Crowding in or Crowding Out? Evidence from Discontinuity in the Assignment of Business R&D Subsidies

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Abstract

We employ a regression discontinuity design to study the effects of a flagship business R&D subsidy programme in the Czech Republic on R&D investment, patenting and economic performance of the supported firms. The R&D subsidies stimulated R&D expenditure in small and medium-sized enterprises (SMEs) but not in large firms. In SMEs, public funding succeeded in crowding in private R&D investment, and 1 unit of public subsidy was associated with about 2.5 units of additional R&D expenditure. The positive effects on R&D expenditure of SMEs were sustained after the original projects ended, possibly thanks to subsequent subsidies from the same funding provider. SMEs receiving large subsidies relative to their pre-treatment sales also saw sustained increases in patenting, sales and employment. We do not find any evidence of positive effects of the subsidies on large

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firms and show that financing constraints play an important role in explaining the effect heterogeneity.

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JEL: D22, H25, H32, L53, O31, O38

1 Introduction

Externalities and information asymmetries inherent to the innovation process make private funding of business research and experimental development (R&D) fall short of what is socially desirable (Arrow, 1962; Klette et al., 2000; Hall, 2002). For this reason, governments use public funds to subsidise the R&D activities of private companies. In OECD economies alone, government funding of business R&D exceeds USD 100 billion per year, about half of which is due to direct support in the form of subsidies, loans and public procurement (OECD, 2023).

This paper investigates whether government subsidies to business R&D lead to additional R&D activity that would not take place in the absence of the subsidies, and whether they crowd out or crowd in private R&D expenditure, both during the subsidies and in the longer term. Previous studies have either relied on regression or matching techniques assuming that the potential outcomes with and without treatment are independent of the actual receipt of treatment as long as certain observable covariates are held constant[1] (e.g. Czarnitzki et al., 2007; Görg and Strobl, 2007; Bérubé and Mohnen, 2009, and many others), or have not directly observed information on firms' R&D activities (e.g. Bronzini and Iachini, 2014; Howell, 2017; Santoleri et al., 2022). Exploiting a discontinuity in

[1]This condition is commonly referred to as "unconfoundedness", "ignorable treatment assignment", "selection on unobservables" or "conditional independence" (Imbens, 2004).

the assignment of support in a flagship business R&D subsidy programme in the Czech Republic, this paper brings the first evidence of the causal effects of R&D subsidies on R&D inputs of the supported firms from a regression discontinuity (RD) design.

When it comes to the effect of subsidies on business R&D expenditure, theory can support two broad scenarios (Takalo et al., 2013). In the first one, all, or most, R&D projects financed with the help of the subsidies would take place even in the absence of the support. Public funding does not induce additional R&D activity but mainly *crowds out* private funds. In the alternative scenario, the public funding translates into additional R&D expenditure and may even *crowd in* additional R&D expenditure from private sources. Determining which of the two scenarios is the case in reality is challenging for at least three reasons.

Firstly, it requires a strategy for separating the causal effects of subsidies from the influence of other factors that determine firms' R&D activities. To this end, previous studies have largely relied on controlling for observable firm characteristics in a regression or matching framework. However, if some factors affecting firms' R&D expenditure and correlated with the receipt of subsidies are not observed by researchers, such estimates will not recover causal effects. Unfortunately, as pointed out by Kauko (1996), in the context of business R&D subsidies, the presence of such unobservable factors is not just a theoretical possibility, but the most likely scenario. This is because firms with intentions to invest more in R&D and with stronger R&D ideas are more likely to apply for R&D subsidies and more likely to have their projects selected, but they are also likely to spend more on R&D, with or without subsidies. As intentions to pursue R&D and the quality of R&D ideas are rarely observed in firm-level data, estimates that rely on conditioning on observables could entail a strong bias.

Secondly, testing for crowding out or crowding in requires data on firms' R&D expenditure, but such information generally does not appear in firm financial accounts[2] and is

[2]Listed firms are an exception, but most direct support for business R&D goes to smaller firms, which are usually not publicly listed.

instead collected by statistical agencies. The resulting microdata are typically accessible to researchers only in an anonymised form that does not allow one to link the data to administrative records from the relevant funding provider.

Thirdly, understanding the effects of R&D subsidies on private R&D expenditure requires that the effects be examined not only during the subsidies but also in the longer-term (Zúñiga-Vicente et al., 2014). On the one hand, the subsidies could simply bring forward R&D projects that would have taken place later. On the other hand, the subsidies could have longer term positive effects on firms' R&D performance (Levy and Terleckyj, 1983; Zúñiga-Vicente et al., 2014), for example, if projects that were started thanks to the subsidies continue even after the subsidies stop, or if the supported firms are more likely to receive subsequent public funding (Antonelli and Crespi, 2013). Analysing the effects of R&D subsidies over time requires sufficiently long panel data and a sufficient delay of the analysis after the subsidies.[3]

To address these challenges, we analyse the ALFA programme, which took place in the Czech Republic in years 2011-2018. In ALFA, project proposals were awarded evaluation points derived from in-depth assessment by independent evaluators, and the decision regarding which projects would be funded depended on their final ranking and available funds. We exploit administrative information on the scores assigned to each project proposal and employ an RD estimator that compares firms whose projects received scores just below or just above the threshold for obtaining support. We link the administrative records to a rich firm-level panel dataset that combines information on firms' R&D activities, other sources of R&D funding, patenting and economic performance over years 2007-2021.

Our results indicate that R&D subsidies in the ALFA programme had strong and

[3]It is also difficult to explore the dynamics of the effects in studies that do not look at a particular programme but instead estimate the impact of receiving public R&D funding in general, as such a context makes it difficult to separate the long-term effects of subsidies in earlier years from the short-term effects of subsidies in later years.

persistent positive effects on both total and privately-funded R&D expenditures of the supported firms, but the effects differed strongly between small and medium-sized enterprises (SMEs) and large firms. In the SMEs, we find strong evidence of crowding-in of private R&D investment. The estimated effects are positive for both total and privately funded R&D and imply that 1 unit of public subsidy was associated with about 2.5 units of additional R&D expenditure. We also find evidence of a strong persistence in the positive impact of ALFA on R&D expenditure by SMEs, up to 8 years after the award competition. We find that this persistence is associated with subsequent funding from the specific funding provider in charge of the ALFA programme, but not from other sources of public support. We are unable to detect effects on patenting, sales, employment and labour productivity in the full sample of SMEs. However, in a subsample of SMEs that received comparatively large subsidies relative to their pre-treatment sales, we document positive effects on these outcomes, although not on labour productivity. In contrast to SMEs, we do not find any evidence of positive effects of the programme on large firms. Further analysis suggests an important role of financing constraints in explaining this heterogeneity.

The rest of the paper is organised as follows. The remainder of the introduction places the contribution of this paper in the context of related literature. Section 2 introduces the ALFA programme and its evaluation framework. Section 3 describes the dataset and Section 4 explains the empirical specification of the model to be estimated. Section 5 presents the results and Section 6 concludes.

Related Literature. Our study contributes to the literature on the effects of public funding for business R&D and innovation (see a survey by Becker (2015)) and, in particular, to studies examining the impact of direct subsidies for business R&D on firm R&D investment. The question whether public subsidies crowd in or crowd out private R&D expenditure has received considerable attention in the literature, with somewhat mixed results. Among studies reviewed by Zúñiga-Vicente et al. (2014), about 60% found evidence of crowding-in, 20% found evidence of crowding-out and 20% did not find statistically significant evidence of either crowding-in or crowding-out. As an explanation for similarly conflicting results found in their own survey of the literature, Cunningham et al. (2016) propose identification issues, especially the ability of studies to control for unobserved determinants of R&D performance, such as the R&D investment intentions of firms. Along similar lines, a review by the What Works Centre for Local Economic Growth (2015) emphasises the non-random selection into treatment in business R&D subsidy programmes both in terms of who applies for funding and who is eventually selected. It notes that reviewed studies tend to address the selection issues by some combination of matching, difference-in-differences and panel fixed effects methods but "there are also likely to be time-varying unobservable differences that lead to success in getting R&D support[, and t]hese methods cannot account for these underlying factors" (What Works Centre for Local Economic Growth, 2015, p.19). The review identifies only one study investigating the impact of business R&D subsidies on R&D expenditure of firms that uses a credible quasi-experimental variation to overcome the identification challenges.[4] Einiö (2014) implements an instrumental variable strategy exploiting allocation of R&D support among regions of Finland according to an explicit rule based on population density. He finds positive impacts of R&D subsidies on R&D investment, employment and

[4] In total, the review identifies 5 studies that score 4 (and no study scoring 5) on the Maryland Scientific Methods Scale (Sherman et al., 1997). However, among these, 2 studies examine programmes primarily targeting academic or research institutions, and 1 study examines only impacts on economic performance. Bronzini and Iachini (2014) investigate the impact of R&D subsidy programme in Northern Italy using a regression discontinuity design similar to ours but do not observe firm R&D expenditure in their data. They instead estimate the impacts of the programme on tangible and intangible investment from accounting data, finding positive effects for small firms but not large ones. More recently, studying the EU Small and Medium Enterprise Instrument, Santoleri et al. (2022) have similarly estimated the impact of business R&D subsidies on tangible and intangible instrument in an RD design, finding positive effects of the subsidies on investment and also various subsequent outcomes.

sales.[5] Ours is the first paper to estimate the impact of business R&D subsidies directly on firm R&D expenditure in a regression discontinuity design. The study by Einiö (2014) is largely complementary to ours in that it uses a very different identification strategy and thus explores different local average treatment effects. We also explore long term effects over a significantly longer time horizon,[6] compare effects on firms of different sizes and explore the role of financing constraints in explaining this heterogeneity.

Our paper is also related to several recent papers that have leveraged similar discontinuities in subsidy assignment to study the effect of business R&D subsidies on other outcomes, such as patenting, tangible and intangible investment, revenues, survival and subsequent venture capital (VC) financing.[7] A limitation of these studies is that they do not observe information on firm R&D expenditure and its composition. This has several disadvantages. Firstly, they cannot test whether subsidies crowd in or crowd out private R&D expenditure. Secondly, while more patents, higher revenues or a more likely survival are positive outcomes for the supported firms, to the extent that R&D subsidies are motivated by positive externalities of R&D, effects on these outcomes, on their own, do not justify public funding.[8] Thirdly, the unavailability of R&D data means

[5]Einiö's 2014 preferred estimate implies that the subsidies crowded in private R&D expenditure, but the null hypothesis of no crowding-in cannot be rejected at conventional significance levels.

[6]Einiö (2014) examines effects up to 3 years after firms enter the programme, compared to 8 years in our analysis.

[7]See Bronzini and Piselli (2016), Howell (2017) and Wang et al. (2017) for patenting, Bronzini and Iachini (2014) for tangible and intangible investment, Howell (2017) and Wang et al. (2017) for survival, Howell (2017) for revenues and Wang et al. (2017) for subsequent VC financing. Recent work by Santoleri et al. (2022), Iori et al. (2023) and Russo and Santoleri (2023) examines most of these outcomes.

[8]Regardless of what firm-level outcome is used, it may also be affected by R&D subsidies through channels other than increased R&D activity. For example, if filing a patent is a project output required by the funding agency, firms receiving subsidies may be more likely to file patents, even if they do not undertake more R&D projects. The subsidy finance can also directly boost firm survival and allow enough time to file a patent and develop a stream of revenues, and subsequent venture capital investment can be driven by the positive signal of a firm winning a grant rather than by any actual R&D activity

these studies cannot test the validity of the randomization assumption underlying the RD design (Lee and Lemieux, 2010) with regard to the pre-treatment innovation behaviour of the programme participants. Even if the participants did not ex-ante differ in their demographic profiles, financing and outcomes, for which some of the previous papers tested,[9] it cannot be taken for granted that they did not differ in the level, structure and trend of their R&D — arguably the most important factors in this context because applicants' R&D capabilities play a greater role for obtaining the subsidies than their general characteristics.

