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The Interplay between Public Procurement of Innovation and R&D Grants: Empirical Evidence from Belgium

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Abstract

This paper investigates the impact of Public Procurement of Innovation (PPI) and Research and Development (R&D) grants on firms' R&D investment using data from Belgian R&D-active firms over the past decade. Our empirical analysis robustly reveals a non-negligible crowding-out effect between the two instruments, suggesting a substitutive relationship. While each policy individually positively influences R&D investment, their combined implementation diminishes their effectiveness. These results challenge prevailing evidence and emphasize the need for a careful policy implementation, raising policymakers' awareness against a blanket increase in innovation policies without considering potential interactions.

Keywords: Public procurement of innovation, Research and Development, Econometric policy evaluation, Crowding-out

JEL-Classification: H57, O38

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1. Introduction

Public procurement as policy instrument to foster private innovation activities has attracted increasing attention among policy makers recently. Public Procurement amounts to about 15-20% of global GDP[2], with an increasing tendency (OECD, 2023). Accordingly the European Commission states that public procurement “matters more than ever” and asks for an efficient use of public money to achieve strategic policy goals, such as innovation.[3] The idea of using public procurement to promote innovation is to shift governmental spending from already existing, established goods and services towards new technologies and innovative solutions (Edler and Georghiou, 2007; Czarnitzki et al., 2020). In order to accelerate the shift towards new technologies and innovative services, the European Union passed a major policy reform on public procurement in 2014.[4] Before the reform, public procurers could basically only choose existing goods and services from existing catalogues and order those. Since the reform, procurers may also describe desired product features, its functionality and appearance even if such a good or service does not exist yet, but research and development on side of the contract-receiving firm is necessary to deliver the requested product.

Previous contributions on Public Procurement of Innovation (henceforth: PPI) have suggested that this instrument has an enormous potential to promote innovation (see Chiappinelli et al., 2023, for a review on the current state of the literature). From a theoretical perspective, PPI may promote innovation mainly through the following channels: i) it provides a critical market size for firms to scale up their production capacities, ii) it increases expected rates of return while minimizing the risk associated with R&D investments, and iii) it reduces information asymmetries between suppliers and purchasers of innovative solutions (e.g. Geroski, 1990; Edler and Georghiou, 2007; Uyarra et al., 2014). However, little is known about the specific determinants and modalities of a successful implementation of PPI,

[2] See https://www.consilium.europa.eu/en/press/press-releases/2022/06/17/international-procurement-instrument-council-gives-final-go-ahead-to-new-rules-boosting-reciprocity, last retrieved on 24/07/2024.
[3] See https://ec.europa.eu/docsroom/documents/25612, last retrieved on 19/07/2024.
[4] https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A32014L0024, last retrieved on 19/07/2024.

and more empirical research on the contextual and integral factors which affect the innovation outcome of a PPI contract and the firm as a whole is needed (Chiappinelli et al., 2023).

This paper contributes to filling this gap by investigating PPI in the context of a policy mix with R&D grants and their individual and combined effect on innovation inputs, namely R&D investment. Often PPI may not be implemented in isolation, but instead firms benefit from various policy measures in form of grants at the same time. Specifically, a firm receiving a PPI contract may have an incentive to also apply for an additional R&D grant, thus potentially benefitting from two different policies simultaneously. From a theoretical perspective, the effect of a combined implementation of PPI and R&D grants on R&D investment is ambiguous. On the one hand, synergies between both instruments may lead to complementary effects. For instance, the firm might conduct applied research in a more targeted way than previously projected as it learned through the procurement contract about actual market needs and the prospects of immediately selling (large numbers of units of) the good or service may help to remain on target and to bring a product to the market in less time than originally anticipated. On the other hand, however, a firm that has already gotten a grant for R&D may re-direct its (inventive) efforts towards the public procurement's contract requirements instead of the originally envisaged project. In that case, the risk of crowding out arises and one policy instrument is simply substituting the other.

A few empirical studies on PPI and other innovation policies including the interaction of the instruments so far mostly hint towards complementary effects between PPI and other policies (Guerzoni and Raiteri, 2015; Stojčić et al., 2020; Caravella and Crespi, 2021). However, none of these studies was able to exploit panel data and could therefore not account for unobserved heterogeneity among firms. All three studies mentioned above had to rely on cross-sectional data which makes the identified treatment effects questionable, because the obtained results may be confounded by unobserved factors that drive both the receipt of either policy and the firms' innovation activity. One common example for such unobserved factors is simply the creativity of the firms' R&D staff.

Furthermore Guerzoni and Raiteri (2015) do not directly observe the receipt of an R&D grant but employ a somewhat vague survey question on whether the firm was affected by changes in R&D policies. In addition, their outcome variable is only an indicator showing whether the firms' innovation expenditures went up, down or remained constant compared to the previous year. Stojčić et al. (2020) also rely on a cross-section of Eastern European firms but focus on innovation outputs rather than inputs and the former might depend on many more factors than innovation inputs that are more directly affected by the policy instruments. The closest to our study is Caravella and Crespi (2021) because they consider PPI and R&D grants as heterogeneous treatment that may occur simultaneously, but they do not have a panel database at hand that allows accounting for unobserved heterogeneity.

We utilize panel data of Belgian R&D-active firms from 2013 to 2021 to investigate the effectiveness of PPI implemented in combination with R&D grants on R&D investment. By applying a conditional difference-in-differences estimator, we are able to carefully control for potential observable and unobservable confounders. In addition, we address recent concerns about possible bias of the fixed effects estimator in the context of difference-in-differences models with staggered treatments (e.g. Baker et al., 2022; Roth et al, 2023).

We find robust evidence for non-negligible crowding-out effects between both instruments: while both instruments indeed show positive, sizeable and statistically significant effects on firms' R&D investment independently, their combined implementation substantially decreases their individual effectiveness. This result suggests that there is a substitutive relationship between R&D grants and PPI leading to inefficiencies of governmental innovation policies. This insight contradicts existing evidence on the effect of PPI in combination with R&D grants on firms' innovation activities, and contributes to a deeper understanding of the contextual factors in which both instruments, PPI and R&D grants, are effective and efficient. For policy makers, our results suggest that simply increasing the number of innovation policies may not automatically result in higher innovation activity in the economy.

