	0.42** (0.071)
Post-treatment	–0.021 (0.063)	–0.046 (0.071)	–0.036 (0.095)
Pre-treatment	0.009 (0.060)	0.017 (0.054)	0.005 (0.063)
Large	0.18*** (0.052)	0.12*** (0.064)	0.19*** (0.021)
Treatment * Large	0.22*** (0.031)	0.31*** (0.046)	0.43*** (0.058)
Total observations	836	640	415
Treated firms	73	59	39
Matched untreated	219	177	117
R ²	0.371	0.328	0.322

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors in parentheses. Control variables defined in Table 1, as well as firm and year fixed effects are included in all models. The number of observations reduces as the time lag increases, because not all firms are observed in all time periods.

Table 6
Impact of collaborating with SFI research centres on firm-level applied and basic research intensity, heterogeneity analysis for firm size.

Outcome variable: Applied research intensity			
Variable	Impact 1–2 years after treatment	Impact 3–4 years after treatment	Impact 5–6 years after treatment
Treatment	0.51*** (0.087)	0.63*** (0.079)	0.69** (0.067)
Post-treatment	-0.011 (0.063)	-0.017 (0.049)	-0.004 (0.055)
Pre-treatment	0.009 (0.060)	0.007 (0.066)	0.011 (0.058)
Large	0.21** (0.071)	0.16*** (0.048)	0.25* (0.095)
Treatment * Large	0.17*** (0.062)	0.23** (0.073)	0.027** (0.082)
Total observations	836	640	415
Treated firms	73	59	39
Matched untreated	219	177	117
R ²	0.31	0.29	0.27
Outcome variable: Basic research intensity			
Variable	Impact 1–2 years after treatment	Impact 3–4 years after treatment	Impact 5–6 years after treatment
Treatment	-0.07 (0.069)	0.09** (0.086)	0.91 (0.053)
Post-treatment	-0.23 (0.052)	-0.86 (0.038)	-0.04 (0.046)
Pre-treatment	0.009 (0.059)	0.007 (0.075)	0.011 (0.048)
Large	0.01 (0.071)	0.07 (0.048)	0.06 (0.095)
Treatment * Large	0.26 (0.051)	-0.21 (0.084)	0.036 (0.070)
Total observations	836	640	415
Treated firms	73	59	39
Matched untreated	219	177	117
R ²	0.27	0.24	0.32

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors in parentheses. Control variables defined in Table 1, as well as firm and year fixed effects are included in all models. The number of observations reduces as the time lag increases, because not all firms are observed in all time periods.

the share of applied research. In contrast, although large firms also experience an increase in their applied research, the magnitude of the effect is lower at 24%. While both results represent a significant re-orientation to more research-focused activities, they suggest that SFI research centres may reduce some of the risk associated with knowledge creation, through helping internalise knowledge spillovers. Although this does not lead to increased overall R&D investments beyond what large firms achieve, it does appear to enable SMEs to pivot more rapidly towards applied research. Finally, as in our main findings (see Table 3 and 4), we find no significant effects on basic research.

Tables 8, 9, and 10 present the results for our analysis of sector-specific treatment effects. These results pertain to Hypothesis 4, which states that the impact of collaborating with SFI research centres is likely to be greater in high-tech manufacturing and knowledge intensive services sectors. As we may have anticipated on the basis of previous literature (Doran and Jordan, 2016), firms in high-tech manufacturing and knowledge intensive services experience the largest growth in R&D intensity, as well as the proportion of their overall R&D devoted to applied research. These results suggest that the technological opportunities which exist in specific sectors play a significant role in the strength of the mechanisms underpinning each of our hypothesised treatment

Table 7
Impact of collaborating with SFI research centres on firm-level basic and applied research share, heterogeneity analysis for firm size.