Our paper also specifically contributes to understanding the timing of the effects of R&D subsidies. The vast majority of studies only look at contemporaneous or short-term effects (Zúñiga-Vicente et al., 2014). The few that explicitly explore the timing of the effects are usually concerned with a delay between the subsidies and the response of firm R&D expenditure, possibly due to firm adjustment costs (Lucas, 1967), typically finding evidence for a one-, two- or three-year lag in the contemporary relationship between the subsidies and the expenditure (e.g. Levy and Terleckyj, 1983; Lichtenberg, 1984; Mansfield and Switzer, 1984). While multiple authors suggest that the effects of subsidies could last longer than the subsidies themselves (e.g. Levy and Terleckyj, 1983; Lach, 2002; Zúñiga-Vicente et al., 2014), estimates of such long term effects are exceedingly rare, with Cunningham et al. (2016) finding only two papers focusing on the persistence of the effects of subsidies: González and Pazó (2008) conduct a matching analysis on data for Spanish manufacturing firms and find weaker effects when considering the effect persistence, and Roper and Hewitt-Dundas (2016) analyse panel data from Irish manufacturing firms and find mixed results for persistence in innovation input, behavioural and output additionality.[10] In line with existing studies, we find a two-year lag between the

stimulated by the subsidies (Meuleman and De Maeseneire, 2012).

[9] See Bronzini and Iachini (2014), Bronzini and Piselli (2016), Santoleri et al. (2022) and Russo and Santoleri (2023).

[10] The studies employing RD designs are limited to examining short-term (or immediate) effects.

award of a subsidy and an increase in firm R&D expenditure, but we also find long-term effects of the subsidies even 8 years after a subsidy was awarded (i.e. 4-5 years after the end of the associated subsidies).

Finally, our paper complements recent quasi-experimental studies that explore the effects of other types of business R&D support, in particular R&D tax incentives (Rao, 2016; Agrawal et al., 2020; Dechezleprêtre et al., 2023) and R&D loans (Zhao and Ziedonis, 2020). Like these studies, our results highlight an important role of financing constraints in the effectiveness of public support to business R&D.

2 The ALFA Programme

In the Czech Republic, direct subsidies for R&D undertaken in business enterprises, provided through competitive grants, have been a prominent tool of innovation policy since the 1990s. A system of indirect support for R&D in the form of tax deductions was introduced in 2005 and gradually grew in volume, but it has never accounted for more than half of the total support for business R&D (Czech Statistical Office, 2023).

The ALFA programme was administered by the Technology Agency of the Czech Republic (TA CR) and provided funding to projects during the period 2011–2018.[11] The TA CR was established in 2009 with the aim to consolidate government funding for applied research and innovation, and ALFA was its first flagship programme. In total, ALFA provided funding of CZK 9.3 billion (approximately EUR 340 million). In the Czech context, this makes it the second largest programme of its kind to date.

ALFA was organised in four annual calls for proposals that took place in 2010, 2011, 2012, and 2013. The calls are dated by the year in which the call was announced, which we denote as base year t_0 in this paper. The calls were announced and proposals evaluated during the same year, and funding was provided from January of the following

[11] See also `https://www.tacr.cz/program/alpha/`.

year.[12] The primary target group was business enterprises, but research organisations were also eligible for funding. The programme accepted proposals from both individual entities and consortia of several partners. The participation of research organisations in consortia was rewarded extra points in the evaluation in order to promote public-private collaboration. A typical proposal consisted of a consortium headed by a firm, with a research organisation and possibly other firms as partners.

The main objectives of ALFA were defined quite broadly: to boost the performance of business enterprises, to increase competitiveness in the economy and the society, and to enhance the standard of living (TA CR, 2014). The programme was divided into three sub-programmes focused, respectively, on 1) advanced technologies, materials and systems; 2) energy resources and environmental protection; and 3) sustainable development of transport. The latter two subprogrammes were focused on relatively specific topics and, crucially for us, proved to be unsuitable for RD analysis due to the small number of projects that met binary criteria for eligibility to receive support and received evaluator scores reasonably close to the cutoff but ended up not being supported.[13] In contrast, the first subprogramme was designed more broadly and ultimately accounted for the majority of the total projects submitted, and the majority of the total funding.[14] For these reasons, we focus on Subprogramme 1, and henceforth all discussion and results refer to that subprogramme.

The proposals were evaluated by an expert panel with the help of external reviewers.

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[12]One exception to this was the last call, in which the funding started from July, rather than January, of the year following the year of the announcement.

[13]In call 2 of Subprogramme 2 and calls 2 and 4 of Subprogramme 3, there were no projects at all that met the binary criteria but that ended up below the cutoff score for receiving funding. The number of such projects that were additionally within the bandwidth of 5.5 points around the score cutoff was also very low for call 1 of Subprogramme 2 (2 projects), and call 1 (11 projects), and call 3 (10 projects) of Subprogramme 3.

[14]Over the 4 calls, Subprogramme 1 accounted for 55% of submitted project proposals, 44% of funded projects, and 51% of the disbursed funding.

Each project was assessed by two (calls 1 and 2) or three (calls 3 and 4) external reviewers and one rapporteur from the panel. In the first step, several binary criteria, such as whether the project was within the scope of the programme, were used to eliminate ineligible proposals. In the second step, each evaluator awarded 0 to 100 points to each project based on set criteria, such as the quality of the research team and expected impacts of the project. The projects were then ranked according to the average number of points across the three or four evaluators. Whether a proposal that met the binary criteria was awarded a subsidy depended on the amount of funding in a given call.[15]

Table 1: **Number of project proposals by calls**

	Call 1 2010	Call 2 2011	Call 3 2012	Call 4 2013	Total 2010-2013
Total					
Supported	114	107	101	102	424
Unsupported	211	297	496	447	1451
Binary criteria affirmatory					
Supported	114	107	101	102	424
Unsupported	54	113	278	297	742
Bandwith of 5.5 points around cutoff					
Supported	20	57	75	88	240
Unsupported	38	52	130	128	348

Table 1 provides an overview of the number of projects in each annual call. In total, 1,875 project proposals were submitted, of which 424 ended up being supported. This means that slightly fewer than one in four proposals was funded. The number of proposals increased between calls 1 and 2 (325 and 404 proposals) and calls 3 and 4 (597 and 549 proposals), while the number of subsidised projects remained roughly the same; hence, the competition intensified and the success rate dropped in the second half of the programme. At the same time, the share of proposals that were eliminated based on the binary criteria declined over time from 48% in call 1 to 27% in call 4, leaving a greater role for evaluator scores. Consequently, the cutoff for funding rose steadily from 71 to 77, 83 and 85

[15]Note that various adjustments were made in the evaluation procedures over the course of the programme implementation, especially between calls 1 and 2 and calls 3 and 4. These adjustments, however, did not affect the comparability of the evaluation points across calls. Details of the adjustments are available upon request from the authors.

evaluation points in the consecutive calls. As the distribution of the proposals is skewed toward higher scores, the increase in the cutoff score meant that the number of proposals within our baseline bandwith of 5.5 points around the cutoff increased over time even more than the total number of proposals, from 58 proposals in call 1 and 109 proposals in call 2 to 205 proposals in call 3 and 216 proposals in call 4.

The average subsidy size per project and firm was CZK 4.7 million (approx. EUR 190,000), with a median of CZK 3.8 million (approx. EUR 150,000). For comparison, the pre-treatment average and median R&D expenditure of the supported firms were, respectively, CZK 32 million and CZK 13 million, and the average and median sales of these firms were roughly CZK 900 million and CZK 150 million, respectively. Hence, the subsidies were relatively small. Eligible R&D expenses covered the whole spectrum of costs, including personnel, material and travel costs, purchases of services, and tangible and intangible investments, except in the last call, in which investment was not eligible. Supported projects had to commit to produce at least one applied research output as defined at the time of the call announcement by the Office of the Government of the Czech Republic (2022), for example, a patent, prototype or software. The subsidy covered eligible costs of the proposed project up to a maximum of 45–80% in small enterprises, 35–75% in medium enterprises and 25–65% in large enterprises, depending on the call, the type of research, and collaboration with a research organisation. Of the 424 subsidised projects, 157 projects lasted for 3 years and 235 projects lasted for 4 years. Only 14 projects concluded within the first 2 years and 18 projects lasted 5 or 6 years.

3 Data

The primary source of information is the annual R&D survey collected by the Czech Statistical Office (CZSO) that covers the entire population of R&D-performing firms in the Czech Republic. The survey data follow an international methodology for measuring R&D (OECD, 2015) and contain detailed information on business R&D expenditure and its composition in terms of sources of funding and R&D cost types. An important advantage of the R&D survey data for our analysis is that they are collected purely for statistical purposes, and, as a result, firms do not have incentives to misreport their R&D.[16]

The R&D data are linked at the firm-level to additional datasets, using the unique taxpayer identification number (IČO), which is standardized at the national level and allows unequivocal identification of each organisation. The additional datasets include patent records, structural business statistics, firm demographic information and administrative R&D tax relief records from the CZSO, firm financial information from the MagnusWeb database and administrative information on R&D projects supported from public sources from the Research, Development and Innovation Information System of the Czech Republic.[17]

We have further linked the firm-level database to administrative records from the TA CR internal information system. For each project proposal in the ALFA programme, the records state the evaluation points received, the project rank, the cutoff score for a given subprogramme and call, whether the proposal met the binary criteria, whether the project was supported and the composition of the project consortium. The resulting panel data span years 2007-2021, which means that we can observe at least 4 years before the start of the projects ($t-3$ to t) and at least 8 years after the start of the projects ($t+1$ to $t+8$) for all calls.

We consider effects of the treatment on the following variables: i) R&D inputs – R&D expenditures, not only total, but also by the source of funding (private vs. public) and the type of R&D costs (current vs. capital); ii) R&D outputs – the number of patent applications filed in the Industrial Property Office of the Czech Republic; and iii)

[16]In administrative data, firms might try to overreport their R&D expenditure to satisfy project co-financing requirements or receive more R&D tax relief.

[17]The linked database used in this paper has been constructed at the CZSO under the OECD project MicroBeRD+.

Economic performance – employment (full-time equivalent), sales and labour productivity (value added per employee).

In addition, we use a number of other variables as covariates and to test the underlying assumptions of the RD design. They include the outcome variables in the pre-treatment year t_0, firm demographic variables (time since incorporation, a foreign ownership dummy, a dummy for joint-stock companies, a manufacturing dummy, a dummy for head office in the capital city of Prague) and project characteristics (the number of project participants, a dummy for participation of a research organisation in the project consortium). For more detailed definitions of the variables, see Appendix Table A.1.

The members of project consortia included not only business enterprises, but also research organisations (e.g. universities), various state-owned and state-funded organisations, and in a few cases, individuals. To avoid mixing organisations with different characteristics and motivations, we restrict our analysis to profit-oriented private businesses. Specifically, we exclude (i) higher education institutions and research organisations that conduct primarily non-business activities, as listed by the Ministry of Education, Youth and Sports[18] and the Research, Development and Innovation Council;[19] (ii) organisations classified in the business register as public non-financial corporations; and (iii) organisations with out-of-scope legal forms, such as state-funded institutions, state enterprises, associations and sole proprietors.[20]

In total, there are 1,183 firm-project combinations involving profit-oriented private firms, of which 1,024 (87%) we are able to successfully match to the CZSO database.[21] In 11 cases, projects were recommended for funding and ranked above the cutoff but the

[18]See `https://www.msmt.cz/vzdelavani/vysoke-skolstvi/prehled-vysokych-skol-v-cr-3`.

[19]See `http://vyzkum.cz/FrontClanek.aspx?idsekce=560752`.

[20]The final sample includes the following legal forms: private limited company, limited partnership, joint-stock company and co-operative.

