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DISCUSSION PAPER

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R&D Grants and R&D Tax Credits in Belgium: Evidence on the Policy Mix

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Abstract

Drawing on a longitudinal database of Belgian firms over the years 2014-2020, this study investigates the joint effect of R&D grants and R&D tax credits on R&D inputs and innovation outputs. We estimate Conditional Difference-in-Difference (CDiD) models and apply both treatment effects estimators that account for heterogeneous, staggered treatments as well as standard two-way fixed effects DiD estimators. We find positive treatment effects for both grants and tax credits on R&D employment, R&D employment intensity, and total R&D expenditures. R&D tax credits have a significant positive impact on the share of sales of new or improved products. By comparing the results obtained by the two econometric methods, we also find that the standard two-way fixed effects models may lead partially to potentially wrong conclusions about the impacts of such policies, as the traditional estimators may not sufficiently account for the complexity of how the policy instrument affect firm-level outcomes.

Keywords: Policy mix, innovation, R&D grants, R&D tax credits, difference-in-difference

JEL-Classification: D22, H25, L53, O32, O38

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1 Introduction

This study explores the effects of two supply-side policy instruments, namely R&D grants and R&D tax credits on firm-level outcomes, in particular R&D inputs and innovation outputs, with particular attention on the instrument policy mix, i.e. the interplay between the two measures. The concept of policy mix first appears in the macroeconomic policy discourse in the early 1960s, then diffuses into the environmental policy and regulation literature in the late 1990s (Gunningham and Sinclair, 1999; Flanagan et al., 2011). It has then gradually been gaining traction also in the context of innovation policy, especially after the Organization for Economic Cooperation and Development (OECD) devoted a chapter of one of its publications on the issue (OECD, 2010a; Cunningham et al., 2016). Analysts view the policy mix as a tool to deal with the growing complexity of national innovation policy agendas and to improve the efficiency of the individual instruments themselves. Systemic failures in innovation processes are multi-dimensional and best addressed through an *ad hoc* combination of carefully selected policy instruments (Borrás and Edquist, 2013).

Policy interactions, however, can manifest beyond the designing intentions of the conceiving entities. According to the theoretical framework developed in Flanagan et al. (2011), interactions between policy instruments can occur across four dimensions: policy sub-systems (networks of state and non-state institutions shaping policies concerning a particular problem area), governance levels (international, national, regional, local), geographical space, and time. Policies may target the same entities for different goals, or different agents involved in the same process, or affect different processes within the same broader system. There can be interactions even between the same kind of instruments across various dimensions. Consequently, the joint impact of policy mix is not straightforwardly additive: conflicts between policy rationales, goals and implementation approaches among instruments may highlight coordination and coherence failures that actually produce an inefficient and sub-optimal result.

Our study, for instance, examines the interplay between two classes of instruments for R&D policy, i.e. direct grants for R&D and innovation projects and R&D tax credits, in the same geographical context, i.e. the Belgian region of Flanders. The instruments are administered at distinct governance levels (regional for grants, national for tax credits), with overlapping but not fully coincident policy rationales, objectives, and subject populations, as each measure targets diverse micro aspects of the innovation-generating process. The main R&D tax credit scheme is organized as a payroll withholding tax for R&D personnel, i.e., R&D performing companies benefit from lower social security contributions for their R&D staff. The R&D grants are administered by a regional managing authority and firms have to submit project-based research proposals that are subject to peer review.

We apply difference-in-difference (DiD) estimation methods on a panel data of Belgian firms to assess whether R&D grants and tax incentives are complements, i.e. jointly generate additional benefits, or substitutes, that is they obstruct each other by dampening the overall effect of the policies. We additionally employ the vector matching procedure (Lopez and Gutman, 2017) to account for the heterogeneity between supported and unsupported firms in the propensity to participate into a specific R&D program. Finally, we use the generalized DiD estimator outlined in De Chaisemartin and d'Haultfoeuille (2023) to solve for any bias resulting from heterogeneity of policy effects across observed units.

The study contributes to the literature on R&D policy mix in terms of both innovation input and output additionality, and it is the first of its kind, to our knowledge, to address the interaction of R&D policy instruments by applying the latest econometric developments in difference-in-difference estimation.

The remainder of this paper is organized as follows. Section 2 summarizes the R&D policies enacted in Belgium. Section 3 provides a review of the empirical literature on R&D policy mix. Section 4 describes the data. Section 5 illustrates the empirical methodology. Section 6 discusses the results. Section 7 concludes the paper.

2 Policy background

2.1 R&D tax credit schemes

The Belgian federal government maintains four different R&D and innovation tax credit schemes (see Table 1 for an overview). The main scheme that is often referred to as R&D tax credit in Belgium is run by the federal government, and it is actually a partial exemption from advance payment of the withholding tax on the wages of R&D employees. It was initially introduced in 2006 for firms' R&D employees holding Ph.D. degrees. In 2007, it was extended to R&D employees holding master's degrees (except those in the social sciences). Until 2008, the exemption amounted to 25 percent of taxes on wages. It was then increased to 65 percent in 2008 and 75 percent from 2009 onward. Currently, firms that are eligible for partial exemption do not have to pay 80 percent of the withholding tax that is deducted from salaries. In 2018, the scheme was extended to bachelor's degrees with an exemption rate of 40 percent. In 2020, the exemption for bachelor's degree holders was harmonized to 80 percent but limited in the amount to 25 percent (50 percent for SMEs) of the total amount of the applied exemption for employees with a master's degree or PhD. This policy scheme, therefore, provides immediate financial support to all firms conducting R&D; even to firms currently operating unprofitably, such as startups (see, e.g., Dumont 2017; Kelchtermans et al., 2020, for other studies on that scheme, or the OECD INNOTAX portal[2] for a more detailed description of the current policy scheme).

In addition to the payroll withholding tax credit, there are two other volume-based fiscal incentive schemes available in Belgium: the R&D investment deduction, and the tax credit for R&D. The former was introduced in 1992, and applies to R&D investments in patents as well as environment-friendly tangible and intangible assets. The deduction can be applied in two alternative ways: as a one-time deduction of 13.5 percent of the acquisition or investment value of the asset; or spread over a 5-year depreciation period equal to 20.5 percent of the depreciation amount.

The R&D tax credit was established in 2006, and applies to both tangible and intangible capital investments for R&D purposes. Similarly to the investment deduction scheme, the cost reduction under this policy can take two forms: a one-off reduction of 4 euros per 100 euros of investment; or a reduction equal to 6 percent spread over the depreciation period of the asset (5 years). Starting from 2020, rates changed to 3.38 percent and 5.125 percent, respectively.

Both illustrated schemes have similar generosity, and, since 2018, they are mutually exclusive: firms claiming one cannot benefit from the other and vice versa.

Lastly, another innovation-related tax relief scheme is the innovation income deduction (IID), the current patent box regime for Belgium. The IID is based on Action Point 5 of the OECD BEPS Action Plan, and was introduced in July 2016. The scheme substitutes for the Patent Income Deduction (PID), the old regime that has been operative with a 5-year grandfathering period until July 2021. Under PID, firms could deduct 80 percent of the net income generated

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[2] Url: https://stip.oecd.org/innotax/countries/Belgium

by patents. In comparison, IID features two main changes. First, the tax deduction is raised up to 85 percent of the net qualifying income; secondly, the set of IP eligible for deduction has been enlarged to include –besides pending or granted patent documents– also supplementary protection certificates (SPCs), plant variety rights, orphan drug rights and copyright-protected software. As of 2021, the related maximum effective tax rate is reduced to 3.75 percent.

