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R&D policy instrument mix sequencing: evaluating the impact of receiving R&D grants and R&D tax credits over time on firm-level R&D

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ABSTRACT
The R&D policy instrument mix concept has become increasingly important for understanding how public R&D support drives firm-level R&D. To-date, empirical studies have conceptualised the R&D policy instrument mix as a static unit, whereby firms receive different R&D policy instruments at one point in time. However, firms can also receive different instruments in a sequence, over time. While potential sequencing effects are well rehearsed theoretically, this issue remains a major gap in the empirical literature. Our study evaluates, for the first time, how R&D policy instrument mix sequencing impacts firm-level R&D. We construct a unique dataset, comprising 8,556 unique firms, and 36,136 firm-year observations, over a 17-year period for Ireland. Our analysis focuses on two different R&D policy instruments (R&D grants and R&D tax credits) pursuing the same policy objective. We develop a novel approach to measure R&D policy instrument mix sequencing, focusing on the R&D policy instruments firms receive over a four-year time window. We implement this approach using a multi-treatment panel-data matching approach, which addresses issues of selection bias. Our results suggest that R&D policy instrument mix sequencing is highly effective at driving firm-level R&D, and that some sequences are more effective than others. These findings highlight opportunities to realise superior policy outcomes through targeted sequencing.

KEYWORDS
Policy mix; R&D policy instrument mix sequencing; public R&D support; R&D grant; R&D tax credit; impact evaluation

JEL CLASSIFICATION
O25; O30; D04; O38; D22; O31

1. Introduction

The effectiveness of public support to R&D in firms, in terms of incentivising additional private investment in R&D, has been extensively studied (see Becker 2019; Dimos and Pugh 2016). Evidence suggests that both R&D grants and R&D tax incentives, which are the two primary policy instruments to support corporate R&D, generate positive R&D input

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additionality in firms (see Czarnitzki, Hanel, and Rosa 2011; Henningsen, Hægeland, and Møen 2015; Hünermund and Czarnitzki 2019; Hussinger 2008; Rao 2016; Santoleri et al. 2022; Steinmo, Lauvås, and Rasmussen 2022; Thomson 2017). More recently, since the works of Nauwelaers et al. (2009) and Flanagan, Uyarra, and Laranja (2011), the concept of the R&D policy instrument mix has gained increasing attention for better understanding and evaluating the impact of public R&D funding on firm-level R&D (e.g. Acebo and Miguel-Dávila 2023; Flanagan and Uyarra 2016; Martin 2016; OECD 2020; Russo and Pavone 2021). An R&D policy instrument mix occurs when firms receive a combination of different R&D policy instruments that target similar policy goals, as opposed to a single instrument. This can occur at one point in time, but also *over time*, when firms receive policy instruments in a *sequence* (Flanagan, Uyarra, and Laranja 2011; Nauwelaers et al. 2009; Rogge and Reichardt 2016; Schmidt and Sewerin 2019). Evaluation studies considering a mix of R&D policy instruments have focused almost exclusively on firms that receive different instruments at one point in time. R&D policy instrument mix sequencing, however, is almost completely unexplored in empirical analyses. Coburn et al. (2021, 20) have recently lamented this fact, calling for future empirical research 'to study the sequencing of interventions over the long term'. Our study addresses this specific issue, both conceptually and empirically. We achieve this by investigating the following critical research question: What is the impact of receiving R&D grants and R&D tax credits in different sequences over time on firm-level R&D?

By addressing the above, we make two novel contributions to the literature on public funding for R&D. Our first contribution is to bridge a fundamental gap between theory and empirical practice. Beginning with the seminal conceptual work of Flanagan, Uyarra, and Laranja (2011), and thereafter, throughout the development of R&D policy instrument mix theory (Meissner and Kergroach 2021; Rogge and Reichardt 2016; Schmidt and Sewerin 2019), sequencing has always been fundamental to conceptually understanding how policy instruments impact firm-level R&D. For example, some firms may receive an R&D grant in a given year, followed by an R&D tax credit the following year. In cases such as this, Cunningham et al. (2016, 527) argue that 'it may be the sequencing of instruments over time that is of key importance, rather than the actual interplay of instruments at a given phase'. However, almost all previous empirical research has focused on what Rogge and Reichardt (2016, 1630) refer to as 'a static snapshot of a policy mix at a given point in time'. Our paper builds on and extends the empirical literature on the R&D policy instrument mix concept, by examining the impact of R&D policy instrument mix sequencing on firm-level R&D. It does so by providing the first wholly comprehensive empirical analysis of R&D policy instrument mix sequencing.

Our second contribution is to develop a novel methodological approach to measure R&D policy instrument mix sequencing. Empirically examining R&D policy instrument mix sequencing requires a different methodological conceptualisation, than that used by previous studies on this topic. This is because an R&D policy instrument mix sequence occurs *over time*, as firms receive multiple instruments in different years. This is very different to focusing on a situation whereby firms receive a combination of R&D grants and R&D tax credits in one single year. It is necessary, therefore, to conceptualise the sequence within what we term a specific '*time window*', with the sequence's impact unfolding over this time window. To achieve this, we conceptualise different R&D policy instrument mix sequences as discrete units, that occur over time. For example, in a given time window (e.g. four years), a firm may receive two R&D policy instruments. The firm receives the *first* R&D policy instrument in year *t0*, and then a second R&D policy instrument two years later (i.e. $t + 2$). We treat this sequence as one treatment unit, which unfolds over four years (i.e. first policy instrument in year *t0*, second policy instrument in year $t + 2$). We then evaluate the impact of the treatment unit, during all the years comprising the sequence. Such an approach enables us to examine the impact of different R&D policy instrument mix sequences relative to one another, *as well as* situations where firms receive only a single R&D policy instrument.

Our analysis is enabled by the construction of a unique firm-level panel dataset comprising 8,556 unique firms, and 36,136 firm-year observations, for the period 2000–2017 for Ireland. The data provide detailed information on R&D expenditure, the receipt of R&D grants, and R&D tax credit claims. The data reveal that R&D policy instrument mix sequencing is empirically important. When measured over a four-year time window, approximately 30 percent of firms that receive R&D policy instruments, receive them in different sequences over time. Our empirical findings indicate that firms receiving a mix of R&D grants and R&D tax credits in a sequence over time, carry out more additional private R&D expenditure than firms receiving only one of the two instruments. While the sequence of R&D grants followed by R&D tax credits is most effective, all sequences are more effective than receiving single R&D policy instruments. These results highlight the potential for leveraging the impact of an initial R&D policy instrument, with targeted subsequent additional R&D policy instruments. This suggests that there may be opportunities for policymakers to realise superior policy outcomes and improvements through deliberate sequencing, as part of any funding allocation decision-making process.

The remainder of the paper is organised as follows. In Section 2, we review the literature on R&D grants and R&D tax credits, and how their sequencing may impact firm-level R&D. Section 3 details the data, the construction of our measures of R&D policy instrument mix sequences, and our econometric approach. Section 4 presents and discusses our results. Finally, Section 5 concludes, and provides a discussion of the potential policy implications emanating from our analysis and offers avenues for future research.

2. The R&D policy instrument mix and firm-level R&D

Following the work of Nauwelaers et al. (2009) and Flanagan, Uyarra, and Laranja (2011), R&D policy instrument mix theory gained significant prominence for understanding how public R&D funding impacts firm-level R&D (e.g. Flanagan and Uyarra 2016; Meissner and Kergroach 2021; Petrin and Radicic 2023; Rogge and Reichardt 2016; Schmidt and Sewerin 2019; Shi et al. 2023). The R&D policy instrument mix concept 'implies a focus on the interactions and interdependencies between different policies as they affect the extent to which intended policy outcomes are achieved' (Flanagan, Uyarra, and Laranja 2011, 702). The idea behind this concept is the combination of *different* R&D policy instruments that pursue the same policy objective. This can occur at one point in time (i.e. a static mix), but also *over time*, when firms receive different policy instruments in a *sequence*. To-date, empirical studies have solely conceptualised the R&D policy instrument mix as static, occurring at a point in time. The concept of R&D policy instrument mix sequencing is almost completely unexplored in empirical analyses. In this paper, we build on and extend the empirical literature on the R&D policy instrument mix concept, by examining the impact of R&D policy instrument mix sequencing on firm-level R&D.

2.1. R&D grants and R&D tax credits

In most countries throughout the world, R&D grants and R&D tax credits are the main policy instruments used by governments to support private firm-level R&D (Cunningham and Link 2021). While both instruments share similar objectives, they also have distinct characteristics which may influence firm-level R&D differently (see e.g. Hall and Van Reenen 2000, Nana-Cheraa, Roper, and Mole 2023). R&D grants are typically provided to firms for specific R&D projects that are prioritised by funding agencies (Czarnitzki and Lopes-Bento 2014; David, Hall, and Toole 2000). Firms apply for R&D grants prior to starting R&D projects, and funding is provided simultaneously to the performance of the R&D projects, or shortly after completing the projects (Henningsen, Hægeland, and Møen 2015). Recipient firms, therefore, receive immediate cash flow from the government to co-fund the awarded R&D projects. Since R&D grants are awarded for specific projects, funding may involve a bias towards or away from particular types of projects or particular technologies (Lenihan et al. 2024). Complying with eligibility criteria may also influence the recipients' choices as to which projects to seek out for grant funding (Petrin and Radicic 2023). As a result of this, R&D grants change the ranking of projects within firms' R&D portfolios and lead to a different allocation of resources across projects, than would have been the case without grant support. In addition to serving as a source of finance, grant recipients may also benefit from a signalling effect (Feldman et al. 2022). Winning a competition for a subsidy signals to potential investors a high project quality and strong innovative capabilities, which can facilitate the receipt of complementary financing (Busenitz et al. 2005). The external monitoring of grant expenditure by programme authorities may stimulate firms to manage their R&D projects more carefully, although receiving external grants may also introduce financial slack into firms, resulting in less stringent financial management (Teirlinck, Spithoven, and Bruneel 2021).

R&D tax credits are deductions from a firm's corporation tax, which lower the marginal cost of R&D (Rao 2016). In contrast to R&D grants, R&D tax credits are usually claimed after the R&D expenditure has occurred (Thomson 2017). The primary function of R&D tax credits is to overcome liquidity constraints of R&D performing firms (Czarnitzki, Hanel, and Rosa 2011; Dai and Chapman 2022; Thomson 2017), allowing them to undertake projects at the margin of their portfolios (i.e. that they would not have started otherwise, because of too low expected returns). By providing additional liquidity, R&D tax credits are neutral in terms of their portfolio effects, since firms can spend income from such tax credits freely (Neicu, Teirlinck, and Kelchtermans 2016). Firms will, therefore, continue to invest in R&D projects in the order which offers the greatest private return. R&D tax credits are usually also free from discretionary biases that are involved in the award of R&D grant decisions, although some R&D tax credit schemes are restricted to certain types of firms (e.g. SMEs), or differ in generosity by firm type, technology or R&D activity (Appelt and Galindo-Rueda 2023). Provided that firms' R&D activities meet the eligibility criteria, R&D tax credits are predictable (Labeaga et al. 2021). As R&D tax incentives typically run for a long period of time, they provide a reliable basis for long-term financial planning and R&D decisions. Therefore, R&D tax credits may not only induce firms to undertake more R&D, but also encourage them to conduct R&D on a continuous basis (Dai and Chapman 2022, Nana-Cheraa, Roper, and Mole 2023).