[21]This is comparable with the other aforementioned RD studies on this topic. For example, Santoleri et al. (2022) matched 74% of all firm-applications to the dataset at their disposal.

potential recipients did not end up signing the funding contracts due to unanticipated events, such as a break-up of the consortium or a loss of key personnel. These 'non-compliance' cases account for only about 1% of our sample, and we eliminate them from the analysis.[22] Finally, to ensure that our results are not driven by outliers in the form of very large proportional increases and drops in firm R&D activity, which could be associated, for example, with mergers and acquisitions, we drop the 2% of firms with the largest proportional difference between the maximum and minimum total R&D expenditure over the sample period. This leaves us with a final sample of 994 firm-project combinations.

Table 2 provides descriptive statistics of the longitudinal panel dataset within the relevant time window running from the 4$^{\text{th}}$ year before the start of a project ($t-3$) until the 4$^{\text{th}}$ year after the project's end ($t+8$). Firms in our sample have average R&D expenditure of CZK 34 million per year. Most of this expenditure is funded from private sources, but public funding is also important, at about CZK 8 million per year for an average firm. About a quarter of the public funding comes from the TA CR, with most of the rest coming from other national and EU sources of direct public funding. R&D tax relief accounts for less than CZK 1 million a year on average. About 90% of R&D expenditure takes the form of current expenditure (labour costs and materials), while capital R&D expenditure accounts for only about 10% of the total. An average firm files a patent every two years, has about 300 employees, annual sales of about CZK 900 million and labour productivity of CZK 800 thousand per employee. The median firm size is substantially smaller, at just over 100 employees and CZK 170 million of annual sales. An important difference between ALFA and the SBIR and SMEI programmes, studied, respectively, by Howell (2017) and Santoleri et al. (2022), is that firms in ALFA tend to be much older with a median age of 19 years, compared to about 5 years in the case of SBIR and SMEI. About a quarter of the firms are foreign-owned, about half

[22] Keeping the non-compliant firms in the sample and employing a fuzzy RD design leads to virtually identical results.

are joint-stock companies, manufacturing companies account for nearly two-thirds of the sample and about one fifth of the companies are based in the capital of Prague. A typical project had 3 participants, and in almost all projects at least one participant was a research organisation such as a university.

Table 2: **Descriptive Statistics**

	count	mean	p50	sd
Total R&D expenditure	8709	33.80	10.99	94.31
Privately funded R&D expenditure	8709	25.72	5.75	89.20
Direct public R&D funding from TA CR	8709	2.09	0.38	3.82
Direct public R&D funding from other sources	8709	5.16	1.25	12.11
R&D tax relief	8709	0.87	0.00	4.68
Current R&D expenditure	8709	30.54	10.06	81.00
Capital R&D expenditure	8709	3.26	0.00	24.73
Patent applications	8709	0.49	0.00	2.08
Employment (FTE)	7940	330.33	109.00	704.17
Sales	8630	915.45	172.71	3370.71
Labour productivity (thousands CZK / emp.)	7670	795.40	718.45	397.49
Time since incorporation	8709	18.15	19.00	6.30
Foreign-owned (1/0)	8709	0.24	0.00	0.43
Joint-stock (1/0)	8709	0.46	0.00	0.50
Manufacturing (1/0)	8709	0.63	1.00	0.48
Prague (1/0)	8709	0.19	0.00	0.39
Number of project participants	8709	3.03	3.00	1.28
Cooperation with a research org. (1/0)	8709	0.97	1.00	0.17

Notes: All monetary variables except labour productivity are in CZK millions.

4 The RD Design

4.1 Estimation Strategy

To formalise the intuition of the RD design, we adopt the approach first proposed by Thistlethwaite and Campbell (1960). It assumes that assignment of treatment conditional on the running variable – in our case, the score assigned to a project – around the threshold for funding is approximately random. We estimate the following stacked RD regression:

$$Y_{ipt} = \beta T_p + \gamma_-(1-T_p)X_p + \gamma_+ T_p X_p + \sum_{j=1}^{J} \delta_j Z^j_{ipt_0} + \theta_c + \theta_t + \epsilon_{ipt}. \qquad (1)$$

Y_{ipt} is the outcome in year t for firm i participating in project p submitted to call c. Our primary outcome of interest is the firm's total R&D expenditure, but we also consider more detailed outcomes by the source of funding (private, direct from TACR, other direct, tax relief) and the type of costs (current, capital). In addition, we estimate the model with the number of patent applications, sales, employment and labour productivity as outcomes. All outcome variables are included as natural logarithms.[23]

T_p is a dummy variable marking whether project p received a subsidy, and X_p is the running variable, given by each project's average score (number of points) across 3 or 4 evaluators. We normalise the score so that it equals zero at the threshold, i.e., projects with a zero or a positive score were funded, and projects with a negative score were not. Use of higher degree polynomials in the running variable has been shown to lead to noisy estimates, to results that are highly sensitive to the degree of the polynomial, and to poor coverage of confidence intervals, frequently offering empirical support for evidently nonsensical results (Gelman and Imbens, 2019). For this reason, we use a linear polynomial in our running variable and test the robustness of the results to using a quadratic polynomial. As is standard in RD analysis, we use local polynomials that are independently estimated on each side of the threshold (Lee and Lemieux, 2010).

Consistent identification of causal effects in RD designs generally does not require inclusion of additional controls. Controlling for additional predetermined covariates can,

[23] As the individual components of the total R&D expenditure are equal to zero for many firms, we calculate the logarithm for R&D variables other than the total R&D expenditure as $\log(x + K)$, where x is a given component of R&D expenditure and K is a constant specific to variable x. Chen and Roth (2023) show that estimation results with this widely-used transformation are not scale-invariant, as the transformation affects the relative weight of the extensive and intensive margins in the regressions. We take one of the approaches suggested by Chen and Roth (2023) to tackle this issue, which is to establish an explicit trade-off between the extensive and intensive margin. Specifically, we set K to the 5^{th} percentile among all non-zero values of x as observed in 2010. This implies that going from zero expenditure to a strictly positive expenditure on the 5^{th} percentile increases the logarithmised value by 1, and is thus equivalent to an intensive-margin change of $\log(2) \approx 70\%$.

however, increase the precision of estimates (Calonico et al., 2019).[24] For this reason, we include a set of controls $Z^j_{ipt_0}$, which are measured in the pre-treatment year t_0. Firstly, they include pre-treatment values of all the outcome variables we examine. In addition, the controls include the variables for patenting, economic performance, firm demographics and the project characteristics listed in section 3. Finally, we control for year dummies θ_t and call dummies θ_c.

The assumption that projects above and below the threshold are similar, conditional on their score, is unlikely to hold for projects further away from the threshold. Therefore, we restrict the analysis to projects with scores that lie within bandwidth h around the threshold. For the total R&D expenditures, our main outcome of interest, the mean square error (MSE) optimal bandwidth selection procedure with covariates by Calonico et al. (2019) suggests a bandwidth of 5.5 points during the project and 5.4 points after the project. We thus make 5.5 points the baseline bandwidth but, throughout the analysis, also report results based on a narrower bandwidth (4 points), a wider bandwidth (10 points) and an infinite bandwidth.[25]

We estimate Equation 1 using weighted least squares, with weights given by a kernel function $K(X_p/h)$.[26] As a baseline, we use a triangular kernel function, which assigns a linearly smaller weight to observations further away from the threshold, and we test the robustness of the results to alternatively using a uniform kernel function. We report bias-corrected RD estimates and robust standard errors clustered at the firm level (Calonico et al., 2014a).[27]

[24] For similar reasons, researchers often include pre-treatment covariates when analysing randomised experiments.

[25] Among the 4 bandwidths we use, each step towards a narrower bandwidth reduces the number of observations by roughly a quarter.

[26] The estimation is performed in Stata using command rdrobust (Calonico et al., 2014b, 2017).

[27] To estimate the bias of the regression function estimator, we use a second order polynomial. The MSE-optimal bias bandwidths are 9.5 (effects during the project) and 9.4 (effects after the project). We thus, respectively, use bias bandwidths of 9.5, 8, 20 and infinity when the main bandwidths are 5.5, 4,

We separately estimate the effects (i) during the treatment and (ii) after the treatment. For treated firms, we define the last year of the treatment, t_T, as the last year in which at least one project participant received subsidies within a given project. For control firms, we set $t_T = t_0 + 4$, assuming that their projects, if supported, would last for 4 years (i.e. the duration of the majority of projects supported in the programme). We then define the period 'before the subsidy' as years $t_0 - 3$ to t_0, the period 'during the subsidy' as years $t_0 + 1$ to t_T and the period 'after the subsidy' as years $t_T + 1$ to $t_T + 4$.[28]

4.2 Validity Tests

The identification in our RD design rests on the assumption that scores were not manipulated around the cutoff. Such manipulation by the evaluators was made unlikely by the fact that the score received by each project was an average of points awarded independently by three or four evaluators, and that the exact location of the cutoff was not known at the time the points were assigned. In principle, the Board of the Programme and the Board of TA CR had the right to adjust the number of points allocated to a project, but, based on our conversations with TA CR representatives, they exercised this power only rarely, for instance, when inconsistencies in a project budget were exposed ex-post. Even in such cases, it almost never happened that a change in the ranking would affect which proposals were actually funded or not.

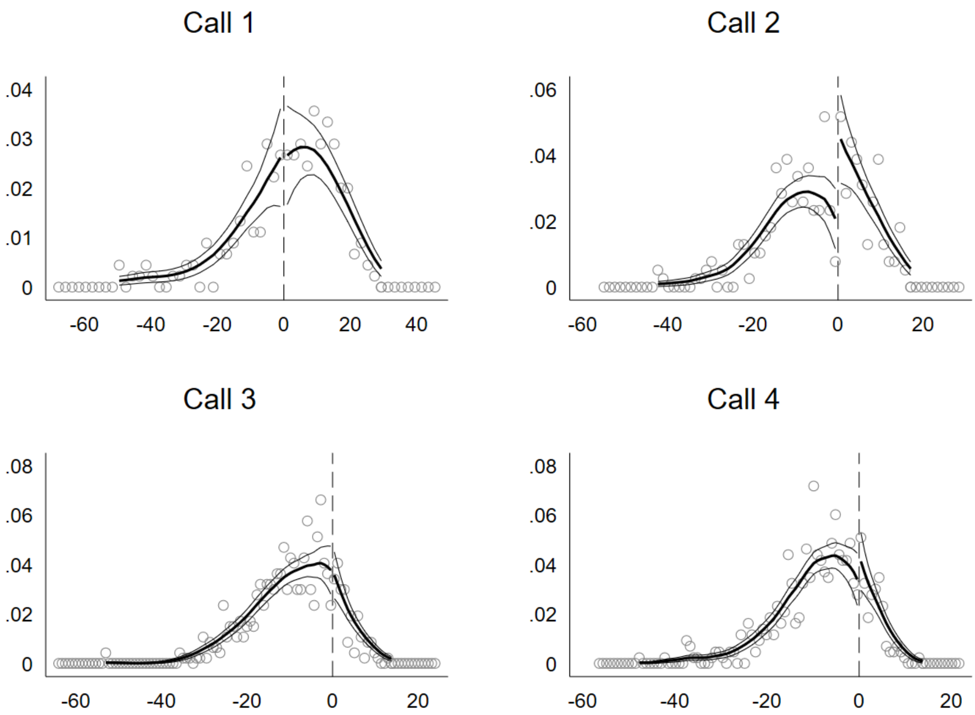
We test the validity of the identifying assumptions in two ways. First, in the upper panel of Figure 1 we show the results of the McCrary (2008) test by call, which compares the density of the distribution of project scores below and above the cutoff. We see no significant discontinuity in the density at the cutoff in calls 1, 3, and 4. In contrast, we

10 and infinity.