Table 1: Overview of fiscal measures for R&D and innovation

Scheme	Year of introduction	Benefit	Policy penetration*
Partial exemption from advance payment of the withholding tax on the wages of R&D employees	1. 2006 for employees holding Ph.D. degrees; 2. extended 2007 to employees with master degrees; 3. extended 2018 to bachelor degrees.	• For Ph.D. and master degrees: 25% of taxes on wages, increased to 65% in 2008, and 75% since 2009; • Since 2018, 40% for bachelor's degrees, increased to 80% in 2020.	92%
R&D investment deduction / tax credit for R&D (mutually exclusive)	1992 / 2006	• One-time deduction of 13.5% of investment or 5-year depreciation of 20.5% • One-time deduction of 4% or 6% spread over 5-year depreciation period.	26%
Innovation income deduction	2016 / 2021	80% / 85% of the net qualifying income	21%

* The policy penetration is calculated from our survey data that is used in the current study. The percentages are the relative share of firms using at least one of the fiscal schemes. The percentages sum up to more than 100% as firms may benefit from multiple schemes.

2.2 R&D grants by the regional Flemish government

The R&D grant programs are administered by the regional authorities in Belgium.[3] As the data in hand pertain Flemish businesses, we focus on the R&D grant schemes offered by VLAIO, the Flemish agency for innovation and entrepreneurship.

VLAIO provides financial support and consultation services targeting Flemish small and large companies, as well as clusters and consortia involving businesses and other nonprofit innovative organizations (e.g., universities, research centers). Its purpose is to promote entrepreneurship, stimulate growth and innovation, facilitate cooperation among firms, and foster an enterprise-friendly environment. Besides, VLAIO assists the Flemish government in the development and implementation of economic policies.

In 2018, VLAIO funded 1,400 companies for a total of 400 million euros, of which around 230 million euros were granted to support innovation and knowledge acquisition. According to agency regulations, a single firm can receive up to eight million euros per year to carry out its R&D projects. VLAIO maintains some variety of grant schemes[4], but the by far most important ones are two newly introduced programs targeting research and development projects, respectively. The subsidy for research activities covers a minimum 50 percent of the project costs. Similarly, development projects enjoy a support rate of 25 percent. More favorable conditions are conceded to small firms (additional 20 percent subsidy rate), medium businesses (10 percent) and partnerships (10 percent), which can increase the subsidy rate up to a maximum of 60 percent for research and 50 percent for development projects.

[3] The federal government has only very few, selective grant programs, such as a scheme for space and aviation.

[4] In total, 27 grant schemes have been administered by VLAIO.

3 Literature review

The empirical research on the joint effectiveness of R&D subsidies and tax incentives is scant if compared to the substantial volume of literature in which the effects of the policies are investigated individually. Our analysis is among very few that use panel data models accounting for unobserved heterogeneity. We therefore discuss other studies that account for firm fixed effects first. This is followed by a brief discussion of findings of other papers that use different approaches.

3.1 Studies accounting for unobserved heterogeneity

Pless (2023) analyses the joint R&D grant and tax credits effectiveness in UK on two different samples: one comprising 7,035 small firms (between 20 and 80 employees) over the period 2005-2017, and the other including around 2,500 large firms observed from 2000 through 2014. The study exploits an exogenous change in the generosity in the tax credit scheme to assess the interplay of the two R&D policies through a quasi-experimental design methodology. In particular, Pless (2023) uses a "difference-in-discontinuity" approach that combines difference-in-difference with regression discontinuity design. The dependent variable is R&D expenditures. As to the small firms, tax credits enhance the effect of R&D grant funding, i.e. the effect of policy mix is positive. The benefit from both interventions increases the more financially-constrained the firms are. Conversely, tax credits and subsidies appear to be substitutes in case of large firms.

Kim and Lee (2020) construct a panel dataset from the 2015, 2016, 2017 waves of the Korean Survey on Technology of SMEs. Applying a difference-in-difference model implemented as fixed effects regression, they find that the interplay of R&D grants and R&D tax credits has a positive effect on the share of R&D expenditures over sales of Korean SMEs. Similarly, Nilsen et al. (2020) account for firm fixed effects in a study for Norway for the period 2002-2013, and find positive effects with respect to output and employment for a sample of R&D starters, but not for firms that conduct R&D regularly. They also conclude that R&D tax incentives are more effective than direct grants. Dumont (2017) applies static and dynamic panel data estimators on a sample of Belgian firms over period 2003–2011, and explores how the combination of several direct and indirect R&D programs, administered at regional and federal level, affects private R&D expenditures. Results indicate a negative but statistically insignificant impact of the policy mix combining R&D grants with tax schemes.

Pang et al. (2020) samples 2,592 firms active in the Zhongguancun Science Park over 2013-2018, and assesses the impact of government subsidies, tax credits and government procurement policies on sales from new product innovations and patent applications. They conduct, among other analyses, a set of Conditional DiD (CDiD) approaches in which firms with different treatment status are matched to control groups, and their findings reveal statistically significant positive synergies of all innovation policy combinations. Similarly, Zhang and Wu (2022) adopt propensity score matching-augmented difference-in-difference regression models and inspect the interaction of credit financing and tax credits on a panel data of Chinese listed companies observed between 2007 and 2019. The policy mix has a positive effect on firms' innovation performance proxied by number of patent applications. Zhou (2022) also uses patent applications as dependent variable and explores the combination of three innovation policies on a sample of Chinese listed SMEs over the years 2015-2019 using a two-way fixed effect regression model. The study shows additionality and complementarity of government subsidies and a national scheme providing a deduction of R&D expenses related to environmental innovations, while government procurement schemes provide no individual and no joint benefits.

Ghazinoory and Hashemi (2021) examine the effectiveness of two R&D schemes introduced in Iran on a sample of 435 high-tech firms (375 SMEs, 60 large firms) using two-period panel database for the years 2015 (pre-intervention) and 2017 (post-intervention). The first scheme is a 15-year exemption from tax, import tariffs and export duties; the second program concerns funding of technological innovation through low-interest or interest-free loans. Dependent variables include two innovation input variables (R&D employees, R&D investment), and two output variables (number of new products, sales of new products). Regression results on outcome differences suggest heterogeneity of treatment effects conditional on firm size. As to SMEs, direct funding to innovation has positive effect on R&D investments, R&D employees and new products; tax exemption, instead, is positive only for R&D investments; the policy mix is not statistically significant. For large firms, instead, R&D loans are effective only on R&D investments; tax exemption has no effect whatsoever; and policy mix is positive only for number of new products.

In summary, the results of few studies accounting for firm-level unobserved heterogeneity make it obvious that more research is needed. So far, one cannot easily identify a pattern of common policy (mix) effects across countries and firm types. The policies seem to some extent be more effective for small or young firms including firms that only recently started R&D activities. Tax credits seem to be associated with more consistent positive effects than R&D grants. The policy mix is found to be positively associated with innovation variables, but these findings are not unambiguous. For larger firms, the evidence is even more conservative.

Given these ambiguities in findings, our study contributes to our further understanding on the effectiveness of a policy mix that is nowadays often applied in industrialized countries.

3.2 Studies not accounting for unobserved heterogeneity

Like our study, Neicu et al. (2016) use Belgian firm-level data. Their database of R&D active companies benefitting from R&D tax credits covers the period 2006-2010. Using a matching estimator the study finds that Belgian firms benefitting from the R&D tax credit focus more on research rather than development when they also receive R&D grants. Furthermore, the R&D grants accelerate the execution of R&D projects that are performed under the tax credit scheme. There is also evidence of scaling up of R&D projects when R&D grants and tax credits are received in combination. They, therefore, conclude that companies benefitting from the policy mix respond more strongly to the R&D tax credits.

Outside Belgium, the most cited paper exploring the innovation policy mix is Guerzoni and Raiteri (2015), who investigate the interplay between R&D tax credits and R&D grants as supply-side policies and public procurement as demand-side policy. They use a survey database in which firms from the EU-27 Member States, Norway and Switzerland were interviewed about their innovation activities. The dependent variable is an indicator variable denoting whether the firms increased their innovation expenditure in the last two years. After applying propensity score matching estimators, they conclude that positive treatment effects are found when the analysis does not account for the policy mix, i.e. when the policies are considered separately. Once the possible interaction of different policy schemes are taken into account, crowding out effects are found.

A recent OECD publication evaluates the innovation input additionality of R&D tax credit schemes using cross-country data, and one section is dedicated to the policy mix with R&D subsidies (OECD, 2023). Using pooled and harmonized microdata covering 17 OECD member countries over the period 2000-2017, evidence of a mutually reinforcing effect of direct and indirect R&D measures is found.