Both R&D grants and R&D tax credits can be subject to crowding-out (David, Hall, and Toole 2000; Santos, Cincera, and Cerulli 2024). Crowding-out occurs when firms apply for R&D grants, or claim R&D tax credits, to cover R&D expenditure they would have undertaken even without the support. To give an indicative example, in the case of R&D grants, crowding-out can occur when firms first decide to conduct a certain R&D project, and then search for funding opportunities. Should they be awarded an R&D grant, the public money is used to substitute their own private funds. This will not increase the amount of financial resources devoted to the R&D project, rather just replace public for private funding. As discussed by Dimos, Fai, and Tomlinson (2023), crowding-out may be reduced by the design of R&D support programmes. For example, if grants are provided for R&D in specific fields of technology only, or in a distinct organisational from (e.g. as a co-operative project). In that way, firms may be stimulated to enter into R&D projects they would otherwise not have started (i.e. the concept of additionality). As discussed by Dimos et al. (2022), relative to R&D grants, the potential for crowding-out is even more prominent with R&D tax credits. This is because the tax reduction is granted only after a firm has conducted and fully financed R&D activities in a given year. Additionality (i.e. no or partial crowding-out) of R&D tax credits requires that firms plan with the tax compensation they will receive in mind, when deciding on the size of their R&D expenditure (Dai and Chapman 2022; Lokshin and Mohnen 2012).

As detailed by Petrin and Radicic (2023), another important difference between R&D grants and R&D tax credits refers to how effective they are with respect to firm size. Crass et al. (2019) highlight that small firms often conduct only one R&D project at a time, and this project is often key to the firm's business strategy (e.g. by technologically updating their existing products, or for entering into new fields of technology). This situation limits the ability of small firms to align their R&D activities to the content or conditions required by R&D grant programmes (Busom, Corchuelo, and Martínez-Ros 2014). By contrast, large firms with a multi-project R&D portfolio will find it easier to align R&D projects to the requirements of grant programmes, or to start additional projects to benefit from grant funding (Rao 2016). However, in cases where small firms can make use of R&D grant programmes, crowding-out is often found to be less likely (Bronzini and Piselli 2016; González and Pazó 2008), reflecting the higher financial constraints for funding R&D in small firms (Petrin and Radicic 2023).

2.2. R&D policy instrument mix and firm level R&D

Recent studies have increasingly focused on analysing the mechanisms that may occur when firms receive both R&D grants and R&D tax credits simultaneously (Dimos et al. 2022; Guerzoni and Raiteri 2015; Neicu 2019; Neicu, Teirlinck, and Kelchtermans 2016; Nana-Cheraa, Roper, and Mole 2023; Petrin and Radicic 2023; Shi et al. 2023). These studies find that both instruments can mutually reinforce one another's impact. One key mechanism for this is complementarity, which enables firms to create and internalise synergies between different R&D activities (Guellec and van Pottelsberghe 2003; Neicu, Teirlinck, and Kelchtermans 2016; OECD 2020). These studies highlight that the complementarity between the two instruments mainly arises from the fact that each instrument addresses a different type of R&D investment decision. Since R&D tax credits provide additional financial means after the completion of an R&D activity, they enable firms to increase and/or sustain R&D investments. R&D grants, in contrast, usually require R&D activities to be designed according to the eligibility criteria of the R&D programme (which, as detailed later, is particularly the case for the Irish R&D support programmes studied in this paper). As such, R&D grants can encourage firms to explore new knowledge and/or areas of technology (Neicu 2019). New discoveries based on R&D grants may, in-turn, stimulate the development of products and services with a particularly high degree of novelty.

In contrast to the above, R&D tax credits are more likely to be used for R&D targeted at improving existing products and services (Steinmo, Lauvås, and Rasmussen 2022). This can also have knock-on effects, and result in the development of new production methods, and improvements to the overall management of innovative processes (Hullova et al. 2019). Combining R&D tax credits and R&D grants can help firms to conduct a broader array of R&D activities, and produce more diverse and/or more ambitious innovations (Douglas and Radicic 2022; Neicu 2019). In this way, receiving a combination of R&D policy instruments can result in complementarity, and lead to a higher level of additionality. This occurs where the impact of the R&D policy instrument mix, is over-and-above, the sum of the impacts of each single policy instrument in the mix (Shi et al. 2023). However, receiving a mix of R&D policy instruments can also lead to substitution (Guellec and van Pottelsberghe 2003; Nauwelaers et al. 2009; Shi et al. 2023). Substitution will occur if a firm uses both instruments to increase the share of public funding for its R&D investments, instead of expanding its own private R&D activities (Dimos, Fai, and Tomlinson 2023). In such a situation, offering funding opportunities through both R&D grants and R&D tax credits will result in lower additionality for each instrument (Nana-Cheraa, Roper, and Mole 2023). While the concepts of complementarity and substitution have been studied in the case of R&D policy instruments at a point in time, the next section examines how they may function regarding a mix of instruments over time.

2.3. R&D policy instrument mix sequencing and firm-level R&D

This section discusses why and how different sequences of R&D grants and R&D tax credits over time may result in differences in firm-level input additionality. For this exercise, we assume that a firm is aware of grant and tax credit support opportunities for R&D, and will choose the policy mix, and its sequencing, which best fits the firm's R&D activities. It is important to note that in the empirical context of Ireland, for which we will test our hypotheses, R&D grants are provided based on specific R&D projects. While R&D tax credits can be claimed on the same project, they cannot be claimed for grant-supported R&D spending (Irish Revenue Commissioners 2022). For example, if a firm spent €100,000 in total on R&D in a given year, and €40,000 of this came from an R&D grant, the firm would only be eligible to claim R&D tax credit support on €60,000 of their R&D spending (i.e. total R&D, minus the R&D grant). This means that while the same R&D project can be funded by both instruments, the same spending cannot be publicly-funded twice. Therefore, a sequential R&D policy instrument mix implies either a sequencing of spending on 'the same' R&D project over time, or a sequencing of different R&D projects at the firm level.[1] Our dataset does not have information about the number of discrete R&D projects each firm is involved in. However, given our empirical context, we assume that each firm decides for each R&D project whether they will use an R&D grant and/or an R&D tax credit in a given year, and this choice will then inform the decision of what R&D instrument(s) (if any) to use in subsequent years.

We begin by examining the situation whereby firms first receive an R&D tax credit, followed by an R&D grant in later periods. In this situation, we suggest that a higher input additionality, as compared to receiving only one type of R&D policy instrument, is likely to occur. This is because, as detailed by Dai and Chapman (2022) among others, R&D tax credits will enable firms to start R&D projects that otherwise would have been postponed, or not pursued, due to too low expected return on investment (e.g. because of too high technological or market uncertainty, too high cost, or too low returns). In the case of larger firms, a broader portfolio of R&D projects enabled by R&D tax credits means that such firms will be able to command a more diverse suite of R&D projects (Lenihan et al. 2024). For smaller firms, R&D tax credits can enable them to engage in R&D as a matter of routine and over longer-term time-horizons (Labeaga et al. 2021). As noted by Dumont (2017), this can enable firms to sustain R&D activities on a continuous basis. In turn, this can result in firms generating more ideas for potential R&D projects, and/or enlarging their R&D portfolio. Therefore, regardless of firm size, we suggest that there will be an increase in the probability that at least one project will match the eligibility criteria of an R&D grant programme, making it more likely that the firm can successfully apply for grant funding. This additional R&D grant funding will free up internal financial resources, which could be used to finance more projects, or to equip existing projects with a higher budget. Such a broader R&D portfolio is likely to generate higher total returns (see Klingebiel and Rammer 2014, on the positive effect of portfolio size on returns from innovation). This will create a situation in which persistent R&D and innovation, prepares the ground for more R&D and innovation (Flaig and Stadler 1994; Holl 2021), allowing firms to continuously increase their R&D expenditure. Based on the above, we present our first hypothesis as follows:

H1: Sequencing R&D support through an R&D tax credit, followed by an R&D grant, will result in higher input additionality, compared to receiving only one of the two R&D policy instruments.

In situations where firms first receive an R&D grant, followed by an R&D tax credit in later periods, a similar result is likely to occur, though through a different mechanism (Dumont 2017; Marino et al. 2016). As detailed by Freel, Liu, and Rammer (2019), one consequence of R&D grant funding is that firms must design R&D projects according to the requirements of the funding programme (e.g. with respect to project length, types of project partners, technology focus, types of cost, project size). In small to medium-sized

[1] In cases where a firm applies for an R&D grant and the application is rejected, it is still possible to claim the expense of this R&D activity under the R&D tax credit scheme (at the end of the financial year).

firms, which usually have very limited resources for R&D, projects designed for R&D grant funding will leave other R&D projects behind, either by limiting the size of these other projects, or by putting them on hold (Radas et al. 2015). In cases where firms receive an R&D tax credit in later periods, the additional funds can be used to start or enlarge these other projects (Czarnitzki, Hanel, and Rosa 2011). At the same time, grant funding is likely to have helped firms to better manage their R&D projects (Nilsen, Raknerud, and Iancu 2020). Therefore, we suggest that this learning effect from R&D grant funding, increases the effectiveness of R&D projects co-financed from R&D tax credits in later periods. This higher effectiveness provides the basis for higher input additionality, as the returns from private investment in R&D will be higher, as compared to a situation when only one type of R&D policy instrument is used. As such, we propose our second hypothesis as follows:

H2: Sequencing R&D support through an R&D grant, followed by an R&D tax credit, will result in higher input additionality, compared to receiving only one of the two R&D policy instruments.