Outcome variable: Applied research share			
Variable	Impact 1–2 years after treatment	Impact 3–4 years after treatment	Impact 5–6 years after treatment
Treatment	1.63 (0.528)	34.13*** (0.327)	39.17*** (0.451)
Post-treatment	-0.236 (0.817)	-0.213 (0.719)	-0.167 (0.901)
Pre-treatment	11.09 (0.271)	8.221 (0.284)	0.977 (0.197)
Large	-10.71 (0.311)	-09.33 (0.447)	0.908 (0.393)
Treatment * Large	0.936 (0.353)	-10.09*** (0.431)	-19.46** (0.603)
Total observations	836	640	415
Treated firms	73	59	39
Matched untreated	219	177	117
R ²	0.21	0.27	0.32
Outcome variable: Basic research share			
Variable	Impact 1–2 years after treatment	Impact 3–4 years after treatment	Impact 5–6 years after treatment
Treatment	-0.43 (0.421)	4.33 (0.215)	-4.07 (0.373)
Post-treatment	-0.072 (0.609)	-0.033 (0.852)	-0.198 (0.764)
Pre-treatment	2.07 (0.601)	4.021 (0.372)	1.079 (0.277)
Large	-0.075 (0.217)	-01.93 (0.326)	0.802 (0.198)
Treatment * Large	0.014 (0.371)	17.08 (0.464)	0.464 (0.472)
Total observations	836	640	415
Treated firms	73	59	39
Matched untreated	219	177	117
R ²	0.16	0.19	0.23

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors in parentheses. Control variables defined in Table 1, as well as firm and year fixed effects are included in all models. The number of observations reduces as the time lag increases, because not all firms are observed in all time periods.

effects. However, unlike our results presented above for SMEs, SFI research centres do not appear to play as powerful a role in enabling firms in less high-tech sectors to internalise knowledge spillovers. In this regard, our results are similar to those found by Vanino et al. (2019). These authors demonstrate that, while research collaborations increase firm performance in all sectors, the positive effects are most pronounced in high-tech and knowledge intensive sectors.

Finally, Tables 11, 12 and 13 move beyond firm-specific variation, to examine Hypothesis 5, which focuses on whether the impact of collaboration is greater in the ICT research domain. SFI research centres are categorised in different research domains, and collaboration across these domains may induce different treatment effects. Table 11 demonstrates that there is a small premium associated with firms that collaborate with ICT-focused research centres. However, this may reflect the technological opportunities firms in the ICT sector have, relative to firms in other sectors (Salavisa et al., 2012). In addition, the ICT sector is more mature and developed than both of the other sectors, which may dictate that investments in R&D have a greater likelihood of achieving a return (Luukkonen and Palmberg, 2007). On the other hand, this may also indicate the level of competition in the ICT sector, which necessitates constant investment in R&D, and, moreover, cultivation of research-specific capabilities (Stucki and Woerter, 2019). Given that we find positive and significant effects for all research domains, this

Table 8
Impact of collaborating with SFI research centres on firm-level R&D intensity, heterogeneity analysis for sector.

Variable	Impact 1–2 years after treatment	Impact 3–4 years after treatment	Impact 5–6 years after treatment
Treatment	0.092** (0.091)	0.133*** (0.079)	0.128*** (0.087)
Post-treatment	−0.034 (0.072)	−0.017 (0.068)	−0.025 (0.057)
Pre-treatment	0.011 (0.067)	0.023 (0.056)	0.008 (0.078)
High-tech manufacturing	0.711*** (0.085)	0.692*** (0.089)	0.720*** (0.074)
Low-tech manufacturing	0.007* (0.074)	0.002** (0.077)	0.013* (0.091)
Knowledge intensive services	0.415*** (0.098)	0.327*** (0.072)	0.421*** (0.069)
Treatment * High-tech manufacturing	0.341*** (0.086)	0.420*** (0.089)	0.396*** (0.092)
Treatment * Low-tech manufacturing	0.041* (0.075)	0.019* (0.069)	0.016** (0.082)
Treatment * Knowledge intensive services	0.212*** (0.094)	0.337*** (0.071)	0.315*** (0.098)
Total observations	836	640	415
Treated firms	73	59	39
Matched untreated	219	177	117
R ²	0.21	0.28	0.19

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors in parentheses. Control variables defined in Table 1, as well as firm and year fixed effects are included in all models. The base category for sector is Less Knowledge Intensive Services (LKIS). The number of observations reduces as the time lag increases, because not all firms are observed in all time periods.

suggests that, in general, SFI research centre collaborations are effective at influencing firms’ R&D investment behaviour. However, the mechanisms which underpin our hypothesised effects appear to be stronger for firms that collaborate with research centres in the ICT research domain.

Table 9
Impact of collaborating with SFI research centres on firm-level basic and applied research intensity, heterogeneity analysis for sector.