Marino et al. (2016) apply different matching techniques and a dose-response function approach for different levels of public support to French data. They consider as policy mix direct R&D grants and the R&D tax credit scheme. They investigate whether direct grants have additional effects on top of the R&D tax credit. They find that under the R&D tax credit scheme, direct R&D grants may be subject to crowding out effects; especially medium-sized R&D grants seem to be not effective. However, some additionality effects are also found for top beneficiary companies. Similarly, Bérubé and Mohnen (2009) investigates the same research question for direct R&D grants in Canada. They use a matching estimator with data from the Canadian Innovation Survey 2005, and find that firms receiving R&D grants on top of benefitting from the R&D tax credit have more likely to introduce new products, among them also world-first market novelties, when compared to the counterfactual in which these firms would have only benefitted from the R&D tax credit. Such a result is also found by Radas et al. (2015) for the R&D intensity and the number of R&D employees. They use matching estimators on a sample of 700 SMEs located in Croatia and observed between 2005 and 2010. Carboni (2011) also uses a matching estimator with a sample of Italian manufacturing firms and investigates R&D spending (per employee). The study finds that tax incentives are more effective than public loans.

Lhuillery et al. (2013) employs multiple methods (OLS, propensity scores, exact match, dose-response analysis) to assess the effect of different R&D programs on a sample of 28 thousand French firms over the period 1993-2009. Results show positive but limited additionality of the analyzed R&D schemes, with tax credits being more effective than grants, while policy mix has no impact whatsoever. Mulligan et al. (2017) carries out an impact evaluation of the policy instrument mix for Ireland. Using firm-level data for R&D grants administered by three different governmental agencies and R&D tax incentives over the period 2006-2014, the study stresses the importance of accounting for temporal dynamics among policy tools in order to evaluate their joint consistency. Results suggest complementary effects on the logarithm of total R&D expenditures per employee when tax credits recipients obtain also grants. Grant awardees, conversely, receive no additional benefits from joining the tax credit scheme.

Ravšelj and Aristovnik (2020) explores innovation policy combination on a sample of Slovenian companies observed over the years 2012–2016. They regress direct and indirect measures, as well as their interaction on the share of R&D expenditures over total assets. A regression including time dummies but not firm fixed effects reveals that R&D grants have a negative effect, fiscal incentives are statistically ineffective, while the combination of the two policies yield a considerably positive effect.

Roper et al. (2023) study the policy mix in the UK and construct a database of British firms observed over the period 2012-2018. The outcomes of interest are three innovation measures: a binary indicator of whether firms have invested in internal R&D, two binary variables indicating introduction of product and process innovations, respectively. Propensity score matching is applied to account for the heterogeneity in the likelihood of treatment participation. The treatment effects are estimated as mean differences between the matched treatment and control groups. In terms of innovation input, both the individual and the joint impacts of R&D grants and tax incentives are positive. As to product and process innovation propensities, only R&D tax credits and policy mix are positive, while the coefficient for grants is not statistically significant.

Petrin and Radicic (2023) employ a dynamic random-effects probit model to estimate the impact of R&D grants, tax credits and their interaction on the propensity of a firm to generate a product or a process innovation. The sample of reference is an unbalanced panel of Spanish manufacturing enterprises covering the period from 2001 to 2016. R&D fiscal incentives appear to exert a positive impact on the likelihood to introduce a product innovation, while the effect of R&D grants and policy mix are statistically inconsistent, regardless of firm size. When it comes to the probability to generate process innovations, the impact of both grants and tax credits is positive, while policy mix is again statistically insignificant. Also with Spanish data, Huergo and Moreno (2017) investigate a multi-actor and multi-instrument policy mix by evaluating three R&D programs: a zero-interest loan scheme offered by the public organization Centre for the Development for Industrial Technology, a national subsidy program, and an EU subsidy program. Using data on 4,407 Spanish firms during the period 2002-2005, there is evidence of complementarity among policy instruments in terms of R&D expenditures, mainly driven by small firms.

Wei and Liu (2015) employ cross-sectional data about 343 innovative enterprises operating in the Chinese province of Anhui for the year 2012. Four instruments of public support to R&D and their interactions are under scrutiny: R&D grants, subsidies for scientific projects in collaboration with public research institutions, innovation regional policy, and R&D tax credits. Results suggest no policy mix combination has a clear-cut impact on firms' patenting activity.

In summary, we conclude from reviewing the literature that the evidence on the innovation policy mix is ambiguous and still scarce; in particular, we have found very few studies that uses possibly the most commonly used econometric approach in policy evaluation in the last decade – the difference-in-difference estimator. The remainder of the paper fills this gap by providing an empirical difference-in-difference study on the effects of the Belgian R&D tax credit scheme and R&D grants.

4 Data

For our econometric study, we construct a firm-level panel from four waves of the Flemish part of the Community Innovation Survey, i.e. the surveys of 2015, 2017, 2019 and 2021. Each survey is a representative cross-section of the Flemish corporate sector in manufacturing and business services, i.e. the majority of firms are small. The innovation survey data are supplemented with VLAIO grant data at the firm level. All firms in our sample are product or process innovators at least in one of the observed years. After data cleaning and dropping of outliers, we obtain an unbalanced panel with a total of 2,867 different firms amounting to 7,693 firm-year observations.

Given the data structure, we can identify the firms in four different situations: whether they got no public R&D funding, only R&D grants, only R&D tax incentives or both in a given year. In the subsequent regression analysis we will use two dichotomous variables, *DGrant* and *DFiscal* and their interaction to identify these states.

As dependent variable for R&D inputs we use the R&D employment headcount (*RDE*), the logarithm of R&D employment (plus 1, *lnRDE*), R&D employment intensity measured as R&D employment divided by total employment, (*RDEint*), and log total R&D expenditures (*lnTotRDexp*). We also explore the effect on two measures for innovation output: the percentage of turnover generated by product innovations that are market novelties (*PctSalesInno1*), and the percentage of revenue from the commercialization of both new and improved products (*PctSalesInno2*).

We also use a number of control variables to account for confounding factors. We control for firm size as measured by the number of employees (net of R&D employees to avoid double counting), and the age of the firm. Both structural variables enter the regression in logarithmic form, *lnEMP* and *lnAGE*. Furthermore, we account for capital intensity in form of total assets per employee, *CapInt* in thousands of Euros. More capital intensive companies might, on the one hand, rely more on technology and thus R&D. On the other hand, capital intensity might also reflect a barrier to entry and therefore capital intensive companies have less of a need to conduct R&D intensely. We also include cash flow per employee, CF/Emp in thousands of Euros, as firms that might have more (liquid) financial resources could be able to invest more into their R&D projects than other companies. Similarly a group dummy indicating that the firm belongs to a conglomerate of companies might also reflect access to higher financial resources. An export dummy is supposed to capture the effect that exposure to international markets and thus most likely more competitive environments might require more sophisticated products and thus corresponding R&D investments.

