// NO.23-009 | 03/2023

DISCUSSION PAPER

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Serving the Right Menu of R&D Policy Instruments to Firms: An Analysis of Policy Mix Sequencing

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Serving the right menu of R&D policy instruments to firms: An analysis of policy mix sequencing

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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 instrument mix as a static unit, whereby firms receive multiple policy instruments at one point in time. However, firms can also receive multiple instruments in a sequence, over time. While sequencing is well rehearsed theoretically, this 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, containing almost 25,000 firm-year observations over a 17-year period for Ireland. Our analysis focuses on R&D grants, R&D tax credits, and publicly-supported academic-industry collaborations, and develops two novel approaches to measure R&D policy instrument mix sequencing. Our results suggest that R&D policy instrument mix sequencing is highly effective at driving firm-level R&D, but that some sequences are more effective than others. These findings highlight opportunities to realise superior policy outcomes through targeted sequencing.

Keywords: Policy mix; Policy instrument mix sequencing; Public R&D support; R&D grant; R&D tax credit; Academic-industry collaboration.

JEL Codes: O25; O30; D04; O38; D22; O31.

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1. Introduction

Investing in Research and Development (R&D) is a key driver of firms' innovation and business performance (Griliches 1979; Vanino et al. 2019), and fundamental for economic growth and national competitiveness (Romer 1990; Jones 2022). At the same time, results of R&D activities are subject to spillovers, limiting the returns for the R&D performer and reducing incentives for private R&D investment (Audretsch et al. 2002; von Brasch et al. 2021). To address this issue, policymakers employ a suite of policy instruments, designed to support firm-level R&D. Chief among such supports are R&D grants, R&D tax credits, and publicly-supported academic-industry collaborations (Montmartin et al. 2018; Cunningham and Link 2021). After several decades of debate and study, the importance of these policy instruments is well-established (e.g. Becker 2015; Dimos and Pugh 2016; Becker 2019).

Since the path-breaking work of Nauwelaers et al. (2009) and Flanagan et al. (2011), the concept of policy instrument *mix* has gained increasing attention, for better understanding and evaluating the impact of public R&D funding on firm-level R&D (Lanahan and Feldman 2015; Martin 2016; Kern et al. 2019; OECD 2020; Russo and Pavone 2021). An instrument mix occurs when firms receive multiple 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 et al. 2011; Rogge and Reichardt 2016; Schmidt and Sewerin 2019). To date, evaluation studies considering a mix of policy instruments have focused almost exclusively on firms that receive different instruments within the same period of time (e.g. Czarnitzki and Lopes-Bento 2014; Guerzoni and Raiteri 2015; Dumont 2017; Stojčić et al. 2020; Heijs et al. 2022). However, the concept of sequencing is almost completely unexplored in empirical analyses. Coburn et al. (2021, p. 20) have recently lamented this fact, calling for future empirical research "to study the sequencing of interventions over the long term". Our study fills this important gap in existing knowledge, by providing the first fully-fledged empirical analysis of the impact of policy instrument mix sequencing 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 et al. (2011), and thereafter, throughout the development of policy instrument mix theory (Rogge and Reichardt 2016;

Schmidt and Sewerin 2019; Howlett 2019; Meissner and Kergroach 2021), 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, p. 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, p. 1630) refer to as "a static snapshot of a policy mix at a given point in time". This static policy instrument mix literature has grown rapidly, and developed significant econometric sophistication. Many recent studies in this cannon have provided key empirical insights (e.g. OECD 2020; Pless 2021; Caloffi et al. 2022; Douglas and Radicic 2022). These studies demonstrate the centrality of the instrument mix concept, to understanding the impact of public R&D funding on firm-level R&D. Notwithstanding this, policy instrument mix *sequencing* remains a crucial missing piece of the empirical puzzle. Our study provides the first wholly comprehensive empirical analysis of this crucial lacuna.

Our second contribution is to develop a novel methodological approach to examine policy instrument sequencing. Focusing specifically on sequencing, requires a different type of model set-up than that used previously in the literature. Evaluations of single policy instruments and/or static instrument mixes have traditionally aimed to compare 'like-with-like', in discrete time periods (see e.g. Dimos and Pugh 2016). As an illustrative example, the impact of receiving an R&D grant and an R&D tax credit in a given year on firms' R&D *ceteris paribus*, relative to firms that received no policy instrument in the same year (Marino et al. 2016; Dumont 2017; Greco et al. 2021; Petrin and Radicic 2023). Empirically examining policy instrument mix sequencing requires a different methodological conceptualisation. A policy instrument mix sequence occurs *over time*, as firms receive multiple instruments in different years. It is necessary therefore, to conceptualise the sequence within *a period of time*, with the sequence's impact unfolding over this time period. A small number of previous studies have examined situations where firms receive *the same* policy instrument repeatedly year-on-year (e.g. Aschhoff 2010; Czarnitzki and Lopes-Bento 2013; Fiorentin et al. 2019; Labeaga et al. 2021). However, research to-date provides no methodological guidance on how to evaluate the impact of more complex instrument mix sequences over time.

To address the above issue, our study develops two novel complementary approaches. Our first approach conceptualises different policy instrument sequences as discrete units that occur over time. For example, in a given time period (e.g. 5 years), a firm may receive two policy instruments. The firm receives their *first* policy instrument in year *t*, and then their second policy instrument two years later (i.e. *t+2*). We treat this sequence as one unit of policy treatment, which unfolds over three years (i.e. first policy instrument in year *t*, second policy instrument in year *t+2*). We then evaluate the impact of the unit, at the end of each of the years comprising the sequence. This approach enables us to examine the impact of different instrument mix sequences relative to one another, *as well as* situations where firms receive only a single policy instrument or a static instrument mix. Our second approach analyses the impact of the *first* policy instrument firms receive, and then, separately, the impact of each subsequent policy instrument they receive over time. This second approach enables us to specifically focus on the impact of each policy instrument, when they are received as part of a sequence. The two approaches are complementary, in that they enable us to examine both the full sequence, as well as each instrument in the sequence.

Our analysis is enabled by the construction of a unique firm-level panel dataset, containing almost 25,000 firm-year observations for the period 2000-2017 for Ireland. Our dataset is composed of annual survey data, combined with unique administrative data on the main R&D policy instruments available to firms in Ireland. The dataset provides detailed information on firms' R&D expenditure, as well as identifying when firms receive R&D grants, claim R&D tax credits, and participate in publicly-supported academic-industry collaborations. To operationalise our novel methodology, we apply this data using a fixed-effects estimation procedure. In our models, we follow a similar approach to Bérubé and Mohnen (2009) and Neicu (2019), by only focusing on firms that received at least one R&D policy instrument over the sample period. As such, our analysis examines the relative impacts of different ways of supporting firm-level R&D; as opposed to the impact of receiving different policy instrument(s), relative to receiving no policy instrument(s). This model set-up allows us to avoid endogeneity issues caused by so-called 'selection into treatment', because all firms have selected into at least one treatment (Fiorentin et al. 2019; Hünermund and Czarnitzki 2019). Given the novelty of our model set-up, we also perform robustness tests employing more traditional methods, to ensure that our main results are not driven by endogeneity.

Our final dataset reveals two important insights on the nature of the policy instrument mix, when sequencing is considered. Firstly, policy instrument mix sequencing is empirically important. When measured over a three-year time period, approximately 48 percent of the firms in our sample receive an initial policy instrument, followed by one or more instruments in the next three years. Secondly, firms receiving one instrument only is a major occurrence, at almost 50 percent of the sample. However, when sequencing is considered, static instrument mix, as defined in almost all previous studies, becomes a marginal issue. Only circa 2 percent of the sample receive a mix of instruments in the same year, *and do not receive* other instruments in a sequence over time.

Our empirical findings indicate that examining the policy instrument mix menu firms are served over time, is crucial for understanding the impact of public R&D support on firm-level R&D. For example, the impact of receiving a single R&D grant or R&D tax credit is positive and significant (compared to all firms, in years where they do not receive any policy instruments), echoing the results from previous analyses (Becker 2015; Dimos and Pugh 2016). However, and importantly, the effect is considerably larger when firms receive an initial R&D grant, followed by an R&D tax credit in a sequence. This pattern is repeated for sequences such as firms receiving an initial R&D tax credit or R&D grant, followed by a mix of both instruments in subsequent years. The story regarding publicly-supported academic-industry collaborations is more nuanced still. When received alone, these policy instruments appear not to have a significant influence on firm-level R&D. However, when such collaborations are followed by R&D tax credits, or a mix of instruments over time, the sequence results in positive and significant effects. These results suggest a crucial temporal dimension in how collaborations influence firms' R&D investment behaviour. In addition, they highlight potential for leveraging the impact of an initial collaboration, with targeted subsequent additional policy instruments. From a policy design perspective, these results highlight the centrality of policy instrument mix sequencing, to understanding how public R&D support impacts firm-level R&D. In addition, our results show that certain instrument mix sequences are particularly impactful. 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 policy instrument mix, placing sequencing within this context. Section 3 details our econometric approach and database. Section 4 presents and discusses our results. Finally, Section 5 concludes, and offers a discussion of potential policy implications.