Variable	Outcome variable: Applied research intensity			Outcome variable: Basic research intensity		
	Impact 1–2 years after treatment	Impact 3–4 years after treatment	Impact 5–6 years after treatment	Impact 1–2 years after treatment	Impact 3–4 years after treatment	Impact 5–6 years after treatment
Treatment	0.121*** (0.076)	0.199*** (0.088)	0.203*** (0.072)	−0.078 (0.099)	0.009** (0.075)	−0.127 (0.063)
Post-treatment	−0.062 (0.082)	−0.075 (0.078)	−0.039 (0.057)	−0.054 (0.081)	−0.018 (0.078)	−0.027 (0.032)
Pre-treatment	0.009 (0.089)	0.015 (0.086)	0.017 (0.061)	0.127 (0.092)	0.319 (0.087)	0.373 (0.061)
High-tech manufacturing	0.831*** (0.085)	0.902*** (0.089)	0.960*** (0.074)	0.792*** (0.093)	0.832*** (0.075)	0.913*** (0.069)
Low-tech manufacturing	0.011* (0.098)	0.008** (0.087)	0.017 (0.069)	0.035 (0.083)	0.019 (0.075)	0.023 (0.069)
Knowledge intensive services	0.501*** (0.088)	0.416*** (0.084)	0.527*** (0.073)	0.481*** (0.088)	0.399*** (0.084)	0.503*** (0.073)
Treatment * High-tech manufacturing	0.681*** (0.071)	0.563*** (0.064)	0.496** (0.082)	−0.027 (0.065)	0.071* (0.082)	−0.091 (0.079)
Treatment * Low-tech manufacturing	0.083* (0.092)	0.009* (0.073)	0.026 (0.067)	−0.071 (0.097)	0.011 (0.081)	−0.029 (0.075)
Treatment * Knowledge intensive services	0.401*** (0.057)	0.357*** (0.093)	0.501** (0.088)	−0.091 (0.076)	0.017** (0.099)	0.081 (0.091)
Total observations	836	640	415	836	640	415
Treated firms	73	59	39	73	59	39
Matched untreated	219	177	117	219	177	117
R ²	0.33	0.29	0.35	0.19	0.23	0.21

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors in parentheses. Control variables defined in Table 1, as well as firm and year fixed effects are included in all models. The base category for sector is Less Knowledge Intensive Services (LKIS). The number of observations reduces as the time lag increases, because not all firms are observed in all time periods.

5. Discussion and conclusions

In 2003, policymakers in Ireland launched a unique international science policy programme, which has to date allocated over €1 billion to establish and maintain a series of research centres. Funded through SFI (Ireland’s science policy funding agency), these research centres have two key policy goals: 1) enhance the national science base by conducting world-leading basic and applied research in STEM areas; and, 2) enhance the economy through collaborations with firms. Countries typically develop this type of research centre programme after several decades of sustained investment in research infrastructure (Intarakumnerd and Goto, 2018). However, Ireland started from a position with little pre-existing research infrastructure beyond its traditional higher education system, to rapidly establish a national research centres programme. This paper provides the first evaluation of how research collaborations formed as part of this policy programme, impact firm-level R&D.

Publicly-funded research centres of this nature are common in many countries (Intarakumnerd and Goto, 2018; OECD, 2011). However, to the best of our knowledge, previous analyses have only examined the impact of such collaborations on firms overall R&D expenditure (Scandura, 2016) or business performance (Vanino et al., 2019). Therefore, our study’s first contribution to the literature is to go beyond firms’ total volume of R&D, and examine firms’ basic and applied research (i.e. the ‘R’ in R&D). In doing so, we respond to recent calls in the literature from Vanino et al. (2019) and Nilsen et al. (2020), who argue that distinguishing between research and development is crucial, when examining the impact of public R&D funding programmes. Our study’s second contribution centres on performing an analysis for heterogeneous treatment effects. To do this, we examine whether our treatment effects vary depending on firm size and sector, as well as the research domain of the research centre firms collaborate with. A final distinct novelty of our study with respect to most previous analyses, is the use of panel data econometrics, designed to account for possible omitted variable bias. To account for this, we performed a PSM-DiD estimation. While the initial PSM seeks to ensure firms that collaborated with SFI research centres are matched with an appropriate control group of statistically identical

Table 10
Impact of collaborating with SFI research centres on firm-level basic and applied research share, heterogeneity analysis for sector.