Table 2: Descriptive statistics

	No R&D funding		Only R&D grants		Only R&D tax credit		Both R&D funding	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
RDE	1.199	4.455	2.636	4.205	9.175	15.256	18.527	39.440
lnRDE	0.375	0.700	0.884	0.855	1.650	1.133	2.180	1.018
RDEint	0.035	0.114	0.105	0.187	0.180	0.259	0.263	0.299
lnTotRDexp	0.823	1.908	2.348	2.713	4.144	3.094	5.955	2.342
PctSalesInno1	2.409	9.654	5.699	14.827	6.658	16.003	11.914	20.946
PctSalesInno2	12.503	25.560	22.476	31.573	24.709	31.371	35.118	33.250
Age	33.173	21.853	32.591	25.040	31.645	24.114	33.643	27.260
Emp (net R&D)	85.585	120.751	91.688	430.598	132.007	511.465	199.114	515.097
CapInt	631.51	4988.654	375.514	1197.395	678.21	4116.624	550.53	2465.393
CF/Emp	36.462	302.637	23.861	130.994	45.371	371.748	42.753	154.881
D(export)	0.592	0.492	0.681	0.466	0.736	0.441	0.839	0.367
D(group)	0.830	0.376	0.774	0.419	0.878	0.328	0.857	0.350
No. obs.	3,392		1,131		811		2,359	
No. firms	1,287		442		298		840	

The descriptive statistics of these variables are shown in Table 1 where we split the panels by public R&D funding status: no public R&D funding (3,392 observations), only R&D grants (1,131 obs.), only R&D tax incentives (811), and both (2,359). The first remarkable observation is that not all R&D-performing firms make use of the R&D tax incentives. They could either be not aware of this public support or prefer to not claim it as it entails some application cost.[5] Even firms that are getting R&D grants do not necessarily also claim the tax advantages for their employees. We otherwise see that the firms that make use of both instruments invest most in R&D, and have higher returns in terms of commercialization of product innovations. Their R&D employment intensity amounts to about 30%, on average. While this also implies that about every fifth employee of these works on R&D, one should keep in mind that most firms are small. The median firm has about 54 employees. The R&D employment intensity is considerably lower for firms that only make use of one policy instrument, about 18% in firms that use the tax benefits, and 11% in firms with R&D grants. In firms that do not make use of any public support this number is only about 4%. A similar trend unravels for the other measures of innovative performance. At a first naïve glance, the descriptive statistics thus suggest additionality of both schemes.

We do not see remarkable differece in firms' age or size among the different subsamples. The export dummy suggests that the firms relying on public support are those that are, on average, more exposed to international competition.

[5] Another problem associated with the payroll withholding tax credit is an ongoing debate about what qualifies as R&D activity. At the time when firms claim the benefit, the public agency does not offer any legal certainty that the Ministry of Finance will accept that tax reduction (cf. https://www.ccrek.be/sites/default/files/Docs/2024_01_VrijstellingenStortingBedrijfsvoorheffing.pdf; unfortunately only available in Dutch).

5 Empirical strategy

5.1 Basic difference-in difference

For our paper, we adopt two-way fixed effects difference-in-difference (DiD) regressions with standard errors clustered at firm level:

$$Y_{it} = \beta_1 DGrant_{it} + \beta_2 DFiscal_{it} + \beta_3 DGrant_{it} \times DFiscal_{it} + \gamma\, X_{it} + \lambda_i + \tau_t \qquad (1)$$

Where Y_{it} refers to the innovation outcomes of interest, X_{it} indicates the set of control variables, λ_i and τ_t are firm and year fixed effects, respectively.

5.2 Vector matching

In addition to canonical DiD regressions, we adopt matching techniques in order to correct for heterogeneity in program participation probabilities.

Firms, as aforementioned, are exposed to two R&D policies at the same time, defining four mutually exclusive treatment states: no treatment, only grant recipients, only tax credits beneficiaries, both treatments. In this sense, the state of receiving both treatments can be recast as being exposed to a third new treatment.

In a setting with multiple treatments, customary matching techniques based on propensity score to account for treatment self-selection can produce inconsistent and untrustworthy covariate balancing. We would therefore rely on the vector matching technique illustrated in Lopez and Gutman (2017).

Given the treatment states t_v ($v \in \{1, 2, 3, 4\}$) and selection covariates X, we adopt a multinomial logistic model on the pre-treatment sample to estimate a vector $R(X)$ of predicted probabilities $r(t_v, X)$, called also generalized propensity scores (GPS):

$$R(X) = \{r(t_1, X), r(t_2, X), r(t_3, X), r(t_4, X)\}$$

The successive step identifies the bounds for common support, which are computed as follows:

$$r(t, X)^{(low)} = \max\big(\min\big(r(t_1, X)\big), \min(r(t_2, X)), \min(r(t_3, X)), \min(r(t_4, X))\big)$$
$$r(t, x)^{(high)} = \min\big(\max\big(r(t_1, X)\big), \max(r(t_2, X)), \max(r(t_3, X)), \max(r(t_4, X))\big)$$

Firms with all GPS's below $r(t, X)^{(low)}$ and above $r(t, x)^{(high)}$ figure as outside common support, hence are dropped. We then re-fit the multinomial logistic model on the resulting sub-sample.

At this point, we choose the untreated group as reference and conduct pairwise matching with replacement between the untreated and the three treated groups using 1-nearest neighbor matching based on the logit transformation of the corresponding GPS, that is:

$$\text{logit}\big(r(t_v, X)\big) \equiv \ln\big(r(t_v, X)\big) - \ln\big(1 - r(t_v, X)\big)$$

Lopez and Gutman (2017) reports that matching on $\text{logit}\big(r(t_v, X)\big)$ instead of $r(t_v, X)$ provide smaller balancing biases.

In order to take into account the whole vector of GPS's, we use k-means clustering on the logit transformation of the remaining two generalized propensity scores as matching restriction.

In other words, we match:

- untreated (t_1) with R&D grant recipients (t_2) using $\text{logit}\big(r(t_1, X)\big)$ as distance metric conditional on both firms belonging to the same stratum defined by applying k-means clustering on $\big\{\text{logit}\big(r(t_3, X)\big), \text{logit}\big(r(t_4, X)\big)\big\}$;
- untreated (t_1) with R&D tax credit recipients (t_3) by $\text{logit}\big(r(t_1, X)\big)$ conditional on k-means strata defined on $\big\{\text{logit}\big(r(t_2, X)\big), \text{logit}\big(r(t_4, X)\big)\big\}$;

- untreated (t_1) with policy mix recipients (t_4) by $\mathrm{logit}\big(r(t_1, X)\big)$ conditional on k-means strata defined on $\big\{\mathrm{logit}\big(r(t_2, X)\big), \mathrm{logit}\big(r(t_3, X)\big)\big\}$.

We enhance the quality of matching by using a caliper equal to 0.25 times the standard deviation of $\mathrm{logit}\big(r(t_1, X)\big)$, and by constraining matched firms to be in the same 2-digit NACE industry. Finally, we coalesce the resulting cohorts of matched units and compute the frequency weights to apply to the DiD regressions.

5.3 Heterogeneity-robust difference-in difference

Goodman-Bacon (2021) demonstrates that a basic DiD estimator resulting from a two-way fixed effect (TWFE) regression can be rewritten as a weighted average of all possible two-group/two-period DiD estimators in the data, with weights summing up to one.

In case of multiple period settings, however, a "forbidden" comparisons issue arises, whereby units in the control group that are untreated in earlier periods but that are treated in later periods are paired to other treated units. As consequence, the weight related to the corresponding DiD estimator becomes negative. When treatments are heterogeneous due to a) subjects receiving treatment at different points in time, and b) subjects being exposed to treatment for different durations, the negative weights may change the sign of the TWFE regression estimator, making the resulting estimate inconsistent (De Chaisemartin and d'Haultfoeuille, 2020). Given the empirical environment under examination is much more complex than the canonical 2-period 2-group setting, applying the customary DiD TWFE regression will possibly produce biased estimates.

Our analysis, moreover, explores the effects of three treatments at a time. In case of multiple treatments, the TWFE regression estimator corresponding to a specific treatment includes another source of bias, i.e. contamination from other treatments. De Chaisemartin and d'Haultfoeuille (2023) identifies such contamination component as the weighted sum of the effect of the other treatments with weights summing up to zero. In brief, the coefficient of interest from the TWFE regression emerges as the addition of the comparisons sum term, on one hand, and the contamination sum term, on the other. Both summands are inconsistent under treatment effect heterogeneity.

We therefore adopt the heterogeneity-robust DiD estimator proposed in De Chaisemartin and d'Haultfoeuille (2023) to account for both sources of bias. De Chaisemartin and d'Haultfoeuille (2023), to our knowledge, is also the only research contribution to have discussed complex DiD designs in a multiple treatment setting. Other similar DiD estimators (e.g. Callaway and Sant'Anna, 2021) are accustomed only to single-treatment analyses so far.

