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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 2.3 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. Supported SMEs also saw their sales increase in the short term, but we do not observe any positive effects of the support on patenting, employment or longer-term sales and productivity. We find evidence that the subsidies crowded out private R&D expenditure in large firms and financing constraints played an important role in explaining the effect heterogeneity.

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, mostly via R&D tax incentives[1] or via grants, the subject of this paper. 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 grants, loans and procurement contracts (OECD, 2025).

This paper investigates whether government subsidies to business R&D provided through cash grants 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. Exploiting a discontinuity in 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. It complements previous studies that have either relied on regression and matching techniques to infer on causality (e.g. Czarnitzki et al., 2007; Görg and Strobl, 2007; Bérubé and Mohnen, 2009, and many others), or have used the RD approach but have not directly observed information on firms' R&D activities (e.g. Bronzini and Iachini, 2014; Howell, 2017; Santoleri et al., 2022).

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

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[1] For recent studies examining the impact of R&D tax incentives, see, for example, Rao (2016), Guceri and Liu (2019), Dechezleprêtre et al. (2023) and Appelt et al. (2025).

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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 funded 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, 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 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 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 on ranking or evaluation points of proposals from the relevant funding provider that is indispensable for leveraging the RD design to identify the causal effects.

Thirdly, understanding the effects of R&D subsidies on private R&D expenditure requires that the effects are 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). However, analysing the effects of R&D subsidies over time requires long panel data and a sufficient delay of the analysis after the subsidies, which cannot be taken for granted.[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 to recover local average treatment effects of the subsidies based on comparing firms whose projects received scores just below or just above the threshold for funding that are likely to be otherwise very similar in both observable and unobservable characteristics. We link the administrative records to a rich firm-level panel dataset that combines information on firms' R&D activities, sources of R&D funding, patenting and economic performance over years 2007–2021.

Our results indicate that the effects of R&D subsidies in the ALFA programme differed noticeably 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 and large for both total and privately funded R&D and imply that 1 unit of public subsidy was associated with about 2.3 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 also find evidence that, in the short term, participation in ALFA increased sales of the supported SMEs, but we do not find any evidence of the programme leading to increased patenting, employment growth or sustained sales and productivity increases. We do not find any positive effects of the programme on large firms, and we present evidence that ALFA actually crowded out private R&D expenditure in 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 grants crowd in or crowd out private R&D expenditure has already received considerable attention in the literature, but 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 one possible reason for similarly diverse results found in their own survey, Cunningham et al. (2016) point to 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 WWCLG (2015) emphasises the non-random selection into treatment in business R&D subsidy programmes. 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. These methods cannot account for these underlying factors" (WWCLG, 2015, p.19).

The latter review identifies only one study investigating the impact of business R&D subsidies on R&D expenditure of firms that uses a 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 sales, although the null hypothesis of no crowding-in cannot be rejected at conventional significance levels. Ours is the first paper to estimate the

[2] Listed firms are an exception, but, in an average OECD country, about two thirds of direct support for business R&D goes to firms with fewer than 500 employees, which are usually not publicly listed (OECD, 2025).

[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.

[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.

impact of business R&D subsidies directly on firm R&D expenditure in the RD design. The study by Einiö (2014) is largely complementary to ours in that it uses a different identification strategy and that we explore the effects over a significantly longer time horizon, 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 (Bronzini and Piselli, 2016; Howell, 2017; Wang et al., 2017), tangible and intangible investment (Bronzini and Iachini, 2014), revenues (Howell, 2017), survival (Howell, 2017; Wang et al., 2017) and subsequent venture capital (VC) financing (Wang et al., 2017). Recent work by Santoleri et al. (2022), Iori et al. (2023) and Russo and Santoleri (2023) examines several of these outcomes. 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.[5] Thirdly, the unavailability of R&D data means these studies cannot test the validity of the randomisation 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,[6] 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.[7] In line with existing studies, we find a two-year lag between the 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 original 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.[8] 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 year.[9] 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 of the economy and the society, and to enhance the standard of living (TACR, 2014). The programme was divided into three subprogrammes 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 eligibility criteria for funding and received evaluator scores reasonably close to the cutoff but ended up not being supported.[10] In contrast, the first subprogramme was designed more broadly and ultimately accounted for the majority of the total projects submitted and most of the total funding. More specifically, the first subprogramme accounted for 55% of submitted project proposals, 44% of funded projects, and 51% of the disbursed funding. For these reasons,

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

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

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

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

[9] 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.