Variable	Outcome variable: Applied research share			Outcome variable: Basic research share		
	Impact 1–2 years after treatment	Impact 3–4 years after treatment	Impact 5–6 years after treatment	Impact 1–2 years after treatment	Impact 3–4 years after treatment	Impact 5–6 years after treatment
Treatment	1.07 (0.371)	0.95*** (0.318)	1.37*** (0.192)	–31.97 (0.913)	–9.11 (0.842)	–17.03 (0.551)
Post-treatment	–0.286 (0.972)	–0.501 (0.851)	–0.309 (0.657)	–0.017 (0.886)	–0.023 (0.671)	–0.052 (0.702)
Pre-treatment	2.077 (0.491)	6.025 (0.387)	1.038 (0.412)	0.939 (0.471)	8.711 (0.533)	9.093 (0.577)
High-tech manufacturing	8.237*** (0.905)	11.973*** (0.899)	9.067*** (0.873)	1.977*** (0.811)	7.671* (0.693)	8.165* (0.751)
Low-tech manufacturing	0.011*** (0.805)	0.018* (0.743)	0.017* (0.829)	0.003** (0.805)	0.009** (0.743)	0.013* (0.829)
Knowledge intensive services	7.591*** (0.618)	6.438*** (0.587)	8.025*** (0.397)	1.591*** (0.705)	7.031** (0.689)	6.127** (0.599)
Treatment * High-tech manufacturing	17.051 (0.976)	15.003*** (0.861)	17.403** (0.682)	–9.07 (0.817)	7.192 (0.533)	0.931 (0.651)
Treatment * Low-tech manufacturing	0.083 (0.593)	0.031* (0.775)	0.057 (0.807)	–16.87 (0.711)	–6.22 (0.803)	–9.031 (0.673)
Treatment * Knowledge intensive services	0.001 (0.154)	9.301*** (0.697)	11.408** (0.587)	–10.02 (0.618)	1.172 (0.603)	–8.001 (0.629)
Total observations	836	640	415	836	640	415
Treated firms	73	59	39	73	59	39
Matched untreated	219	177	117	219	177	117
R ²	0.29	0.31	0.34	0.11	0.17	0.22

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors in parentheses. Control variables defined in Table 1, as well as firm and year fixed effects are included in all models. The base category for sector is Less Knowledge Intensive Services (LKIS). The number of observations reduces as the time lag increases, because not all firms are observed in all time periods.

Table 11
Impact of collaborating with SFI research centres on firm-level R&D intensity, heterogeneity analysis for research domain of research centre.

Variable	Impact 1–2 years after treatment	Impact 3–4 years after treatment	Impact 5–6 years after treatment
ICT	0.611*** (0.084)	0.682*** (0.094)	0.704* (0.088)
Biosciences	0.593*** (0.091)	0.616*** (0.088)	0.623* (0.078)
Underpinning Technology	0.502*** (0.094)	0.483*** (0.099)	0.419*** (0.087)
Post-treatment	–0.032 (0.011)	–0.047 (0.013)	–0.039 (0.017)
Pre-treatment	0.097 (0.018)	0.063 (0.015)	0.041 (0.013)
Total observations	836	640	415
Treated firms	73	59	39
Matched untreated	219	177	117
R ²	0.33	0.29	0.27

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors in parentheses. Control variables defined in Table 1, as well as firm and year fixed effects are included in all models. 'ICT' stands for Information and Communications Technology. The number of observations reduces as the time lag increases, because not all firms are observed in all time periods.

non-collaborating firms, the DiD accounts for possible omitted variable bias, by using the panel structure of our dataset. Therefore, our study is able to make use of our novel panel data to perform a robust analysis.