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

Following the work of Nauwelaers et al. (2009) and Flanagan et al. (2011), policy instrument mix theory gained significant prominence as a means of understanding how public R&D funding impacts firm-level R&D (e.g. Borrás and Edquist 2013; Magro and Wilson 2013; Rogge and Reichardt 2016; Schmidt and Sewerin 2019; Howlett 2019; Meissner and Kergroach 2021). However, *before* these theoretical contributions, there were some notable *empirical* antecedents. In a large-scale study of 17 OECD member countries, Guellec and van Pottelsberghe (2003) found that direct R&D support and R&D tax incentives appeared to be substitutes: Increased intensity of one, reduced the effectiveness of the other at driving firm-level R&D. By contrast, in an influential study based on firms in Canada, Bérubé and Mohnen (2009) demonstrated that receiving both R&D tax credits and R&D grants was more effective, relative to receiving R&D tax credits alone. These early studies serve to highlight that the concept of receiving multiple policy instruments has long been a concern when evaluating the impact of public R&D support on firm-level R&D. As detailed below, a raft of subsequent studies have refined and extended this analysis of policy instrument mix. However, to date, this research has conceptualised the instrument mix as static, occurring at a point in time. Therefore, this section aims to build on these studies, and this unfolds in three parts: (1) We summarise the theoretical mechanisms by which policy instrument mix drives firm-level R&D; (2) We review the key empirical studies which have operationalised the R&D policy instrument mix concept; and, (3) We detail the concept of R&D policy instrument mix sequencing, and formulate hypotheses.

2.1 How does the R&D policy instrument mix impact firm level R&D?

According to Flanagan et al. (2011, p. 702), the 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". At the firm level, two main theoretical mechanisms have been put forward to explain how policy instruments interact in a mix, to produce distinct impacts on firm-level R&D.

The first mechanism focuses on certain aspects of the policy instruments themselves. R&D grants and publicly-supported academic-industry collaborations play a capacity building role in firms (Filipetti and Savona 2017; Caloffi et al. 2018; Hu et al. 2021). These are direct forms of public R&D support, in the sense that they enable policymakers to target specific R&D activities, which they deem as strategically important (Vanino et al. 2019). Typically, such R&D activities are associated with more radical forms of innovation, where both the risk of failure and likelihood of significant knowledge spillovers are greatest (Mulligan et al. 2022). Thus, policymakers seek to incentivise and compensate firms, in the anticipation of achieving a high social return on investment (Veugelers 2021). R&D grants and publicly-supported academic-industry collaborations can also result in certification effects, and enable firms to obtain previously inaccessible resources for R&D, including additional liquidity and external knowledge (Kleer 2010; Bianchi et al. 2019). This, in turn, can translate into increased firm-level R&D (Guellec and van Pottelsberghe 2003; Steinmo et al. 2022).

In contrast, R&D tax credits support a wider range of R&D activities, including more incremental forms of innovation, and R&D activities with lower technological novelty (Stojčić et al. 2020). Firms claim tax relief on the entire quantity of their eligible R&D expenditure, as opposed to specifically targeted projects. As such, firms are free to choose how they invest in R&D, safe in the knowledge that they will be compensated for doing so (Neicu 2019). R&D tax credits are available to all R&D-performing firms, and the predictability of this R&D support can result in firms committing to longer-term R&D investments (Hall and van Reenen 2000; Sterlacchini and Venturini 2019). A key example of this, is R&D tax credits enabling firms to hire more R&D employees (Teirlinck et al. 2021).

When two types of policy instruments (e.g. grants and credits) are received *together*, they can mutually reinforce one another's impact. This can occur by enabling firms to create and internalise synergies between different aspects of their R&D portfolios (Haegeland and Møen 2007; Bérubé and Mohnen 2009; Neicu et al. 2016; OECD 2020). For example, new discoveries arising when developing new products and services can enable firms to improve already existing products and services (Steinmo et al. 2021). 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 (Szücs 2018; Hullova et al. 2019). Moreover, as noted above, while R&D tax credits enable firms to increase their R&D employee base; R&D grants and academic-industry collaborations can encourage firms to explore new knowledge. Therefore, combining R&D tax credits and R&D grants and/or publicly-supported academic-industry collaborations can enable firms carry out R&D projects which were previously not possible (Douglas and Radicic 2022). In this way, receiving multiple policy instruments can result in complementarity, where the impact of the mix on firm-level R&D is over-and-above the sum of each single policy instrument in the mix.

However, receiving a mix of policy instruments can also result in substitution effects (Guellec and van Pottelsberghe 2003; Nauwelaers et al. 2009; Borrás and Edquist 2013). This relationship is best explained by the second mechanism underpinning how policy instrument mix drives firm-level R&D. When applied to the field of public R&D funding, the 'Matthew effect' describes a situation where the same group of firms continue to receive multiple policy instruments, at the expense of other firms (Fiorentin et al. 2019). Antonelli and Crespi (2013) describe a *vicious* Matthew effect as occurring where firms receive multiple policy instruments because they become expert at filing in applications, as opposed to their inherent need for support, or what the support will enable them to achieve.[1] In such cases, receiving a mix of instruments is not likely to be optimal. The latter may also result in deadweight spending effects, thus implying an inefficient use of scarce public resources for R&D funding (Haapanen et al. 2017; Feldman et al. 2022).

In contrast, the Matthew effect can also be *virtuous*. In this case, firms receive multiple policy instruments because they have the greatest suite of novel ideas, which would not be acted upon in the absence of public R&D support. As these firms receive more policy instruments, their R&D capacity increases, and they are better able to realise future innovation success, thus necessitating further policy instruments (Labeaga et al. 2021). In reality, both vicious and virtuous Matthew effects likely exist in tandem in the economy, and which one dominates is an important empirical question, as highlighted almost a decade ago by Antonelli and Crespi (2013).

2.2 Previous studies on the effectiveness of R&D policy instrument mix

To-date, empirical studies on R&D policy instrument mix have mainly focused on the econometric risks associated with not accounting for firms receiving multiple policy instruments, as opposed to how the mix could be targeted to achieve greatest impact (see e.g. Czarnitzki and Lopes-Bento 2014; Neicu et al. 2015; Radas et al. 2015; Radicic and Pugh 2017). Crucial among such studies, was that by Guerzoni and Raiteri (2015), who theoretically

[1] In an adjacent debate, pertaining to the Small Business Innovation and Research (SBIR) programme in the US, Lanahan and Feldman (2018) discuss the potential occurrence of so-called 'SBIR mills'. SBIR mills are firms whose main business strategy is to win public R&D funding for the initial R&D phase of an innovation project. As such, they receive many repeated SBIR grants over time.

described, and empirically demonstrated, the so-called ‘hidden treatment problem’. These authors found large and non-trivial differences between the impact of single R&D grants, R&D tax credits, or innovation public procurement contracts, on firm-level R&D, relative to receiving any mix of these instruments. Moreover, they highlighted that ignoring the potential for firms receiving a mix of instruments, and examining each instrument individually, can lead to significant under- and/or over-estimation of impacts (see also Mulligan et al. 2019). It is important to note that the above studies are all cross-sectional in nature. As such, they operationalise the instrument mix as firms receiving two or more instruments at the same point in time, as a static instrument mix. The overarching finding from these studies is that receiving a static instrument mix, tends to produce greater firm-level impacts, relative to receiving single instruments. More recent studies which confirm these earlier results, in a wide variety of country contexts and settings, include Neicu (2019), Stojčić et al. (2020), Ghazinoory and Hashemi (2021), Greco et al. (2021), Teirlinck et al. (2021) and Douglas and Radicic (2022).

Relative to the extensive cross-sectional literature noted above, the emergence of more detailed panel datasets has enabled some more recent studies to employ a greater degree of econometric sophistication. Such studies have produced more ambiguous results. In firm-level samples from France and Belgium respectively, Marino et al. (2016) and Dumont (2017; 2019), find that receiving a mix of R&D grants and R&D tax credits can have a lower impact (or no impact), relative to receiving a single policy instrument. Petrin and Radicic (2023) report similar findings, regarding a mix of R&D grants and R&D tax credits for a sample of firms in Spain. However, also using Spanish panel data, Heijs et al. (2022) show that receiving a mix of R&D grants from regional, national, and European sources, produces a greater impact on firm-level R&D, when compared to R&D grants from any individual governance level. Similarly, in a panel dataset comprising firms in China, Pang et al. (2020) show that receiving any mix of R&D grants, R&D tax credits, and government innovation procurement contracts, is more effective than any individual policy instrument on their own. Finally, Pless (2021) provides an important large-scale panel study for the United Kingdom. This study shows that higher R&D tax credit rates substantially enhance the impact of R&D grants on small firms’ R&D. However, for large firms, the opposite relationship holds. The 2021 analysis by Pless, therefore, highlights the impact of policy instrument mix, while also bringing to the fore nuances such as firm size, which can have an influence (see also Castellacci and Lie 2015).

Notwithstanding the significant development in the empirical literature noted above, much work remains. This point is borne out in two recent studies. The first study pertains to an OECD

(2020) report, which evaluates the firm-level impacts of R&D grants and R&D tax credits in 20 countries. Employing unique and highly-detailed micro-data for each economy, the study finds that each instrument is "more effective in the presence of the other" (p. 67). Despite the report's comprehensive nature, the OECD (2020, p. 67) conclude that their analysis only "*hints at* a potential complementarity between R&D tax incentives and direct support" (emphasis added), calling for more detailed future analyses to give specific guidance to policymakers. In the second study, Coburn et al. (2021, p. 3) state that empirical studies on policy instrument mix "presently remain at an early stage of development", which can only provide relatively ambiguous policy recommendations. These studies highlight that, even in the most advanced empirical research, policy instrument mix has only just reached the 'proof-of-concept' stage. In summary, evidence to date points to policy instrument mix as clearly being an important factor when evaluating public R&D funding. However, research to date falls short in terms of providing clear and unambiguous recommendations to policymakers on which policy instrument mixes are most effective.