[10] 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.

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
Bandwidth of 5.5 points around cutoff					
Supported	20	57	75	88	240
Unsupported	38	52	130	128	348

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. 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.[11]

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 evaluation points in the consecutive calls. As the distribution of the proposals is skewed towards 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 4.6 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 CZK 31 million and CZK 13 million, respectively, 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, a utility model, a prototype or a 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.[12]

The R&D data are linked at the firm-level to additional datasets, using the unique taxpayer identification number (IČO), which is standardised 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.[13]

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 recommended for funding, 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 ($t_0 - 3$ to t_0) and at least 8 years after the start of the projects ($t_0 + 1$ to $t_0 + 8$) 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) economic performance — employment (full-time equivalent), sales, sales per employee 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 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.

[11] 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.

[12] 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.

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

Table 2
Descriptive statistics.

	Count	Mean	p50	sd
Total R&D expenditure	8823	33.56	11.00	93.74
Privately funded R&D expenditure	8823	25.51	5.74	88.65
Direct public R&D funding from TA CR	8823	2.10	0.38	3.82
Direct public R&D funding from other sources	8823	5.13	1.25	12.04
R&D tax relief	8823	0.86	0.00	4.65
Current R&D expenditure	8823	30.34	10.09	80.52
Capital R&D expenditure	8823	3.22	0.00	24.57
Patent applications	8823	0.48	0.00	2.07
Employment (FTE)	8051	326.41	106.00	700.10
Sales	8740	905.03	169.76	3350.71
Sales per employee	8034	2175.68	1732.01	1461.50
Labour productivity (valude added per employee)	7914	760.27	691.00	405.91
Time since incorporation	8823	18.07	19.00	6.32
Foreign-owned (1/0)	8823	0.24	0.00	0.42
Joint-stock (1/0)	8823	0.46	0.00	0.50
Manufacturing (1/0)	8823	0.62	1.00	0.48
Prague (1/0)	8823	0.19	0.00	0.39
Number of project participants	8823	3.03	3.00	1.28
Cooperation with a research organisation (1/0)	8823	0.97	1.00	0.17

Notes: All monetary variables are in CZK millions, except sales per employee and labour productivity, which are in CZK thousands.

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[14] and the Research, Development and Innovation Council;[15] (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.[16]

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.[17] In 11 cases, projects were recommended for funding and ranked above the cutoff but the 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.[18] 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 1% 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.[19]

Table 2 provides descriptive statistics of the longitudinal panel dataset within the relevant time window running from the 4th year before the start of a project ($t_0 - 3$) until the 4th year after the project's end ($t_T + 4$). 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, materials and services), 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 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.

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:

$$Y_{ipt} = \beta T_p + \gamma_{-}(1 - T_p)X_p + \gamma_{+} T_p X_p + \sum_{j=1}^{J} \delta_j Z^j_{ip(t_0-1)} + \theta_c + \theta_t + \epsilon_{ipt}. \quad (1)$$

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 subsidy from TACR, other direct

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

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

[16] The final sample includes the following legal forms: private limited company, limited partnership, joint-stock company and co-operative. The excluded organisations in groups (ii) and (iii) represent about 12% of the total R&D across all organisations excluding group (i).

[17] 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.

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

[19] The excluded outliers represent only about 0.2% of the total R&D across all sample firms.

subsidies, tax relief) and the type of costs (current, capital). In addition, we estimate the model with the number of patent applications, sales, sales per employee, labour productivity and employment as outcomes. All outcome variables are included as natural logarithms.[20]

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, however, increase the precision of estimates (Calonico et al., 2019).[21] For this reason, we include a set of controls $Z^j_{ip(t_0-1)}$, which include pre-treatment values of all the outcome variables we examine together with additional variables describing firm demographics and project characteristics, listed in Section 3. Finally, we control for year dummies θ_t and call dummies θ_c. Values of some variables in year t_0 – in particular R&D expenditure – could be affected by the treatment, as firms learned about being selected for support in the same year t_0.[22] For this reason, we measure all pre-treatment controls in year $t_0 - 1$.