2. Literature

For several decades, the field of economics has shown great interest in examining the effects of innovation policies on the innovative activities of companies (see, e.g., Edler and Fagerberg, 2017, for an overview of the literature). The following sections summarize what is known about the effectiveness of both policies of interest, i.e. PPI and R&D grants, and how they perform in different contexts. Afterwards, we discuss potential effects of a combined implementation of both instruments, examining potential complementarities but also reasons for crowding-out effects among the policy instruments.

2.1 Public Procurement of Innovation

In recent years, there has been a growing focus on demand-side policies, particularly public procurement, as a tool for innovation policy. In Europe, there was a major policy reform in 2014 which renewed the public procurement directives.[5] The aim of this procurement reform was to shift the massive governmental demand from already established products, possibly based on outdated technology, towards not-yet existing products and innovative technologies (Edler and Georghiou, 2007; Czarnitzki et al, 2020). With these new directives, procurement contract requirements were less rigid and allowed the procurers to address the functionality, the desired design or performance characteristics of a product or service rather than a description of a specific, already existing product or service from a catalogue. Prior to the reform, the procurement tenders required a very specific, narrow description of the product or service to procure. This created a major obstacle for procurers to implement innovative products, since new technologies or innovative solutions are usually difficult to describe ex-ante, or the procurers simply lacked awareness of their existence. In addition, the use of award criteria in tenders which also address innovative aspects or environmental considerations has been given a renewed legal framework. This encouraged procurers to not simply choose the solution

[5] Directives 2014/24/EU and 2014/25/EU

with the cheapest price, but also consider alternative, new and potentially innovative technologies with lower life-cycle-costs (Czarnitzki et al., 2020).

This legislative policy reform prompted academics to investigate the potential of PPI as an innovation policy tool. Czarnitzki et al. (2020) exploit the fact that Germany was a forerunner in implementing the European-wide legislative reform already several years earlier in 2009. Applying a variety of estimation methods, they differentiate between standard public procurement and PPI and find a positive effect of PPI on innovative turnover of firms in Germany, even though they point out that this effect is limited towards rather incremental instead of radical innovations. For standard public procurement without innovative aspects in the tender no innovation-enhancing effects were found. Based on these findings, Krieger and Zipperer (2022) investigated the potential of public procurement tenders with additional environmental award criteria on the winning firms' likelihood of introducing environmental innovations. More specifically, they identify a 20 percentage point increase in the probability of a firm to introduce more environmentally friendly products.

An earlier contribution by Aschoff and Sofka (2009) provides additional evidence on the effect of public procurement on the market success of firms' innovations for a sample of more than 1100 German firms between 2000 and 2002. For the US, Slavtchev and Wiederhold (2016) investigated how the technological content of procurement contracts affects private R&D investment at the state-level for the time period 1999 to 2009. Utilizing administrative federal procurement data and applying panel fixed effect estimators, the authors identify a positive, causal effect of high-technology public procurement on R&D investment. The earliest work on the relationship between public procurement and innovation goes back to Lichtenberg (1988), who identified a positive relation between the value of government contracts and private firms' R&D-investment in a small sample of US firms between 1979 and 1984.

Recently, Chiappinelli et al. (2023) conducted a literature review on public procurement of innovation. While it highlights that many studies suggest an enormous potential for PPI to spur innovation, it also emphasizes that the literature on PPI is yet limited and inconclusive. According to the authors, more empirical evidence is needed on the long-term effects of PPI on different (innovation) outcomes with panel data, the specific design how PPI should be implemented, what potential barriers might be for a successful PPI implementation and which role PPI plays in the innovation policy mix.

2.2 R&D Grants

Researchers investigate the effect of R&D grants on R&D investment since decades. Since firms always have an incentive to apply for R&D grants, the question arises if grants lead to more R&D in the business sector, or if public money simply substitutes private money which would have also been invested into R&D without the grant. This phenomenon is commonly referred to as crowding-out.

Numerous studies with different foci and contexts have been conducted in order to investigate if R&D grants crowd-out private investment. David et al. (2000) reviewed more than three decades of evidence on the nexus between R&D grants and innovation activities and conclude that the literature prior to the year 2000 did not yet yield conclusive evidence on possible crowding-out effects. David et al. highlight the concern of selection bias arising in many empirical studies prior to the year 2000, and thereby triggered a great revival of this strand of literature as scholars then started to apply modern econometric techniques on estimating treatment effects of policy in presence of possible self-selection effects. Hall and Maffioli (2008) consequently focus specifically on studies taking potential selection bias into account and conclude that for the vast majority of them positive effects on R&D investment could be identified. A more recent literature review by Zúñiga-Vicente et al. (2014) reveals considerable heterogeneity regarding the effects and further provides explanations of the cause for this heterogeneity, highlighting the dynamic aspects and composition of firm R&D, the constraints faced by the firm (such as financial constraints), and the amount and source of public grants. Dimos and Pugh (2016) conduct a meta study on 52 firm-level studies published since the year 2000 and reject (full) crowding-out of private investment by R&D grants.[6]

While the literature on the effects of certain innovation policies investigated in isolation is vast, studies on the mix and interplay of policies are much more rare. Czarnitzki et al. (2007) investigate how R&D grants interact with R&D collaboration for samples of German and Finnish firms in terms of R&D and patent activity. By estimating econometric matching models with heterogeneous treatments, they find generally positive effects of collaboration on innovation activities and complementary effects between both treatments: In Finland, R&D collaboration and R&D grants yield positive treatment effects for treated firms compared to the counterfactual situation in the absence of treatments. However, for German firms which only receive grants for individual research projects, no positive treatment effect was found. For both countries the authors find that firms receiving either a R&D grants or are active R&D collaborators would increase their R&D investment by receiving both treatments in combination.

Czarnitzki and Lopes-Bento (2014) consider heterogeneous treatments based on the origin of R&D grants. They investigate the effects of national R&D funding versus EU-programs on innovation inputs and outputs for a sample of German firms. Their findings indicate that funding from both sources implemented in isolation as well as in combination leads to higher innovation inputs. With respect to innovation outputs, the authors point out that nationally funded firms and those firms receiving funding from both sources produce more patents which are also of higher value in terms of citations. Thus, the authors reject full crowding out for the co-existence of simultaneous funding from different sources.