2.3 R&D policy instrument mix sequencing: A missing piece of the puzzle?

Policy instrument mix sequencing has been hypothesised as a key factor determining the impact of public R&D funding on firm-level R&D. Flanagan et al. (2011, p. 710) note that it is unlikely that "complementarities in practice can be achieved by the simple accumulation of instrument after instrument … [because] theoretically complementary instruments may begin to interact in negative or contradictory ways if layered one upon the other". When discussing some ambiguous findings from studies which examine the static instrument mix, Cunningham et al. (2016, p. 527) note 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". Therefore, theory suggests that sequencing can play a key role in driving the effectiveness (or lack thereof) of the instrument mix at stimulating firm-level R&D (see also: Kern and Rogge 2016; Sovacool 2016; Schmidt and Sewerin 2019; Howlett 2017; 2019; Meissner and Kergroach 2021).

However, with some partial exceptions that hint at potential sequencing effects, the concept of R&D policy instrument mix sequencing has not been explored in empirical studies to-date. The few studies which do exist serve to highlight the potential importance of sequencing, but provide little guidance on the most effective instrument mix sequences (Aschhoff 2010;

Czarnitzki and Lopes-Bento 2013; Fiorentin et al. 2019; Labeaga et al. 2021).[2] In the most recent example, Labeaga et al. (2021) examine firms that claim repeated R&D tax credits over time, using a sample of firms in Spain. In the parlance of Flanagan et al. (2011), this constitutes an instrument mix of 'the same' policy instrument over time, as opposed to different instruments at the same time (or over time). In their study, Labeaga et al. (2021) hypothesise that filing R&D tax credit claims has non-trivial administrative costs, and once an initial claim has been made, significant incentives exist for firms to claim persistently. However, it is *a priori* unclear if such repeated claims will enhance firm-level outcomes (in terms of higher R&D spending or more innovation). Therefore, examining this hypothesis, Labeaga et al. (2021) empirically show that receiving R&D tax credits year-on-year, has a positive and significant impact on the number of firms' new product innovations.

The above discussion demonstrates that instrument mix sequencing can play a key role in determining the impact of policy instruments on firm-level outcomes. In addition, the very limited evidence to-date, suggests that there may be positive effects associated with receiving instruments in a sequence over a given time period, as opposed to just receiving single policy instruments (or static instrument mixes) over the same point in time. However, previous theoretical and empirical research provides no guidance on *which* sequences may be more or less effective (or ineffective) at driving firm-level R&D.

In light of the above discussion, our study formulates two hypotheses, which enable us to explore policy instrument mix sequencing:

Hypothesis 1: Receiving a mix of R&D policy instruments over time, will have a greater impact on firm-level R&D, relative to receiving a single policy instrument or static instrument mix.

Hypothesis 2: The impact of receiving a mix of R&D policy instruments over time will differ, based on the type of instruments received, and the sequence in which they are received.

[2] It should be noted that some empirical studies use past receipt of public R&D funding as a control variable, when examining the impact of single policy instruments (e.g. Hussinger 2008; Boeing 2016; Mulligan et al. 2021). These studies show that past public R&D funding is a significant predictor of whether firms receive future public R&D support.

Section 3: Methodology and data

Our paper develops two novel and complementary approaches for analysing the impact of R&D policy instrument sequencing on firm-level R&D. We operationalise these approaches using a unique dataset, capturing the main R&D policy instruments available to firms in Ireland, from 2006 to 2017. These administrative data are combined with annual survey data, capturing firms' R&D activities, covering the period from 2000 to 2017.

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). In 2019, for example, total government support for firm-level R&D in Ireland represented 0.21 percent of total Gross Domestic Product (GDP), which is slightly above the OECD average of 0.2 percent (OECD 2021). Moreover, while the average growth of OECD firm-level government R&D support was 0.05 percent of GDP between 2015 and 2019, this was more than double (circa 0.13 percent) in Ireland (OECD 2021).

As detailed by Cunningham and Link (2021), in an international comparison of the types of public R&D support instruments available to firms, there are three main types of R&D policy instruments available to firms in Ireland: (1) Direct support through R&D grants; (2) Indirect support through R&D tax credits; and, (3) Collaborative R&D support through publicly-supported academic-industry collaborations. Of these support types, R&D tax credits are by far the largest, representing 85 percent of total government support for firm-level R&D in the country (OECD 2021).[3] 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 expenditure (Revenue Commissioners 2022). Our administrative data capture all R&D tax credit claims from 2006 to 2017 (see Panel A, Table A1, in the Supplementary material accompanying this paper).

Beyond R&D tax credits, firms in Ireland can also apply for many 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).[4] R&D policy instruments

[3] 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

[4] 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

available to firms from IDA Ireland include competitive R&D grants, and funding for R&D collaborations between firms and public research institutions (e.g. universities, research centres). EI on the other hand, focuses on domestic Irish-owned firms (Enterprise Ireland 2022), which are predominantly Small- and Medium-sized Enterprises (SMEs).[5] While EI offers similar types of R&D policy instruments to those provided by IDA Ireland, they are tailored to the needs of the domestic Irish industrial base.[6] Panel B in Table A1, in the Supplementary material accompanying this paper, presents the R&D policy instruments available to firms from IDA Ireland and EI, and the number of firms that received these instruments from 2006 to 2017.

Finally, firms can engage in publicly-supported academic-industry collaborations enabled by instruments from EI and IDA Ireland, as well as with Science Foundation Ireland's (SFI) network of publicly-funded research centres (SFI 2022). In contrast to EI and IDA Ireland, SFI primarily funds scientific research in research centres, based in Higher Education Institutions (HEIs). SFI-funded research centres are key pillars of the innovation ecosystem in Ireland, providing cutting edge knowledge to firms through collaborative research projects (Ryan et al. 2018; Mulligan et al. 2022). Our administrative data include all collaborations between firms and SFI-funded research centres, as well as collaborative instruments from EI and IDA Ireland, from 2006 to 2017 (See Panel C, Table A1, in the Supplementary material accompanying this paper).

Our combined administrative dataset comprises the population of firms that engaged with at least one of the above policy instruments, from 2006 to 2017, totalling 3,364 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 (by post), 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 circa 65 percent each

[5] 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).

[6] For more information on the R&D policy instruments available from EI, see: https://www.enterprise-ireland.com/en/Research-Innovation/.

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).[7] As such, ABSEI is specifically designed to cover a large, representative sample of the foreign-owned and domestic firms who have engaged with EI and IDA Ireland. Therefore, ABSEI provides an ideal platform to examine the sequencing of R&D policy instruments over time.

Our effective sample (i.e. usable in our analysis) is determined by the firms which responded to the ABSEI survey from 2000 to 2017. Using the period from 2000 to 2017 ensures that we can observe the R&D expenditure of all firms that received R&D policy instruments, prior to receiving such support. This is important, as some firms received R&D policy instruments during the initial years of the period covered by our administrative data (i.e. 2006, 2007, 2008, etc., of the full 2006 to 2017 period). Our final sample comprises 2,369 unique firms that received at least one of the R&D policy instruments discussed in Section 3.1. These firms represent around 71 percent of the population of firms included in the administrative data. The final dataset is an unbalanced panel with 24,736 firm-observations, with an average of 1,455 firm-observations per year, and an average of 10.4 observations per firm, from 2000 to 2017.

3.4 Dependent variables

From a policy perspective, the most immediate outcome of R&D policy instruments is an increase in firm-level R&D expenditure (Busom and Vélez-Ospina 2020; Mina et al. 2021; Gao et al. 2021). Therefore, firms' R&D expenditure is the most appropriate dependent variable for analysing the firm-level impact of R&D policy instrument sequencing. Empirical studies typically measure firm-level R&D expenditure in two ways: (1) Using the natural logarithm of firms' total R&D expenditure (Dumont 2017; Hottenrott et al. 2017; Caloffi et al. 2022); and, (2) Using firms' total R&D expenditure, normalised by firm size. This is predominantly carried out by using firms' levels of turnover (Aiello et al. 2019; Martínez-Noya and García-Canal 2021), or firms' number of employees (Lee et al. 2014; Baumann and Kritikos 2016; Busom and Vélez-Ospina 2020). Normalising our dependent variable by firm size is particularly important in Ireland. This is because over 98 percent of firms are SMEs, but large-sized firms are responsible for circa 66 percent of national firm-level R&D expenditure (CSO 2022).

[7] The ABSEI survey specifically includes all client firms of Enterprise Ireland, IDA Ireland.

To ensure that our results are not dependent on the specific definition of the dependent variable, we follow the recommendation of Aiello et al. (2019), and use both of the above measures of firm-level R&D. More specifically, we use: (1) The natural logarithm of firms' total R&D expenditure; and, (2) The natural logarithm of firms' total R&D expenditure divided by their number of employees. We normalise our second dependent variable by firms' number of employees, as opposed to their turnover. This is to avoid issues associated with business cycles, accounting manipulations, and asset sales. Among others, Lee et al. (2014) and Busom and Vélez-Ospina (2020), have argued that these factors are more likely to affect firms' turnover, rather than their number of employees.

3.4 R&D policy instrument sequencing

Our analysis develops and operationalises two novel empirical approaches to study R&D policy instrument sequencing over time. To do this, we group the R&D policy instruments in our data into three main categories, as detailed below.