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 5.9 points during the subsidy and 4.7 points after the subsidy. We 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. Among the 4 bandwidths we use, each step towards a narrower bandwidth reduces the number of observations by roughly a quarter.

We estimate Eq. (1) using weighted least squares, with weights given by a kernel function $K(X_p/h)$.[23] 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., 2014b).[24]

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 $t_T + 4$.[25]

Finally, it is important to note that firms applying to ALFA could also receive public support for their R&D from other direct subsidy programmes or from R&D tax incentives.[26] The estimated effects would likely be greater in a world where no other sources of funding existed, and, in that respect, our estimates represent a lower bound.[27] Within ALFA, firms could also apply in multiple calls, and they could also submit multiple projects in a given call. In our sample, 24% of firms have multiple project applications in the same call, and 27% re-apply for support in one of the later calls. We treat each of these applications as a separate observation, but we acknowledge the fact that multiple observations can belong to the same firm by clustering the standard errors at the firm level. We also test the robustness of our results to dropping firms with multiple project applications in the same call and to dropping firms which re-applied in a later call of the ALFA programme.

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

[20] 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 5th 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 5th percentile increases the logarithmised value by 1, and is thus equivalent to an intensive-margin change of $\log(2) \approx 70\%$.

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

[22] This would be the case, for example, if some supported firms postponed R&D expenditure from t_0 till $t_0 + 1$ or subsequent years, to count it against co-financing requirements of ALFA.

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

[24] To estimate the bias of the regression function estimator, we use a second order polynomial. The MSE-optimal bias bandwidth (during the project) is 9.5. We, respectively, use bias bandwidths of 9.5, 8, 20 and infinity when the main bandwidths are 5.5, 4, 10 and infinity.

[25] 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.

[26] R&D expenditure within the projects supported by ALFA (both the subsidy and the private co-financing) was not eligible for R&D tax support. In the Czech Republic, the value of R&D tax incentives (as a share of GDP) is among the lowest of OECD countries with R&D tax incentives in place (OECD, 2025), and only a quarter of R&D-performing Czech SMEs use R&D tax incentives (Appelt et al., 2025). For this reason, potential interactions between R&D grants and R&D tax incentives are somewhat less consequential in the Czech case than they might be in other contexts. See Pless (2024) for a recent study on the interaction between the two policy instruments.

[27] Jacob and Lefgren (2011) find scientific funding from the National Institutes of Health (NIH) to have surprisingly weak effects on the publication productivity of the supported researchers and argue that this is because the researchers who were just below the cutoff in the NIH competitions were able to secure funding from other sources.