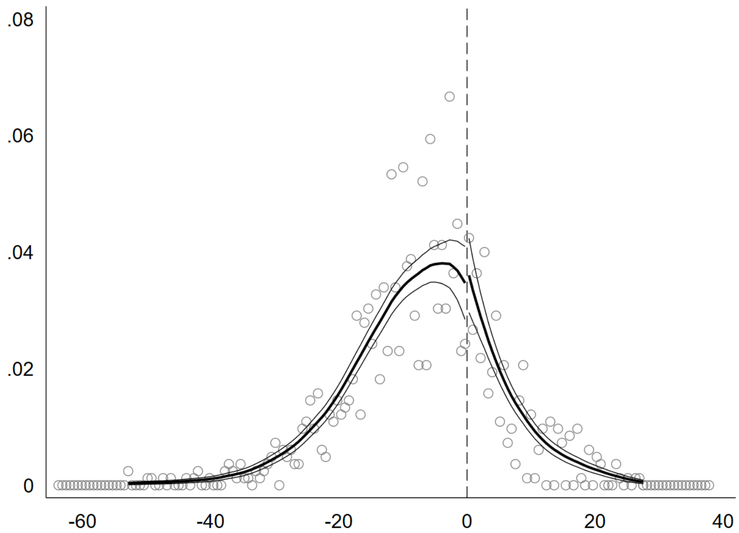
[28]We test the robustness of the results to setting the duration of all projects to 4 years, defining the period 'during the subsidy' as years $t_0 + 1$ to $t_0 + 4$ and the period 'after the subsidy' as years $t_0 + 5$ to $t_0 + 8$ for all firms, independent of the projects' actual duration. We find virtually identical results with this alternative approach.

Figure 1: **Density of Project Scores Around the Cut-Off**

(a) By Call



(b) Analysis Sample (excl. Call 2)



Notes: The figures plot the density of project proposals along the scores received around the cut-off, following McCrary (2008). Panel (a) plots the density separately for each call of the ALFA programme. Panel (b) plots the density for data combining calls 1, 3 and 4.

observe a substantial and statistically significant discontinuity in call 2. To avoid the risk that the scores were indeed adjusted around the cutoff in call 2 and that this would bias our results, we exclude call 2 from all subsequent analyses. In the lower panel of Figure 1, we show results of the McCrary test for the analysis sample of combined calls 1, 3, and 4. The figure shows no evidence of discontinuity in the density around the cut-off for these projects.

Table 3: **RD Estimates Before the Treatment ($t_0 - 3$ to t_0)**

	Before the subsidy							
Band.	Infinite	Wide	Baseline	Narrow	Infinite	Wide	Baseline	Narrow
	Log total R&D expenditure				Log privately funded R&D expenditure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	-0.12	-0.11	0.04	0.09	-0.13	-0.06	0.02	0.04
	(0.23)	(0.25)	(0.30)	(0.33)	(0.24)	(0.26)	(0.32)	(0.36)
N (left)	1742	1254	762	595	1742	1254	762	595
N (right)	1082	862	622	497	1082	862	622	497
	Log direct public funding from TACR				Log direct public funding from other sources			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	-0.02	0.04	0.15	0.19	-0.07	-0.01	0.07	0.03
	(0.11)	(0.13)	(0.16)	(0.17)	(0.21)	(0.23)	(0.27)	(0.29)
N (left)	1742	1254	762	595	1742	1254	762	595
N (right)	1082	862	622	497	1082	862	622	497
	Log R&D tax relief				Log current R&D expenditure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	-0.25	-0.52*	-0.43	-0.43	-0.10	-0.11	-0.01	0.01
	(0.28)	(0.31)	(0.38)	(0.41)	(0.20)	(0.20)	(0.24)	(0.27)
N (left)	1742	1254	762	595	1742	1254	762	595
N (right)	1082	862	622	497	1082	862	622	497
	Log capital R&D expenditure				Log patent applications			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	-0.12	-0.15	-0.19	-0.31	-0.05	-0.03	0.01	-0.00
	(0.22)	(0.24)	(0.30)	(0.34)	(0.07)	(0.08)	(0.09)	(0.10)
N (left)	1742	1254	762	595	1742	1254	762	595
N (right)	1082	862	622	497	1082	862	622	497
	Log employment				Log sales			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	-0.06	-0.04	0.01	0.04	-0.29	-0.22	-0.23	-0.22
	(0.32)	(0.34)	(0.41)	(0.44)	(0.37)	(0.40)	(0.48)	(0.52)
N (left)	1619	1180	726	575	1683	1217	742	583
N (right)	1029	816	585	471	1043	833	598	480
	Log labour productivity				Firm age			

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	-0.14*	-0.14	-0.17	-0.13	-0.68	-0.67	-1.03	-0.87
	(0.08)	(0.09)	(0.12)	(0.13)	(0.94)	(1.03)	(1.33)	(1.45)
N (left)	1499	1082	664	524	1742	1254	762	595
N (right)	934	751	540	435	1082	862	622	497
	Foreign-owned (0/1)				Joint-stock (1/0)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	-0.02	-0.04	-0.08	-0.07	-0.08	-0.01	0.02	0.05
	(0.08)	(0.09)	(0.11)	(0.12)	(0.10)	(0.11)	(0.14)	(0.16)
N (left)	1742	1254	762	595	1742	1254	762	595
N (right)	1082	862	622	497	1082	862	622	497
	Manufacturing (1/0)				Prague (0/1)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.14*	0.12	0.10	0.12	-0.05	-0.06	-0.03	-0.03
	(0.08)	(0.09)	(0.12)	(0.14)	(0.07)	(0.07)	(0.11)	(0.12)
N (left)	1742	1254	762	595	1742	1254	762	595
N (right)	1082	862	622	497	1082	862	622	497
	Number of project participants				Cooperation with a research organisation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.42*	0.39	0.34	0.25	0.03	0.04	0.05*	0.02
	(0.22)	(0.26)	(0.37)	(0.41)	(0.03)	(0.03)	(0.03)	(0.02)
N (left)	1742	1254	762	595	1742	1254	762	595
N (right)	1082	862	622	497	1082	862	622	497

Notes: *** 1%, ** 5%, * 10%. The table reports placebo RD estimates of the effect of ALFA on various firm characteristics in pre-treatment years $t_0 - 3$ to t_0. It estimates Equation 1 using weighted least squares (with weights given by a triangular kernel function), for an infinite bandwidth and bandwidths of 10, 5.5 and 4 points around the cutoff. Standard errors are clustered at the firm level.

If the assignment of treatment conditional on the score received by a project around the cut-off is approximately random, we should not observe any pre-treatment differences between the treated and control observations around the cut-off (Lee and Lemieux, 2010). To see if this is the case, we conduct placebo tests in which we estimate a version of our estimating equation with outcomes given by various firm and project characteristics observed in the 4 years before the start of the project ($t_0 - 3$ to t_0). Table 3 shows results of 72 placebo tests, using 18 outcome variables and the 4 different bandwidths: infinite, wide (10 points), baseline (5.5 points) and narrow (4 points). The definition of significance levels implies that, in the absence of any pre-treatment differences around the cut-off, roughly 7 of these tests should be significant at the 10% level and 4 at the 5% level out of pure luck. This is more than what we see, with only 5 of the tests proving to be significant at the 10% level and none at the 5% level. The placebo tests thus do not indicate the presence of systematic differences in the pre-treatment characteristics of firms below and above the cut-off.

In summary, after excluding call 2, we see no evidence of score manipulation based on the McCrary (2008) test, and no evidence of differences in pre-treatment characteristics around the cut-off. These two facts together make us reasonably confident that any differences in post-treatment firm outcomes, as presented in the next section, have a causal interpretation.

5 Results

5.1 Overall Effects on R&D Expenditure

The main findings for the effects of the ALFA programme on firm R&D expenditure are depicted graphically in Figure 2 and reported in Table 4. We present the results of the RD estimation separately for the period during ($t_0 + 1$ to t_T) and after ($t_T + 1$ to $t_T + 4$) the subsidy. The figure compares the natural logarithm of the total R&D expenditure for applicants whose projects were placed just below and just above the cutoff, using the baseline bandwidth of 5.5 points around the cutoff. The cutoff is delineated by zero on the horizontal axis, and the fitted lines that facilitate the comparison are estimated by linear regressions separately above and below the cutoff. Panel (a) of Figure 2, based on the full sample of firms, indicates larger R&D expenditure during the subsidy for firms above the cutoff, and the same continues to hold after the subsidy.

This finding is confirmed in panel (a) of Table 4, which shows corresponding results for 4 different choices of bandwidth: infinite, wide (10 points) and narrow (4 points), as well as the baseline (5.5 points).[29] The results suggest that participation in ALFA increased firms' total R&D expenditure by about 35% on average during the subsidy and 42% after the subsidy.[30] The point estimates are quite consistent across the different bandwidths (with the exception of the effects after the subsidy using the infinite bandwidth), and they are statistically significant at least at 10% level both during and after the subsidy when the baseline bandwidth is used. Panel (a) of Table 4 further indicates positive effects of the programme on privately funded R&D expenditure, both during and after the subsidies, suggesting *crowding in* private funds.

We test the robustness of these results to a series of changes in our baseline specification: using a zero-degree polynomial or a quadratic polynomial, rather than a linear polynomial; using a uniform kernel, rather than a triangular one; defining the periods during and after the subsidy as $t_0 + 1$ to $t_0 + 4$ and $t_0 + 5$ to $t_0 + 8$ irrespective of each project's actual duration; and not dropping any outliers from the analysis (see Appendix Table A.2). The point estimates are broadly consistent across all these alternative specifications, they are statistically significant at 10% level with at least some choice of bandwidth and in all cases using the baseline bandwidth except of the quadratic polynomial.[31]

5.2 Effects on R&D Expenditure by Firm Size

Next, we explore the effects of the ALFA programme separately for small and medium size enterprises (SMEs), defined as firms with fewer than 250 employees, and large firms in the pre-treatment year t_0. Doing so is motivated by the fact that SMEs and large

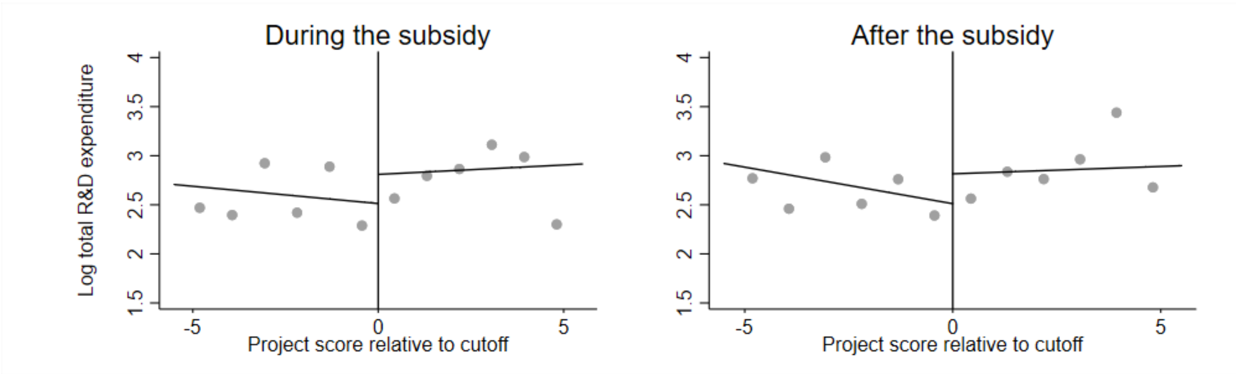
[29] Among the 4 bandwidths we use, each step towards a narrower bandwidth reduces the number of observations by roughly a quarter.

[30] $e^{0.30} - 1 \approx 35\%$ and $e^{0.35} - 1 \approx 42\%$.