Hottenrott et al. (2017) do further contextualize the effects of R&D grants on R&D investment and differentiate between research-targeted, development-targeted and mixed-projects. They find that while research grants yield positive direct effects on net research spending as well as positive cross

[6] R&D tax credits are a related policy which is not further considered in this paper. For a surveys on R&D tax credits, see Hall and Van Reenen (2000) or Castellacci and Lie (2015), and for recent evidence see, e.g., Rao (2016) or Melnik and Smith (2024).

effects on development, development grants are less effective for stimulating development expenditures. Finally, Szücs (2020) finds evidence for an innovation stimulating effect of the three European Commission Framework programs for small firms and for R&D-intensive firms, but not for other firms.

2.3 Public Procurement of Innovation in combination with R&D grants

The idea of implementing either PPI, or R&D grants, or both, goes back to a long-standing debate about the initial source of innovation: some scholars favor the technology push hypothesis arguing that the supply-side sparks initial research, promotes the development and finally induces the diffusion of an innovation (Bush, 1945); others lean more to the demand-pull hypothesis arguing that the demand-side has a predetermining role in sparking and incentivizing innovation (Schmookler, 1966). This long-standing debate resulted in a consensus among both sides that a well-balanced combination of technology-push as well as demand-pull instruments is necessary in order to optimally stimulate innovation (Mowery and Rosenberg, 1979).

This consensus has been prevailing for decades and prompted policy makers to implement both instruments, R&D grants and PPI. The demand-side policies stand in stark contrast to classic, supply-side policies, such as R&D grants, as the latter are bottom-up, i.e. firms apply with proposals on what could be invented and developed, whereas demand-sided policies such as governmental procurement is a top-down policy, i.e. governments determine the direction of R&D, but not the specific technology. Employing a mix out of several innovation policies simultaneously became common practice in industrialized countries (Flanagan et al., 2011; Meissner and Kergroach, 2021) and thus also got onto the agenda of academics who shifted from analyzing innovation policies in isolation to examining their collective impact and effectiveness (cf., e.g., Czarnitzki et al., 2007, for a mix of R&D grants and R&D collaborations; Czarnitzki and Lopes-Bento, 2013, for a mix of national and EU policies; Petrin and Radicic, 2023, for R&D grants and R&D tax credits).

From a theoretical point of view, the effects of a combined implementation of PPI and R&D grants are ambiguous. On one hand, both instruments can complement each other: while R&D grants may rather lead to disruptive, radical innovations, the effect of PPI seems somewhat more limited towards rather incremental innovations (Czarnitzki et al., 2020, Stojčić et al., 2020). In that case, both instruments would be supplementary to each other and incentivize research projects which would have not existed without the simultaneous implementation of both instruments. On the other hand, both instruments can also be substitutive: If the implementation of both instruments is not well coordinated, governments may simultaneously support overlapping projects and thus create inefficiencies (Link and Link, 2009). For instance, a firm receiving a PPI contract which requires the development of an innovative solution always has an incentive to also apply for a R&D grant with a similar project proposal. It is questionable that such an R&D grant would actually promote additional innovation activities at the firm, or if it would simply crowd out the effect of the PPI contract.

Only few papers address this phenomenon and investigate public procurement in combination with further policy tools empirically. Aschhoff and Sofka (2009) compare the effects of public procurement R&D grants and knowledge spillovers from basic research conducted at universities with respect to their impacts on firms' sales with innovative products. They find that while public procurement and knowledge spillovers from universities promote innovation success to a similar extent, public procurement appears to be particularly effective for smaller firms in regions under economic stress. Guerzoni and Raiteri (2015) argue that R&D grants often occur in combination with other treatments such as PPI and R&D tax credits. When accounting for all treatments, they find that R&D grants remain comparably effective as in previous studies that did not control for other treatment. However, public procurement of innovation turns out to be even more effective than other tools. The authors also find that the combination of both instruments exerts a particularly high impact on innovation activities, thus suggesting a complementary nature of both instruments. In a similar vein, Caravella and Crespi (2021) investigate the effects of regular public procurement and innovative public procurement in combination with supply-side measures (soft loans, tax deduction and grants) on R&D investment and find that their effectiveness drastically increases if combined with each other. For the context of catching-up economies in central and eastern Europe, Stojčić et al. (2020) find that the highest effect on innovation outputs can be achieved when firms receive both financial support and innovation-oriented public procurement contracts.

In their recent literature review, Chiappinelli et al. (2023) summarize the current state of the literature about PPI and highlight the urgent need for further empirical investigations on how PPI performs relative to and in combination with other policy instruments, examining potential complementarities and opposing forces in a broader policy mix under different contextual factors. Also for policy makers, the more applicable and interesting question is if and how PPI in combination with direct R&D grants affects R&D investment decisions at the firm-level.

3. Econometric Methodology

In our empirical analysis, we investigate the effect of PPI and R&D grants on R&D investment and their interplay with each other. Consequently, firms can be exposed to three different treatments: (i) they receive only a PPI contract, (ii) they receive only a R&D grant, (iii) they receive both, a PPI contract and a R&D grant in a certain period. In our subsequent analysis, we follow the literature on R&D investment surveyed by Becker (2015) and model our R&D investment equation by a two-way fixed effect panel data model of the form:

$$\log(R\&D_{it}) = \beta_0 + \beta_1 PPI_{it} + \beta_2 R\&D\ Grant_{it} + \beta_3 PPI_{it} \times R\&D\ Grant_{it} + \beta_4 X_{it} + \gamma_i + \lambda_t + \xi_{it}, \qquad (1)$$

where $R\&D_{it}$ denotes R&D expenditures of firm i in year t. The model controls for time-constant, unobserved firm differences by the firm-specific effect γ_i and common macro-economic shocks by a full set of year dummies λ_t. ξ_{it} is the error term. Effectively, this two-way fixed effects estimation identifies the average treatment effects on the treated by comparing the difference between changes in R&D investment of treated firms before and after the treatment, on one hand, and changes in R&D investment between treated firms and untreated firms (i.e. difference-in-differences).[7]

The vector X_{it} includes a set of control variables. We identify the following key determinants for a firm's R&D investment: first, firm size can affect R&D investment since larger firms might exploit economies of scope among multiple R&D projects and can exploit a higher operational flexibility with respect to input utilization (Pindyck, 1988). We use the number of employees of a firm in a given year as a proxy for firm size in our regression model. Since this variable is highly skewed, it enters our regression in logarithms *(log(EMP)).*

Second, product market rivalry can affect the firm' s R&D investment decision: on the one hand, product market competition may increase the firms innovation incentives to invest into R&D to distinguish from competitors with novel products or technologies. On the other hand, firms might also be more hesitant from investing into R&D since it bears a bigger risk of not fully internalizing the expected gains from their investment (Aghion et al., 2005; 2009). We model firms' exposure to product market rivalry by including their turnover shares generated with exports *(EXP)*. The underlying idea is that firms with higher exporting activity are active on more markets and thus have to compete against more rivals, while those being active purely on the domestic market compete with less rivals (cf. Czarnitzki et al., 2020).