We now focus on comparing the two R&D policy instrument mix sequences as discussed above, in terms of their relative impacts on firm-level R&D. We suggest that receiving an R&D grant first, followed by an R&D tax credit in later periods, will result in higher levels of R&D additionality (compared to the situation whereby the order in which firms receive these instruments is reversed). A key argument for a higher additionality of an R&D grant followed by an R&D tax credit, is that R&D grant funding can enable significant learning effects in firms (Dimos et al. 2022). This is especially the case if firms use R&D grant funding to engage in R&D activities that are more distant to their existing R&D capabilities (Lee, Wu, and Pao 2014; Nilsen, Raknerud, and Iancu 2020; Perez-Alaniz et al. 2023; Santoleri et al. 2022). If a firm decides to engage in new areas of R&D, grants can provide a higher amount of financing (relative to R&D tax credits), enabling more investment in building-up new R&D capabilities and exploring new fields of technology or application (Dimos, Fai, and Tomlinson 2023). Provided that these new R&D activities lead to new knowledge, subsequent funding through R&D tax credits can enable firms to explore this knowledge, and develop it further towards market applications (Neicu 2019). Since these applications are likely to constitute new market offers and meet customer demands not yet addressed by the firm, they promise high returns (Acebo and Miguel-Dávila 2023). Hence, firms should be willing and able to invest larger amounts of private funds in these development projects, resulting in a high level of R&D additionality (Testa, Szkuta, and Cunningham 2019).

We next consider the opposite case, when firms decide to finance their R&D activities through R&D tax credits first, before using R&D grants to either continue their R&D portfolio or to start new R&D projects. In this case, recent research by Dimos et al. (2022) suggests that a lower level of additionality is likely (compared to the reverse order of the two instruments). The key argument for this is that R&D tax credits will primarily be used for expanding the firm's core R&D activities and to explore R&D projects at the margins of the firm's R&D portfolio. The outcomes of these tax credit supported-R&D projects are less likely to change a firm's R&D capabilities and command of technologies, producing a less radical change to the firm's product offerings. The incentives for firms to invest a higher amount of private R&D to conduct these R&D activities are hence lower than in the opposite case. If R&D grants are used in a second step to explore new areas of R&D, the level of complementarity between tax credit-funded R&D projects and grant-funded R&D projects will be lower than in the reverse order. Based on this reasoning, our third and final hypothesis is as follows:

H3: Sequencing R&D support through an R&D grant, followed by an R&D tax credit, will result in higher input additionality, compared to receiving an R&D tax credit followed by an R&D grant.

In reality, more complex R&D policy instrument mix sequences than the ones discussed above are likely to emerge (e.g. an R&D grant followed by a simultaneous use of both instruments). For these more complex situations, one may also expect higher input additionality than if firms received any of these instruments on their own. However, suggesting possible differences in the effects that these more complex R&D policy instrument mix sequences have on firm-level R&D, when compared to one another, may not be possible. A key reason for this is that multiple overlapping mechanisms can be at play at the same time. Having provided a theoretical discussion on the mechanisms through which we expect R&D policy instrument mix sequencing to result in additional firm-level R&D, we proceed to a discussion of our methodology and data.

3. Methodology and data

The goal of our paper is to evaluate the impact of R&D policy instrument mix sequencing on firm-level R&D. To achieve this, we construct a unique and novel dataset, based on two main sources. The first source comprises administrative data from the funding agencies and government bodies responsible for allocating the two main R&D policy instruments available to firms in Ireland, from 2006 to 2017: R&D grants, and R&D tax credits. These detailed administrative data are combined with our second source, comprising annual survey data on firms' R&D activities, covering the period from 2000 to 2017. The longer time period pertaining to the latter source of data ensures that we are able to capture key information on all firms, in the period before they received R&D grants and/or claimed R&D tax credits.

3.1. Institutional background and administrative data

The Irish Government plays a key role in supporting R&D in firms based in Ireland (DETE 2021). Government support for firm-level R&D in Ireland includes both R&D grants and R&D tax credits and has been increasing steadily since 2006, in a process of catching up with other OECD countries (OECD 2023). Of these two support types, R&D tax credits are by far the largest, representing 85 percent of total government support for firm-level R&D in Ireland (OECD 2023).[2] R&D tax credits are available to all R&D performing firms based in Ireland. Firms can claim up to 25 percent of eligible R&D

[2]For more information on the details of the R&D tax credit scheme, see: https://www.revenue.ie/en/companies-and-charities/reliefs-and-exemptions/research-and-development-rd-tax-credit/index.aspx.

expenditure (Irish Revenue Commissioners 2022). In addition, firms can apply for direct funding up to 80 percent of the costs of an R&D project (Lenihan, Mulligan, and O'Driscoll 2020). Our administrative data capture all R&D tax credit claims from 2006 to 2017 (see Panel A in Table A1 of the Supplementary Material accompanying this paper).

Firms in Ireland can also apply for different types of direct R&D grants, from the Industrial Development Agency (IDA) Ireland, and Enterprise Ireland (EI). IDA Ireland focuses on attracting and embedding foreign-owned multinational firms to Ireland, and R&D support plays a key role in this (IDA Ireland 2021).[3] EI, on the other hand, focuses on domestic Irish-owned firms (Enterprise Ireland 2022), which are predominantly Small and Medium-sized Enterprises (SMEs).[4] While EI offers similar types of R&D grants to those provided by IDA Ireland, they are tailored to the needs of the domestic Irish industrial base.[5] Panel B in Table A1 of the Supplementary Material accompanying this paper presents the different types of R&D grants available to firms from IDA Ireland and EI, and the total number of R&D grants and R&D tax credits received by firms, from 2006 to 2017.

Our combined administrative dataset comprises the population of firms that received at least one of the above policy instruments, from 2006 to 2017, totalling 3,348 unique firms.

3.2. Firm level data

We merge the above administrative data with firm-level information from the Annual Business Survey of Economic Impact (ABSEI). ABSEI is an annual panel survey, conducted by Ireland's Department of Enterprise, Trade and Employment (DETE). The survey covers a population of approximately 4,000 firms annually, with a response rate of approximately 65 percent each year. The ABSEI dataset is unique, because it is obtained from a sample frame covering all firms that have ever engaged with Ireland's enterprise development agencies (DETE 2020).[6] As such, ABSEI is specifically designed to cover a large representative sample of the foreign-owned and domestic firms who have engaged with IDA Ireland and EI. Therefore, ABSEI provides an ideal platform to examine the sequencing of R&D policy instruments over time.

Merging firm-level data with the administrative data results in an unbalanced panel, with 8,556 unique firms and 36,136 firm-year observations, from 2000 to 2017. As Figure 1 illustrates, of the 3,348 unique firms included in the administrative dataset, only 2,300 firms also feature in the ABSEI survey. Our working sample thus specifically comprises 2,300 firms receiving at least one R&D grant and/or R&D tax credit, and 6,256 firms that do not receive any such form of support. Following standard practice, we refer

[3]For more on the R&D policy instruments available to firms from IDA Ireland, see: https://www.idaireland.com/scale-with-ida/funding-programmes-incentives.

[4]The European Union recommendation 2003/361 defines small-sized firms as firms with less than 50 employees, medium-sized firms as firms between 50 and 249 employees, and large-sized firms as firms with 250 employees or more. The recommendation also classifies firms according to their turnover or balance sheet (see http://data.europa.eu/eli/reco/2003/361/oj.), but the number of employees is the most commonly used classification (Eurostat 2019).

[5]For more information on the R&D policy instruments available from EI, see: https://www.enterprise-ireland.com/en/supports/funding-and-grants.

[6]The ABSEI survey specifically includes all client firms of Enterprise Ireland and IDA Ireland.

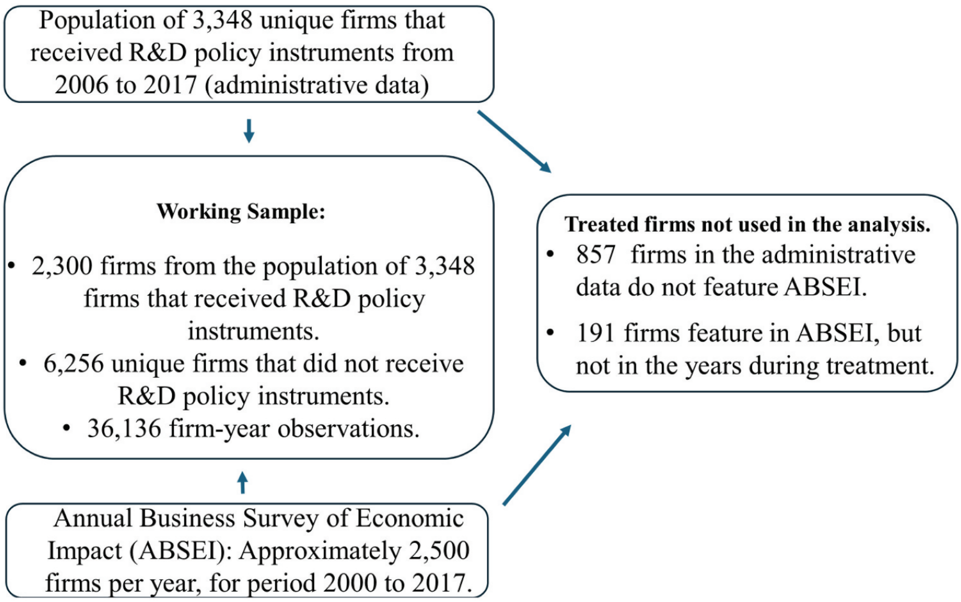

Figure 1. Diagram of working sample.

to these firms, respectively, as 'treated' and 'untreated'. In this context, there is a potential risk to the external validity of our analysis, if the 2,300 treated firms in our working sample are systematically different to the overall population of 3,348 treated firms. Table B1 in the Supplementary Material accompanying this paper presents the results of representativeness tests, which we carried out in line with previous studies, such as Bianchini et al. (2019), Lenihan et al. (2024), and Mulligan et al. (2022). Specifically, the tests compare key firm-level characteristics between the firms in our working sample, and the whole population of treated firms, as included in the administrative data. As Table B1 shows, our working sample is highly representative of the population of firms in the administrative data.

Moreover, as noted earlier, our dataset is an unbalanced panel. Table 1 shows the composition of our dataset, in terms of the number of times that firms are observed in the

Table 1. Number of times that unique firms feature in our working sample.

	Full sample		Treated		Untreated	
Categories	N	(%)	N	(%)	N	(%)
Feature only once	873	10.2	97	4.2	576	9.2
Feature two times	1,378	16.1	99	4.3	951	15.2
Feature three times	659	7.7	113	4.9	444	7.1
Feature four times	1,241	14.5	265	11.5	951	15.2
Feature five times	693	8.1	150	6.5	532	8.5
Feature six times	419	4.9	166	7.2	313	5.0
Feature more than six times	3,294	38.5	1,412	61.4	2,490	39.8
Total	8,556	100	2,300	100	6,256	100

Firms that appear only once are removed from the analysis. Firms featuring two times are included, if these data permit observing the time periods before and after firms are treated. For example, if Firm A was treated in *t0*, and we have one observation for this firm for *t-1* and another for *t+1*, Firm A is used in the analysis. Contrary to this, Firm A would be dropped if both observations pertain to years before or after *t0*.

panel. As Table 1 shows, approximately 66 percent of firms in the total sample feature at least four times in our dataset, with 24 percent of firms featuring between two to three times. Finally, approximately 10 percent of firms (873 firms) feature in the dataset only once.