3.4.1 Grouping of R&D policy instruments

Applying the recommendations of Zúñiga-Vicente et al. (2014) and Reichardt and Rogge (2016) to our novel data, we group the R&D policy instruments into three categories. These categories are (1) R&D grants, (2) R&D tax credits, and, (3) Collaborative R&D support (see Table A1, in the Supplementary material accompanying this paper). R&D grants comprise policy instruments that are allocated directly to firms, and that support internal R&D activities in firms (Enterprise Ireland 2022; IDA Ireland 2021). Collaborative R&D support comprises policy instruments that enable R&D collaborations between firms and public research organisations, such as universities and research centres (Enterprise Ireland 2022; IDA Ireland 2021; SFI 2022). Grouping the policy instruments is necessary, so as to obtain policy instrument sequences with sufficient observations for the empirical analysis. This approach follows previous studies, that focus on the static R&D policy instrument mix (see, for recent examples: OECD 2020; Meissner and Kergroach 2021; Russo and Pavone 2021). In contrast, R&D tax credits are a standalone category.

3.4.2 Operationalising the R&D policy instrument sequence

As detailed in Section 2.2 above, the existing empirical literature on the R&D policy instrument mix has mainly focused on the mix of policy instruments that firms receive at the same point in time. An analysis of policy instrument sequencing, requires identifying the order in which firms receive R&D policy instruments *over time*. This necessitates a different type of methodological approach from previous empirical studies, as firms can receive similar policy instrument sequences, in what we term different 'time windows'. To identify these sequences, we develop two novel and complementary approaches, which focus on different aspects of how R&D policy instrument sequencing can impact firm-level R&D. It is important to emphasise that the novel approaches detailed below are necessary, because we examine policy instrument sequences over time, as opposed to single policy instruments at a point in time.

Our first approach operationalises each policy instrument sequence as an individual treatment unit.[8] In doing this, our initial step is to identify the specific policy instrument (or static mix) that firms received *first,* and the year in which they received this treatment. In the context of our study, firms can receive: (1) R&D grants; (2) R&D tax credits; and/or, (3) Collaborative R&D support; either individually or combined, in any given year. We denote the years in which firms received their *first* policy instrument (or static mix) as year $t=0$. Our next step is to identify the 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 $t=0$. For example, if firm A received a first policy instrument in 2010, we denote the year 2010 as $t=0$. We then focus on the policy instruments received by firm A, from 2011 to 2017, denoted as years $t+1$ to $t+7$.

Our next step in constructing the sequence as an individual treatment unit, is to define the time windows in which firms receive sequences of policy instruments. In our data, approximately 47 percent of firms received more than one policy instrument in a sequence over time. Moreover, approximately 75 percent of these firms did so within a three-year window, after they received their *first* treatment (i.e. $t+1$ to $t+3$). Almost all of the firms that received policy instrument sequences, did so within a period of five years after they received the *first* policy instruments or mixes (i.e. $t+1$ to $t+5$). Based on this, we focus on the policy instrument sequences that occurred during the period $t=0$ to $t+3$. As a robustness test, we then repeat this analysis, but focus on the sequences occurring during the period $t=0$ to $t+5$.

Finally, in our first approach, we capture the different policy instrument sequences observed in our data, by means of binary variables. For example, in Table 1 below, the variable *R&D grant followed by R&D tax credit* equals 1 if firms received an R&D grant in $t=0$, followed by an

[8] The word 'treatment' is the most commonly used terminology to describe public R&D support being allocated to firms (see e.g. OECD, 2020). As such, in this study, we use this terminology to denote firms that receive any type of R&D policy instrument (or static mix of R&D policy instruments), in any given year.

R&D tax credit, during any of the years from *t+1* to *t+3*. Our data is organised in a panel, and most firms did not receive policy instruments in all years comprising the sequence. Therefore, the variable *R&D grant followed by R&D tax credit* only equals 1 in the specific years in which the firms received these policy instruments, during the sequence. More specifically, if firms claimed an R&D tax credit in *t+2*, the variable *R&D grant followed by R&D tax credit* will equal 1 in *t=0*, equal 0 in *t+1*, equal 1 in *t+2*, and equal 0 in *t+3*. Table 1 presents descriptive statistics on the different policy instrument sequences observed in our data, by using this first methodological approach.

Table 1: Policy instrument sequences using the first methodological approach

Policy instrument sequences	**Sequencing: T + 3 years following t=0**		**Sequencing: T + 5 years following t=0**	
	Firms	**Obser-vations**	**Firms**	**Obser-vations**
Panel A: Received policy instrument(s) in one year only				
R&D tax credit only	162	162	114	114
R&D grant only	755	755	686	686
Collaborative R&D support only	267	267	217	217
Mix of different policy instruments once only	54	67	44	57
Panel B: Received the same policy instrument(s) over time				
R&D tax credit (repeated years)	321	1,185	342	1,752
R&D grant (repeated years)	68	257	75	394
Collaborative R&D support (repeated years)	52	326	57	251
Instrument mix (repeated years)	63	241	74	390
Panel C: Received different policy instrument(s) over time				
R&D tax credit *followed* by R&D grant	-	20	-	42
R&D tax credit *followed* by collab. R&D support	-	15	-	11
R&D grant *followed* by R&D tax credit	188	703	211	1,085
R&D grant *followed* by collaborative R&D support	34	130	35	181
Collaborative R&D support *followed* by R&D grant	23	89	22	116
collab. R&D support *followed* by R&D tax credit	28	110	59	334
R&D tax cr. *and* R&D grant *followed* by R&D tax cr.	54	205	58	277
R&D tax credit *followed* by an instrument mix	127	495	154	857
R&D grant *followed* by an instrument mix	132	513	164	943
collab. R&D support *followed* by an instrument mix	32	120	48	251
Total	2,369	5,660	2,369	7,958

Note: Panel A includes firms that received only one policy instrument. Panel B includes firms that received a first policy instrument, in t= 0, and then received the same policy instrument during the period *t+1* to *t+3*, or *t+1* to *t+5*, depending on the column. Panel C includes firms that received a first policy instrument in t= 0, and then received a different policy instrument during the period *t+1* to *t+3*, or *t+1* to *t+5*. A mix of instruments refers to firms that received any of the following combinations: (1) R&D grant + R&D tax credit; (2) R&D grant + Collaborative R&D support; (3) R&D tax credit + Collaborative R&D support; and, (4) All of the above. The categories included in the variables capturing 'an instrument mix' in Table 1 are too small to be considered individually, and thus we aggregate them. -Due to statistical disclosure control, we do not provide the exact number of firms in categories which have 10 or fewer observations.

Our second methodological approach focuses on the individual effect of each R&D policy instrument, when deployed as part of an R&D policy instrument sequence. We use this second approach to obtain a more in-depth understanding of the complementarity or substitution effects occurring amongst different R&D policy instruments within sequences. Moreover, using a different definition of policy mix sequencing results in different R&D policy instrument sequence categories. In doing so, this second methodological approach serves as a means of ensuring that our findings are consistent across different model specifications and sequencing definitions.

In the same way as our first approach, to operationalise our second approach, we focus on the policy instruments that firms received *first* (in *t=0*). In contrast to our first approach, however, our second approach then focuses on the policy instruments that *immediately followed* firms' first instruments (i.e. *t+1*, *t+2* or *t+3*). We do this separately, using a series of binary variables, as opposed to one treatment unit in the first approach. More specifically, we define three binary variables that equal 1 if a firm's first treatment (in *t=0*) was an R&D grant, R&D tax credit, or a Collaborative R&D support, respectively (or otherwise, equal 0). For firms that received a mix of policy instruments at the same point in time (e.g. an R&D grant and an R&D tax credit in *t=0*), the binary variables equal 1 in each of the single policy instrument categories. This enables a higher level of precision in the standard errors when estimating our empirical models (see Section 3.5), by increasing the number of observations in each of the policy instrument categories. We employ a similar approach for the next policy instruments that immediately *follow* firms' *first* policy instrument(s). Table 2 presents the variables obtained from this second approach.

Table 2 Policy instrument sequences obtained from the second methodological approach

Policy Instrument Sequences: T+ 3 years following t=0	Number of firms	Number of observations
Panel A: Policy instruments that firms received first (t = 0)		
R&D tax credit *first*	736	863
R&D grant *first*	1,329	1,508
Collaborative R&D support *first*	427	427
Panel B: Policy instruments that immediately followed the first policy instrument		
R&D tax credit *follows* R&D tax credit	535	1,487
R&D tax credit *follows* R&D grant	405	498
R&D tax credit *follows* collaborative R&D support	74	123
R&D grant *follows* R&D tax credit	118	138
Collaborative R&D support *follows* R&D tax credit	57	71
R&D grant *follows* R&D grant	182	261
R&D grant *follows* collaborative R&D support	40	114
Collaborative R&D support *follows* collaborative R&D support	101	153
Collaborative R&D support *follows* collaborative R&D support	72	162
Total	4,076	5,805
Note: The difference in number of firms between Table 1 and Table 2 is because we double-count firms that received a mix of policy instruments, in each of the individual categories for the individual instrument. For example, firms that received an R&D tax credit, and an R&D grant, will be included in both groups. Moreover, firms in Panel A are also recorded in Panel B if they received more than 1 policy instrument. For example, firms that claimed R&D tax credits and then received an R&D grant, are recorded in two categories: 'R&D tax credit *first'*, and in the category*: 'R&D tax credit follows R&D grant'*.		