6 Results

6.1 Basic DiD regressions

Table 2 shows the basic two-way fixed effects regression results that conform to a difference-in-difference methodology for multiple periods. The results are shown for our first two dependent variables, i.e., the number of R&D employees and the logarithm of this variable. We investigate a logarithmic specification in order to account for the skewness of the variable in levels. All subsequent tables have the same format: we present the results obtained from four models for each dependent variable. The first regression only includes the R&D grant dummy (Dgrant), and the second model only includes the R&D tax credit dummy (DFiscal). The third model includes both dummy variables and in the fourth model, we added the interaction term.

We show all four models in order to explore how sensitive the results are to the inclusion or exclusion of treatment variables.[6]

Table 3: Innovation input and R&D policy mix, TWFE DiD Regressions 2014-2020

	R&D employees (*RDE*)				ln(*RDE*)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DGrant	0.619**		0.441*	0.630**	0.194***		0.172***	0.270***
	(0.256)		(0.256)	(0.268)	(0.025)		(0.025)	(0.032)
DFiscal		1.868***	1.821***	2.014***		0.257***	0.240***	0.339***
		(0.297)	(0.299)	(0.356)		(0.030)	(0.030)	(0.035)
DGrant				-0.470				-0.238***
X DFiscal				(0.518)				(0.040)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observ.	7,528	7,528	7,528	7,528	7,693	7,693	7,693	7,693
adj. R-sq	0.962	0.963	0.963	0.963	0.843	0.845	0.846	0.848
No. Firms	2,823	2,823	2,823	2,823	2,867	2,867	2,867	2,867

Standard errors clustered at firm level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

The results on R&D employment in levels show positive treatment effects of both the R&D grants and tax credits, and no statistically significant crowding-out among the policies as shown by the insignificant interaction term. When the log of R&D employment is considered, however, we find crowding-out effects among the instruments. The magnitude of the positive effect of R&D grants is almost offset completely when firms also receive an R&D tax credit. Note, however, that we cannot exactly claim that the R&D grants' effect is nullified when also a tax credit is received. We can only conclude that the sum of the two effects as shown in col. (8) 0.270 + 0.339 is decreased by 0.238 if the firms participate in both schemes. It does not mean that one specific policy has a lesser effect.

We find a very similar pattern when another functional form is explored. Table 3 shows the results for models using the R&D employment intensity and the log of R&D expenditures (we

[6] Note that the relegate the discussion of the common trend assumption which is essential for the consistency of the DiD estimator to subsection 5.3 where we discuss the more general heterogeneity-robust estimations.

do not use levels of expenditures as the distribution in the sample is very skewed and therefore any result might be driven by a few large R&D spenders). We find again strong evidence for positive effects of the policy schemes when applied independently of each other, but the interaction term in columns (4) and (8) again shows crowding-out effects among the schemes.

Table 4: Innovation input and R&D policy mix, TWFE DiD Regressions 2014-2020

	R&D employment intensity (*RDEint*)				ln(total R&D expenditures)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DGrant	0.015***		0.013***	0.018***	0.732***		0.679***	0.893***
	(0.004)		(0.004)	(0.004)	(0.113)		(0.111)	(0.133)
DFiscal		0.020***	0.019***	0.024***		0.784***	0.731***	1.023***
		(0.004)	(0.004)	(0.004)		(0.125)	(0.122)	(0.155)
DGrant				-0.012**				-0.688***
X DFiscal				(0.006)				(0.161)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observ.	7,551	7,551	7,551	7,551	4,553	4,553	4,553	4,553
adj. R-sq	0.934	0.934	0.934	0.934	0.801	0.801	0.804	0.805
No. Firms	2,815	2,815	2,815	2,815	1,838	1,838	1,838	1,838

Standard errors clustered at firm level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 4 shows the results for the innovation output variables, and those are more inconclusive. We find positive effects of participation in the R&D tax credit scheme across all models, but the R&D grants are insignificant. There is also no significant finding on possible crowding-out effects.

In summary, the standard two-way fixed effects models show strong positive effects of each policy scheme on innovation input measures when the schemes are considered independently. If firms benefit from both R&D tax credits and R&D grants, we find evidence of crowding out effects among the instruments. For innovation outputs, only the R&D tax credit scheme seems to generate positive effects. However, one has to keep in mind here that we estimate reduced form of a complex model of the innovation process where innovation inputs are transformed into innovation outputs through R&D efforts, inventive activity and commercialization efforts.

Table 5: Innovation output and R&D policy mix, TWFE DiD Regressions 2014-2020.

	Percent of sales from new products				Percent of sales from new or improved products			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DGrant	1.051		0.830	1.147	0.279		-0.051	0.601
	(0.797)		(0.793)	(1.048)	(1.632)		(1.634)	(2.129)
DFiscal		2.645***	2.566***	2.887**		4.445**	4.449**	5.057**
		(0.941)	(0.941)	(1.142)		(1.829)	(1.840)	(2.220)
DGrant				-0.765				-1.361
X DFiscal				(1.651)				(2.948)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observ.	7,168	7,168	7,168	7,168	4,501	4,501	4,501	4,501
adj. R-sq	0.367	0.369	0.369	0.369	0.387	0.389	0.389	0.389
No. Firms	2,703	2,703	2,703	2,703	1,899	1,899	1,899	1,899

Standard errors clustered at firm level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

6.2 Conditional DiD regressions

In order to further investigate the robustness of the TWFE results, we now turn to conditional DiD models where we have employed the vector-matching technique to form more comparable control groups. We show the results where one nearest neighbor is picked for each treated firm. Thus the firm observations in the regression sample are comparable in their likelihood to receive either R&D grants, or R&D tax credits or their combination. Table 5 contains the regression results for the four innovation input measures. For an easier comparison of the results between the non-matched and the matched samples, we re-print the standard TWFE results first (columns 1, 3, 5, and 7) and then present the results obtained with the matched samples next (columns 2, 4, 6 and 8).

The CDiD results largely confirm the TWFE results. The effects of the policies are positive and statistically significant, when the firms participate in either one of the policy schemes. However, crowding-out effects among the schemes occur when firms participate in both schemes simultaneously when the R&D employment intensity and the log of R&D employment are considered. The formerly negative effect for the log of the total R&D expenditure in the TWFE model is not confirmed by the matched sample. The estimated coefficient drop in absolute magnitude and the standard error increases.

Table 6: Innovation input and R&D policy mix, Matched TWFE DiD Regressions 2014-2020.

	R&D employees		ln(R&D employees)		R&D employment int.		ln(total R&D expenditure)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DGrant	0.630**	1.000***	0.270***	0.310***	0.018***	0.024***	0.893***	0.966***
	(0.268)	(0.311)	(0.032)	(0.042)	(0.004)	(0.005)	(0.133)	(0.168)
DFiscal	2.014***	3.455***	0.339***	0.429***	0.024***	0.031***	1.023***	1.433***
	(0.356)	(0.506)	(0.035)	(0.045)	(0.004)	(0.005)	(0.155)	(0.201)
DGrant	-0.470	-0.647	-0.238***	-0.296***	-0.012**	-0.008	-0.688***	-0.331
X DFiscal	(0.518)	(0.671)	(0.040)	(0.064)	(0.006)	(0.009)	(0.161)	(0.290)
1-NN VM	No	Yes	No	Yes	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observ.	7,528	3,823	7,693	3,644	7,551	3,615	4,553	2,348
adj. R-sq	0.963	0.772	0.848	0.766	0.934	0.905	0.805	0.722
No. Firms	2,823	1,236	2,867	1,200	2,815	1,183	1,838	871

Standard errors clustered at firm level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

In Table 6 the TWFE findings are also confirmed with the matched samples. The R&D tax credits scheme has positive and significant treatment effects, and the R&D grant dummy as well as the interaction term are insignificant.

In summary, the results of standard TWFE DID models and CDID models with vector-matched samples confirm that some crowding-out among the two policy instrument may occur.

Table 7: Innovation output and R&D policy mix, Matched TWFE DiD Regressions 2014-2020.