3.3. Dependent variable

From a policy perspective, the most immediate outcome of an R&D policy instrument is an increase in firm-level R&D expenditure, which is commonly referred to as input additionality (Busom and Vélez-Ospina 2020; Mina et al. 2021). Therefore, our analysis focuses on firms' R&D expenditure as the dependent variable. Empirical studies typically measure firm-level R&D expenditure in two ways: (1) Using the natural logarithm of firms' total R&D expenditure (Caloffi et al. 2022; Dumont 2017); and (2) Using firms' total R&D expenditure, normalised by firm size (i.e. R&D intensity). As Alessandri and Pattit (2014) and Lenihan et al. (2024) note, using R&D intensity can introduce biased correlations into the econometric models, resulting from changes in the denominator used to normalise the variable (e.g. turnover or number of employees). For example, firms may continue to carry out R&D despite lower levels of turnover, resulting in a spurious increase in the measure of firm-level R&D expenditure (Busom and Vélez-Ospina 2020). Therefore, we define our dependent variable as total firm-level expenditure on R&D (in natural logarithm).

3.4. Measuring R&D policy instrument mix sequencing

An analysis of R&D policy instrument mix sequencing requires identifying the order in which firms receive different R&D policy instruments over time. To identify these sequences, we develop a novel approach following the three steps as outlined below. Our first step is to identify the R&D policy instrument that firms received *first*, and the year in which they received it (denoted as *t0)*. In any given year, firms can receive an individual R&D grant, an individual R&D tax credit, or both combined (i.e. a static mix). We then identify the R&D policy instrument (or static mix) that firms received *after* their first treatment. We repeat the process for all years after firms' *first* treatment. In doing so, we assign the value of $t+n$ ($n = 1 \ldots 17$) to each of the years following *t0*.

Our second step is to define the 'time window' in which to evaluate the impact of these sequences, on firm-level R&D. From a theoretical perspective, firms seek R&D policy instruments to engage in R&D activities that are unlikely to be financed internally (due to high risk or low marginal returns). Moreover, some firms, especially large-sized firms, tend to focus on R&D portfolios, rather than engaging in single R&D projects, in order to maximise complementarities across R&D projects and minimise risks (Klingebiel and Rammer 2014). However, the potential complementarities across different R&D projects in firms' R&D portfolios are unlikely to take place instantaneously. It may take some time (i.e. a lag) for firms to adjust their resources for such complementarities to arise (Hullova et al. 2019; Percival and Cozzarin 2008). As a result of this, we need to consider that firms may not seek to obtain R&D policy instruments year-on-year. Instead, they may allow time between R&D policy instruments, to ensure that they can reconfigure their resources, in a way that they can accommodate additional R&D projects (Kaiser and

Kuhn 2012; Mulligan et al. 2022). This is especially true for some firms, such as small-sized firms, which typically do not have specific R&D units, meaning that R&D activities may be carried out by the same employees involved in other activities such as, for example, manufacturing, design, and sales (Hullova et al. 2019).

Considering the above, we focus on the year in which firms receive their *first* R&D policy instrument (i.e. *t0*), and the three years after this initial year (i.e. *t* + *1*, *t* + *2*, and *t* + *3*), totalling four years. Our selected time window is based on the recommendations of the *Oslo Manual* (OECD/Eurostat 2018) and the practice of innovation surveys in the European Union (Community Innovation Survey – CIS). The CIS uses a three-year observation period for collecting firm-level R&D and innovation data. The length of the observation period should ensure that R&D and innovation activities, from the beginning to their completion, are covered. However, the manual also notes that this time window (i.e. three years) can be inappropriate for R&D activities that require longer lead times. As specifically noted by the *Oslo Manual* (OECD/Eurostat 2018, 185), 'a short observation period might result in assigning different innovation activities and outputs to different years, such as the use of co-operation, the receipt of public funding, and sales from new products. This could hamper some relevant analyses on innovation patterns and impacts'. Therefore, we focus on a time window of four years, as this enables sufficient time for firms to reconfigure their resources, as they receive a combination of different R&D policy instruments over time (for further discussion of this type of time lag effect in firm-level R&D, see Kaiser and Kuhn 2012; Mulligan et al. 2022; Vanino, Roper, and Becker 2019). The selected time window is supported by our data, as approximately 80 percent of firms that received R&D policy instrument mix sequences, did so within a time window of four years.

Our third and final step in this process, is to conceptualise R&D policy instrument mix sequences as individual 'treatment units'. To achieve this, our approach captures the different R&D policy instrument mix sequences as observed in our data, using binary variables. Table 2 presents the individual treatment units observed by following our above approach, along with the number of firms in each individual treatment unit.[7]

As Table 2 shows, we observe five individual treatment units. The first two comprise firms that receive only R&D tax credits, or only R&D grants, representing approximately 70 percent of treated firms. The remaining three treatment units comprise R&D policy instrument mix sequences over time. More specifically, the sequence *R&D tax credit followed by an R&D grant* comprises situations in which firms received an R&D tax credit first (in *t0*), followed by an R&D grant (in *t* + *1*, *t* + *2* and/or *t* + *3*). In turn, the sequence *R&D grant followed by an R&D tax credit* comprises situations in which firms received an R&D tax grant first (in *t0*), followed by an R&D tax credit (in *t* + *1*, *t* + *2* and/or *t* + *3*). These two instances represent approximately 24 percent of all treated firms. Finally, the sequence *R&D tax credit and R&D grant, followed by an R&D tax credit* comprises situations where firms received an initial static mix comprising an R&D tax credit and an R&D grant first

[7]As Table 1 shows, when merging administrative data and survey data, the final dataset is an unbalanced panel. This means that the working sample does not capture all observations in the administrative data. However, this issue does not affect our measures of R&D policy instrument mix sequences, as these are obtained directly from the administrative data, which captures all treated firms, enabling accurate measurement. Section 3.5 discusses this point further, with respect to measuring treatment effects.

Table 2. Policy instrument mix sequences found using our methodological approach.

	Sequencing: *t+3* years following *t0*	
R&D policy instrument mix sequences	Firms	Observations
Only R&D tax credits	654	2,495
Only R&D grants	965	3,081
R&D tax credit *followed by* an R&D grant	151	682
R&D grant *followed by* an R&D tax credit	407	1,707
R&D tax credit and R&D grant *followed by* an R&D tax credit	101	429
Total number of firms/observations	2,278	8,394

The category ***Only R&D tax credits*** comprises firms that receive an R&D tax credit during *t0* to *t+3*, and no other R&D policy instrument. The category ***Only R&D grants*** comprises firms that receive an R&D grant during *t0* to *t+3*, and no other R&D policy instrument. The category ***R&D tax credit followed by an R&D grant*** comprises firms that receive an R&D tax credit in *t0*, and at least one R&D grant during *t+1*, *t+2* and/or *t+3*. The category ***R&D grant followed by an R&D tax credit*** comprises firms that receive an R&D grant in *t0*, and at least one R&D tax credit during *t+1*, *t+2* and/or *t+3*. Finally, the category ***R&D tax credit and R&D grant followed by an R&D tax credit*** comprises firms that receive an R&D tax credit and an R&D grant in *t0*, and at least one R&D grant during *t+1*, *t+2* and/or *t+3*. Some firms received different combinations of R&D policy instruments, which are not suitable for the empirical analysis due to their small group sizes. Therefore, we do not include such firms in the final analysis. This explains the difference between the total number of treated firms presented in this table, and the total number of firms discussed in Section 3.1. The tabulations included in this table are obtained by considering the full sample of firms that received R&D tax credits and/or R&D grants that feature in the ABSEI survey. For the specific number of firms used in each specific analysis, see Tables E1 to E11 in the Supplementary Material accompanying this paper.

(in *t0*), followed by an R&D tax credit (in $t + 1$, $t + 2$ and/or $t + 3$). Of the treated firms, 4.3 percent received this form of treatment. The bottom of Table 2 provides precise definitions of these sequences.

Besides the above treatment units, a critical insight which emerged when operationalising our empirical approach is that once the issue of sequencing is considered, only 22 firms in our sample received a mix of R&D tax credits and R&D grants in *t0*, *and did not receive* other instruments in a sequence over time. This represents only approximately 1 percent of the sample of treated firms. Given the low number of firms that receive this 'static' type of R&D policy instrument mix, it is not possible to include this category as a unique treatment unit in our analysis.

3.5. Empirical model

Evaluating the impact of R&D policy instruments on firm-level R&D requires careful consideration of endogeneity due to the well-known selection into treatment problem (e.g. Caloffi et al. 2022; Czarnitzki, Hanel, and Rosa 2011; David, Hall, and Toole 2000; Greco et al. 2022; Labeaga et al. 2021). A selection bias can occur from two sources. Firstly, firms may self-select into treatment by actively seeking to obtain R&D support. Secondly, R&D policy instruments typically target specific firms and/or R&D activities. Programme managers will select those firms among all applicants that comply with eligibility criteria and are best suited for achieving specific policy goals (Mina et al. 2021; Santoleri et al. 2022). Such a deliberate selection process by programme managers is often the case for R&D grant programmes (Hünermund and Czarnitzki 2019). R&D tax credits, in turn, tend to focus on R&D activities that are within a specified eligibility criterion, and therefore, may be biased towards more R&D intensive firms (Czarnitzki, Hanel, and Rosa 2011; Thomson 2017). This makes supported firms intrinsically different from firms that do not receive funding from R&D policy instruments (Caloffi et al. 2022; Hünermund and Czarnitzki 2019). As highlighted by several studies, failing to address the issue of endogeneity due to the above noted double-selection issue can bias estimation results (Nilsen, Raknerud, and Iancu 2020).

A common way of addressing the selection issues described above has been to use a non-parametric matching approach (Caloffi et al. 2022; Nilsen, Raknerud, and Iancu 2020). In the context of a binary choice situation (i.e. only one type of treatment), these approaches focus on comparing firms that receive an R&D policy instrument (i.e. treated firms), *vis-à-vis* statistically similar firms that do not receive an R&D policy instrument (i.e. untreated firms). One commonly used matching methodology, is to match treated and untreated firms by using a propensity score matching (PSM) approach. PSM relies on the conditional independence assumption (CIA), where treatment and outcome are assumed to be statistically independent for firms with the same set of observable characteristics (Rubin 1977). As the large canon of studies on this topic note, PSM is an appropriate evaluative strategy to examine both R&D grants and R&D tax credits (Czarnitzki and Lopes-Bento 2014; Hünermund and Czarnitzki 2019; Lenihan et al. 2024; Vanino, Roper, and Becker 2019).