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 (Greco et al. 2020; Labeaga et al. 2021; Caloffi et al. 2022). This issue arises because R&D policy instruments are not allocated to firms at random. Firms seek to obtain R&D policy instruments (i.e. they self-select into an instrument). Moreover, some policy instruments are competitive in nature (e.g. R&D grants), and programme managers may select those firms that are best suited for achieving specific policy goals. For example, programme managers may select more R&D capable firms, and/or firms with a strong innovative track record (Hünermund and Czarnitzki 2019). This makes supported firms intrinsically different from firms not seeking R&D policy instruments (Hottenrott et al. 2018; Hünermund and Czarnitzki 2019; Nilsen et al. 2020; Caloffi et al. 2022). As highlighted by several key works, endogeneity due to this double-selection issue can bias estimation results, if not controlled for (Baltagi 2005; Wooldridge 2010; Nilsen *et al.* 2020; Mulligan et al. 2022). Studies that evaluate the impact of R&D policy instruments on firm-level outcomes typically address these sources of selection bias by instrumenting the allocation of R&D policy support (Dumont 2017; Szczygielski et al. 2017; Hewitt-Dundas et al. 2019). This is typically achieved by using non-parametric matching techniques (Nilsen et al. 2020; Caloffi et al. 2022). Alternatively, some studies use a regression discontinuity design (Dechezleprêtre et al. 2016; Santoleri et al. 2022). Such approaches ultimately rely on comparing firms that received policy instruments (i.e. treated firms), *vis-à-vis* statistically similar firms that did not receive policy instruments (i.e. untreated firms).

In our study, we seek to understand whether firm-level R&D outcomes vary, as firms benefit from different types of R&D policy instrument sequences. As a result, our study follows Bérubé and Mohnen (2009) and Neicu (2019), by only focusing on firms that receive at least one R&D policy instrument over our sample period. Hünermund and Czarnitzki (2019) discuss the confounding effects of endogeneity, when analysing the impact of an R&D policy instrument between firms that applied for and obtained funding, and firms that applied for funding but were not funded. As they articulate, focusing on a sample of all applicant firms "avoids this potential source of confounding" (p. 117). This is also the case in the context of our study. A key reason for this, is that while the firms in our sample can be different to the overall population of firms (i.e. most notably untreated firms), they are similar to one another in one crucial respect; They all receive at least one R&D policy instrument at some point, over the sample period. Our approach is similar to several other studies that avoid issues of endogeneity due to self-selection, by excluding untreated firms from their analyses (see, e.g. Bérubé and Mohnen 2009; Neicu et al. 2016; Neicu 2019; Fiorentin et al. 2019).

While accounting for selection into treatment is our main concern, our analysis also needs to consider issues related to unobserved heterogeneity and hidden treatment effects, that can persist amongst treated firms (Nilsen et al. 2020; Labeaga et al. 2021; Afcha and Lucena 2022). Given the panel-structure of our data, we control for these issues by using a firm fixed-effects econometric model (Asteriou and Hall 2011; Hille and Möbius 2019). A key advantage of the firm fixed-effects model, is that it permits controlling for unobserved heterogeneity and hidden treatment effects, by capturing within-firm variances over time (Greene 2002; Wooldridge 2010). The fixed-effect model is commonly used by similar studies to ours, that also benefit from panel data (e.g. Barbosa and Silva 2018; Tingvall and Videnord 2018; Acheson and Malone 2020; Gao et al. 2021). Our model is specified in the following way:

$$RD_{it} = \alpha + \sum_j \beta_1 Z_{itj} + \beta_2 Y_{itj} + \delta \mathrm{t} + \vartheta \mathrm{i} + \varepsilon_{it} \qquad (1)$$

In Equation (1), *RD* is the R&D expenditure of firm *i* in year *t*. β_1 (*1…k*) denotes the associated coefficients from the variables in vector Z, which includes a set of time-varying control variables that can affect firm-level R&D expenditure, and which are discussed below. Our analysis focuses on the coefficients denoted as β_2 (*1…k*) from vector Y, which contains the policy instrument sequences, as discussed in Section 3.4.2. The model includes time fixed-effects *t*, firm-level fixed-effects *i*, and a constant α. The time fixed-effects *t* capture business cycle effects, which may affect firms' R&D expenditures, while the firm fixed-effects *i* capture the within-firm variance across the years in our sample. As Equation (1) is estimated using a sample of firms that receive at least one policy instrument during 2006 to 2017, the constant α captures the R&D expenditures of these firms during the years in which they do not receive any policy instruments. Finally, ε denotes a firm-specific and time-specific error term.

Our model (in vector Z) controls for time-variant firm characteristics that can affect firms' abilities to identify and pursue R&D opportunities. Moreover, our model includes a continuous variable measuring firms' sales growth (total sales in *t=0* minus total sales in *t-1*/ total sales in *t-1*), as this can affect firms' abilities to finance their R&D activities (González-Bravo et al. 2020). We also control for the intensity of firms' exporting activities (Altomonte et al. 2016), with a continuous variable measuring firms' exports to sales ratio (i.e. total exports/total sales). Finally, we include a continuous variable measuring firms' number of employees (in logs), to account for heterogeneities in firm-level R&D expenditure between firms of different sizes (Perez-Alaniz et al. 2022). In addition, approximately eight percent of our sample receive R&D policy instruments in the years after the treatment window defined in our analysis (i.e. beyond *t+3* or *t+5*, depending on the window being considered). Therefore, we control for these additional policy instruments in binary form, for treatments received in all of the years after the time window being considered (i.e. *t+4* to *t+7*).

We first estimate Equation (1), by including the variables in Table 1. Here, the associated coefficients (denoted as β_2) indicate the impact that different policy instrument sequences have on firm-level R&D. For robustness, we then estimate Equation (1) with the variables from Table 2, which enable an understanding of the impact of the *first* policy instrument(s), and those that *follow*, separately. As Section 4 demonstrates, our findings are robust across the two empirical approaches and time windows we use (i.e. *t+3* and *t+5*).

Finally, as noted in Section 1, we also test the robustness of the findings obtained employing our novel analysis, by using a more traditional method developed previously in the literature, to specifically deal with potential endogeneity. As such, Table C1, in the Supplementary material accompanying this paper, presents the results of a Heckman (1979) selection model to control for endogeneity due to self-selection, as proposed by Dumont (2017). As this approach is not suitable for analysing the issue of policy instrument sequencing, we only focus on static R&D policy instrument mixes as observed in our data. The findings from this additional analysis support the main findings obtained, when employing our novel approaches. This indicates that our main findings are robust, and not driven by issues of endogeneity.

4. Results and discussion

Table 3 presents the results of our first methodological approach, which conceptualises each policy instrument sequence as an individual treatment unit. Table C1 in the Supplementary material accompanying this paper does the same for our second approach, which, in contrast to our first approach, focuses on the impact of each *individual* policy instrument, within each sequence. As described in Section 3.5, we change the parameters of our modelling approaches in several ways, to ensure that our findings are not sensitive to specific choices of model set-up. Therefore, in both tables (Table 3 here, and Table C1 in the Supplementary material), Columns 1 and 2 pertain to instrument sequences occurring within the period of three years, after firms received their *first* R&D policy instrument. Columns 3 and 4 do the same for the period of up to five years. Moreover, the findings in Columns 1 and 3 are obtained when measuring firm-level R&D as firms' total expenditure (in natural logarithm). In contrast to this, the dependent variable in Columns 2 and 4 is firms' total R&D expenditure divided by their number of employees (i.e. R&D intensity). Table 3 here and Table C1 (contained in the Supplementary material) reveal that our findings are consistent across all empirical approaches, suggesting they are robust.[9]

Table 3 shows that R&D policy sequencing is highly effective at driving firm-level R&D. We find 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. However, the impacts of such R&D policy instruments are *considerably larger,* and in many instances *more than double,* when firms receive them as part of a sequence of *the same* policy instrument over time (e.g. an R&D tax credit in year $t=0$, followed by another R&D tax credit in $t+1$). A similar impact is

[9] As noted in Section 3.5, Table B2 in the Supplementary material accompanying this paper, presents a robustness test which indicates that our main findings not driven by endogeneity.

observed when firms receive R&D policy instrument sequences comprising a combination of R&D tax credits and R&D grants, over time. Importantly, here we find that the order in which firms receive different R&D policy instruments makes a significant difference. Specifically, our findings indicate that receiving an R&D grant first, followed by an R&D tax credit, is the most impactful sequence. These findings highlight 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 contrast to R&D grants and R&D tax credits, when examining collaborative R&D support, Table 3 reveals a more nuanced picture. Table 3 reveals that, when received alone, collaborative R&D support tends not to drive firms' R&D. However, when firms receive collaborative R&D support *followed by* R&D tax credits, R&D grants, or a mix of instruments, the results are positive and significant. In line with Caloffi et al. (2022), these results may highlight the potential opportunity associated with a deliberate targeted sequencing of the policy instruments firms receive over time. Finally, receiving a mix of R&D policy instruments at one point in time only (e.g. a static mix of R&D grant and R&D tax credit in year *t*, and no subsequent instrument), does not result in higher levels of firm-level R&D. This result is particularly important because, as detailed in Section 2, the literature to date has focused almost exclusively on this type of static instrument mix. In contrast, our analysis shows that receiving a mix of R&D policy instruments *as part of sequence over time*, is highly effective at driving firm-level R&D. These empirical results confer with the theoretical work of Flanagan et al. (2011) and Rogge and Reichardt (2016), who highlight the fundamental importance of including the temporal dimension in any conceptualisation of the policy instrument mix.