Third, we include the patent-stock of a firm, which is calculated by the perpetual inventory method with a 15% rate of obsolescence of knowledge capital (e.g. Grilliches and Mairesse, 1984; Jaffe, 1986; Hall, 1990) to account for differences in innovation capabilities.[8] We expect that firms with higher past innovation capabilities invest more into R&D than others (Czarnitzki and Toole, 2013). We include the patent stock per employee in our regression models, i.e. we normalize the patent stock by dividing it

[7] Recently raised concerns point out that the two-way fixed effects estimator may yield biased estimates in context of difference-in-differences estimates with staggered treatments (e.g. Baker et al., 2022; Roth et al, 2023). We address these concerns in section 6.

[8] We calculate the patent stock as follows: $PS_{i,t} = PS_{i,t-1} * 0.85 + patent\ applications_{i,t}$

by the number of employees first (*PS/EMP*). Also, this variable enters the model with squared values to account for potential non-linearities *($(PS/EMP)^2$)*.

Fourth, labor productivity enters our model, since more productive firms might be more likely to be picked for an R&D grant or a public procurement contract by the government (Czarnitzki and Lopes-Bento, 2013). Furthermore more productive firms generate higher turnovers and are typically more profitable and thus have more opportunities to shift additional resources towards R&D.

In addition, many firm-level factors typically modelled in the empirical literature on R&D investment implicitly enter our model by including firm fixed effects: For instance, the location of a firm matters for its R&D investment decision: A firm located closer to a city might benefit from a well-developed infrastructure and knowledge or technology spillovers from neighboring firms or universities, making them more R&D active (Jaffe et al., 1993; Audretsch and Feldman, 1996; Singh and Marx, 2013). Also, a firm being incorporated into a group of multiple firms impact the firm's R&D investment decision since it allows to exploit potential economies of scope in the R&D process (Czarnitzki and Lopes-Bento, 2013). Even though we could measure these variables, both factors are usually time-constant and are therefore absorbed by the firm fixed effects.

In addition to controlling for observable factors, our empirical panel model also allows to control for unobserved heterogeneity: for instance, some firms might be managed by particularly capable or motivated managers, or some firms might have particularly creative R&D employees. Both factors would most likely positively affect a firm's R&D expenditures, without being directly observed in the data. If we would not control for these factors, we would possibly overestimate the treatment effects. By including firm fixed effects, these unobserved factors are accounted for in our model. This methodological approach separates this study from earlier contributions on the potential interactions between PPI and R&D grants (such as Guerzoni and Raiteri, 2015; Stojčić et al., 2020; Caravella and Crespi, 2021).

One assumption for the unbiasedness of our estimated treatment effects from our difference-in-differences approach is the quasi-random allocations of the treatments. In our application that implies that firms would not get selected by the governments based on specific characteristics. However, this assumption is unlikely to hold in our set-up, and instead governments might tend to apply a 'picking-the-winner' strategy in their selection process: for instance, governments might pick firms for a R&D grant or a PPI contract that have already proven that they have been particularly R&D active or innovative in the past. If that is the case, our panel data model would overestimate the actual effect of the different treatments on firms' R&D investment. Therefore we complement our baseline two-way fixed effects difference-in-differences model with a conditional difference-in-differences approach. A conditional difference-in-differences approach matches or reweights similar firms to approximate the experimental setting of a random assignment of the different treatments. Untreated firms which are more similar to the treated firms get a higher weight in the estimation than untreated firms which are less similar. A conditional difference-in-differences approach is effective to control for both: Selection into the treatment based on observable characteristics with the matching or reweighting approach, and selection due to unobserved time-constant firm-specific characteristics with the subsequent difference-in-differences estimation which accounts for fixed effects (Heckman et al., 1998).

We therefore decide to complement our baseline difference-in-differences estimation with a entropy balancing approach. The entropy balancing approach ensures that the first moments of the distribution of each matching variable are identical for the groups of treated firms (i.e., firms receiving a R&D grant, a PPI contract or both) and for the control group (i.e., firms not getting any treatment). Non-treated firms are weighted such that the untreated observations yield the same moments as one finds for the groups of treated firms (see Hainmueller, 2012). In contrast to the other matching approaches, entropy balancing has the advantage of being efficient: instead of dropping any observations in the sample, it exploits all available observations in the control group and therefore does not result in a loss of information (Czarnitzki et al., 2023; Trunschke et al., 2024).

Combining both methods, difference-in-differences and entropy balancing, our empirical analysis allows a causal interpretation of the different treatment effects on R&D investment. In line with previous empirical works on the effectiveness of R&D grants and PPI summarized in Section 2, we would expect the coefficients β_1 and β_2 in our model to be positive, indicating a positive causal effect of both treatments on R&D investment. Coefficient β_3 captures the interaction of both treatments, R&D grants and PPI. Thus, it reveals the additional effect of receiving a PPI contract conditional on already receiving a R&D grant simultaneously (and vice versa). The expected direction of the coefficient is ambiguous and therefore is of central interest of this study: if positive, it would indicate that both instruments, PPI and R&D grants, are complementary to each other and spark synergy effects which translate into higher R&D investment. Exemplarily a firm receiving a R&D grant could invest the additional financial means in more fundamental research, while the PPI contract would complement the grant with incentives to invest into more applied research and development activities aiming at a commercialization of a novel technology. In contrast, if negative, it would suggest that both instruments are conflicting. Exemplarily a firm which already received a R&D grant and in addition also receives a PPI contract simultaneously would re-direct its effort towards the PPI contract instead of the originally envisaged project (or vice versa), and the public money for the R&D grant would be invested inefficiently.