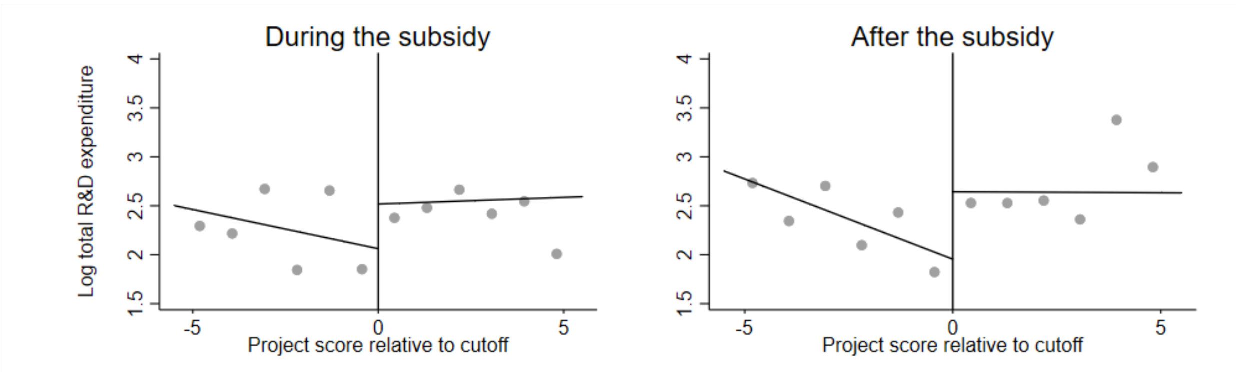
[31] In Appendix Table A.5, we show that keeping in the sample the 11 firms with scores above the cutoff that ended up not signing the funding agreement and employing a fuzzy RD design has no material effect on the results.

Figure 2: **Effects on Total R&D Expenditure**

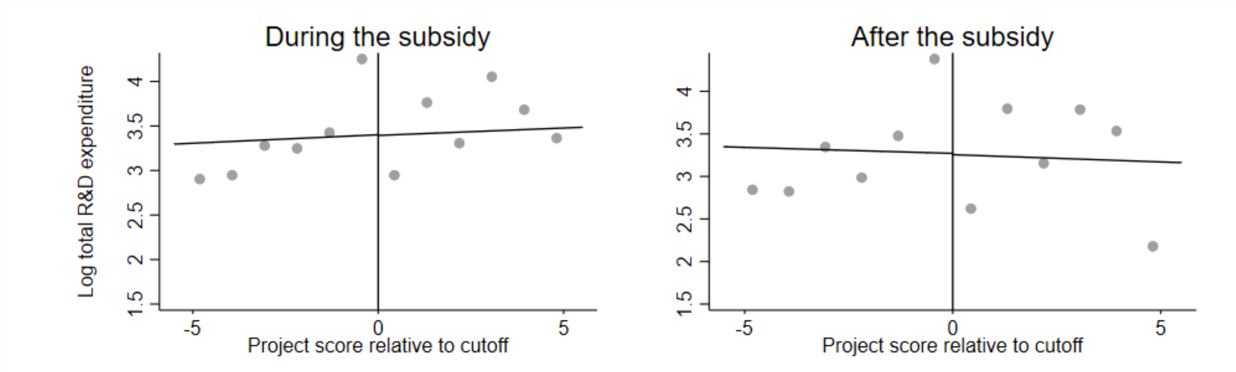
(a) All firms



(b) SMEs



(c) Large firms



Notes: The figures show RD plots comparing the log total R&D expenditure below and above the cutoff, separately during the subsidy ($t_0 + 1$ to t_T) and after the subsidy ($t_T + 1$ to $t_T + 4$). The results are based on estimating Equation 1 using weighted least squares (with weights given by a triangular kernel function), for a bandwidth of 5.5 points around the cutoff, controlling for pre-treatment firm characteristics and year and call fixed effects.

Table 4: **Effects on R&D Expenditure**

	During the subsidy				After the subsidy			
Band.	Infinite	Wide	Baseline	Narrow	Infinite	Wide	Baseline	Narrow
	(a) All firms							
	Outcome: Log total R&D expenditure							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.25***	0.31***	0.30**	0.21	0.08	0.25	0.35*	0.30
	(0.09)	(0.10)	(0.15)	(0.16)	(0.15)	(0.16)	(0.21)	(0.22)
N (left)	1459	1072	669	526	1280	943	601	477
N (right)	925	756	545	449	860	691	499	419
	Outcome: Log privately funded R&D expenditure							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.17	0.25*	0.41*	0.34	0.17	0.37*	0.59*	0.58*
	(0.12)	(0.14)	(0.23)	(0.25)	(0.18)	(0.21)	(0.32)	(0.35)
N (left)	1459	1072	669	526	1280	943	601	477
N (right)	925	756	545	449	860	691	499	419
	(b) SMEs							
	Outcome: Log total R&D expenditure							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.32***	0.39***	0.49***	0.42**	0.28	0.48**	0.80***	0.77***
	(0.12)	(0.13)	(0.17)	(0.19)	(0.20)	(0.20)	(0.25)	(0.27)
N (left)	1035	752	451	348	894	647	389	303
N (right)	681	548	371	301	616	485	327	273
	Outcome: Log privately funded R&D expenditure							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.30**	0.43**	0.81***	0.76***	0.38	0.66**	1.09***	1.10**
	(0.13)	(0.17)	(0.27)	(0.29)	(0.25)	(0.28)	(0.41)	(0.44)
N (left)	1035	752	451	348	894	647	389	303
N (right)	681	548	371	301	616	485	327	273
	(c) Large firms							
	Outcome: Log total R&D expenditure							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.03	0.04	-0.09	-0.20	-0.14	-0.10	-0.04	-0.06
	(0.15)	(0.14)	(0.16)	(0.17)	(0.19)	(0.21)	(0.30)	(0.32)
N (left)	424	320	218	178	386	296	212	174
N (right)	244	208	174	148	244	206	172	146
	Outcome: Log privately funded R&D expenditure							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	-0.15	-0.17	-0.21	-0.21	-0.18	-0.12	-0.00	0.07
	(0.20)	(0.17)	(0.19)	(0.19)	(0.20)	(0.20)	(0.28)	(0.29)
N (left)	424	320	218	178	386	296	212	174
N (right)	244	208	174	148	244	206	172	146

Notes: *** 1%, ** 5%, * 10%. The table reports RD estimates of the effect of the subsidies on total and privately funded R&D expenditure, separately during the subsidy ($t_0 + 1$ to t_T) and after the subsidy ($t_T + 1$ to $t_T + 4$) and separately for all firms, SMEs and large firms. The results are based on estimating Equation 1 using weighted least squares (with weights given by a triangular kernel function), for an infinite bandwidth and bandwidths of 10, 5.5 and 4 points around the cutoff, controlling for pre-treatment firm characteristics and year and call fixed effects. Standard errors are clustered at the firm level.

firms differ in the nature of their R&D,in their innovation incentives and capabilities and in the constraints they face. Importantly, SMEs are more likely to be financially constrained (Hall and Lerner, 2010), and they can be expected to disproportionately benefit from the "certification" effects of receiving a competitive subsidy (Feldman and Kelley, 2006; Meuleman and De Maeseneire, 2012). At the same time, large firms tend to undertake more R&D projects in parallel and, consequently, can more easily identify a project that is likely to succeed in a subsidy competition among projects that they would undertake in any case. Existing studies also suggest that firms of different size respond differently to business R&D subsidies (González and Pazó, 2008; Bronzini and Iachini, 2014; Romero-Jordán et al., 2014).

Panels (b) and (c) of Figure 2 document the results for SMEs and large firms, respectively. The figures for SMEs again show a substantially larger R&D expenditure above the cutoff, but the difference is greater and clearer than using the full sample (panel (a)). In contrast, the results for large firms do not show any difference between firms above and below the cutoff, indicating that the subsidies did not increase R&D expenditure in large firms.

Again, corresponding results for other that the baseline bandwidth are shown in panels (b) and (c) of Table 4. The estimates for SMEs are stronger than those for the full sample and highly statistically significant using most bandwidths. Using the baseline bandwidth, they imply that the ALFA programme increased the total R&D expenditure of the supported SMEs by about 63% on average during the subsidy and 122% after the subsidy.[32] These results imply that, during the subsidy, 1 unit of a subsidy generated roughly 2.5 units of additional R&D spending.[33] The estimated effects on the privately

[32] $e^{0.49} - 1 \approx 63\%$ and $e^{0.80} - 1 \approx 122\%$.

[33] Writing dR for an absolute change in R&D expenditure, ΔR for a proportional change in R&D expenditure and dG for subsidies received in a given year, $\frac{dR}{dG} = \frac{\Delta R}{\frac{dG}{R}}$. The ratio of an annual subsidy to pre-treatment R&D expenditure for an average supported SME is 0.25 (to prevent the mean to be driven by a few outliers with very high subsidy-to-initial R&D ratios, we winsorise the ratios at the 98th

funded R&D expenditure of SMEs are also positive and large. Together, these results represent strong evidence of the subsidies leading to crowding in of private R&D investment in the case of SMEs. In Appendix Table A.3, we show that the results for SMEs are robust to a range of alternative specifications.

In contrast, there is no evidence that the subsidies stimulated R&D expenditures in large firms, either during or after the subsidy. The point estimates for total R&D expenditure are all not statistically significant at the conventional levels and close to zero or even negative, in particular for privately funded R&D expenditure during the subsidy (implying crowding out of private investment). In Appendix Table A.4, across the robustness checks, we consistently estimate effects that are close to zero and insignificant. The only exception is that using a quadratic polynomial leads to statistically significant *negative* coefficients during the subsidy for the two narrowest bandwidths. Most likely, this is a result of estimating a quadratic polynomial with a limited number of observations. As discussed earlier, use of higher-degree polynomials can lead to unreliable results (Gelman and Imbens, 2019), especially in small samples.

What can explain such different results for SMEs and large firms? One potential explanation is that, for many large firms, the subsidies are small relative to the firms' R&D budgets, and, as a result, the impact of the subsidies is difficult to estimate with sufficient precision in a limited sample. We test this explanation in panel (a) of Table 5. Rather than splitting firms according to their size, we split the supported firms according to the size of the subsidies they received in ALFA relative to their pre-treatment R&D expenditure. Specifically, we split the supported firms into those above and below the median of the subsidy-to-R&D ratio. During the subsidy, we indeed find larger and more statistically significant effects for firms that received more sizeable subsidies relative to their initial R&D expenditure. After the subsidy, we do not see a clear difference between the two groups, with the estimates exhibiting similar point estimates but larger standard errors making most estimates insignificant. Overall, intensity of treatment seems to be

percentile). This leads to $\frac{dR}{dG} = \frac{63\%}{25\%} = 2.52$.

able to explain some of the effect differences between SMEs and large firms, but it is unlikely to be the whole story.

Financial constraints represent another common explanation of differential effects of public support for SMEs and large firms. SMEs are known to be more likely to be financially constrained (Hall and Lerner, 2010), and studies have indicated stronger effects of both direct and indirect support for business R&D on financially constrained firms.[34] As financial constraints are difficult to directly observe, various proxies have been used in the literature instead. Age represents a common such proxy (e.g. Bronzini and Iachini, 2014; Dechezleprêtre et al., 2023), with the idea that younger firms are more financially constrained because they have limited internal resources and, at the same time, are subject to more severe information asymmetries in the credit markets as their reputation has not yet been established. A common definition of young firms is firms that are 5 years old or younger. A challenge in our case is that firms in our sample tend to be quite old, and fewer than 10% of them were young by this definition in the pre-treatment year t_0. Nevertheless, we show the separate results for young and old firms in panel (b) of Table 5. The results for the narrower bandwidths, based on firms close to the cutoff, indeed suggest much stronger effects for younger firms, while results using the wider bandwidths do not reveal much difference between the two groups. In any case, the results for young firms are based on a very small number of observations, and thus they should be treated with extreme caution.

Given the challenges with the age proxy in our sample, we turn to a different strategy to test the importance of financing constraints. Specifically, we split firms into those with below-median and above-median value of the Altman Z-score (Altman, 1968) at time t_0. The Altman Z-score was originally designed to predict company bankruptcies, and it is a popular measure of financial distress. Firms with high values the Z-score are likely

[34]See, for example, Howell (2017), Bronzini and Iachini (2014) and Santoleri et al. (2022) for R&D subsidies, Kasahara et al. (2014), Rao (2016) and Dechezleprêtre et al. (2023) for R&D tax incentives and Zhao and Ziedonis (2020) for R&D loans.