Table C1 in the Supplementary material accompanying this paper, presents the results from our second methodological approach. As described in Section 3.4.2, this approach enables an understanding of the impact of the *first* R&D policy instrument firms receive, and each R&D policy instrument that *follows,* in instrument sequences over time. In Table C1 (see Supplementary material), we observe that R&D grants and R&D tax credits have positive and significant impacts on firm-level R&D, when received on their own (i.e. not as part of a sequence over time), or as the *first* instrument in a sequence. However, the impacts of these R&D policy instruments differ, depending on what firms receive next in the sequence over time. More specifically, R&D tax credits are highly effective when firms receive them in sequences over time (i.e. either repeated R&D tax credits each year, or a sequential mix of different instruments). However, *subsequent* R&D grants are only effective in a sequence, when firms receive them after an R&D grant *first*. Consistent with Table 3, we do not find

R&D grants to be effective when firms receive them either after R&D tax credits, or collaborative R&D support. Again, we find that collaborative R&D support tends not to result in higher levels of firm-level R&D. In summary, therefore, our second methodological approach results in similar findings to that of our first approach. This indicates that our findings are not sensitive to different definitions and measures of R&D policy instrument mix sequencing.

Table 3: Impact of R&D policy instrument sequence on firm-level R&D

	3-year Time Window (T+3)		5-year Time Window (T+5)	
	Log. R&D exp. (1)	**Log R&D int. (2)**	**Log. R&D exp. (1)**	**Log R&D int. (2)**
R&D tax credit once	0.407**	0.318***	0.484***	0.416***
	(0.137)	(0.123)	(0.183)	(0.167)
R&D grant once	0.230***	0.181***	0.284***	0.207***
	(0.062)	(0.056)	(0.066)	(0.060)
Collaborative R&D support once	0.032	0.015	0.039	0.026
	(0.094)	(0.086)	(0.104)	(0.097)
R&D grant and Collaborative R&D support once	.0963*	0.520	0.585	0.508
	(0.528)	(0.541)	(0.592)	(0.546)
Instrument mix once	0.193	0.190	-0.039	-0.089
	(0.250)	(0.199)	(0.284)	(0.232)
R&D tax credit (repeated years)	0.623***	0.515***	0.435***	0.272***
	(0.102)	(0.089)	(0.107)	(0.090)
R&D grant (repeated years)	0.539***	0.407***	0.864***	0.582***
	(0.222)	(0.186)	(0.274)	(0.257)
Collaborative R&D support (repeated years)	-0.101	-0.089	0.038	0.025
	(0.234)	(0.195)	(0.230)	(0.221)
Instrument mix (repeated years)	1.042***	0.715***	1.057***	0.752***
	(0.212)	(0.178)	(0.231)	(0.204)
R&D tax credit *followed by* R&D grant	0.192	0.145	0.616**	0.346*
	(0.226)	(0.311)	(0.317)	(0.205)
R&D grant *followed by* R&D tax credit	0.880***	0.726***	1.033***	0.869***
	(0.123)	(0.104)	(0.129)	(0.116)
R&D grant *followed by* collaborative R&D support	0.358*	0.254	0.643**	0.513*
	(0.213)	(0.191)	(0.325)	(0.307)
Collaborative R&D support *followed by* R&D tax credit	0.677**	0.570**	0.606***	0.447***
	(0.287)	(0.277)	(0.194)	(0.180)
Collaborative R&D support *followed by* R&D grant	-0.704	-0.548	-0.261	-0.457
	(0.597)	(0.344)	(0.484)	(0.410)
R&D tax credit and R&D grant *followed by* R&D tax credit	0.880***	0.678***	0.836***	0.501**
	(0.203)	(0.173)	(0.246)	(0.232)
R&D tax credit *followed by* instrument mix	0.864***	0.623***	0.847***	0.583***
	(0.126)	(0.112)	(0.132)	(0.120)
R&D grant *followed by* instrument mix	0.961***	0.763***	1.069***	0.779***
	(0.126)	(0.111)	(0.116)	(0.103)
Collaborative R&D support *followed by* instrument mix	0.639**	0.475***	0.690***	0.582**
	(0.320)	(0.271)	(0.269)	(0.259)
Treatment in t+4	0.228***	0.153***	-	-
	(0.030)	(0.024)		
Treatment in t+5	0.261***	0.168***	-	-
	(0.035)	(0.028)		
Treatment in t+6	0.242***	0.183***	0.315***	0.234***
	(0.042)	(0.036)	(0.046)	(0.039)
Treatment in t+7	0.258***	0.163***	0.331***	0.218***
	(0.054)	(0.050)	(0.056)	(0.052)
Sales growth	0.004	0.022***	0.010	0.027***
	(0.010)	(0.005)	(0.011)	(0.006)
Ratio of export to sales	-1.992***	-0.113	-1.987***	-0.111
	(0.092)	(0.085)	(0.092)	(0.085)
Number of employees	0.003***	0.000	0.003***	0.001
	(0.000)	(0.000)	(0.000)	(0.003)
Year Controls (2001 to 2017)	Yes	Yes	Yes	Yes
Constant	3.625***	-0.256**	3.619***	-0.259***
	(0.107)	(0.099)	(0.106)	(0.099)
Observations	24,736	24,736	24,736	24,736
Number of Firms	2,369	2,369	2,369	2,369
Rho	0.652	0.606	0.648	0.603
Weighted R^2	0.156	0.056	0.144	0.057

Note: Results obtained with a fixed-effect regression model. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Rho refers to interclass-correlation, which is the variance that can be explained by differences across panels. The Weighted R^2 shows the overall variance which is explained by our model. The insignificant results for the variable 'Number of employees' in Columns 2 and 4 relate to the fact that the dependent variable is total R&D divided by number of employees.

Our combined findings from Table 3 here and Table C1 (in the Supplementary material) provide strong evidence regarding the critical importance of R&D policy mix sequencing for encouraging firm-level R&D. Our findings are robust across: (1) Different measures of firm-level R&D; (2) Different temporal windows in which the sequences occur; and, (3) Different conceptualisations of policy mix sequencing. In all cases, firm-level R&D expenditure is significantly higher when firms receive R&D policy instruments sequences over time, when compared to receiving single instruments (or a mix of instruments) at one point in time. These factors support our Hypothesis 1, which posited that receiving a mix of R&D policy instruments over time has a greater impact on firm-level R&D, relative to receiving a single policy instrument or static instrument mix. Therefore, our findings provide novel empirical evidence in support of existing theoretical arguments, which point to the importance of R&D policy instrument sequencing (Flanagan et al. 2011; Cunningham et al. 2016; Labeaga et al. 2021; Pang et al. 2021).

Our findings also highlight the existence of significant differences in the extent to which different R&D policy instrument sequences, drive firm-level R&D. This supports our Hypothesis 2, which posited that the impact of receiving a mix of R&D policy instruments over time will be different, depending on the type of instruments received, and the sequence in which they are received. In line with studies focused on the Mathew effect, in the context of R&D tax credits (Pereira and Suárez 2018; Labeaga et al. 2021), and R&D grants (Antonelli and Crespi 2013; Fiorentin et al. 2019), we find such R&D policy instruments to be most effective when received recurrently, over time. Our findings build on and extend these studies, by also showing that R&D tax credits and R&D grants are also highly effective when received *together*, in sequences over time. Moreover, our findings show that combining either of these two R&D policy instruments with collaborative R&D support in sequences over time, can also drive firm-level R&D. However, our results reveal that the most effective combination of R&D policy instruments over time, pertains to recurrent sequences of R&D tax credits or R&D grants, and sequences comprised of an initial R&D grant, followed by an R&D tax credit. Therefore, our results provide strong evidence indicating that the R&D policy instrument mix menu served to firms over time, plays a key role in determining the impact of public R&D support on firm-level R&D.

Finally, our results suggest that collaborative R&D support has a more limited effect on firm-level R&D, when received at one point in time, or on a recurrent basis. Work by Cassiman et al. (2018), Fudikar and Hottenrott (2018) and Hewitt-Dundas et al. (2019), provide a possible explanation for these results. These studies suggest that firms seek to engage with public research organisations (e.g. universities and research centres), to perform R&D activities which they cannot perform internally. As a result, firms may not necessarily *increase* their R&D expenditure during the collaborative project, but rather *shift* their internal R&D expenditure towards such collaborations. Moreover, as noted by Mulligan et al. (2022), the impact of collaborative R&D support on firm-level R&D takes time to fully materialise. These points are perhaps borne out by the fact that, as our results show, receiving collaborative R&D support, *followed by* an R&D tax credit, produces positive and significant effects. As such, firms may develop new R&D capacity during a collaboration, and then leverage these new skills with an R&D tax credit in a later period. Our interpretation here is consistent with earlier work by Scandura (2016) and Hewitt-Dundas et al. (2019), in the sense that firms need to enhance their R&D capabilities first, in order to benefit from collaborations with public research organisations. This further highlights the importance of sequencing when analysing the impact of R&D policy instrument mixes, on firm-level R&D.