Our analysis suggests three main empirical findings that offer new insights on the impact of publicly-funded research centre collaborations on firm-level R&D investment behaviour. First, firms that collaborated with SFI research centres experienced an increase in their in-house R&D intensity in the 1–2 year period after the collaboration begins. The magnitude of this impact increases over time. The second insight offered

by the analysis, is that collaborating with publicly-funded research centres can stimulate the research component of firms' in-house R&D, but it takes time for this impact to materialise. Firms that collaborate with SFI research centres significantly increase the proportion of applied research in their in-house R&D, in the 3–4 and 5–6 year periods following the collaboration's start date. This result represents a significant re-orientation of firms' R&D investment towards applied research. Thirdly, firm-specific heterogeneity plays a key role in determining the strength of our observed treatment effects. While the impact of collaboration on firms' overall in-house R&D is greater for large firms, SMEs experience a greater increase in applied research orientation. This suggests that the mechanisms driving the impact of collaboration on firm-level R&D are most pronounced in large firms, who may already have sufficient absorptive capacity to internalise the knowledge spillovers from the collaboration. In contrast, SMEs may need to build up the specific scientific part of their absorptive capacity to reap the full benefits of collaboration.

From a policy perspective, our findings suggest two potential implications. The first implication concerns the specific impacts associated with a major shift in national science policy on firm-level R&D. Results from the Irish experience of the strategic decision to embrace large-scale, targeted investment in basic and applied research suggest that this type of policy programme is a viable policy option for other countries. However, it is perhaps important to highlight that Ireland had reached a relatively high level of industrial development by the time the research centres programme was introduced (DBEI, 2012). This stage of development enabled Ireland to allocate significant funding to the programme, and implement it in a rapid timescale (DBEI, 2014; SFI, 2018). Economies with a less-advanced industrial base, and/or lower research capacity in their higher education system, may struggle to achieve the same returns as Ireland, if the underlying conditions are not as favourable. In addition, Ireland is a small country, and policy experimentation can often be most effectively trialled in this context (OECD, 2011). Though beyond the scope of this paper, the specific

Table 12

Impact of collaborating with SFI research centres on firm-level basic and applied research intensity, heterogeneity analysis for research domain of research centre.

Outcome variable: Applied research intensity			
Variable	Impact 1–2 years after treatment	Impact 3–4 years after treatment	Impact 5–6 years after treatment
ICT	0.903*** (0.091)	0.952*** (0.083)	0.894* (0.075)
Biosciences	0.883*** (0.083)	0.826*** (0.079)	0.794* (0.098)
Underpinning Technology	0.712*** (0.098)	0.731*** (0.089)	0.707*** (0.077)
Post-treatment	−0.067 (0.009)	−0.011 (0.011)	−0.024 (0.013)
Pre-treatment	0.081 (0.012)	0.073 (0.025)	0.055 (0.021)
Total observations	836	640	415
Treated firms	73	59	39
Matched untreated	219	177	117
R ²	0.36	0.31	0.29
Outcome variable: Basic research intensity			
ICT	−0.013 (0.01)	0.193** (0.011)	0.141 (0.023)
Biosciences	0.032 (0.012)	0.101*** (0.078)	0.105 (0.033)
Underpinning Technology	−0.024 (0.012)	−0.073 (0.041)	−0.104 (0.063)
Post-treatment	−0.043 (0.028)	−0.014 (0.011)	−0.088 (0.025)
Pre-treatment	0.007 (0.063)	0.001 (0.072)	0.035 (0.052)
Total observations	836	640	415
Treated firms	73	59	39
Matched untreated	219	177	117
R ²	0.22	0.26	0.21

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors in parentheses. Control variables defined in Table 1, as well as firm and year fixed effects are included in all models. 'ICT' stands for Information and Communications Technology. The number of observations reduces as the time lag increases, because not all firms are observed in all time periods.

conditions under which this type of large-scale policy initiative was able to succeed is an important issue which merits further study. Notwithstanding these points, the Irish experience suggests that other countries with similar underlying conditions could benefit from this form of targeted investment in the science base.¹⁴

Our study's second policy implication concerns the specific way in which this major policy programme was operationalised in Ireland, and is suggestive of how to build industry-relevant research capacity within selected fields of the higher education system, where little pre-existing infrastructure existed. SFI research centres' dual mandate to conduct scientific research *and* collaborate with firms sets the programme up as a capacity building policy instrument. Other more common policy instruments (such as R&D grants which incentivise firms to collaborate with universities) allocate funding directly to firms. However, in the case of SFI research centres, it happens the other way around. In this instance, the main incentive for firms to collaborate with SFI research centres is to work with leading academics and research teams, and the

¹⁴ An important caveat is that our study is based on a relatively small sample of firms. Although our sample is representative (see Appendix C in Supplementary material), the sample size remains a limitation for our study. Therefore, the implications for policy in Ireland, but especially for other countries seeking to learn from the Irish experience, should be considered with this in mind.