4. Data

Our main data source is the Community Innovation Survey (CIS) from Flanders, the Dutch-speaking northern region of Belgium. The survey is carried out biennially since 2005 and asks questions related to the firms' innovation activities and performance. We create a panel database by combining five survey waves from 2013 to 2021. Over 11,000 different firms replied to the survey during our sample period. However, many firms only answered the survey once or never engaged into any innovation activities during the sample period. For subsequent panel-econometric estimations, we require that each firm entering the panel is observed at least twice, and we also limit the sample to firms that have at least once invested into R&D. Thus, our final estimation sample comprises 2,063 different firms, out of which each firm is observed on average for approximately three waves.

We exploit two questions which were asked in the surveys: firms were asked if they received a public procurement contract in the CIS waves 2017, 2019 and 2021. If yes, the firms were asked to indicate whether they were required to innovate regarding their product portfolio or their production processes or whether they needed to conduct R&D activities. This distinction between traditional and innovative public procurement contracts is a unique feature of innovation survey data. Approximately 11% of all firms in our sample received at least one PPI contract during our sample period, i.e. a contract under which they were required to innovate or to conduct R&D related to a public procurement contract.

Firms were also asked if they received financial public support from either the Flemish government or the European Union during the survey period. This question was posed in all the survey waves we use. Thus, we can directly observe in our data which firms received at least one R&D grant during the sample period, which was the case for 35% of the firms in our sample. Of particular interest for our subsequent analysis are those firms which received both, a PPI contract as well as a R&D grant simultaneously. That is the case for 167 different firms during our sample period. Approximately over half of the firms in our sample received no treatment, i.e., neither a R&D grant nor a PPI contract during the whole sample period. This group is going to serve as our baseline control group in our empirical analysis.

In addition, each wave of the Community Innovation Surveys asks for the firms' R&D investment. In line with previous empirical work using R&D investment, we focus on internal R&D investment as our dependent variable in our econometric analysis. Also, the survey asks for the number of employees, turnover, share of turnover generated with exports and the core industry of a firm. We use these questions to create our control variables as described in Section 2. We include lagged values of these variables to avoid endogeneity concerns to the extent possible. Finally we use PATSTAT to retrieve information on the number of firm patent applications at the European Patent Office to construct the patent stock of each firm.

Descriptive statistics of the variables used are presented in **Table 1** for our total sample of 6,036 firm-year observations. The average R&D investment in the sample amounts to about 1 million EUR. About 8% of firm-year observations have a contract of public procurement of innovation, and R&D grants are more frequent with 22%. The average annual employment is about 100 in headcounts, and 41% of the observations are firm-years with positive exports. The average labor productivity amounts to 430,000 EUR of revenues per employee. The average count of the patent stock in the firm-year observations amounts to about half a patent (0.53). We use the patent stock per employee in the subsequent regressions to avoid multicollinearity with the employment variable.

Table 1: Descriptive statistics (N = 6036)

	Mean	Std. Dev.	Min.	Max.
R&D Investment (in thd. EUR)	1025.72	3615.94	0.00	74856.00
PPI (0/1)	0.08	0.28	0.00	1.00
R&D Grant (0/1)	0.22	0.41	0.00	1.00
EMP	100	133	0	837
EXP (%)	41.08	37.72	0.00	100.00
Labor Productivity (in million EUR)	0.43	2.16	0.00	146.03
PS/EMP	0.01	0.05	0.00	1.66
Patent Stock	0.53	4.34	0.00	128.98
N	6036			

Unit of observation is the firm-year level.

We also report descriptive statistics of our sample prior and post reception of the first treatment (either PPI, R&D grants or both) throughout the sample period in **Table 2Error! Not a valid bookmark self-reference.**.[9] Of particular interest in our analysis is the level of R&D investment of firms. On average, untreated firms invest approximately half a million Euro annually into R&D. However, this variable is highly skewed, because we have a few large firms in our database with very high R&D

[9] We do not report statistics separately for the receipt of PPI and R&D grants, as firms may receive different combinations of both instruments over time, and therefore the data cannot be summarized easily in a short table.

investment, while most of the firms invest substantially less. Half of the firms in our database invest not more than 150,000 EUR annually into R&D.[10] Finally, we observe that firms in pre-treatment time periods invest more than twice as much as untreated firms. After getting treated for the first time during the sample period, those firms turn out to increase their R&D investment even further. However, as described in the previous section, this increase does not necessarily reflect a causal reaction of a firm's exposure to the different treatments. We discuss the different treatments and their causal effects on R&D investment in the next section.

Table 2: Descriptive Statistics by treatment status

	Untreated		**Treated**			
			Pre-Treatment		Post-Treatment	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
R&D investment (in th. EUR)	504.71	1879.49	1163.20	3856.51	1768.04	5110.81
EMP	92	115	111	149	107	149
Labor Productivity	0.41	1.03	0.50	4.48	0.42	1.17
EXP (%)	38.72	37.35	41.72	37.54	44.42	38.17
PS/EMP	0.00	0.03	0.01	0.09	0.01	0.06
Patent Stock	0.17	1.52	1.08	6.12	0.78	5.81
N	3010		1121		1905	

Unit of observation is the firm-year level.

Regarding the control variables, we see that treated firms are on average larger in terms of employment than their untreated counterparts, and they also achieve a higher labor productivity. Also, we observe that treated firms engage more in exporting than untreated firms, and they have a patent stock which is on average more than five times as high as the one from untreated firms.

5. Empirical Results

As a first step, we present outcomes derived from an (unconditional) difference-in-differences approach. Results are displayed in **Table 3**.

[10] Due to this skewed distribution of R&D investment, the variable enters our final regression in logs after adding the smallest observed value above zero in our sample (i.e. 0.1) in order to deal with zeros when taking the log.