Table 5: **The Role of Relative Subsidy Size and Credit Constraints**

	Outcome: Log total R&D expenditure							
	During the subsidy				After the subsidy			
Band.	Infinite	Wide	Baseline	Narrow	Infinite	Wide	Baseline	Narrow
	(a) By subsidy size relative to initial R&D expenditure							
	Large							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.32***	0.40***	0.36**	0.24	0.06	0.17	0.36	0.31
	(0.11)	(0.12)	(0.15)	(0.16)	(0.19)	(0.21)	(0.25)	(0.26)
N (left)	1459	1072	669	526	1280	943	601	477
N (right)	426	336	237	198	374	284	204	176
	Small							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.20*	0.23**	0.23	0.16	0.16	0.34*	0.39*	0.36
	(0.10)	(0.11)	(0.16)	(0.17)	(0.16)	(0.18)	(0.22)	(0.22)
N (left)	1459	1072	669	526	1280	943	601	477
N (right)	499	420	308	251	486	407	295	243
	(b) By firm age							
	Young							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.26***	0.24***	0.89***	0.81***	-0.07***	0.11	0.15**	1.25***
	(0.00)	(0.09)	(0.31)	(0.21)	(0.00)	(0.16)	(0.07)	(0.29)
N (left)	50	31	17	13	46	28	16	12
N (right)	39	30	22	14	34	26	18	12
	Old							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.26***	0.31***	0.31**	0.20	0.05	0.21	0.35*	0.27
	(0.10)	(0.11)	(0.15)	(0.17)	(0.15)	(0.17)	(0.21)	(0.22)
N (left)	1409	1041	652	513	1234	915	585	465
N (right)	886	726	523	435	826	665	481	407
	(c) By Altman Z-score							
	Low							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.28**	0.43***	0.44**	0.35	0.33	0.61**	0.80**	0.83**
	(0.13)	(0.14)	(0.22)	(0.25)	(0.25)	(0.26)	(0.33)	(0.35)
N (left)	719	529	320	250	617	452	279	220
N (right)	421	345	265	226	399	328	257	219
	High							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.19	0.26*	0.19	0.00	-0.04	0.08	0.21	0.07
	(0.12)	(0.14)	(0.18)	(0.18)	(0.17)	(0.17)	(0.20)	(0.21)
N (left)	695	518	336	265	631	471	310	245
N (right)	455	378	266	213	416	336	229	192

Notes: *** 1%, ** 5%, * 10%. The table reports RD estimates of the effect of the subsidies on total R&D expenditure, separately during the subsidy (t_0+1 to t_T) and after the subsidy (t_T+1 to t_T+4). The results are based on estimating Equation 1 using weighted least squares (with weights given by a triangular kernel function), for an infinite bandwidth and bandwidths of 10, 5.5 and 4 points around the cutoff, controlling for pre-treatment firm characteristics and year and call fixed effects. Standard errors are clustered at the firm level.

to find it very difficult, or costly, to borrow in the credit markets.[35] Conveniently, the median Z-score in our sample is 2.98, and Z-score of 3 or more is generally considered the 'safe zone' where firms are free of financial distress.[36] We report the results in panel (c) of Table 5. We estimate large and statistically significant effects of ALFA for firms with relatively low values of the Altman Z-score. In contrast, the estimates for firms with relatively high Z-scores are small and in all but one case statistically insignificant at the conventional levels. Together, these results represent strong evidence for financing constraints playing an important role in the observed effect heterogeneity.

5.3 Short-term vs. long-term effects

The results in Table 4 show that participation in ALFA led to increased R&D expenditure not only during the subsidies, but also after the subsidies received within a given project of the ALFA programme expired. We describe the evolution of the effects over time for the SMEs in more detail in Figure 3, which, for the baseline bandwidth, shows estimates of the effect on total R&D expenditure separately for each post-treatment year. It indicates somewhat weaker effects in the first two years.[37] In Appendix Figure A.1, we show that these are due to strong crowding out of other sources of direct public funding in the first two years. This is consistent with the idea that some firms sought public funding for the same R&D project from multiple sources, and when they succeeded in the ALFA programme, they turned the alternative sources down.

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[35] Bronzini and Iachini (2014) also use the Altman Z-score as a proxy for firm financial constraints.

[36] The original Z-score was applied to publicly listed firms. As the vast majority of firms in our sample are private, we instead use a variant of the Z-score applicable to private companies. It is calculated as $Z' = 0.717A + 0.847B + 3.107C + 0.420D + 0.998E$, where A is given by the ratio of working capital to total assets, B by the ratio of retained earnings to total assets, C by the ratio of EBIT to total assets, D by the ratio of the book value of equiaty to total liabilities and E by the ratio of sales to total assets.

[37] This is in line with studies that analyse a delay between subsidies and the response of firm R&D expenditure and typically find evidence of a one-, two- or three-year lag (Levy and Terleckyj, 1983; Lichtenberg, 1984; Mansfield and Switzer, 1984).

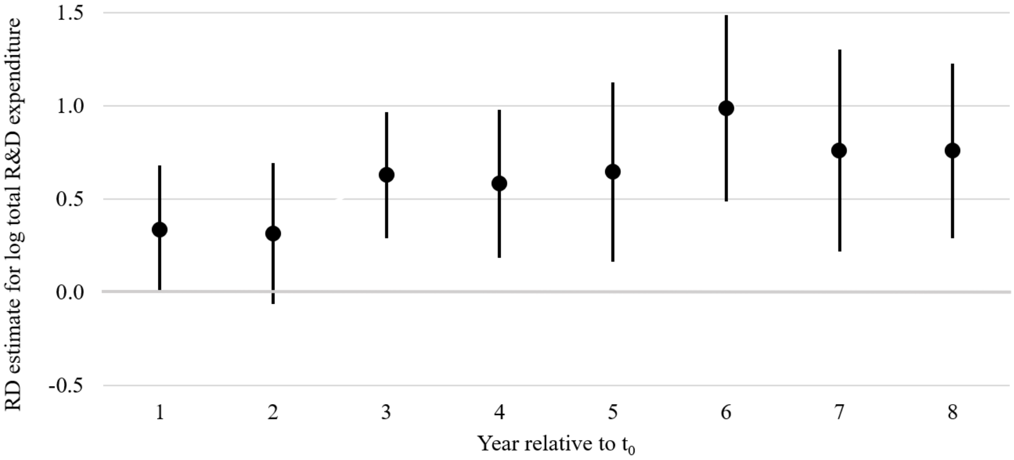
After the first two years, Table 4 shows elevated R&D expenditure for the firms that were supported in ALFA, even in the period after the subsidy and with no sign of the effects fading in the later years. What can explain the persistence of the effects? One possibility is that the subsidies allow firms to purchase R&D-related capital such as lab equipment or specialised software, which in turn increases returns to subsequent R&D expenditure. We explore this possibility in panel (a) of Table 6, where we split total R&D expenditure by type of costs into current expenditure, such as wages and materials, and capital investment, such as machinery and buildings. The results show a strong evidence of positive effects of ALFA on current expenditure but not on capital expenditure, indicating that capital investments cannot explain the persistence of effects on total R&D expenditure.

An alternative possibility is that SMEs supported in ALFA became more likely to receive subsequent public funding. We test whether this was the case in panel (b) of Table 6, where we explore the effects of ALFA on direct public R&D funding from TA CR, direct public R&D funding from other sources and indirect public R&D funding through R&D tax relief. The results suggest that supported firms not only received much more funding from TA CR during the projects (by definition), but also after the original projects expired. [38] This could mean that a successful application to ALFA made SMEs more likely to apply for subsequent subsidies, or that it gave them extra credibility that made their subsequent project proposals more likely to succeed. It could also be the case that the subsidized projects started new lines of research that made the supported SMEs spend more on R&D — and apply for additional subsidies — in subsequent years. However, the fact that we do not see similar positive long-run effects on direct public R&D funding from other sources or on R&D tax relief (see Table 6) indicates that the

[38]This is reminiscent of the *Matthew effect* observed in scientific funding (Merton, 1968; Bol et al., 2018), whereby receiving an award at one point in a researcher's career makes the researcher more likely to receive further awards in the future. The *Matthew effect* has been documented in the context of business R&D subsidies by Antonelli and Crespi (2013).

increased probability of subsequent public funding is specific to the relationships between the TA CR and the supported firms.

Figure 3: **Effects on Total R&D Expenditure By Year Relative To t_0 (SMEs)**



Notes: The figure displays results of RD estimates of the effect of the subsidies on total R&D expenditure separately for each year relative to t_0, together with their 90% confidence intervals based on standard errors clustered at the firm level. The results are based on estimating Equation 1 using weighted least squares (with weights given by a triangular kernel function), for the baseline bandwidth of 5.5 points around the cutoff, controlling for pre-treatment firm characteristics and year and call fixed effects.

5.4 Impact on Patenting and Economic Performance

So far, we have documented that, for SMEs but not large firms, ALFA succeeded in boosting R&D expenditure, both during the subsidy and in the longer term. We now turn to the question whether the additional R&D expenditure by SMEs resulted also in better performance. We report RD estimates of the effects of ALFA on patenting, sales, employment and labour productivity of the full sample of SMEs in Appendix Table A.6. Estimates for all outcomes, all bandwidths and both during and after the subsidy are close to zero and statistically insignificant. However, it is important to note that even for SMEs the subsidies were relatively small in proportion to the firms' sales, with an average (median) ratio of an annual subsidy to pre-treatment sales among supported SMEs of

Table 6: **Effects on Components of R&D Expenditure (SMEs)**

	During the subsidy				After the subsidy			
Band.	Infinite	Wide	Baseline	Narrow	Infinite	Wide	Baseline	Narrow
				(a) Types of R&D costs				
				Outcome: Log current R&D expenditure				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.28***	0.30***	0.31***	0.26**	0.31**	0.46***	0.61***	0.58***
	(0.08)	(0.09)	(0.11)	(0.12)	(0.15)	(0.16)	(0.20)	(0.21)
N (left)	1035	752	451	348	894	647	389	303
N (right)	681	548	371	301	616	485	327	273
				Outcome: Log capital R&D expenditure				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.04	0.07	0.04	0.07	0.04	0.09	-0.15	-0.25
	(0.17)	(0.20)	(0.26)	(0.28)	(0.22)	(0.23)	(0.28)	(0.28)
N (left)	1035	752	451	348	894	647	389	303
N (right)	681	548	371	301	616	485	327	273
				(b) Publicly-funded R&D expenditure				
				Outcome: Log direct public R&D funding from TA CR				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.86***	1.04***	1.15***	1.04***	0.28	0.56***	0.89***	0.93***
	(0.15)	(0.15)	(0.18)	(0.20)	(0.20)	(0.20)	(0.25)	(0.27)
N (left)	1035	752	451	348	894	647	389	303
N (right)	681	548	371	301	616	485	327	273
				Outcome: Log direct public R&D funding from other sources				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	-0.03	-0.08	-0.33*	-0.30	0.12	0.16	0.03	0.18
	(0.13)	(0.14)	(0.19)	(0.21)	(0.17)	(0.19)	(0.24)	(0.25)
N (left)	1035	752	451	348	894	647	389	303
N (right)	681	548	371	301	616	485	327	273
				Outcome: Log R&D tax relief				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	-0.12	-0.13	-0.32	-0.46	-0.33	-0.35	-0.38	-0.61
	(0.22)	(0.26)	(0.38)	(0.40)	(0.24)	(0.29)	(0.44)	(0.47)
N (left)	1035	752	451	348	894	647	389	303
N (right)	681	548	371	301	616	485	327	273

Notes: *** 1%, ** 5%, * 10%. The table reports RD estimates of the effect of the subsidies on components of R&D expenditure, separately during the subsidy ($t_0 + 1$ to t_T) and after the subsidy ($t_T + 1$ to $t_T + 4$). The results are based on estimating Equation 1 using weighted least squares (with weights given by a triangular kernel function), for an infinite bandwidth and bandwidths of 10, 5.5 and 4 points around the cutoff, controlling for pre-treatment firm characteristics and year and call fixed effects. Standard errors are clustered at the firm level.