5. Conclusion

Since the key initial work of Nauwelaers et al. (2009) and Flanagan et al. (2011), the concept of policy instrument mix has gained much attention when evaluating the impact of public R&D support on firm-level R&D, amongst both academics (Lanahan and Feldman 2015; Martin 2016; Kern et al. 2019; Russo and Pavone 2021), and policymakers alike (OECD 2020; European Commission 2021). Almost all studies in this rapidly expanding area of research, have to date however, conceptualised and empirically estimated the R&D instrument mix as static, occurring when firms receive multiple instruments at one point in time (e.g. Czarnitzki and Lopes-Bento 2013; 2014; Guerzoni and Raiteri 2015; Dumont 2017; Stojčić et al. 2020; Heijs et al. 2022). Although previous contributions have notably advanced our knowledge in the field of R&D policy instrument mix evaluation, our paper addresses a key gap in this literature: The impact of receiving R&D policy instruments in a *sequence*, over time, on firm-level R&D. Our results clearly demonstrate that the R&D policy instrument mix menu served to firms over time, has key implications for the impact of public R&D support on firm-level R&D.

In doing so, we respond to direct calls for further research by Cunningham et al. (2016) and Coburn et al. (2021). These studies highlight the importance, for empirical research, of understanding policy instrument mix sequencing effects on firms' R&D. Indeed, the concept of sequencing has from the outset been important within the R&D policy instrument mix theory (e.g. Flanagan et al. 2011; Rogge and Reichardt 2016; Schmidt and Sewerin 2019). However, to the best of our knowledge, the firm-level impacts of R&D policy instrument mix sequencing have never heretofore been addressed in the empirical literature. It is this key challenge that we tackle in this paper. Our analysis reveals that policy instrument mix sequencing plays a crucially important role in driving firms' R&D. Indeed, when conceptualised as a sequence over time, the role of static policy instrument mix becomes almost redundant, for two main reasons: (1) The vast majority of firms in our sample who receive a mix of policy instruments, do so in a sequence over time, and the impacts of this sequencing are large and significant; and, (2) When sequencing is taken into consideration, few firms receive a mix of instruments at a single point in time, and the impacts of such static mixes are limited. This type of analysis was not possible in most previous studies, due to limited data availability. We overcome this limitation by exploiting a unique dataset, and as such, our study builds on and extends previous research, to clearly highlight the key role of policy instrument mix sequencing in driving firm-level R&D.

In our analysis, we construct a novel dataset, drawing on unique administrative data for firms in Ireland that received R&D policy instruments from 2006 to 2017, and annual survey data on firms' R&D activities for the period 2000 to 2017. Furthermore, we developed two wholly new and complementary empirical approaches for conceptualising and analysing the impact of R&D policy instrument sequencing, on firm-level R&D. The salient findings emerging from this analysis show that, receiving a single R&D grant or R&D tax credit, has a positive and significant effect on firm-level R&D. Notwithstanding this, the impact of such R&D policy instruments are significantly larger, and in many cases more than double, when firms receive them recurrently over time, as part of a sequence. We observe similar effects when firms receive R&D grants followed by R&D tax credits, but not *vice versa*. Finally, our results suggest that, on their own, publicly-supported academic-industry collaborations do not tend to drive firm-level R&D. In fact, these R&D policy instruments only result in positive and significant effects when they are followed by R&D tax credits, or a mix of instruments, over time. A variety of robustness tests support all of our main results.

Our paper contributes to the empirical literature on the R&D policy instrument mix in two main ways. Our first novel contribution is to bridge the gap between theory and empirical analysis, in how R&D policy instrument mix impacts firm-level R&D. To the best of our knowledge, our study represents the first time that R&D policy instrument sequencing is empirically analysed. In doing so, our analysis adds clarity to the somewhat ambiguous existing empirical evidence regarding the impact of the R&D policy instrument mix on firm-level R&D (Cunningham et al. 2016; Dumont 2017; Coburn et al. 2021; Greco et al. 2021; Petrin and Radicic 2023; Teirlinck et al. 2021; Douglas and Radicic 2022). Therefore, our paper offers novel insights, which represent a critical step forward in the empirical literature regarding the impact of the R&D policy instrument mix on firm-level R&D.

Our study's second contribution concerns the development of a novel empirical strategy for analysing the impact of R&D policy instrument *sequencing*. As noted above, most previous studies on this topic have, to date, focused solely on the R&D policy instrument mix that firms receive at a point in time (i.e. the static R&D policy instrument mix). However, analysing the impact of R&D policy instrument sequencing requires a different approach, as R&D policy instrument sequences can take place across different time windows. To overcome this issue, we develop two novel and complementary empirical approaches. Our first approach is to conceptualise R&D policy instrument sequences over time, as individual and distinct treatment units. Our second approach specifically focuses on the *additional* effect of each specific R&D policy instrument, when received as part of a sequence over time. When used together, these two empirical approaches enable us to achieve a comprehensive understanding of the impact of different R&D policy instrument sequences over time, on firm-level R&D. Therefore, our study contributes to the literature, by introducing novel empirical tools for conceptualising and investigating the importance of R&D policy instrument mix sequencing on firm-level outcomes.

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 recently noted by Caloffi et al. (2022), the R&D policy instrument mixes received by firms are typically unplanned. This is in the sense that mixes as provided by policymakers are typically not designed or deliberate (e.g. specifically targeting a discrete group of firms, with a specific policy instrument in one year, followed by another [perhaps different] policy instrument in subsequent years, in order to achieve superior outcomes). Therefore, when considering the R&D policy instrument mix menu served to firms, 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 of limitations. Acknowledging such limitations can serve as a springboard for future research on this topic. As several studies note, R&D policy instruments can be effective at driving more firms to invest in R&D (i.e. extensive margin), rather than at increasing the R&D spending of firms that already invest in R&D (i.e. intensive margin; see e.g. Huergo and Moreno 2017; Fiorentin et al. 2019; Caloffi et al. 2022). However, we are unable to disaggregate our analysis to study the impact of such sequences on the extensive and the intensive margins. This is due to a limited number of observations in some of the R&D policy instruments sequences considered. For this same reason, we are unable to account for other factors that can play important roles in determining the impact of R&D policy instruments, such as examining sequencing in specific industrial sectors (Castellacci and Lie 2015). Future studies (given data availability) can expand our research in this regard. Moreover, our novel dataset solely pertains to firms based in Ireland. It would be interesting if future studies replicated our analysis in other country settings. Finally, we only focused on the effect of R&D policy instrument 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.

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

Acknowledgements:

This publication has emanated from research conducted with the financial support of Science Foundation Ireland under Grant number 17/SPR/5328. For the purpose of Open Access, the authors have applied a CC BY public copyright license to any Author Accepted Manuscript version arising from this submission. Results are based on analysis of strictly controlled Research Microdata Files provided by the Central Statistics Office (CSO). The CSO does not take any responsibility for the views expressed or the outputs generated from this research. We gratefully acknowledge the Central Statistics Office, the Department of Enterprise, Trade and Employment, Enterprise Ireland, IDA Ireland, and Science Foundation Ireland, for providing data for this research.

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Supplementary material

Table A1: Policy instruments included in the administrative data (Total Sample N=3,296)

Policy Instrument	Funding Agency	R&D Policy instrument type	Total 2006-2017
Panel A: Revenue Commissioners			
R&D Tax Credit	Revenue Commissioners	R&D Tax Credit	7,981
Panel B: Industrial Development Agency (IDA) Ireland and Enterprise Ireland (EI)			
Business Innovation Initiative / Company Expansions Including R&D	EI	R&D grant	361
Intellectual Property (IP) Assistance Scheme	EI	R&D grant	72
Innovation Partnerships	EI/IDA	Collaborative R&D support	672
Innovation Vouchers	EI/IDA*	Collaborative R&D support	1,194
Innovative HPSU	EI	R&D grant	968
R + D Capability/ R&D Feasibility	IDA	R&D grant	106
R&D Fund	IDA	R&D grant	1,989
R&D Innovation	EI	R&D grant	606
RD&I Feasibility	EI	R&D grant	148
Strategic R&D/ Shannon R&D	EI	R&D grant	146
Technical Feasibility	EI	R&D grant	1,226
Panel C: Science Foundation Ireland (SFI)			
SFI research centre collaboration	SFI	Collaborative R&D support	1,399
Total			17,300

Note: * R&D policy instruments from Enterprise Ireland, but foreign-owned firms can access them through IDA Ireland. Due to statistical disclosure control, similar R&D policy instruments judged to have too few observations are grouped.

Appendix B: Model specification for Heckman two-stage selection model

As outlined in Section 3.5 of the main paper, to ensure our main results are not driven by endogeneity, we estimated a Heckman (1979) selection model, as proposed by Dumont (2017). As this approach is not suitable for analysing the issue of policy instrument sequencing, we only focus on static R&D policy instrument mixes as observed in our data.

By following Dumont's (2017) approach, we first analysed the types of R&D policy instrument mixes, observed in our data. As we specifically considered R&D tax credits, R&D grants, and Collaborative R&D support, the possible instrument mixes were as follows:

1) No Instrument
2) R&D tax credits
3) R&D Grants
4) Collaborative R&D support
5) R&D tax credits and R&D grants
6) R&D tax credits and Collaborative R&D support
7) R&D grants and Collaborative R&D support
8) All three R&D policy instruments (i.e. R&D tax credits and R&D grants and Collaborative R&D support).

As we discuss in our main paper (Section 3.5), the issue of endogeneity due to selection bias arises because R&D policy instruments are not allocated to firms at random; firms seek to obtain R&D policy instruments (i.e. they self-select). This makes firms receiving such policy instruments (i.e. treated firms) intrinsically different from firms not seeking R&D policy instruments (Hottenrott et al. 2018; Hünermund and Czarnitzki 2019; Nilsen et al. 2020; Caloffi et al. 2022).