Table 3: Difference-in-Differences regressions for log(R&D investment)

	(1)	(2)	(3)	(4)
PPI	0.650**		0.596**	0.867**
	(0.201)		(0.201)	(0.271)
R&D Grant		0.646***	0.621***	0.709***
		(0.136)	(0.136)	(0.145)
PPI x R&D Grant				-0.678**
				(0.311)
log(EMP)	0.608**	0.580**	0.564**	0.570**
	(0.207)	(0.205)	(0.206)	(0.206)
EXP	0.006**	0.006**	0.005**	0.005*
	(0.003)	(0.003)	(0.003)	(0.003)
Labor Productivity	-0.039***	-0.040***	-0.039***	-0.040***
	(0.005)	(0.005)	(0.005)	(0.005)
PS/EMP	4.096*	4.292*	4.061*	4.192*
	(2.101)	(2.193)	(2.202)	(2.204)
$(PS/EMP)^2$	-3.382	-3.551	-3.416	-3.512
	(2.892)	(3.100)	(3.085)	(3.102)
N	6036	6036	6036	6036
adj. R^2	0.078	0.080	0.082	0.082

Dependent variable is R&D investment in logs. Firm and industry-year FE included.
Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

PPI and R&D grants both have a positive and significant effect on R&D investment in columns (1) and (2) of **Table 3** where the two variables are included separately in the regression model. Both coefficients turn out to be quite comparable in terms of magnitude. On average, a firm receiving a PPI contract or a R&D grant witnesses an increase in R&D investment by approximately 70%[11], all else constant. Column (4) shows the regression results when the interaction term is included. While both individual coefficients of PPI and R&D grant remain positive, the coefficient for the interaction term is negative and statistically significant, indicating that the effectiveness of the policy tools diminishes when a firm receives a combined PPI and Grant treatment. In terms of magnitude, the size of the estimated coefficient for the interaction terms suggests that one instrument almost entirely crowds-out the other. These initial findings suggest the presence of almost full crowding-out, highlighting the potential inefficiency in combining these two policy tools.

[11] $70\% = (\exp(0.646 - 1)) * 100$

As described in Section 3, we further investigate our results also taking a potential `picking-the-winner' strategy by the government into account. Specifically, we implement an entropy balancing approach. Thus we balance treated firms and untreated firms by constructing a set of matching weights based on the first moment of covariates, and reconduct our baseline difference-in-differences estimation taking these weights into account. We create these weights for each firm based on the first observed (untreated) period in the sample.

Table 4: Weighted Conditional Difference-in-Differences for log(R&D investment) with entropy balancing

	(1)	(2)	(3)	(4)	(5)
PPI	0.588**	0.530**		0.468**	0.921**
	(0.215)	(0.218)		(0.213)	(0.352)
R&D Grant		0.688***	0.523***	0.503***	0.973***
		(0.192)	(0.147)	(0.147)	(0.236)
PPI x R&D Grant					-0.778**
					(0.347)
log(EMP)	0.303	0.241	0.545**	0.538**	0.242
	(0.293)	(0.289)	(0.239)	(0.240)	(0.248)
EXP	0.007*	0.006	0.005*	0.005*	0.003
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Labor Productivity	-0.039***	-0.038***	-0.039***	-0.038***	-0.039***
	(0.008)	(0.007)	(0.005)	(0.005)	(0.007)
PS/EMP	7.372**	7.401**	5.550**	5.463**	7.765**
	(3.449)	(3.456)	(2.593)	(2.585)	(3.576)
$(PS/EMP)^2$	-6.574**	-6.693**	-4.578	-4.546	-6.459*
	(2.952)	(3.012)	(3.238)	(3.210)	(3.303)
Entropy weight adjustment for receiving	PPI	PPI	R&D grant	R&D grant	PPI and R&D grant
N	5834	5834	5436	5436	5941
adj. R^2	0.113	0.118	0.100	0.102	0.165

Dependent variable is R&D investment in logs. Firm and Industry-year FE included.
Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results of the conditional difference-in-difference estimations employing the entropy balancing weights are presented in **Table 4**. Again the coefficients of interest appear to be statistically significant and sizeable, emphasizing the R&D investment enhancing effects that PPI as well as R&D grants trigger. With respect to their magnitude, Column (1) suggests that receiving a PPI contract entails an increase in R&D investment by approximately 66%[12]. The magnitude of the coefficient for R&D grants is similar and leads to an increase of approximately 62% in R&D investment (see col. 3). In our sample, the median firm invested approximately 150,000 EUR each year into R&D. Thus, receiving a R&D grant or a PPI contract leads to an increase by approximately 100,000 EUR for the median firm, equivalent to hiring approximately one or two more R&D employees (see Czarnitzki and Lopes-Bento, 2013). These results emphasize the sizeable impact of both instruments, PPI and R&D grants, as long as they are implemented independently. However, with respect to potential crowding-out effects the entropy balanced difference-in-differences approach reveals a significant and negative interaction term in Column (5), further underscoring substantial crowding-out effects between PPI and R&D Grants. To further investigate the extent of the identified crowding-out effect, we conduct a F-test in which we test for the hypothesis that the total estimated effect of applying both instruments combined is equal to applying only one of the two instruments individually.[13] For both tests, we cannot reject the hypotheses. This result shows that applying both instruments combined brings no significant additionality for R&D investment in comparison to just applying one instrument individually, and thus one instrument fully crowds-out the other.

In summary we show that implementing PPI or R&D Grants in isolation significantly enhances R&D investment in recipient firms. The substantial investment increases observed indicate the effectiveness of these policies in stimulating R&D investment and innovation activities. However, the negative interaction term implies that the combined use of PPI and R&D Grants may not yield additive benefits and even leads to significant crowding-out among instruments.

[12] $66\% = \exp(0.588 - 1) * 100$

[13] Specifically, we test the following two hypotheses: $\widehat{\beta_1} + \widehat{\beta_2} + \widehat{\beta_3} = \widehat{\beta_1}$ and $\widehat{\beta_1} + \widehat{\beta_2} + \widehat{\beta_3} = \widehat{\beta_2}$

6. Validity and Robustness

We employ a variety of validity and robustness tests to further underscore our empirical findings.