0.094 (0.013).[39] This makes it challenging to estimate the economic effects in the full sample of SMEs with sufficient precision. The standard error of the estimated effect on sales during the subsidy, using the baseline bandwidth, is 0.09. With this standard error, the true effect would have to be greater than 0.15 (an increase of 16%) to be detected at a 10% significance level (a t-value of 1.65). This would require annual private rates of return of the additionally induced R&D expenditure of about 67%.[40] It seems unreasonable to expect such high rates of return,[41] especially given that the additionally induced R&D projects are, from the perspective of the firms, marginal projects that would not have been undertaken in the absence of the subsidies.

To overcome this challenge, we also estimate the effects on patenting and economic outcomes for the subsample of supported SMEs that received large subsidies relative to their pre-treatment sales. In particular, we focus on SMEs with above median values of the subsidy-to-sales ratios. For these firms, we find that participation in ALFA led to more patent applications and increased sales and employment, both during the subsidy and in the longer run, although not to greater labour productivity (see Table 7). In particular, during the subsidy and using the baseline bandwidth, it led to a 23% increase in patenting, 24% increase in sales and 10% increase in employment, and these increases were sustained even after the subsidies stopped. The results for sales imply a private rate of return of 22%.[42] Such rate of return is reasonable for marginal projects that firms would not have undertaken in the absence of the subsidies and that were, at least in theory, selected for public support based on their potential for generating spillovers, not necessarily high private returns. It is, however, also well below the rate of return that

[39] To prevent the mean to be driven by a few outliers with very high subsidy-to-initial R&D ratios, we winsorise the ratios at the 98th percentile.

[40] Writing dS and ΔS for absolute and proportional changes in sales, respectively, $\frac{dS}{dR} = \frac{dS}{dG} / \frac{dR}{dG} = \frac{\Delta S}{\frac{dG}{S}} / \frac{\Delta R}{\frac{dG}{R}} = \frac{16\%}{9.4\%} / \frac{63\%}{25\%} = 67\%$.

[41] Hall et al. (2010) conclude that the most likely range for returns to R&D is 20-30%.

[42] $\frac{dS}{dR} = \frac{\Delta S}{\frac{dG}{S}} / \frac{\Delta R}{\frac{dG}{R}} = \frac{24\%}{51\%} / \frac{93\%}{42\%} = 22\%$.

would have been needed to detect economic effects in the full SME sample.

Table 7: **Effects on Patenting and Economic Performance (SMEs with large subsidy-to-sales ratio)**

	During the subsidy				After the subsidy			
Band.	Infinite	Wide	Baseline	Narrow	Infinite	Wide	Baseline	Narrow
	Outcome: Log patent applications							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.10	0.20***	0.21**	0.17*	0.11*	0.17**	0.09	0.00
	(0.07)	(0.08)	(0.10)	(0.10)	(0.07)	(0.07)	(0.09)	(0.09)
N (left)	1035	752	451	348	894	647	389	303
N (right)	259	203	122	104	227	181	112	97
	Outcome: Log sales							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.07	0.17*	0.22**	0.24**	0.03	0.21	0.26*	0.20
	(0.09)	(0.09)	(0.10)	(0.10)	(0.14)	(0.14)	(0.15)	(0.14)
N (left)	1019	742	445	342	850	614	373	293
N (right)	247	197	117	99	202	163	97	82
	Outcome: Log employment							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.10***	0.12***	0.10*	0.10**	0.06	0.16**	0.20**	0.14
	(0.04)	(0.04)	(0.05)	(0.05)	(0.07)	(0.07)	(0.08)	(0.09)
N (left)	992	735	442	339	720	523	320	251
N (right)	227	183	107	95	160	136	75	68
	Outcome: Log labour productivity							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.01	-0.05	0.01	0.05	0.05	-0.02	-0.02	-0.03
	(0.06)	(0.07)	(0.08)	(0.08)	(0.06)	(0.07)	(0.09)	(0.09)
N (left)	994	732	439	341	732	527	324	260
N (right)	211	174	103	90	159	131	77	67

Notes: *** 1%, ** 5%, * 10%. The table reports RD estimates of the effect of the subsidies on patenting and economic performance, separately during the subsidy ($t_0 + 1$ to t_T) and after the subsidy ($t_T + 1$ to $t_T + 4$). The results are based on estimating Equation 1 using weighted least squares (with weights given by a triangular kernel function), for an infinite bandwidth and bandwidths of 10, 5.5 and 4 points around the cutoff, controlling for pre-treatment firm characteristics and year and call fixed effects. Standard errors are clustered at the firm level.

6 Conclusion

Governments subsidise business R&D because private funding of R&D falls short of what is socially desirable. Yet, essential questions about the effects of such subsidies still wait for satisfactory answers. Firstly, existing research is inconclusive with regard to whether such subsidies crowd in or only crowd out private R&D spending, as studies so far have either lacked a convincing identification strategy, or they have not observed actual information on R&D expenditure. Second, even if R&D subsidies do boost firms' R&D expenditure, there is little evidence as to whether the effects evaporate as soon as the subsidies stop, or whether R&D subsidies lead to persistent changes in firms' R&D-related behaviour.

In this paper, we address these questions in the context of the ALFA programme, a flagship business R&D subsidy scheme in the Czech Republic. Applying a regression discontinuity to rich statistical and administrative firm-level data, we find strong and persistent effects of the subsidies on R&D expenditure, but only in SMEs, and not in large firms. SMEs increase their privately funded R&D expenditure while they receive funding from the programme, which indicates substantial crowding-in effects of the subsidies, as 1 unit of subsidy is associated with 2.5 units of additional R&D expenditure. Importantly, R&D expenditure of the supported SMEs remains elevated even several years after the original subsidies expire, and this persistence appears to be associated with the ability of these firms to gain subsequent support from the same funding provider. In a subsample of SMEs that received comparatively large subsidies relative to their pre-treatment sales, we also document positive effects on patenting, sales and employment, although not on labour productivity. In contrast to SMEs, we do not find any evidence of positive effects of the programme on large firms, and we show that financing constraints play an important role in explaining the effect heterogeneity.

While our results are based on a single programme in one country, they are relevant much more broadly. The TA CR modelled ALFA upon programmes of direct business R&D support existing in other European countries, with the programme text specifically referring to activities of TA CR's counterparts in Sweden and Finland (TA CR, 2014). In fact, we would argue that ALFA is more representative of business R&D support offered by national governments in many countries, especially in Europe, than the start-up-focused programmes analysed by most of the existing RD studies on this topic (e.g. Howell, 2017; Zhao and Ziedonis, 2020; Santoleri et al., 2022) Our results suggest that business R&D subsidies like those given in the ALFA programme can be a powerful tool for stimulating R&D investment and innovation in the private sector, but also that they will be more effective — at least in terms of their input additionality — if directed towards firms that are more likely to be subject to financing constraints, such as start-ups and other younger SMEs.

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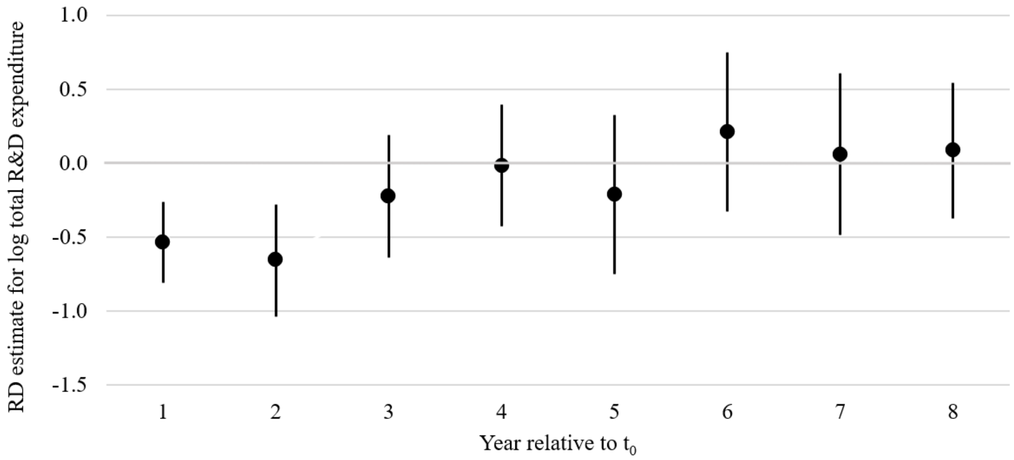
A Additional Tables and Figures

Figure A.1: **Effects on Direct Public R&D Funding from Other Sources by Year Relative to t_0 (SMEs)**



Notes: The figure displays results of RD estimates of the effect of the subsidies on total R&D expenditure separately for each year relative to t_0, together with their 90% confidence intervals based on standard errors clustered at the firm level. The results are based on estimating Equation 1 using weighted least squares (with weights given by a triangular kernel function), for the baseline bandwidth of 5.5 points around the cutoff, controlling for pre-treatment firm characteristics and year and call fixed effects.

Table A.1: **Variable Definitions**

Variable	Definition
Total R&D expenditure	Total intramural R&D expenditure (millions CZK)
Privately funded R&D expenditure	Intramural R&D exp. funded by private sources (bus. enterprise sector, incl. internal funds, private non-profit sector and higher education sector; all in Czechia and abroad) minus R&D tax relief (millions CZK)
Direct public R&D funding from TA CR	Intramural R&D expenditure funded directly by TA CR (millions CZK)
Direct public R&D funding from other sources	Intramural R&D expenditure funded directly by other public sources (millions CZK)
R&D tax relief	Intramural R&D expenditure funded indirectly through R&D tax relief
Current R&D expenditure	Current intramural R&D expenditure (labour costs, materials, supplies, energy, equipment, etc., millions CZK)
Capital R&D expenditure	Capital intramural R&D expenditure (acquisition of tangible and intangible fixed assets, millions CZK)
Patent applications	Number of applications filed in a given year in the Industrial Property Office of the Czech Republic
Employment	Number of employees in full-time equivalent (FTE)
Sales	Sales of products and services (millions CZK)
Labour productivity	Value added per employment (thousands CZK)
Time since incorporation	Number of years since a firm was registered in the business register
Foreign-owned	Dummy variable with value 1 if the firm belongs to a foreign- controlled institutional subsector (1/0)
Joint-stock	Dummy variable with value 1 if the legal form of the firm is a joint-stock company (1/0)
Manufacturing	Dummy variable with value 1 if the principal activity of the firm is manufacturing (1/0)
Prague	Dummy variable with value 1 if the seat of the firm is registered in Prague (1/0)
Number of project participants	Number of project participants in the project proposal consortium
Cooperation with a research organisation	Dummy variable with value 1 if the project proposal consortium included a research organisation (1/0)

Notes: R&D variables follow the harmonised methodology of OECD (2015).

Table A.2: **Robustness Checks (all firms)**

	During the subsidy				After the subsidy			
Band.	Infinite	Wide	Baseline	Narrow	Infinite	Wide	Baseline	Narrow
				Baseline				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.25***	0.31***	0.30**	0.21	0.08	0.25	0.35*	0.30
	(0.09)	(0.10)	(0.15)	(0.16)	(0.15)	(0.16)	(0.21)	(0.22)
N (left)	1459	1072	669	526	1280	943	601	477
N (right)	925	756	545	449	860	691	499	419
				Zero-degree polynomial				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.18**	0.20**	0.27***	0.29***	0.12	0.11	0.24*	0.28*
	(0.08)	(0.08)	(0.09)	(0.10)	(0.11)	(0.12)	(0.14)	(0.15)
N (left)	1459	1072	669	526	1280	943	601	477
N (right)	925	756	545	449	860	691	499	419
				Quadratic polynomial				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.31**	0.28*	0.16	0.15	0.31*	0.35	0.26	0.27
	(0.12)	(0.15)	(0.21)	(0.20)	(0.19)	(0.21)	(0.26)	(0.25)
N (left)	1459	1072	669	526	1280	943	601	477
N (right)	925	756	545	449	860	691	499	419
				Uniform kernel				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.25***	0.29***	0.30**	0.30**	0.07	0.12	0.37*	0.31
	(0.09)	(0.10)	(0.13)	(0.15)	(0.15)	(0.16)	(0.20)	(0.23)
N (left)	1459	1097	684	556	1280	966	612	496
N (right)	925	778	559	474	860	715	508	446
				During = 4 years				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.24**	0.31***	0.28*	0.19	0.07	0.24	0.35*	0.30
	(0.09)	(0.10)	(0.15)	(0.17)	(0.15)	(0.16)	(0.21)	(0.22)
N (left)	1459	1072	669	526	1280	943	601	477
N (right)	984	797	573	471	850	681	491	413
				Outliers kept				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.17*	0.24**	0.27*	0.21	0.01	0.22	0.36*	0.37*
	(0.10)	(0.11)	(0.15)	(0.16)	(0.16)	(0.17)	(0.21)	(0.22)
N (left)	1496	1101	694	542	1309	966	620	488
N (right)	940	771	560	464	870	701	509	429

Notes: *** 1%, ** 5%, * 10%. The table reports RD estimates of the effect of the subsidies on total R&D expenditure, separately during the subsidy ($t_0 + 1$ to t_T) and after the subsidy ($t_T + 1$ to $t_T + 4$). The results are based on estimating Equation 1 using weighted least squares (with weights given by a triangular kernel function), for an infinite bandwidth and bandwidths of 10, 5.5 and 4 points around the cutoff, controlling for pre-treatment firm characteristics and year and call fixed effects. Standard errors are clustered at the firm level.