In this study, we seek to compare the treatment effects on firm-level R&D of five different R&D policy instrument mix sequences. This means that the PSM approach for binary choices is unsuitable in the context of our study. However, as outlined by Lechner (1999, 2002) and Imbens (2000), and applied in the specific context of R&D policy instruments by Greco et al. (2022) and Douglas and Radicic (2022), amongst many others, the PSM approach can be extended to consider multiple treatments. Following Lechner (1999), the first step to apply this approach in the context of multiple treatments, is to estimate firms' probabilities of receiving each of the different treatments. This is achieved by estimating the following multinomial logit model:

$$Treatment_{ikt} = \beta_0 + \beta_1 x_{it-1,2} + \varepsilon_{it} \quad (1)$$

In Equation (1), the term $Treatment_{ikt}$ is a categorical variable measuring whether firm i received the treatment k in year t. The term $x_{it-1,2}$ is a set of independent variables that affect firms' probabilities of receiving each of the treatments (as presented in Table 3 below). Finally, ε_{it} is the error term for firm i in time t. Our analysis comprises five individual R&D policy instrument mix sequences, as presented in Table 2. Table C1 in the Supplementary Material accompanying this paper presents the results of this estimation.

The second step is to use the propensity scores, as obtained from estimating Equation (1), to create counterfactual scenarios. This is a similar process to the traditional binary choice PSM approach, whereby treated and control firms are matched according to their propensity scores, when such scores fall within a predetermined range of common support. In our specific case, the common support region is determined by considering all treatments (i.e. all R&D policy instrument mix sequences). This is an important feature of the approach adopted here, as it ensures that we can obtain firms' probabilities of receiving any of the five R&D policy instrument mix sequences, before receiving/not receiving a specific treatment (Caloffi et al. 2022; Douglas and Radicic 2022). This is desirable in our specific case, given our focus on comparing the *relative* impacts of different R&D policy instrument mix sequences on firm-level R&D.

To construct appropriate control groups, we follow the recommendation of Imai, Kim, and Wang (2021), and focus on firms' pre-treatment histories. This is in contrast to only focusing on the immediate pre-treatment periods. We achieve this by including a set of independent variables in Equation (1), that capture firms' key R&D and firm-level performance characteristics during the period of two years before treatment. We specifically focus on a two-year pre-treatment period to capture key dynamics in firms' trajectories, in terms of R&D spending and other key performance measures, as defined in Table 3.

In line with Henningsen, Hægeland, and Møen (2015) and Holl (2021), we measure firms' pre-treatment R&D levels. To do this, we include a categorical variable measuring the magnitude of firms' R&D expenditure (Nilsen, Raknerud, and Iancu 2020). Moreover, we include a categorical variable measuring the level of firms' R&D growth, to ascertain the trend of firms' R&D spending before treatment. Some recent studies, including those of Vanino, Roper, and Becker (2019) and Lenihan et al. (2024), propose including measures of firms' performance to improve the quality of the matches.

Table 3. Independent variables used for obtaining the propensity scores.

Variable name	Definition
Lag of Total R&D	Average R&D expenditure for the two years pre-treatment. Following Nilsen, Raknerud, and Iancu (2020), the variable is then included as a categorical variable. Our specific variable is included in the following way: = 1 if firms' R&D expenditures are within the first quartile of the distribution of their relevant NACE sectors; = 2 if firms' R&D expenditures are within the second and third quartiles; and = 3 if firms' R&D expenditures are within the top quartile.
Lag of Total R&D Growth*	Growth of R&D expenditure for the two years pre-treatment. The variable is included as a categorical variable, in the following way: = 1 if afirms' growth of R&D expenditure is below 0 (i.e. total R&D has decreased); = 2 if afirms' R&D expenditure is equal to 0 (i.e. total R&D expenditure has stayed the same), and = 3 if afirms' growth of R&D expenditure is above 0 (i.e. R&D expenditure has increased).
Lag of Export to Sales Ratio	Average ratio of export to sales for the two years pre-treatment. Following the example of Mulligan et al. (2022), this variable is included in categorical form. In our specific case, the variable is included in the following way: = 1 if firms' exports to sales ratio is below or equal to 0.5 (i.e. 50%); and = 2 if firms' exports to sales ratio is above or equal to 0.5 (i.e. 50%).
Lag of Sales Growth	Sales growth between the previous two years pre-treatment in the sample. In line with Douglas and Radicic (2022) and Perez-Alaniz et al. (2023), this is a continuous variable which is obtained with the following formula $[(t\text{-}1 - t\text{-}2)/t\text{-}2] \times 100$.
Lag of GVA per Worker	Average Gross Value Added (GVA) per worker for the two years pre-treatment. In line with Vanino, Roper, and Becker (2019), the variable is then included as a categorical variable. In our specific case, the variable is included in the following way = 0 if GVA per worker is below the 50 percent of distribution of GVA per worker within each NACE sector; =1 if GVA per worker is above 50 percent of the distribution within each NACE sector.
Firm size	Dummy Variable = 0 if firms have fewer than 50 employees; and = 1 if firms have 49 or more employees. The rationale for (and practice of) grouping medium and large-sized firms together in Ireland has been established by, among others, Roper and Hewitt-Dundas (2008), McGuirk, Lenihan, and Hart (2015), Lenihan, McGuirk, and Murphy (2019), and Perez-Alaniz et al. (2023). This is because medium-sized firms in Ireland carry out R&D activities in a similar way to large-sized firms, as opposed to the small-sized group category.
Firm ownership	Dummy Variable = 0 if firms are domestically owned, and = 1 if firms are subsidiaries of foreign-owned multinational enterprises (Lenihan et al. 2024; Perez-Alaniz et al. 2023).
Region	Categorical variable, as follows: = 1 if firms are located in Dublin (capital city), = 2 if firms are located in border regions of Ireland, and = 3 if firms are outside of Dublin. These regions correspond to regions of Ireland, as defined by the Annual Business Survey of Economic Impact (ABSEI) survey.
NACE Sectors	Dummy variables for 12 NACE sectors (defined in Table D1 of the Supplementary Material accompanying this paper).

The variables *Lag of Total R&D*, *Lag of Gross Value Added (GVA) per Worker*, and *Lag of Export to Sales Ratio* take the value of the previous year only, if data for the two previous years are not available. *We include this variable to capture firms' R&D expenditure trajectories before treatment. While the variable shares similarities with the variable *Lag of Total R&D*, the two variables are sufficiently different, in the sense that the inclusion of both variables in our model did not result in issues of multicollinearity.

Therefore, building on these studies, we include: (1) A categorical variable measuring different levels of firms' exports to sales ratios; and (2) A categorical variable to capture firms' productivity levels (gross value added per worker). In addition to these variables, considering the level of firms' sales is important, as this can determine the extent to which firms can finance R&D activities internally (Perez-Alaniz et al. 2023). We capture this information, by including a continuous variable measuring sales growth between the two previous pre-treatment years. Finally, we include: (1) A binary variable measuring if firms are small-sized or larger-sized firms (Lenihan, McGuirk, and Murphy 2019; McGuirk, Lenihan, and Hart 2015; Roper and Hewitt-Dundas 2008); (2) A categorical variable to measure the regions in Ireland where firms are located, to capture regional disparities in firms' R&D activities (Cerulli et al. 2022; Harris, Li, and Trainor 2009); and (3) Dummy variables measuring NACE sector code, as defined in our dataset.

Finally, to ensure that the matching process is carried out successfully, our approach comprises an exact matching procedure, in a similar way to Vanino, Roper, and Becker (2019) and Lenihan et al. (2024). More specifically, our approach is designed to only allow matches between: (1) Firms of the same size category; (2) Firms from the same sector, as defined by the NACE sector codes in Table D1 of the Supplementary Material accompanying this paper; (3) Firms located in the same region; and (4) Firms that can be observed in the data before and during the treatment period (i.e. t - 2 to $t+3$). We also use the optimal narrow caliper of 0.2 points of the standard deviation of the propensity scores, as recommended by Austin (2011).[8]

For our main analysis, we employ a similar approach to previous studies such as, among others, Hünermund and Czarnitzki (2019) and Mina et al. (2021), and use a 1:1 nearest neighbour matching approach. We obtain the average treatment effects of the different R&D policy instrument mix sequences on firm-level R&D, by estimating Equation (2):

$$\mathrm{E}\left(\mathrm{aTTe}_{kj}\right) = \mathrm{E}\left(\mathrm{YT_{ij}}|\mathrm{RD}k = 1, X = x\right) - \mathrm{E}\left(\mathrm{YC}_{kj}|\mathrm{RD} = 0, \mathrm{X} = \mathrm{x}\right) \quad (2)$$

In Equation (2), aTTe denotes the average treatment effect of the R&D policy instrument mix sequence k on the outcome variables j, which in our case is firm-level R&D. $\mathrm{YT_i}|\mathrm{RD} = 1$ is the outcome variable j for firms receiving the R&D policy instrument mix sequence k, which is observable. $\mathrm{YT}_i|\mathrm{RD} = 0$ is the outcome variable j for the counterfactual scenario, if treated firms had not received such support (RD = 0), which is constructed based on the observable characteristics x (i.e. the variables presented in Table 3). This enables us to estimate the impact that each R&D policy instrument mix sequence has on firm-level R&D, *vis-à-vis* a control group of statistically similar untreated firms. To compare the relative treatment effects across different R&D policy instrument sequences, we follow a similar approach to that adopted by Caloffi et al. (2022) and Douglas and Radicic (2022).

[8]In all cases, we match firms that can be observed during the same time period. For example, if a treated firm received the first R&D policy instrument in 2010 (i.e. *t0*), we match this firm with an untreated firm in 2010. We then compare their average R&D spending during the period 2010 to 2013. However, in order to maximise the possibility of matches, we relax this requirement when testing Hypothesis 3, which refers to the relative impact on firm-level R&D between the two distinct R&D policy instrument mix sequences considered in this paper. In this case, we allow up to a 2 year difference. For example, if a treated firm received the first R&D policy instrument in 2010 (i.e. *t0*), we match this firm with a firm that received a different treatment in 2009, 2010, or 2011.

Specifically, we estimate Equation (3), which compares the levels of firm-level R&D between firms receiving different R&D policy instrument mix sequences:

$$\mathrm{E}(\mathrm{aTTe}_{m-1}) = \mathrm{E}\left(\mathrm{YT}_{ij}|\mathrm{RD}k = m, X = x\right) - \mathrm{E}\left(\mathrm{YC}_{kj}|\mathrm{RD} = 1, \mathrm{X} = \mathrm{x}\right) \tag{3}$$

Equation (3) is an extension of Equation (2), and directly compares the levels of firm-level R&D of firms that receive an R&D policy instrument mix sequence *m*, relative to the levels of R&D spending of firms receiving an R&D policy instrument mix sequence *l*. In matching firms in these two groups, we use the propensity scores previously obtained by estimating Equation (1).