6.1 Common Trends Assumption

The validity of our results gained from the difference-in-differences analysis is subject to the common trend assumption. The common trend assumption states that both groups of firms, i.e. treated firms and untreated firms, would have developed similarly in terms of R&D investment if the treatment would not have occurred. Only if both group of firms developed similar prior to the treatment, we can assume that they would have also developed parallel ex-post in the counterfactual scenario of not receiving the treatment. We can empirically test this assumption by interacting the treatment indicators with pre-treatment periods in supplementary regressions. Significant lead-treatment interactions would reveal that firms adjust their R&D investment depending on an expected treatment in the future, and thus the estimated effects from our difference-in-difference regression would be biased. Results of the tests are reported in **Table 5** in the appendix and show that no significant coefficients could be identified. Thus, we do not have to reject the common trends assumption and can interpret our results as causal estimates.[14]

6.2 Staggered treatments

Recent developments in the difference-in-differences literature raised concerns about the validity of the two-way fixed effects estimator if the treatment occurs staggered, i.e. not at one, but at multiple points during the sample period. This setting also applies in our study, since firms can receive a R&D grant and/or a PPI contract in different time periods. This could potentially bias our estimated coefficients of our two-way fixed effects regression, since it might induce "forbidden" comparisons between already treated units (e.g. Baker et al., 2022; Roth et al., 2023). Therefore, we implement a

[14] It should be noted that due to the unbalancedness of our panel, our options for testing the common trend more broadly are restricted unfortunately. A more modern, and rigid procedure is, for instance, suggested by Dette and Schumann (2024).

robustness check, in which we re-estimate our coefficients from equation (1) but we estimate them for each treatment cohort individually, while keeping only never-treated firms in our control group. For instance, we estimate the effects for a subsample of firms, which received a PPI contract during the survey period 2014-2016 only in comparison to never-treated firms, which have not received any treatment throughout our sample period. This clean subsample analysis allows to avoid the aforementioned “forbidden” comparison among already-treated firms. Results are presented in **Table 6** in the appendix. While the majority of our baseline results gets supported by this analysis, we observe that a few coefficients turn statistically insignificant. However, this could be due to possible small-sample limitation of this analysis, which excludes many treated units. For instance, while we observe over 70 firms which received a PPI contract and R&D grant simultaneously for the cohort in 2017, and over 90 for cohort 2019, we only observe 22 for cohort 2021, consequently resulting in low statistical power of the estimated coefficient. Aside from this sample size limitation, this robustness analysis additionally supports the results estimated in our baseline two-way fixed effects analysis.

6.3 Standard public procurement versus PPI

The positive and significant effect for PPI observed in our estimations could also be based on the public procurement contract itself, but not on its originally envisaged idea as an innovation policy tool, that is the contracted innovation element in the procurement. For instance, the estimated effect could be driven by an indirect effect in which firms increase their R&D investment as a reaction to increased sales following upon the procurement contract. If that would be the case, we would encounter an omitted variable bias in our estimate for the effect of PPI. Thus, in this robustness check we also control for the receipt of traditional public procurement contracts next to PPI contracts. If the observed effect of PPI would be driven by the aforementioned indirect effect, we would expect the coefficient for PPI in equation (1) to turn statistically insignificant from zero. However, as **Table 7** in the appendix reveals, we do not find substantial changes in the significance level of the coefficient of interest, PPI and the corresponding interaction effects. Thus we can conclude that the observed effect of PPI is mainly driven by its innovative component, and not potential indirect effects of the public procurement contract itself.

6.4 Multiple subsequent treatments over time

A fraction of the firms in our sample does not only receive one, but instead several treatments over time. For instance, a firm could receive a R&D grant in 2017 and 2019, and a PPI contract in 2019. Thus, disentangling the effect of R&D grants or PPI contracts on R&D investment would not be trivial, since the estimated coefficients could be biased by earlier received treatments. Therefore we conduct a robustness check, in which we only keep firms which have been treated with either a R&D grant, a PPI contract or both only once, but not before or afterwards again. The control group consists of never-treated firms. This clean comparison avoids multicollinearity among treatments and thus allows us to verify that the estimated effects are not contaminated by a few firms which receive multiple treatments during the sample period. **Table 8** in the appendix presents results gained from a conditional difference-in-differences analysis for this subsample. The robustness check supports our baseline results.

7. Conclusion

We empirically investigate the effect of PPI, R&D grants and their interplay with each other on R&D investment for a sample of more than two thousand R&D active firms over nine years. Implementing a (conditional) difference-in-difference estimator, we find evidence that PPI contracts and R&D grants have economically strong and statistically significant positive effects on firms' R&D investment, both significantly boosting firms' R&D investments by 66% to 70%. However, their combined implementation reveals substantial crowding-out effects, i.e., one instrument almost entirely crowds-out the other, implying that firms substitute public funds partially for private resource if they receive innovation support from both instruments.

These results are novel and contradict previous research on the interplay of PPI with R&D grants, which mostly hint towards complementary effects of both instruments (Guerzoni and Raiteri, 2015; Stojčić et al., 2020; Caravella and Crespi, 2021). We mainly expect three reasons for our results to differ from previous research: first, we employ panel data and thus are able to control for unobserved heterogeneity which might partially drive the results of earlier studies. Second, our data allows for a cleaner empirical analysis than in earlier studies, since we are able to directly observe the receipt of the different treatments as well as the firms' R&D investment.[15] Third, our study differs since it investigates the relationship between PPI and R&D grants in a well-developed and highly-innovative country, Belgium. In contrast, previous studies mainly focused on countries in which "the institutional and administrative framework is characterized by low level performances" (Caravella and Crespi, 2021: 663, focus on Italy) or on transformation economies (Stojčić et al. (2020) focus on central and eastern European countries). In these countries and their institutional contexts governmental demand plays a much more predominant role for firms' innovation activities and therefore potential crowding-out effects might be less pronounced.

Our results have substantial implications for policy makers. The simultaneous implementation of PPI contracts and R&D grants is based on the idea of one instrument complementing the other, thereby leading to higher total R&D investment. Our empirical evidence challenges this assumption and reveals that this theoretical premise does not necessarily hold on average, and that firms instead might substitute public grants and procurement contracts with grant elements for innovation tasks partially for private funds if they benefit from both schemes simultaneously. This insight may be important for refining governmental strategies to promote innovations and their diffusion. The current practice of granting R&D projects to firms based on submitted proposals is a bottom-up policy approach. The practice of distributing implicit R&D grants within innovative public procurement is a top-down approach. Such practice might lead to a self-selection of suppliers free-riding on the implicit grant

[15] Guerzoni and Raiteri (2015) could not observe the receipt of R&D grants directly, but had to use a hypothetical question on how firms would react to changes in the innovation policy framework in Italy.

element, as they may have coincidentally developed a product or service with the demanded functionalities recently with the help of an R&D grant awarded by another public agency which is typically not coordinating with the public procuring authorities.