	Percent of sales from new products		Percent of sales from new or improved products	
	(1)	(2)	(3)	(4)
DGrant	1.147	1.825*	0.601	2.783
	(1.048)	(1.108)	(2.129)	(2.330)
DFiscal	2.887**	3.529***	5.057**	8.382***
	(1.142)	(1.241)	(2.220)	(2.428)
DGrant	-0.765	-0.444	-1.361	-4.348
X DFiscal	(1.651)	(2.259)	(2.948)	(3.971)
1-NN VM	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observ.	7168	3813	4501	2613
adj. R-sq	0.369	0.334	0.389	0.404
No. Firms	2703	1229	1899	952

Standard errors clustered at firm level in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

6.3 Heterogeneity-robust DiD regressions

Now we turn to the treatment heterogeneity-robust estimations, i.e., we account for the staggered adoption of treatments. Table 7 shows the average treatment effect on the treated across all time periods for the first two dependent variables, R&D employment and its logarithmic values. Ideally the table should be interpreted in combination with Figure 1 and in which we plot the estimated annual treatment effects.

The first observation that can be made in Table 7 is that the previously positive treatment effects of the two policy instruments are confirmed when considered independently. The term "placebo" in the table denotes a test of the common trend assumption. There we hypothetically model that the treatment has been received in the pre-treatment period t-2 (each survey wave covers a two-year period). As the placebo is never statistically significant, the common trend assumption does not have to be rejected. This can also be seen in Figure 1 and Figure 2 as the estimated confidence intervals in the pre-treatment period include the value zero. We furthermore find that the absolute effect of the fiscal measure is higher than the effect of the grant. This seems plausible as the major fiscal policy is a withholding tax measure that applies to the wages of all R&D personnel while the R&D grants are given for one specific project that will be carried out by a project team that is typically a (small) subgroup of a firm's total R&D personnel. In Figure 1 it can be seen that the effect of the policies evolve over time until time period t+6, but the effect of a grant remains more or less constant between period t+4 and t+6. This seems plausible as only a few projects will last more than 4 years. It can also be seen that the individual annual effects of the R&D grants are not statistically significant in periods t+4 and t+6, but the tabled result for the average treatment effect across all time periods is statistically significant at the 5% level. In Figure 2 where we use the logarithmic value of R&D employment, we find that the effects are largest in the period t+2 and then decrease afterwards.

Table 8: Innovation input and R&D policy mix, Heterogeneity-robust DiD Regressions 2014-2020.

	R&D employees			ln(R&D employees)		
	(1)	(2)	(3)	(4)	(5)	(6)
DGrant	1.281**			0.240**		
	(0.584)			(0.100)		
DFiscal		5.152***			0.424***	
		(0.891)			(0.096)	
Policy mix			-1.302			-0.436
			(4.655)			(0.465)
Placebo	-1.050	-0.834	–	-0.089	-0.149	–
	(0.620)	(0.656)	–	(0.152)	(0.113)	–
1-NN VM	No	No	No	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observ.	4,514	4,434	2,237	1775	1757	2130
Switchers	225	292	9	180	216	8

Standard errors clustered at firm level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Figure 1: Annual treatment effects on R&D employment

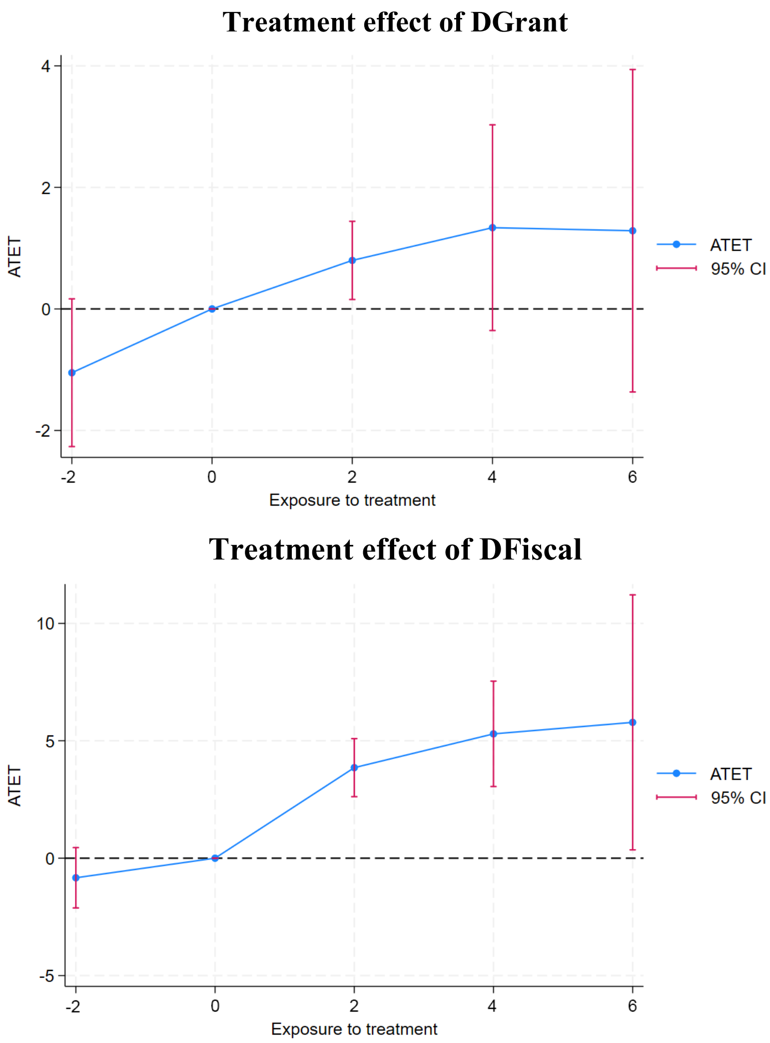


Table 7 also shows that the interaction term is no longer significant. We thus do no longer have to reject the hypothesis of no crowding-out among the two policy instruments.

Figure 2: Annual treatment effects on ln(R&D employment)