It is important to note that in measuring the impact of R&D policy instrument mix sequencing, we use firms' average R&D spending (in natural logarithm) during the time window of four years, following the receipt of the *first* R&D policy instrument (i.e. *t0* to *t+3*). A key reason for this is that firms claim R&D tax credits based on their R&D expenditure during the same year (Thomson 2017). In the case of R&D grants, firms typically receive funding as they progress their funded R&D projects (Cerulli et al. 2022; Mina et al. 2021). However, it is unlikely that the impacts of these R&D policy instruments on firm-level R&D wear off immediately (Dimos et al. 2022; Fiorentin, Pereira, and Suarez 2019). This is also similar to most studies that evaluate the impact of R&D policy instruments using survey data, such as the Community Innovation Survey (Czarnitzki and Lopes-Bento 2014; Douglas and Radicic 2022; Dumont 2017; Hussinger 2008).[9]

As presented in Section 4.3, we test the robustness of our results with several strategies. We test the sensitivity of our results when using a 1:3 matching approach (instead of a 1:1), in line with Guerzoni and Raiteri (2015) and Caloffi et al. (2022). Moreover, some of the firms in our sample received repeated R&D tax credits and/or R&D grants. We ensure that this issue of repeated R&D subsidies is not affecting our main results, by estimating our main analysis with and without firms that received repeated R&D subsidies. Importantly, to ensure that our results are robust to different measures of R&D policy instrument mix sequences, we carry out our main analysis by starting the measures of R&D policy instrument mix sequences from the year 2009 onwards, as opposed to the year 2006. Finally, we implement an inverse probability weighting with regression adjustment approach (i.e. IPWRA), in a similar way to Radicic and Pugh (2017), Greco et al. (2022), Douglas and Radicic (2022), and Chowdhury and Audretsch (2024).

4. Results and discussion

This section presents and interprets our main findings, which are presented as average treatment effects. Before this, we discuss some key descriptive statistics and the balance check statistics that validate our matching approach. We then proceed to present our key

[9]As Table 1 shows, our dataset does not permit observing all firms during all of the years comprising this outcome window. To overcome this issue, we use the average levels of R&D spending (in natural logarithm), adjusted for the number of times that the firms are observed during the outcome period. This means that for firms which can be observed for four years (*t0* to *t + 3*), we add the total value of the R&D spending for the four years, and divide by 4. In a similar way, for firms which can only be observed for 3 years, we add the total value of the R&D spending for the three years, and divide by 3.

robustness tests, which show that our main findings are robust to different specifications of the model and different measures of R&D policy instrument mix sequencing.

4.1. Descriptive statistics and balance tests

Table 4 presents the descriptive statistics for all firms in the sample. The table provides summary statistics for the variables used in the analysis, for both treated and untreated firms, covering the whole period of the data, from 2000 to 2017. On average, firms that received R&D policy instrument mix sequences have higher levels of R&D expenditure, in comparison to firms that did not receive such instruments. In addition, treated firms exhibit an increasing year-on-year trend, in their levels of R&D expenditure (as measured by total R&D growth), in comparison to untreated firms. Moreover, treated firms have

Table 4. Descriptive statistics.

	Total sample	Untreated firms	Only R&D tax credits	Only R&D grants	R&D tax credit followed by an R&D grant	R&D grant followed by an R&D tax credit	R&D tax credit and R&D grant followed by an R&D tax credit
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Lag of Total R&D	4.371	4.228	5.164	4.096	5.608	4.701	5.410
	(2.264)	(2.253)	(2.053)	(0.238)	(1.894)	(2.144)	(1.792)
Lag Total R&D Growth	−1.394	−1.738	2.687	2.096	2.658	1.781	2.703
	(24.674)	(24.429)	(23.353)	(25.720)	(20.431)	(24.636)	(40.285)
Lag of Exports to Sales	0.523	0.503	0.603	0.523	0.653	0.591	0.650
	(0.392)	(0.392)	(0.382)	(0.389)	(0.365)	(0.386)	(0.374)
Lag of Sales Growth	5.644	4.976	6.912	6.768	12.075	8.914	9.829
	(24.740)	(23.583)	(27.732)	(26.678)	(30.822)	(29.375	(30.376)
Lag GVA per Worker	0.657	0.653	0.698	0.654	0.659	0.670	0.659
	(0.474)	(0.475)	(0.458)	(0.475)	(0.474)	(0.470)	(0.474)
Firm Size	0.249	0.253	0.304	0.189	0.287	0.200	0.210
	(0.432)	(0.435)	(0.460)	(0.391)	(0.453)	(0.400)	(0.408)
Foreign-Owned	0.190	0.194	0.234	0.171	0.181	0.111	0.130
	(0.393)	(0.396)	(0.423)	(0.376)	(0.385)	(0.314)	(0.337)
Firms located in Dublin	0.353	0.341	0.320	0.405	0.410	0.448	0.480
	(0.478)	(0.474)	(0.466)	(0.491)	(0.492)	(0.497)	(0.500)
Firms located outside of Dublin	0.534	0.541	0.577	0.504	0.486	0.467	0.431
	(0.498)	(0.498)	(0.494)	(0.500)	(0.500)	(0.499)	(0.495)
Firms located in border counties	0.111	0.116	0.102	0.090	0.102	0.084	0.088
	(0.314)	(0.320)	(0.303)	(0.286)	(0.303)	(0.278)	(0.284)
Number of Firms	8,556	6,256	741	965	151	407	101
Number of Firm-observations	36,136	27,666	2,495	3,081	682	1,707	429

The column ***Total Sample*** comprises all firms in the sample. The column ***Untreated Firms*** comprises firms in the sample that did not receive R&D policy instruments, which we use in our analysis to construct the control group. See Table 1 for a detailed description of all treatment categories (i.e. the other column headings). Some firms received other different combinations of R&D policy instruments (e.g. R&D grants and R&D tax credits in the same year, and an R&D tax credit and R&D grant, followed by an R&D grant). However, these groups were not suitable for the empirical analysis, due to having too few observations. Therefore, we do not include such firms in the analysis. The base category for Firm Size is small-sized. The base category for Foreign-Owned is domestically owned. The descriptive statistics in this table have been obtained using the full period from 2000 to 2017, and by including all treated and untreated firms in the working sample. Tables E1 to E11 in the Supplementary Material accompanying this paper provide further information on the treated firms used in the analysis.

higher levels of exporting and productivity, when compared to untreated firms. We also observe the distribution of larger-sized firms and foreign-owned firms to be higher, for those firms receiving only R&D tax credits, in comparison to firms receiving (1) Only R&D grants; (2) Other R&D policy instrument mix sequences; and (3) Firms in the untreated-control group. The descriptive statistics presented in Table 4, therefore, highlight the importance of using a multi-treatment matching approach.

Tables E1 to E11 in the Supplementary Material accompanying this paper present the results of a series of statistical tests for balance between: (1) Treated and matched untreated firms; and (2) Firms that received different treatment units (i.e. different R&D policy instrument mix sequences). To achieve this, we use a series of tests designed by Leuven and Sianesi (2018), based on the prior work of Rosenbaum and Rubin (1985). These tests have been implemented by, among others, Caloffi et al. (2022), Mulligan et al. (2022), Lenihan et al. (2024), and Vanino, Roper, and Becker (2019), to assess the reliability of the matching process which underpins the measurement of average treatment effects. The tests show that our panel matching approach has resulted in statistically similar treatment and control groups. Based on the results of our balance tests, we can ascertain that we have met the key criteria as specified by Rosenbaum and Rubin (1985), and our analysis is not biased by firms' observable characteristics, in the pre-treatment period. With the reliability of our matching established, we now proceed to present and discuss our main findings, and robustness tests.

4.2. Main results

Table 5 presents the findings of our main analysis, which are obtained by matching each treated firm with one statistical twin, based on their observable characteristics during the two years before treatment (i.e. *t - 1* and *t - 2*). Panel A shows that receiving a single R&D tax credit or R&D grant (i.e. not as part of a sequence over time) has positive and significant effects on firm-level R&D (Rows 1 and 2). These findings are in line with several previous studies, which ascertain that R&D tax credits and R&D grants have positive and significant input additionality effects in firms (Dimos et al. 2022; Labeaga et al. 2021, Lenihan et al. 2024; Nana-Cheraa, Roper, and Mole 2023; Neicu, Teirlinck, and Kelchtermans 2016; Petrin and Radicic 2023). Moreover, the coefficient in Row 1 of Panel B confirms that the impact of R&D tax credits on firm-level R&D is significantly higher, relative to R&D grants ($p > 0.05$). From a theoretical perspective, the higher R&D input additionality associated with R&D tax credits may be due to the specific characteristics of R&D tax credits, relative to R&D grants.

In the case of R&D tax credits, firms are free to choose the R&D projects they engage in (Czarnitzki, Hanel, and Rosa 2011; David, Hall, and Toole 2000). This often means that firms may use the funding made available by R&D tax credits to carry out the most profitable R&D projects available, with relatively low risk (Dimos et al. 2022; Thomson 2017). The predictability of R&D tax credits may also encourage firms to carry out longer-term R&D investments, safe in the knowledge that they will be subsidised. One key example of this is firms hiring more R&D employees, because of R&D tax credits (Sterlacchini and Venturini 2019; Teirlinck, Spithoven, and Bruneel 2021). In contrast to this, R&D grants are typically targeted at priority areas for policymakers, which may not be necessarily fully aligned with firms' core R&D priorities (Vanino, Roper, and Becker

Table 5. Main results for the impact of R&D policy instrument mix sequencing on firm-level R&D.

	Treated	Control	Difference (α)
Panel A Treatment vs Control			
1. Only R&D tax credit	5.478	4.742	0.736***
			(0.156)
2. Only R&D grant	5.060	4.610	0.450**
			(0.236)
3. R&D tax credit *followed by* an R&D grant	5.923	5.043	0.880***
			(0.286)
4. R&D grant *followed by* an R&D tax credit	6.155	4.827	1.328***
			(0.264)
5. R&D tax credit and an R&D grant, *followed by* an R&D tax credit	6.157	4.663	1.494***
			(0.352)
Panel B Treatment vs Treatment	**Treated (A)**	**Treated (B)**	**Difference (α)**
1. Only R&D tax credit (A) vs Only R&D grant (B)	5.446	5.095	0.351**
			(0.182)
2. R&D tax credit *followed by* an R&D grant (A) vs Only R&D tax credit (B)	5.918	5.533	0.385*
			(0.199)
3. R&D tax credit *followed by* an R&D grant (A) vs Only R&D grant (B)	5.918	5.518	0.400**
			(0.177)
4. R&D grant *followed by* an R&D tax credit (A) vs Only R&D tax credit (B)	6.129	5.509	0.620***
			(0.266)
5. R&D grant *followed by* an R&D tax credit (A) vs Only R&D grant (B)	6.129	5.222	0.907***
			(0.278)
6. R&D grant *followed by* an R&D tax credit (A) vs R&D tax credit *followed by* an R&D grant (B)	6.129	5.918	0.211**
			(0.103)

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. Estimation results based on a 1:1 nearest neighbour matching approach. The coefficients α in Panel A relate to the average additional R&D (in natural logarithm) from each policy instrument and are obtained by a comparison of means between treated and untreated firms. The coefficients α in Panel B relate to the average difference in additional R&D (in natural logarithm), which is obtained when comparing the firms that received each of the policy instruments considered. See Table 2 for a detailed description of all treatment categories. Tables E1 to E11 in the Supplementary Material accompanying this paper present the balance statistics, showing that treated and control firms were well balanced before treatment.