Our study has some limitations which set some promising avenues for future research. In particular, we do only observe whether a firm received a R&D grant and/or a PPI contract, but not the corresponding size of both instruments. Thus, additional data sources including the monetary value of both instruments would be necessary to investigate what the marginal benefit for firms' R&D investment of spending one additional monetary unit into R&D grants is in comparison to PPI contracts. Also, future research could include a more nuanced perspective to address for which type of R&D performers R&D grants or PPI contracts are more or less effective. In particular with respect to recently raised concerns about the composition of private R&D and the declining share of scientific research relative to applied development activities (e.g. Arora et al., 2018; Akcigit et al., 2021; Mezzanotti and Simcoe, 2023) policy makers could benefit from an analysis investigating the different effects which both instruments exert on the different components of Research and Development separately. Unfortunately our data has currently not been rich enough to investigate these questions.

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Appendix

Table 5: Common Trends Assumption

	(1)	(2)	(3)	(4)	(5)
Lagged PPI	-0.488		-0.557		-0.541
	(0.511)		(0.503)		(0.504)
Lagged Grant		-0.319		-0.315	-0.270
		(0.411)		(0.408)	(0.410)
PPI	0.619^{**}		0.561^{**}	0.596^{**}	0.834^{**}
	(0.204)		(0.205)	(0.201)	(0.274)
R&D Grant		0.622^{***}	0.624^{***}	0.596^{***}	0.692^{***}
		(0.140)	(0.136)	(0.140)	(0.149)
PPI x R&D Grant					-0.682^{**}
					(0.311)
Log(EMP)	0.609^{**}	0.576^{**}	0.564^{**}	0.560^{**}	0.567^{**}
	(0.206)	(0.206)	(0.206)	(0.206)	(0.206)
EXP	0.006^{**}	0.005^{**}	0.005^{**}	0.005^{**}	0.005^{**}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Labor Productivity	-0.039^{***}	-0.040^{***}	-0.039^{***}	-0.039^{***}	-0.040^{***}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
PS/EMP	4.115^{*}	4.220^{*}	4.083^{*}	3.990^{*}	4.153^{*}
	(2.100)	(2.193)	(2.202)	(2.202)	(2.204)
$(PS/EMP)^2$	-3.382	-3.507	-3.417	-3.373	-3.476
	(2.891)	(3.088)	(3.086)	(3.074)	(3.093)
Constant	-1.449	-1.297	-1.313	-1.313	-1.314
	(2.016)	(1.993)	(1.992)	(2.005)	(1.998)
N	6036	6036	6036	6036	6036
adj. R^2	0.078	0.080	0.082	0.082	0.082

Dependent Variable is R&D investment in logs. Firm and Industry-year FE included.
Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Estimating Treatment Effects for each cohort individually

	(1) 2017	(2) 2019	(3) 2021	(4) 2017	(5) 2019	(6) 2021	(7) 2017	(8) 2019	(9) 2021
PPI	0.645**	0.423	1.020**				0.853**	0.871**	0.896**
	(0.280)	(0.381)	(0.474)				(0.291)	(0.291)	(0.291)
R&D Grants				0.077	0.816**	1.542***	0.699***	0.690***	0.697***
				(0.181)	(0.285)	(0.326)	(0.149)	(0.150)	(0.150)
PPI x R&D Grants							-0.850**	-0.737*	-0.247
							(0.405)	(0.397)	(0.558)
N	5499	5250	5157	4731	4269	3952	5765	5683	5646
adj. R^2	0.073	0.070	0.075	0.072	0.072	0.076	0.078	0.076	0.080

Dependent Variable is R&D investment in logs. Firm and Industry-year FE, and all control variables included. Control group consists only of never-treated firms. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: PPI vs. Standard PP

	(1)	(2)	(3)	(4)
PPI	0.596**		0.536**	0.808**
	(0.210)		(0.211)	(0.280)
R&D Grants		0.646***	0.623***	0.710***
		(0.136)	(0.136)	(0.145)
PPI x R&D Grants				-0.673**
				(0.311)
Standard PP	-0.139	-0.305*	-0.154	-0.149
	(0.194)	(0.184)	(0.193)	(0.193)
log(EMP)	0.614**	0.591**	0.571**	0.576**
	(0.207)	(0.206)	(0.206)	(0.206)
EXP	0.006**	0.005**	0.005**	0.005*
	(0.003)	(0.003)	(0.003)	(0.003)
Labor Productivity	-0.040***	-0.040***	-0.039***	-0.040***
	(0.005)	(0.005)	(0.005)	(0.005)
PS/EMP	4.159**	4.382**	4.130*	4.257*
	(2.107)	(2.207)	(2.210)	(2.211)
$(PS/EMP)^2$	-3.407	-3.581	-3.445	-3.538
	(2.902)	(3.121)	(3.098)	(3.114)
Constant	-1.467	-1.331	-1.334	-1.343
	(2.022)	(1.985)	(1.999)	(2.003)
N	6036	6036	6036	6036
adj. R^2	0.078	0.081	0.082	0.082

Dependent Variable is R&D investment in logs. Firm and Industry-year FE included.
Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Subsample of firms which were treated only once

	(1)	(2)	(3)	(4)	(5)
PPI	0.699**	0.495		0.496	1.002**
	(0.320)	(0.341)		(0.340)	(0.470)
R&D Grant		0.978**	0.778***	0.732***	1.850***
		(0.334)	(0.202)	(0.203)	(0.299)
PPI x R&D Grant					-1.850**
					(0.637)
log(EMP)	0.076	0.033	0.335	0.320	-0.020
	(0.465)	(0.460)	(0.301)	(0.302)	(0.513)
EXP	0.009	0.009	0.007*	0.007*	0.007
	(0.007)	(0.007)	(0.004)	(0.004)	(0.005)
Labor Productivity	-0.040***	-0.038***	-0.039***	-0.038***	-0.044***
	(0.009)	(0.008)	(0.005)	(0.005)	(0.007)
PS/EMP	18.028*	15.316	5.858**	5.818**	22.157**
	(10.217)	(11.181)	(2.263)	(2.256)	(9.390)
PS/EMP	-24.036	-16.063	-6.858***	-6.859***	-30.121**
	(21.108)	(22.949)	(1.783)	(1.756)	(13.883)
Constant	-1.022	-0.856	-0.155	-0.117	1.241
	(2.907)	(2.886)	(2.170)	(2.182)	(3.078)
Entropy weight adjustment for receiving	PPI	PPI	R&D grant	R&D grant	PPI and R&D grant
N	4456	4456	4349	4349	4479
adj. R^2	0.123	0.129	0.114	0.115	0.315

Dependent Variable is R&D investment in logs. Firm and Industry-year FE included.
Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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