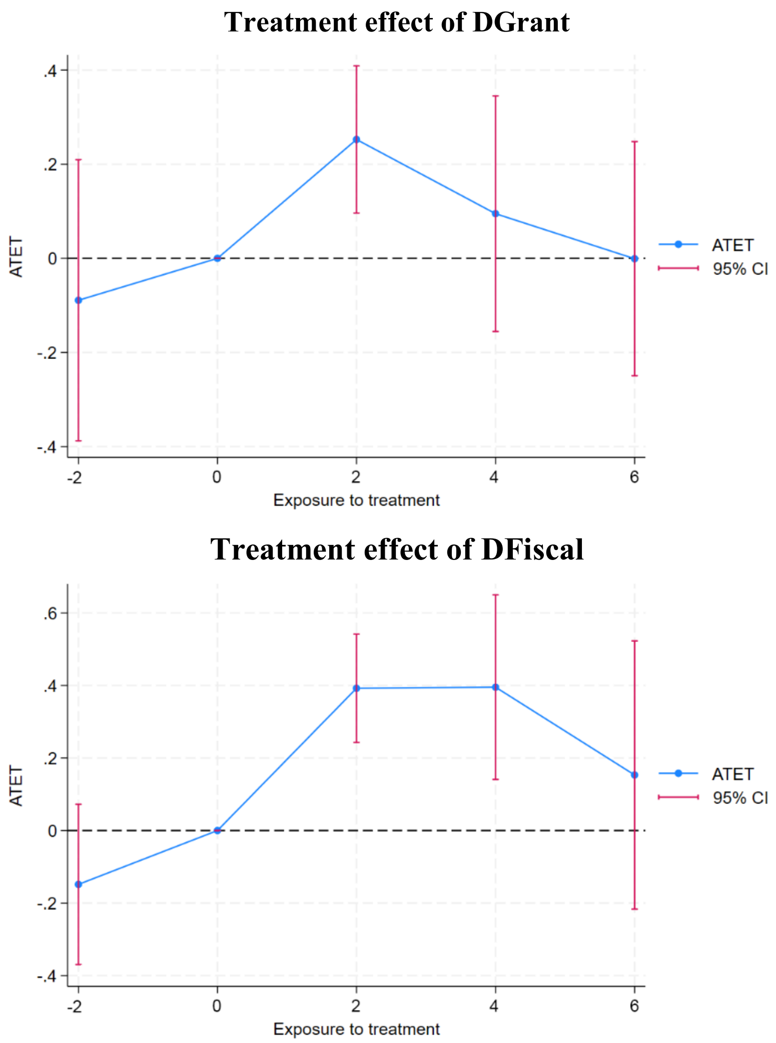


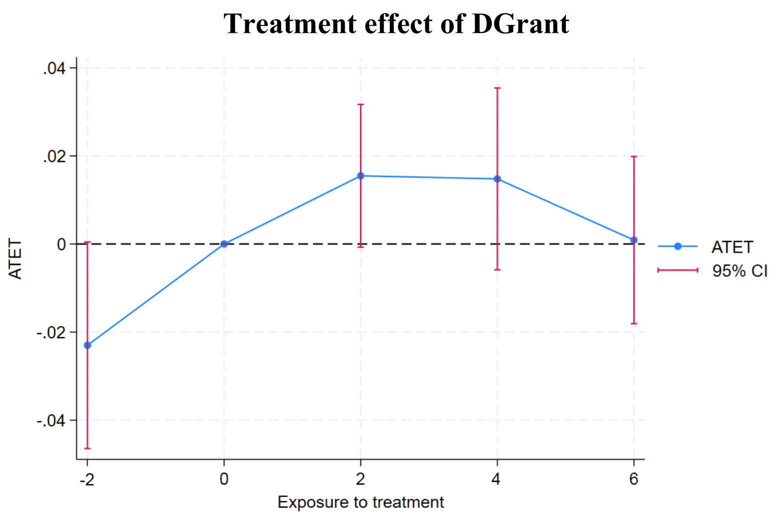
Table 8 as well as Figure 3 and Figure 4 present the results for the two other dependent variables of R&D inputs, the R&D employment intensity and the logarithm of total R&D expenditure. The results can be summarized very briefly, as they confirm the previous finding for R&D employment and its logarithmic values. We find that both policy instruments yield positive treatment effects, and the absolute magnitude of the effect of the fiscal policies is larger than the effect of R&D grants. We find no crowding-out effects among the two instruments once we account for the staggered adoption of the policies.

Table 9: Innovation input and R&D policy mix; heterogeneity-robust DiD Regressions 2014-2020.

	R&D employment intensity			ln(total R&D expenditures)		
	(1)	(2)	(3)	(4)	(5)	(6)
DGrant	0.018**			0.937**		
	(0.009)			(0.462)		
DFiscal		0.027***			1.624***	
		(0.007)			(0.411)	
Policy mix			-0.011			-0.495
			(0.023)			(0.492)
Placebo	-0.023	-0.012	–	0.213	-0.894*	–
	(0.012)	(0.010)	–	(0.528)	(0.468)	–
1-NN VM	No	No	No	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observ.	4,319	4,214	2,120	1012	1021	777
Switchers	213	267	7	93	91	3

Standard errors clustered at firm level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Figure 3: Annual treatment effects on R&D employment intensity



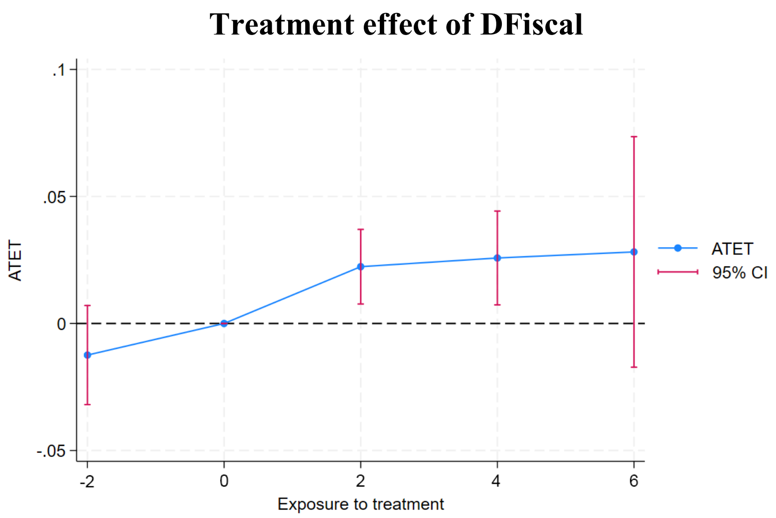


Figure 4: Treatment effects on ln(total R&D expenditure)

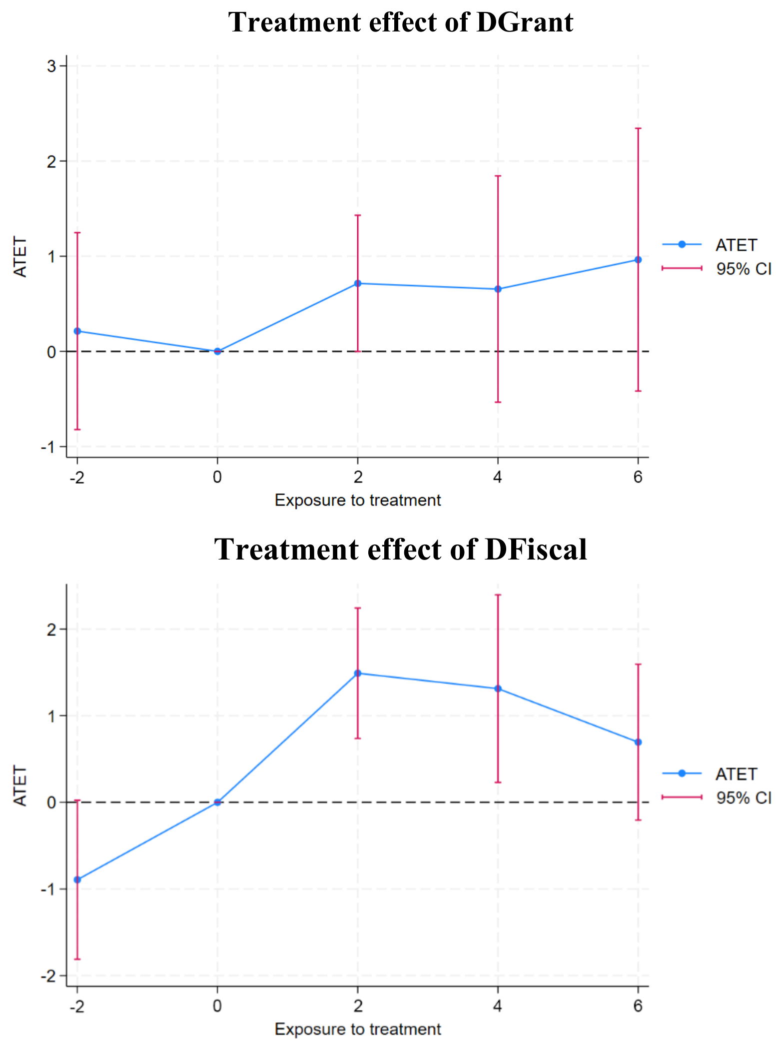


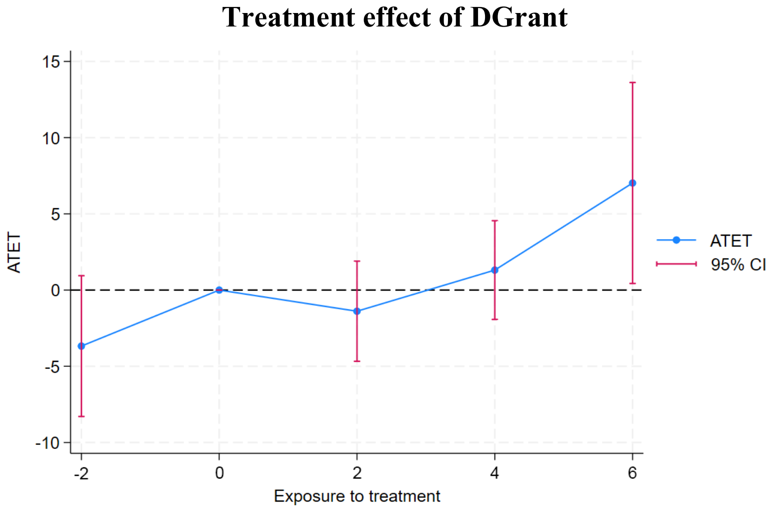
Table 9 as well as Figure 5 and Figure 6 report the estimation results for the innovation output variables. The results of the heterogeneity-robust methodology basically confirm what was found with the conditional DiD. We only find positive effects of the fiscal policies, on average. The R&D grants do not show positive treatment effects, and we do not find any evidence for crowding-out effects. When looking at the annual treatment effects, however, we find that R&D grants start to unfold positive effects on market novelties as well as sales with other new products after four years have elapsed since the grant. This seems plausible as it may take a number of year to reap benefits from R&D projects in the market. We might find earlier effects for the fiscal measures as the payroll withholding tax has a more persistent pattern than the more intermittent R&D grant receipts.