Table 13

Impact of collaborating with SFI research centres on firm-level basic and applied research share, heterogeneity analysis for research domain of research centre.

Outcome variable: Applied research share			
Variable	Impact 1–2 years after treatment	Impact 3–4 years after treatment	Impact 5–6 years after treatment
ICT	29.51 (0.521)	27.85*** (0.449)	31.71** (0.612)
Biosciences	37.54 (0.563)	20.25*** (0.219)	27.61** (0.686)
Underpinning Technology	9.01 (0.721)	11.32** (0.815)	20.01* (0.751)
Post-treatment	−0.047 (0.615)	−0.092 (0.721)	−0.104 (0.637)
Pre-treatment	12.065 (0.193)	20.026 (0.186)	1.034 (0.217)
Total observations	836	640	415
Treated firms	73	59	39
Matched untreated	219	177	117
R ²	0.32	0.29	0.24
Outcome variable: Basic research share			
ICT	−29.01 (0.536)	−3.17 (0.521)	−0.031 (0.307)
Biosciences	6.11 (0.796)	3.87 (0.751)	−0.107 (0.652)
Underpinning Technology	−01.91 (0.817)	−4.15 (0.536)	−12.007 (0.442)
Post-treatment	−0.018 (0.096)	−0.029 (0.081)	−0.091 (0.071)
Pre-treatment	0.032 (0.182)	1.012 (0.204)	0.096 (0.364)
Total observations	836	640	415
Treated firms	73	59	39
Matched untreated	219	177	117
R ²	0.21	0.19	0.23

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Robust standard errors in parentheses. Control variables defined in Table 1, as well as firm and year fixed effects are included in all models. 'ICT' stands for Information and Communications Technology. The number of observations reduces as the time lag increases, because not all firms are observed in all time periods.

life-span of research centres will in all likelihood far out-live that of an individual funded R&D project.¹⁵ In addition, the requirement that 30 per cent of funding must come from industry partners ensures that research centres remain committed to knowledge translation as well as knowledge creation. In summary, for countries seeking to develop their publicly-funded science base *and* harness it to enhance the economy, dual mandate research centres appear to be an effective policy intervention. Our findings suggest that this specific form of dual-mandate research centres programme is at the very least worth exploring by policymakers in different international contexts.

While this study provides new insights on the effectiveness of publicly-funded research centres as a science policy instrument, it is important to highlight two specific limitations, which presents an opportunity for future research. Firstly, the analysis considers the impact of research centre collaborations on firm-level R&D intensity and composition, but does not examine firm-level innovation or firm performance. Our dataset contains no measure of firm-level innovation (e.g. sales from new products), to facilitate such an analysis. In addition, the firm performance impacts of projects focused more on research, as opposed to

¹⁵ For example, Scandura (2016) highlights that funded firm-university R&D projects last three years on average, while the SFI research centres have been in continuous existence since 2003.

development, are likely to occur over a long time scale (Coad et al., 2020). Although our dataset has a sufficient number of treated firms to examine R&D effects, these firms are distributed over the full period 2007–2017. To accurately access the firm performance impacts of research centre collaborations would require one of two extensions to our study: 1) a panel dataset of similar length to ours, but with a much larger cohort of treated firms in the initial 1–2 years, that are observed throughout the dataset (i.e. a highly balanced panel); and, 2) a much longer dataset which follows treated firms over 20–30 years. Notwithstanding these challenges, future research would benefit from examining the innovation and longer-term performance impacts of research centre collaborations. Secondly, future research would benefit from including control variables capturing firms' technological record prior to collaboration, such as patents. No variable capturing firm-level patenting behaviour was available to this study, but future studies could refine their matching approach by the use of this variable. Despite these limitations, this study represents a significant step forward in terms of understanding how publicly-funded research centres impact firms' R&D investment behaviour.

CRedit authorship contribution statement

Kevin Mulligan: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Helena Lenihan:** Conceptualization, Methodology, Validation, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Justin Doran:** Methodology, Software, Validation, Writing – original draft, Writing – review & editing. **Stephen Roper:** Conceptualization, Validation, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

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