2019). A key example of this is R&D grants targeting more ambitious and riskier R&D projects, that firms would not finance on their own (Santoleri et al. 2022). Moreover, as noted by Busom, Corchuelo, and Martínez-Ros (2014), firms experiencing financial constraints will be more likely to seek R&D grant funding, as opposed to claiming R&D tax credits. As these authors posit, this relates to such firms preferring to secure funding before committing to R&D projects. Therefore, these critical differences between R&D tax credits and R&D grants can result in firms committing somewhat fewer financial resources to an R&D grant-supported project, relative to R&D tax credits (Dimos et al. 2022).

Crucially for our study, we find that the impact of R&D grants and R&D tax credits is *considerably larger*, when firms receive them as part of a sequence over time, relative to receiving single instruments. More specifically, we find that receiving a sequence comprised of an R&D tax credit first (i.e. in $t0$), *followed by* an R&D grant (in $t + 1$, $t + 2$ and/or $t + 3$), has a higher impact on firm-level R&D, than when firms receive either of these single R&D policy instruments alone (Rows 2 and 3 of Panel B). Rows 4 and 5 of Panel B show that similar results occur when firms receive the opposite sequence, comprising an R&D grant (in $t0$), *followed by* an R&D tax credit (in $t + 1$, $t + 2$ and/or $t + 3$). In terms of sequences comprising an R&D tax credit *followed by* an R&D grant, the impact on firm-level R&D is around 0.38 log points higher, than when firms receive only R&D tax credits, and approximately 0.4 log points higher, than when firms receive only R&D

grants ($p < 0.1$ and $p < 0.05$ respectively).[10] These findings concur with several previous studies, which report that R&D grants and R&D tax credits can result in higher levels of R&D additionality when received as part of an R&D policy instrument mix, than when received on their own (Douglas and Radicic 2022; Greco et al. 2022; Neicu 2019; Stojčić, Srhoj, and Coad 2020; Teirlinck, Spithoven, and Bruneel 2021).

The above noted higher input additionality, is likely the result of complementarities arising as firms use R&D grants and R&D tax credits in different areas of their R&D portfolios (Dumont 2017; Lenihan et al. 2024; Marino et al. 2016). In Hypothesis 1, we posited that a sequence of support through an R&D tax credit, *followed by* an R&D grant, will result in higher input additionality, relative to receiving only one of the two instruments alone. A key mechanism driving this input additionality in this case, is that R&D tax credits can enable sustained firm-level R&D, and thus, generate new innovative ideas (Dai and Chapman 2022; Thomson 2017). Firms, in turn, can focus on developing new R&D projects that meet the eligibility criteria for grant funding. At the same time, R&D grant funding can enable firms to free up internal financial resources, and finance more projects internally (Freel, Liu, and Rammer 2019; Lenihan et al. 2024). Our results support this mechanism, as they show that receiving a sequence comprised of an R&D tax credit first, *followed by* an R&D grant, results in higher levels of input additionality. This is in comparison to firms receiving any of these two instruments alone. Therefore, based on our results, Hypothesis 1 is supported.

In a similar way to the above, Hypothesis 2 posited that sequencing of R&D support through an R&D grant, *followed by* an R&D tax credit, will result in higher levels of input additionality, compared to receiving only an R&D grant or an R&D tax credit. For this specific sequence, however, a distinct mechanism exists, when compared to the previous sequence of an R&D tax credit, *followed by* an R&D grant. In this specific case, one of the consequences of obtaining R&D grants is that firms need to tailor their R&D projects to meet the eligibility criteria of this funding stream (Freel, Liu, and Rammer 2019; Mina et al. 2021). As a result, firms with limited internal financial resources may leave other potential R&D projects behind, either by putting them on hold, or by limiting their scope (Radas et al. 2015). The availability of R&D tax credits, therefore, may enable firms to resume those projects, or enlarge them (Czarnitzki, Hanel, and Rosa 2011; Thomson 2017). We suggest that this is the theoretical mechanism which underpins our results, and, as such, that Hypothesis 2 is also supported by our analysis.

Regarding Hypothesis 3, we suggested that a sequence comprised of an R&D grant first, *followed by* an R&D tax credit, will result in higher input additionality, compared to receiving an R&D tax credit *followed by* an R&D grant. Our findings support this hypothesis. Precisely, our findings in Panel B, Row 6 of Table 5, indicate that receiving an R&D grant first (in $t0$) *followed by* an R&D tax credit (in $t + 1$, $t + 2$ and/or $t + 3$), is more impactful than if the order in which firms received the two instruments was reversed. This difference is approximately 0.211 log points ($p < 0.05$). This highlights that the specific temporal sequencing of some instruments (e.g. A before B, not B before A), plays a crucial role in determining impact. In other words, the order in which firms

[10]As we show in Section 4.3, the coefficients for Table 4, Panel B, Row 2, are positive and significant at the 95 percent level in the 1:3 matching specification, and at the 99 percent level when considering the inverse probability weighting approach.

receive different R&D policy instruments does indeed make a significant difference. Therefore, this finding aligns with the theoretical work of Flanagan, Uyarra, and Laranja (2011) and Rogge and Reichardt (2016), who highlight the fundamental importance of including the temporal dimension in any conceptualisation of the R&D policy instrument mix. In addition, and in line with Caloffi et al. (2022), this highlights a potential opportunity associated with a deliberate targeted sequencing of the R&D policy instruments firms receive over time.

The above findings relating to different sequences can be explained by some key differences in the mechanisms which underpin our hypotheses. For example, a potential mechanism driving the above difference may be that R&D grants enable firms to engage in riskier and more novel R&D projects, which they would not have carried out in the absence of grant funding (Hünermund and Czarnitzki 2019; Mina et al. 2021; Santoleri et al. 2022). As a result of this, firms may identify new ideas for R&D projects that could complement and/or enhance their existing R&D projects, which were initially enabled by the direct grant funding. Therefore, subsequent funding through R&D tax credits can enable firms to explore these additional ideas and projects in the years that follow. While this mechanism is somewhat similar to the mechanisms discussed above for the case of R&D tax credits, a key difference is that the ideas resulting from grant funding may require firms to engage in more novel and distant R&D projects. As a result, firms may need to commit more of their own internal funding to drive these R&D projects (Mina et al. 2021; Santoleri et al. 2022).

Finally, we observe that receiving a mix comprising an R&D tax credit and an R&D grant first (i.e. a static mix in *t0*), *followed by* an R&D tax credit (in $t + 1$, $t + 2$ and/or $t + 3$), appears to have the highest impact on firm-level R&D. Follow up tests presented in Table H1 of the Supplementary Material accompanying this paper indicate that this finding is statistically significant, when compared to the average treatment effects for the categories: (1) Only R&D tax credit; (2) Only R&D grant. However, we do not find that receiving this specific sequence results in higher levels of firm-level R&D, when compared to the categories (3) R&D tax credit *followed by* an R&D grant; and (4) R&D grant *followed by* an R&D tax credit. In these latter cases, the results are not statistically significant. As alluded to by Flanagan, Uyarra, and Laranja (2011) and others, this may relate to the fact that accumulating several R&D policy instruments may not necessarily produce the desired policy outcomes. In fact, this may result in substitution effects, as firms may not use the funding made available through various R&D policy instruments, to engage in additional R&D projects. Based on other related studies, firms may require some time to adjust their R&D resources before engaging in new projects (Hullova et al. 2019; Kaiser and Kuhn 2012; Mulligan et al. 2022). Therefore, receiving a combination of different R&D policy instruments at one point in time, can potentially result in firms using this additional funding to substitute for their own R&D expenditure, rather than using the additional funding for new R&D projects. Our results lend support to these arguments.

4.3. Robustness tests

We now proceed to investigate the robustness of our main findings, by using four different approaches. Table 6 presents a summary of the results, which we obtain using

Table 6. Summary of robustness tests for the impact of the R&D policy instrument mix sequencing on firm-level R&D.

	Robustness 1 (1:3 Direct Matching)	Robustness 2 (No Repeated R&D Subsidies)	Robustness 3 (Only Repeated R&D Subsidies)	Robustness 4 (Sequences beginning in 2009)	Robustness 5 (Inverse Probability Weighting with Regression Adjustment)
Panel A Treatment vs Control					
1. Only R&D tax credit	0.836***	0.308**	1.089***	0.512***	0.767***
	(0.120)	(0.133)	(0.160)	(0.193)	(0.068)
2. Only R&D grant	0.659***	0.187*	0.511**	0.473**	0.672***
	(0.152)	(0.10)	(0.252)	(0.334)	(0.055)
3. R&D tax credit *followed by* an R&D grant	1.352***	0.737**	1.169***	0.552**	0.135***
	(0.197)	(0.345)	(0.258)	(0.213)	(0.080)
4. R&D grant *followed by* an R&D tax credit	1.494***	1.307**	1.386***	1.417***	1.615***
	(0.176)	(0.664)	(0.551)	(0.316)	(0.084)
5. R&D grant and an R&D tax Credit, *followed by* an R&D tax credit	1.538***	1.477***	-	1.105***	0.867***
	(0.269)	(0.357)		(0.384)	(0.175)
Panel B Treatment vs Treatment					
1. Only R&D tax credit vs Only R&D grant	0.290**	0.427	0.427*	0.228	0.095
	(0.131)	(0.288)	(0.258)	(0.243)	(0.081)
2. R&D tax credit *followed by* an R&D grant vs Only R&D tax credit	0.406**	0.338*	0.203*	0.223*	0.583***
	(0.158)	(0.193)	(0.108)	(0.120)	(0.172)
3. R&D tax credit *followed by* an R&D grant vs Only R&D Grant	0.615***	0.553**	1.169***	0.381**	0.676
	(0.136)	(0.209)	(0.258)	(0123)	(0.221)***
4. R&D grant *followed by* an R&D tax credit vs Only R&D tax credit	0.709***	0.791***	0.791**	0.809***	0.845***
	(0.194)	(0.251)	(0.251)	(0.297)	(0.318)
5. R&D grant *followed by* an R&D Tax Credit vs Only R&D Grant	0.795***	0.812***	1.103***	0.735**	0.940***
	(0.200)	(0.290)	(0.368)	(0.318)	(0.347)
6. R&D grant *followed by* an R&D Tax Credit vs R&D tax credit *followed by* an R&D grant	0.204*	0.691**	-	0.726**	0.261**
	(0.118)	(0.251)		(0.335)	(0.113)