Table 10: Innovation output and R&D policy mix; heterogeneity-robust DiD Regressions (2014-2020).

	Sales' share from new products			Sales' share from new or improved products		
	(1)	(2)	(3)	(4)	(5)	(6)
DGrant	0.310			5.906		
	(1.676)			(4.072)		
DFiscal		5.529***			13.508***	
		(1.732)			(3.221)	
Policy mix			5.235			1.967
			(19.580)			(51.655)
Placebo	-3.675	-1.134	–	-12.990	8.716	–
	(2.356)	(2.520)	–	(8.619)	(7.287)	–
1-NN VM	No	No	No	No	No	No
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observ.	4,721	4,626	2,352	2,023	1,838	1,536
Switchers	230	282	7	133	151	4

Standard errors clustered at firm level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Figure 5: Share of sales from market novelties



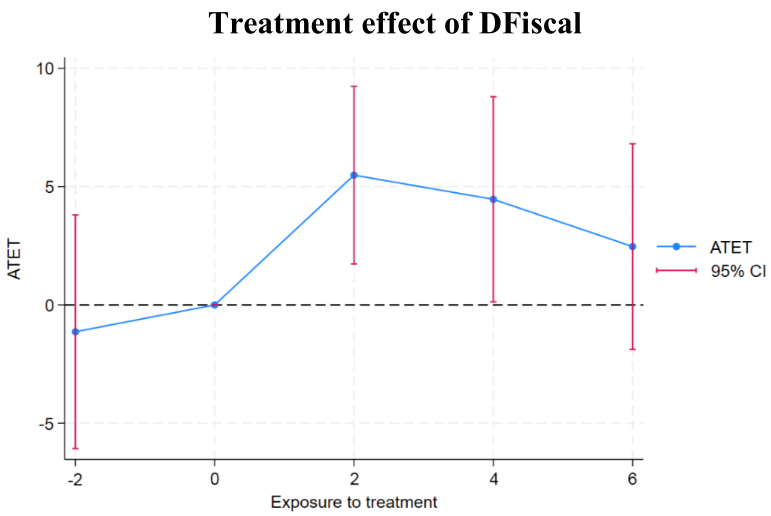
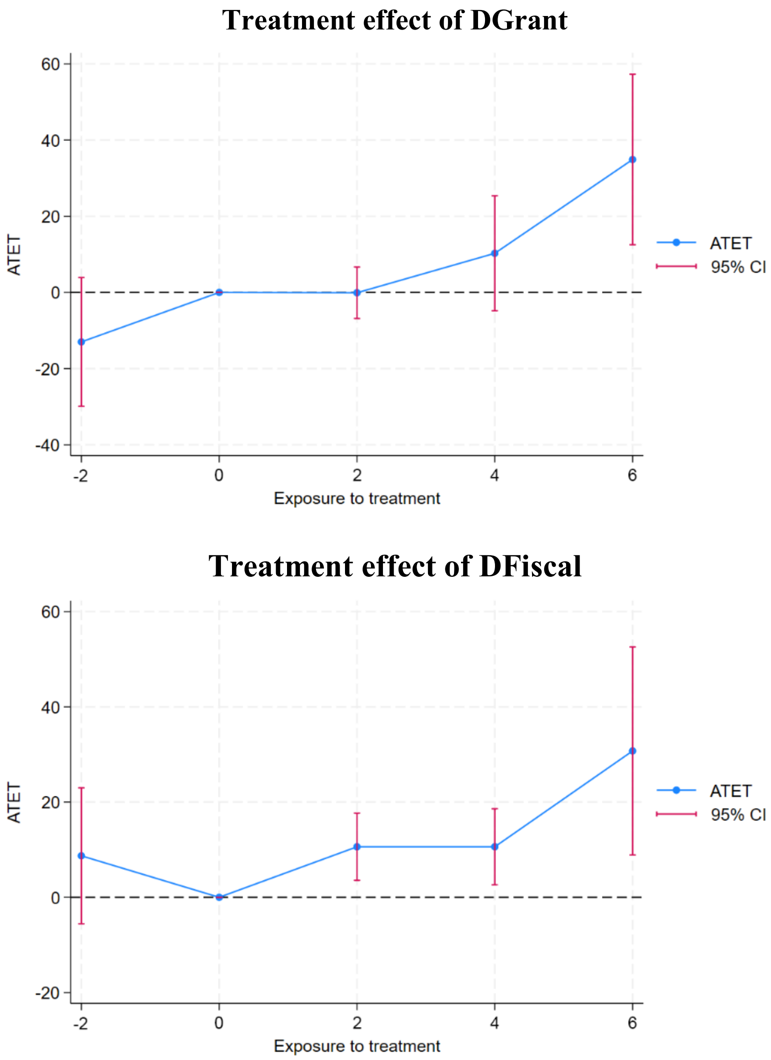


Figure 6: Share of sales from all new or improved products



7 Conclusion

The present study explored the treatment effects of fiscal policies for R&D and innovation in the business sector as well as the effects of R&D grants and their interaction using a panel of Belgian firms. The existing literature on the mix of such policies is scarce, and documents ambiguous results.

Our study shows that these ambiguities in findings might be partially be driven by heterogeneity in, and appropriateness of, the used methodologies. We apply commonly used methods such as difference-in-difference (DiD) models and Conditional DiD (CDiD) and show that the results obtained with these methods could be misleading by also applying the more flexible, recently developed heterogeneity-robust DiD regression models by De Chaisemartin and d'Haultfoeuille (2023). This estimator accounts for the staggered adoption of the treatment as well as the presence of multiple treatments. The commonly used (C)DiD estimation techniques may result in "forbidden" comparisons whereby units in the control group that are untreated in earlier periods but that are treated in later periods are paired to other treated units which leads to inconsistent weighting schemes of these observations in the estimation of the average treatment effect. Furthermore, the estimator allows controlling for the "contamination from other treatments" in case of a multiple treatment setting like ours.

The sources of bias of the common DiD and CDiD estimators show in our applications that we could confirm prior findings from the literature that both R&D grants and fiscal policies targeted at R&D and innovation yield positive treatment effects on R&D inputs at the firm-level. Regarding the crowding-out effects among the two policies, that is, the firms' investment responses when they receive both treatments in parallel, the common (C)DID estimators yield negative treatment effects for the interaction of the two policy instruments. When applying the more general heterogeneity-robust estimator, however, we find that the independent, positive effects of the two policies persist, but we do not longer find evidence on crowding-out effects among the two policies. We therefore conclude that employing a policy mix of fiscal incentives and direct R&D grants does not necessarily lead to a inefficient use of public resources as suggested in earlier studies using less rigorous methodologies (cf. e.g. Guerzoni and Raiteri, 2015, Marino et al., 2016, Mulligan et al., 2017).

When innovation output in form of sales with new products is considered, we only find robust, positive effects for the fiscal measures targeted at R&D and innovation. This finding could have multiple explanations. The R&D grants are typically assigned to projects that might entail higher social value than the average R&D and innovation project, and to projects that are more uncertain regarding their outcomes. This higher associated risk might be reflected in lower likelihoods to discover and develop marketable innovations. In addition, a possible limitation of our analysis could be that the occurrence of R&D grants is more intermittent and therefore the link between innovation outcomes and an R&D grant as input might be more complex than what our reduced form approach can model. A more thorough investigation of such processes may require more sophisticated structural modelling approaches.

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