Table A.3: **Robustness Checks (SMEs)**

	During the subsidy				After the subsidy			
Band.	Infinite	Wide	Baseline	Narrow	Infinite	Wide	Baseline	Narrow
				Baseline				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.32***	0.39***	0.49***	0.42**	0.28	0.48**	0.80***	0.77***
	(0.12)	(0.13)	(0.17)	(0.19)	(0.20)	(0.20)	(0.25)	(0.27)
N (left)	1035	752	451	348	894	647	389	303
N (right)	681	548	371	301	616	485	327	273
				Zero-degree polynomial				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.22**	0.24**	0.35***	0.38***	0.24	0.26*	0.49***	0.61***
	(0.10)	(0.10)	(0.11)	(0.11)	(0.15)	(0.16)	(0.17)	(0.18)
N (left)	1035	752	451	348	894	647	389	303
N (right)	681	548	371	301	616	485	327	273
				Quadratic polynomial				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.38***	0.43**	0.41*	0.44*	0.54**	0.73***	0.78**	0.78**
	(0.14)	(0.18)	(0.24)	(0.23)	(0.23)	(0.26)	(0.33)	(0.32)
N (left)	1035	752	451	348	894	647	389	303
N (right)	681	548	371	301	616	485	327	273
				Uniform kernel				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.31***	0.35***	0.46***	0.51***	0.27	0.31	0.73***	0.77***
	(0.12)	(0.12)	(0.16)	(0.19)	(0.20)	(0.21)	(0.24)	(0.28)
N (left)	1035	766	462	370	894	658	396	316
N (right)	681	566	385	319	616	505	336	292
				During = 4 years				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.31***	0.39***	0.47***	0.39**	0.27	0.47**	0.80***	0.78***
	(0.12)	(0.13)	(0.18)	(0.19)	(0.20)	(0.20)	(0.25)	(0.27)
N (left)	1035	752	451	348	894	647	389	303
N (right)	725	578	390	316	608	477	320	268
				Outliers kept				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.20	0.29**	0.43**	0.39**	0.18	0.43**	0.81***	0.86***
	(0.13)	(0.14)	(0.18)	(0.19)	(0.21)	(0.21)	(0.25)	(0.27)
N (left)	1068	781	476	364	921	670	408	314
N (right)	696	563	386	316	626	495	337	283

Notes: *** 1%, ** 5%, * 10%. For SMEs, the table reports RD estimates of the effect of the subsidies on total R&D expenditure, separately during the subsidy ($t_0 + 1$ to t_T) and after the subsidy ($t_T + 1$ to $t_T + 4$). The results are based on estimating Equation 1 using weighted least squares (with weights given by a triangular kernel function), for an infinite bandwidth and bandwidths of 10, 5.5 and 4 points around the cutoff, controlling for pre-treatment firm characteristics and year and call fixed effects. Standard errors are clustered at the firm level.

Table A.4: **Robustness Checks (large firms)**

	During the subsidy				After the subsidy			
Band.	Infinite	Wide	Baseline	Narrow	Infinite	Wide	Baseline	Narrow
				Baseline				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.03	0.04	-0.09	-0.20	-0.14	-0.10	-0.04	-0.06
	(0.15)	(0.14)	(0.16)	(0.17)	(0.19)	(0.21)	(0.30)	(0.32)
N (left)	424	320	218	178	386	296	212	174
N (right)	244	208	174	148	244	206	172	146
				Zero-degree polynomial				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.07	0.03	0.07	0.07	0.01	-0.14	-0.04	-0.01
	(0.11)	(0.10)	(0.13)	(0.13)	(0.13)	(0.14)	(0.18)	(0.20)
N (left)	424	320	218	178	386	296	212	174
N (right)	244	208	174	148	244	206	172	146
				Quadratic polynomial				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	-0.03	-0.22	-0.56***	-0.68***	0.01	-0.23	-0.33	-0.46
	(0.18)	(0.18)	(0.20)	(0.19)	(0.29)	(0.32)	(0.42)	(0.42)
N (left)	424	320	218	178	386	296	212	174
N (right)	244	208	174	148	244	206	172	146
				Uniform kernel				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.03	0.06	-0.09	-0.10	-0.14	-0.20	-0.07	-0.06
	(0.15)	(0.14)	(0.16)	(0.19)	(0.19)	(0.19)	(0.29)	(0.34)
N (left)	424	331	222	186	386	308	216	180
N (right)	244	212	174	155	244	210	172	154
				During = 4 years				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.01	0.03	-0.09	-0.21	-0.14	-0.09	-0.03	-0.06
	(0.14)	(0.14)	(0.16)	(0.17)	(0.20)	(0.21)	(0.31)	(0.32)
N (left)	424	320	218	178	386	296	212	174
N (right)	259	219	183	155	242	204	171	145
				Outliers kept				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.01	0.04	-0.09	-0.20	-0.21	-0.08	-0.04	-0.06
	(0.14)	(0.14)	(0.16)	(0.17)	(0.20)	(0.21)	(0.30)	(0.32)
N (left)	428	320	218	178	388	296	212	174
N (right)	244	208	174	148	244	206	172	146

Notes: *** 1%, ** 5%, * 10%. For large firms, the table reports RD estimates of the effect of the subsidies on total R&D expenditure, separately during the subsidy ($t_0 + 1$ to t_T) and after the subsidy ($t_T + 1$ to $t_T + 4$). The results are based on estimating Equation 1 using weighted least squares (with weights given by a triangular kernel function), for an infinite bandwidth and bandwidths of 10, 5.5 and 4 points around the cutoff, controlling for pre-treatment firm characteristics and year and call fixed effects. Standard errors are clustered at the firm level.

Table A.5: **Effects on R&D Expenditure — Fuzzy RD**

	During the subsidy				After the subsidy			
Band.	Infinite	Wide	Baseline	Narrow	Infinite	Wide	Baseline	Narrow
				(a) All firms				
				Outcome: Log total R&D expenditure				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.25***	0.31***	0.30**	0.21	0.08	0.25	0.35*	0.30
	(0.10)	(0.10)	(0.15)	(0.16)	(0.15)	(0.16)	(0.21)	(0.22)
N (left)	1455	1068	669	526	1276	939	601	477
N (right)	938	765	554	457	868	697	505	425
				Outcome: Log privately funded R&D expenditure				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.17	0.24*	0.41*	0.34	0.18	0.37*	0.59*	0.59*
	(0.12)	(0.14)	(0.23)	(0.25)	(0.19)	(0.22)	(0.33)	(0.36)
N (left)	1455	1068	669	526	1276	939	601	477
N (right)	938	765	554	457	868	697	505	425
				(b) SMEs				
				Outcome: Log total R&D expenditure				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.32***	0.39***	0.49***	0.42**	0.29	0.48**	0.80***	0.77***
	(0.12)	(0.13)	(0.17)	(0.19)	(0.20)	(0.20)	(0.25)	(0.27)
N (left)	1035	752	451	348	894	647	389	303
N (right)	686	549	372	301	618	485	327	273
				Outcome: Log privately funded R&D expenditure				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.30**	0.43**	0.81***	0.76***	0.39	0.66**	1.09***	1.10**
	(0.13)	(0.17)	(0.27)	(0.29)	(0.25)	(0.28)	(0.41)	(0.44)
N (left)	1035	752	451	348	894	647	389	303
N (right)	686	549	372	301	618	485	327	273
				(c) Large firms				
				Outcome: Log total R&D expenditure				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.02	0.05	-0.08	-0.19	-0.14	-0.10	0.01	0.02
	(0.15)	(0.15)	(0.17)	(0.18)	(0.20)	(0.22)	(0.32)	(0.34)
N (left)	420	316	218	178	382	292	212	174
N (right)	252	216	182	156	250	212	178	152
				Outcome: Log privately funded R&D expenditure				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	-0.17	-0.17	-0.19	-0.18	-0.18	-0.13	0.04	0.15
	(0.21)	(0.18)	(0.19)	(0.20)	(0.21)	(0.21)	(0.29)	(0.31)
N (left)	420	316	218	178	382	292	212	174
N (right)	252	216	182	156	250	212	178	152

Notes: *** 1%, ** 5%, * 10%. The table reports RD estimates of the effect of the subsidies on total and privately funded R&D expenditure, separately during the subsidy ($t_0 + 1$ to t_T) and after the subsidy ($t_T + 1$ to $t_T + 4$) and separately for all firms, SMEs and large firms. The results are based on estimating a fuzzy counterpart to Equation 1 using weighted least squares (with weights given by a triangular kernel function), for an infinite bandwidth and bandwidths of 10, 5.5 and 4 points around the cutoff, controlling for pre-treatment firm characteristics and year and call fixed effects. Standard errors are clustered at the firm level.

Table A.6: **Effects on Patenting and Economic Performance (SMEs)**

	During the subsidy				After the subsidy			
Band.	Infinite	Wide	Baseline	Narrow	Infinite	Wide	Baseline	Narrow
	Outcome: Log patent applications							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.01	0.03	-0.06	-0.09	-0.02	0.01	-0.05	-0.09
	(0.06)	(0.07)	(0.08)	(0.09)	(0.05)	(0.05)	(0.08)	(0.08)
N (left)	1035	752	451	348	894	647	389	303
N (right)	681	548	371	301	616	485	327	273
	Outcome: Log sales							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.03	0.06	0.03	0.02	-0.04	-0.00	-0.09	-0.18
	(0.07)	(0.07)	(0.09)	(0.10)	(0.10)	(0.11)	(0.14)	(0.14)
N (left)	1019	742	445	342	850	614	373	293
N (right)	665	538	364	294	581	457	306	254
	Outcome: Log employment							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.02	0.01	-0.02	-0.03	-0.04	0.01	0.01	-0.04
	(0.03)	(0.03)	(0.04)	(0.04)	(0.06)	(0.06)	(0.08)	(0.08)
N (left)	992	735	442	339	720	523	320	251
N (right)	642	521	350	286	506	400	259	221
	Outcome: Log labour productivity							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.02	0.01	-0.01	-0.03	0.04	0.02	-0.10	-0.13
	(0.04)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)	(0.08)	(0.09)
N (left)	994	732	439	341	732	527	324	260
N (right)	621	512	350	285	503	395	267	222

Notes: *** 1%, ** 5%, * 10%. The table reports RD estimates of the effect of the subsidies on patenting and economic performance, separately during the subsidy ($t_0 + 1$ to t_T) and after the subsidy ($t_T + 1$ to $t_T + 4$). The results are based on estimating Equation 1 using weighted least squares (with weights given by a triangular kernel function), for an infinite bandwidth and bandwidths of 10, 5.5 and 4 points around the cutoff, controlling for pre-treatment firm characteristics and year and call fixed effects. Standard errors are clustered at the firm level.