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. Tables F1–F5 of the Supplementary Material accompanying this paper present the full results for each of the analyses presented in this summary table. The coefficients in Panel A relate to the average additional R&D (in natural logarithm) from each policy instrument, obtained by comparing the means of treated and matched untreated firms. The coefficients in Panel B relate to the average difference in additional R&D (in natural logarithm), which is obtained when comparing the firms that received each of the treatment categories, relative to one another. See Table 2 for a detailed description of all treatment categories. To test the sensitivity of our main analysis, each Column replicates the main analysis under different conditions: 1) By following a 1:3 direct matching methodology; 2) By excluding firms that received repeated R&D subsidies; 3) By only considering firms that received repeated R&D subsidies; 4) By starting the R&D instrument sequences in the year 2009. The dash (-) means that the analysis was not possible due to insufficient number of observations. Finally, Column 5 presents the results of a IPWRA approach, using all firms in our working sample, where Panel B presents the significance of the Wald Test for hypothesis testing, based on the coefficients presented in Panel A.

these four different approaches. Tables F1–F5 in the Supplementary Material accompanying this paper present the full set of results, for each of the four approaches. The first approach is to repeat our main analysis, by matching each treated firm with the closest three untreated firms, based on their propensity scores (i.e. 1:3 Exact Matching). Again, firms are matched based on their R&D and performance characteristics during the previous two years before being treated. As Column 1 of Table 6 shows, this alternative matching process yields very similar results to those presented in Table 5. In fact, the coefficients in Panel B are larger in magnitude, and have a higher level of statistical significance than those presented in Table 5. This supports our main findings.

Our second approach is to consider the issue of so-called repeated R&D subsidies. This occurs when firms receive the same R&D policy instrument repeatedly over time (Shi et al. 2023). While the focus of our paper is on situations where firms receive a combination of *different* R&D policy instruments, we cannot ignore this issue. This is because receiving either R&D tax credits or R&D grants repeatedly over time, can impact firm-level R&D (Fiorentin, Pereira, and Suarez 2019; Labeaga et al. 2021). Moreover, as presented in Table F2 in the Supplementary Material accompanying this paper, the issue of repeated R&D subsidies is prevalent in our sample. To ascertain whether this issue is affecting our main results, we repeat the matching process, while specifically accounting for firms receiving repeated R&D subsidies. To achieve this, we follow the approach adopted by Shi et al. (2023), and repeat the above analysis separately for: (1) Firms that received repeated R&D subsidies (Column 2 of Table 6); and (2) Firms that did not receive repeated R&D subsidies (Column 3 of Table 6). In this case, while we observe some changes in the estimated coefficients, the findings are in line with those of our main approach. Based on this, we conclude that the issue of repeated R&D subsidies affects our results only in terms of the *magnitude* of the impact estimations. However, it does not affect the key conclusions from our main findings.

Since our administrative data only starts in the year 2006, it is possible that some firms may have been treated before this year. As a result, there is the possibility of a potential omitted treatment bias, in the specific case of those firms that are considered as receiving their *first* R&D policy instrument in 2006. To ensure that our findings are not affected by this bias, we repeat our analysis, by only focusing on firms receiving R&D policy instrument mix sequences from the year 2009 onwards. As our data permits observing the years 2006, 2007 and 2008, this ensures that the firms being analysed did not receive any treatment, before our first observation of a treatment in the sequence (i.e. *t0*). Column 4 of Table 6 presents the findings obtained with this alternative data set-up, by following the same 1:1 direct matching specification used in our main approach. As Column 4 of Table 6 shows, our results from this analysis are fully in line with those obtained with our main approach. This strongly suggests that omitted treatment bias is not an issue in our study.

Finally, while our main approach enables a clear research design and interpretation of results, it does not fully exploit the sample size which is available to us in our constructed dataset. This is because the large majority of the untreated sample is not used in PSM analysis, after the propensity score is estimated. Some studies, such as those by Greco et al. (2022) and Douglas and Radicic (2022), have noted that using larger control groups can enhance traditional PSM approaches. Moreover, they note that this can be achieved by using an Inverse Probability Weighting with Regression Adjustment approach (IPWRA). Several previous studies, including those of Radicic and Pugh (2017), Greco et al. (2022), Douglas and Radicic (2022), and Chowdhury and Audretsch (2024), have also highlighted the suitability of this approach for obtaining robust treatment effect estimations in multi-treatment settings. Therefore, we implement this approach to test the robustness of our main analysis. In implementing this approach, a first step is to estimate firms' probabilities of receiving each of the types of treatment being studied (in a similar way to our main approach). The second step is creating a counterfactual using all firms in the sample, by weighting the characteristics of untreated firms with inverse values of the propensity scores (Lechner 1999).

Column 5 (Panel A) of Table 6 presents the impacts of R&D policy instrument mix sequencing on firm-level R&D, as obtained with the IPWRA approach. The reported coefficients are the average treatment effects of receiving single R&D policy instruments, and R&D policy instrument mix sequences, *vis-à-vis* a control group comprising untreated firms. In Panel B, Column 5 reports the outcomes of Wald Tests, which formally test our hypotheses. The results of the Wald Test almost universally support our main analysis. The sole difference between the results as presented in Column 5 of Table 6 and those as obtained with our main approach, pertains to Row 1 of Panel B. This coefficient captures differences in the impact on firm-level R&D, between R&D tax credits and R&D grants, and is not statistically significant. This differs from our main approach, which reports this difference to be statistically significant. All remaining findings are fully in line with our main approach.

Based on the results obtained with our detailed robustness tests, we conclude that our main results are robust to different model specifications and measures of R&D policy instrument mix sequencing.

5. Conclusion

Analysing the role of combining different types of R&D policy instruments in supporting R&D activities of firms has received increasing attention in recent years, both by academics (Flanagan and Uyarra 2016; Martin 2016; Russo and Pavone 2021; Shi et al. 2023), and policymakers (OECD 2020; European Commission 2020). However, almost all studies to-date have conceptualised and empirically analysed the R&D policy instrument mix as a static unit, occurring when firms receive a combination of different instruments at the same time (e.g. Czarnitzki and Lopes-Bento 2014; Dumont 2017; Guerzoni and Raiteri 2015; Heijs, Guerrero, and Huergo 2022; Stojčić, Srhoj, and Coad 2020). The goal of our paper is to extend this research, by investigating the mix of R&D policy instruments in a *sequence* over time. Using detailed firm-level panel data from Ireland on the two most important R&D policy instruments, R&D grants and R&D tax credits, we analyse the role of R&D policy instrument mix sequencing on firm-level R&D. We find significantly higher R&D input additionality for firms that receive R&D grants and R&D tax credits as part of a sequence over time, compared to firms that receive a single R&D grant or R&D tax credit. In addition, our results suggest that the most effective way to drive input additionality, is when firms first receive an R&D grant, *followed by* an R&D tax credit. As such, our results suggest several potential implications for both research and policy on the effectiveness of public support for R&D.

Our paper contributes to the empirical literature on the R&D policy instrument mix in two main ways. Our first contribution is to bridge the gap between theory and empirical analysis, in how the R&D policy instrument mix impacts firm-level R&D. By empirically analysing R&D policy instrument mix sequencing, we aim to add further clarity to the somewhat ambiguous existing empirical evidence, regarding the impact of the R&D policy instrument mix on firm-level R&D (Coburn et al. 2021; Cunningham et al. 2016; Douglas and Radicic 2022; Dumont 2017; Greco et al. 2022; Petrin and Radicic 2023; Teirlinck, Spithoven, and Bruneel 2021). Our second contribution concerns the development of a novel empirical strategy for R&D policy instrument mix *sequencing*. We conceptualise each R&D policy instrument mix sequence over time as individual and distinct treatment units. Following this, we use a panel matching approach to analyse the R&D expenditure of treated firms, *vis-à-vis* a pure control group of firms that share a statistically identical pre-treatment history. Finally, we compare the treatment effects across the different treatment units (i.e. the sequences). This empirical approach enables us to achieve a comprehensive understanding of the impact of different R&D policy instrument mix sequences over time, on firm-level R&D.

From a policy perspective, our study provides clear evidence on the centrality of sequencing for determining the effectiveness of existing R&D policy instruments. However, as noted by Caloffi et al. (2022), the R&D policy instrument mixes received by firms are typically unplanned. This is in the sense that such R&D policy instrument mixes, as provided by policymakers, are typically not designed or deliberate. Therefore, when considering the R&D policy instrument mix firms receive over time, our results suggest that policymakers may usefully consider the sequence in which R&D policy instruments are provided over time. This is potentially very important for policymakers in terms of R&D policy instrument design, allocation, and implementation, and moreover, as they evaluate the eventual impact of public R&D support on firm-level R&D.

Notwithstanding our rich data, as well as our conceptual and methodological contributions, our analysis is not free from limitations. Firstly, we only focused on the effect of R&D policy instrument mix sequences on firm-level R&D, as this is the most immediate outcome of R&D policy instruments. Future studies may usefully explore other firm-level outcomes, such as firms' innovative outputs, increased employment, and the performance of firms in the market. Secondly, future research would benefit from an analysis specifically focused on the different time windows for the firm-level impacts of R&D policy instrument mix sequencing to unfold. Finally, our analysis must rely on binary measures of whether firms received R&D grants and/or R&D tax credits. As such, we were unable to examine the total amount of funding firms receive through one, or a mix of different R&D policy instruments. To the best of our knowledge, this issue is present in all previous studies on the R&D policy instrument mix, even in the most recent analyses, which have access to highly detailed datasets (see e.g. Nana-Cheraa, Roper, and Mole 2023; Lenihan et al. 2024; Petrin and Radicic 2023; Shi et al. 2023). While this is a limitation of our study, our matching approach considers firms with statistically similar histories, in terms of their R&D spending. This is particularly important in the context of Ireland, because R&D policy instruments are based on a percentage of the applicant's R&D spending. Therefore, we can assume that treated firms with similar levels of R&D spending received similar levels of R&D support, regardless of the specific R&D policy instrument received. Despite this, should datasets of superior quality become available in the future, moving beyond binary measures of R&D policy instruments to capture the actual amount of funding received, represents a potentially important avenue for future research.

Despite the above limitations, our paper offers critical insights for advancing our understanding of the importance of R&D policy instrument mix sequencing for driving firm-level R&D. In doing so, our paper provides novel evidence regarding a crucial element of the concept of the R&D policy instrument mix, which up until now, has been empirically ignored. Continuing to overlook this element of the R&D policy instrument mix puzzle, may result in public support for firm-level R&D being less effective than it otherwise could be.

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