To control for selection bias, Dumont (2017) proposes a two-stage model, which extends a model initially proposed by Heckman (1979). By following Dumont's (2017) approach, we first estimated the probability of each of the firms in our sample, to obtain an R&D policy instrument. Since firms can receive seven different forms of treatment, as noted above, we estimated a multinomial logit model. In line with Dumont (2017), we included the same firm-level control variables used in our main models, but also included whether firms also received treatment in the previous year, and the type of treatment that they received (i.e. see variable R&D support Yes= 1 [*t-1*], in Table B1 below). We also included the natural logarithm of firms' R&D spending in the year before being treated [i.e. see variable Log R&D spending (*t-1*), in Table B1). Table B1 presents the results of this first-stage multinomial regression model.

Once firms' probabilities to receive treatment were obtained, we then estimated the Inverse Mills Ratios (IMRs). The IMR is the probability density function, divided by the cumulative distribution function (Mills, 1926). As highlighted by Dubin and McFadden (1984), two-stage selection models which comprise of a first stage with a multinomial outcome, require the inclusion of multiple IMRs (i.e. total number of possible treatments – 1). In our specific case, therefore, we include a total of 6 IMRs in our second stage regression.

Our second stage regression estimated the impact of the above R&D policy instruments, and their static mixes, on firm-level R&D. In line with our main models (see Section 3.5 of the main paper), for this second stage, we used a fixed-effects panel regression model. Importantly, this second-stage model included the six IMRs, obtained from the first-stage model described above. We repeated the process for our two outcome variables (i.e. Logarithm of total R&D spending, and Logarithm of Total R&D spending intensity). As noted by Dumont (2017, p. 1855) "the statistical significance of these variables will provide an indication on the relevance of the selection bias".

As Table B2 below shows, the results obtained by following Dumont's (2017) proposed approach are in line with our main results. This indicates that the results of our main models (described in Section 3.5 of the main paper) are robust, and not caused by issues of endogeneity.

Table B1: Probability of firms obtaining R&D policy instrument, or mixes, during 2006 to 2017 (Multinomial Logit Model).

	R&D Tax Credit (1 = Yes)	R&D Grant (1 = Yes)	Collab. R&D support (1 = Yes)	R&D Tax Credit and R&D Grant (1 = Yes)	R&D Tax Credit and R&D collab. support (1 = Yes)	Collab R&D support and R&D Grant (1 = Yes)	All Three (1 = Yes)
R&D support Yes= 1 (t-1)	0.562***	-0.182***	0.261***	0.596***	0.715***	-0.146	0.827***
	(0.019)	(0.054)	(0.053)	(0.032)	(0.042)	(0.224)	(0.107)
Log R&D expenditure (*t-1*)	0.263***	-0.052***	-0.091***	0.394***	0.329***	-0.030	0.398***
	(0.009)	(0.010)	(0.016)	(0.032)	(0.037)	(0.044)	(0.066)
Sales Growth	-1.316	0.016	-0.011	-0.197	-1.781	0.011	0.010
	(1.080)	(0.023)	(0.032)	(0.697)	(1.823)	(0.032)	(0.046)
Export to Sales Ratio	0.209***	-0.105	-0.305***	0.145	0.133	-0.156	-0.076
	(0.056)	(0.073)	(0.115)	(0.142)	(0.229)	(0.332)	(0.051)
Log. Number of Employee	-0.001**	0.001	-.0001	-0.001***	-0.001***	0.005***	-0.004
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.004)
Year control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-3.010***	-1.358***	-1.441***	-2.801***	-2.811***	-1.115***	-2.106***
	(0.141)	(0.113)	(0.166)	(1.850)	(0.371)	(0.455)	(0.681)
Observations	22,017	22,017	22,017	22,017	22,017	22,017	22,017
Log Likelihood	-17,871.81	-17,871.81	-17,871.81	-17,871.81	-17,871.81	-17,871.81	-17,871.81
Pseudo R^2	0.125	0.125	0.125	0.125	0.125	0.125	0.125

Note: Results obtained with a multinomial logit regression. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Pseudo R^2 shows the overall variance which is explained by our model.

Table B2: Impact of R&D policy instrument, and their mixes, during 2006 to 2017 (Fixed-effects model).

	Log R&D expenditure (1)	Log R&D intensity (2)
R&D Tax Credit	0.116*** (0.036)	0.084*** (0.035)
R&D Grant	0.446*** (0.050)	0.388*** (0.046)
Collab R&D support	0.139*** (0.057)	0.102** (0.056)
R&D Tax Credit **and** R&D Grant	0.284*** (0.068)	0.203*** (0.059)
R&D Tax Credit **and** R&D collab support	0.194** (0.097)	0.096 (0.084)
Collab R&D support **and** R&D Grant	0.498*** (0.175)	0.540*** (0.160)
All three Instruments	-0.311 (0.290)	-0.235 (0.193)
Sales Growth	1.742*** (0.382)	1.398*** (0.332)
Export Sales	-2.321*** (0.140)	-0.559*** (0,148)
Ln. Number of Employees	0.005*** (0.001)	0.001*** (0.000)
Mills 1	-0.447*** (0.210)	0.355 (0.224)
Mills 2	1.451*** (0.225)	0.805*** (0.242)
Mills 3	-1.501*** (0.185)	-1.047*** (0.204)
Mills 4	-2.283*** (0.646)	-1.690*** (0.704)
Mills 5	3.773*** (0.712)	1.879*** (0.763)
Mills 6	2.154*** (0.632)	1.724*** (0.782)
Year Controls	Yes	Yes
Constant	24.175*** (3.266)	9.422*** (3.416)
Observations	22,016	22,016
Firms	2,354	2,354
Rho	0.582	0.543
Weighted R^2	0.245	0.299

Note: Results obtained with a fixed-effect regression model. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Rho refers to interclass-correlation, which is the variance that can be explained by differences across panels. The Weighted R^2 shows the overall variance which is explained by our model

Table C1: Impact of each R&D policy instrument within sequences, on firm-level R&D (Second Approach)

	3-year Time Window		5-year Time Window	
	Log. R&D expenditure (1)	**Log R&D intensity (2)**	**Log R&D expenditure (3)**	**Log R&D intensity (4)**
R&D tax credit *first*	0.546***	0.477***	0.544***	0.471***
	(0.076)	(0.065)	(0.077)	(0.066)
R&D grant *first*	0.218***	0.193***	0.225***	0.197***
	(0.053)	(0.046)	(0.053)	(0.046)
Collaborative R&D support *first*	-0.121	-0.103	-0.130	-0.109
	(0.083)	(0.078)	(0.083)	(0.074)
R&D tax credit *follows* R&D tax credit	0.485***	0.350***	0.447***	0.296***
	(0.079)	(0.069)	(0.078)	(0.067)
R&D tax credit *follows* R&D grant	0.767***	0.570***	0.794***	0.560***
	(0.090)	(0.076)	(0.081)	(0.073)
R&D tax credit f*ollows* collab. R&D	0.492***	0.429***	0.340*	0.290*
support	(0.179)	(0.151)	(0.202)	(0.170)
R&D grant *follows* R&D tax credit	0.168	0.013	0.175	-0.030
	(0.315)	(0.263)	(0.228)	(0.190)
Collab. R&D support *follows* R&D tax	0.328	0.382	0.332	0.303
credit	(0.370)	(0.324)	(0.328)	(0.288)
R&D grant *follows* R&D grant	0.802***	0.589***	0.693***	0.539***
	(0.188)	(0.162)	(0.162)	(0.136)
R&D grant *follows* collaborative R&D	0.270	0.185	0.168	0.077
support	(0.275)	(0.242)	(0.270)	(0.250)
Collaborative R&D support *follows* R&D	0.543***	0.460***	0.504***	0.432***
	(0.171)	(0.126)	(0.149)	(0.142)
Collaborative R&D support *follows*	0.035	-0.051	0.092	0.007
collaborative R&D support	(0.235)	(0.208)	(0.231)	(0.206)
Treatment in T+4	0.183***	0.118***		
	(0.028)	(0.023)	-	-
Treatment in T+5	0.218***	0.134***		
	(0.033)	(0.027)	-	-
Treatment in T+6	0.206***	0.154***	0.226***	0.168***
	(0.041)	(0.036)	(0.042)	(0.036)
Treatment in T+7	0.216***	0.131***	0.238***	0.146***
	(0.053)	(0.049)	(0.053)	(0.043)
Sales Growth	0.004	0.023***	0.004	0.023***
	(0.010)	(0.005)	(0.010)	(0.005)
Export to Sales	-2.006***	-0.123	-2.008***	-0.125
	(0.092)	(0.085)	(0.092)	(0.085)
Employment	0.003***	0.000	0.003***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Year Controls (2001 to 2017)	Yes	Yes	Yes	Yes
Constant	3.637	-0.246***	3.641***	-.243***
	(0.112)	(.099)	(0.107)	(0.099)
Observations	24,736	24,736	24,736	24,736
Number of Firms	2,369	2,369	2,369	2,369
Rho	0.655	0.610	0.654	0.610
Weighted R^2	0.134	0.049	0.136	0.051

Note: Results obtained with a fixed-effect regression model. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Rho refers to interclass-correlation, which is the variance that can be explained by differences across panels. The Weighted R^2 shows the overall variance which is explained by our model.

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