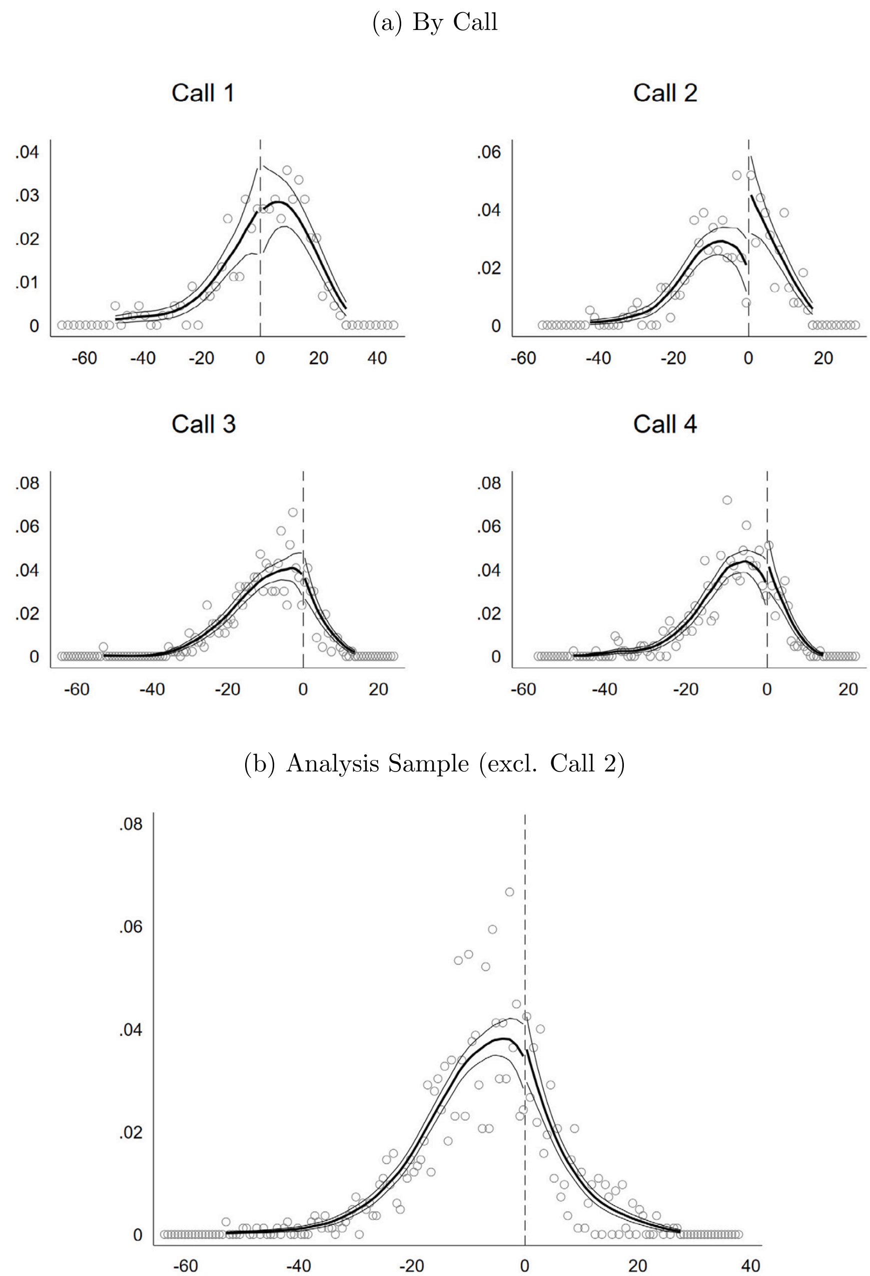

Fig. 1. Density of project scores around the cut-off.
Notes: The figures plot the density of project proposals along the scores received around the cut-off, following McCrary (2008). Panel (a) plots the density separately for each call of the ALFA programme. Panel (b) plots the density for data combining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

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 Fig. 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 observe a substantial and statistically significant discontinuity in call 2. To avoid the risk that there was manipulation around the cutoff in call 2 and that this would bias our results, we exclude call 2 from all subsequent analyses.[28] In the lower panel of Fig. 1, we show results of the McCrary test for the analysis sample of combined calls 1, 3, and

[28] Call 2 differed from the other calls in two important ways. First, due to exceeding the target ratio of subsidies to total project budgets (including

Table 3
RD estimates before the subsidy ($t_0 - 3$ to t_0).

Band	Before the subsidy							
	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	−0.11	−0.07	0.07	0.11	−0.11	−0.02	0.04	0.05
	(0.24)	(0.25)	(0.30)	(0.34)	(0.24)	(0.26)	(0.32)	(0.36)
N (left)	1768	1276	782	611	1768	1276	782	611
N (right)	1097	877	637	512	1097	877	637	512
	Log direct public funding from TACR				Log direct public funding from other sources			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.01	0.05	0.15	0.19	−0.06	0.00	0.08	0.04
	(0.11)	(0.12)	(0.15)	(0.16)	(0.21)	(0.22)	(0.26)	(0.29)
N (left)	1768	1276	782	611	1768	1276	782	611
N (right)	1097	877	637	512	1097	877	637	512
	Log R&D tax relief				Log current R&D expenditure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.26	−0.51*	−0.43	−0.43	−0.09	−0.08	0.01	0.02
	(0.27)	(0.30)	(0.36)	(0.40)	(0.20)	(0.20)	(0.24)	(0.27)
N (left)	1768	1276	782	611	1768	1276	782	611
N (right)	1097	877	637	512	1097	877	637	512
	Log capital R&D expenditure				Log patent applications			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.11	−0.12	−0.15	−0.25	−0.05	−0.03	0.01	0.01
	(0.22)	(0.23)	(0.30)	(0.33)	(0.07)	(0.08)	(0.08)	(0.10)
N (left)	1768	1276	782	611	1768	1276	782	611
N (right)	1097	877	637	512	1097	877	637	512
	Log employment				Log sales			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.09	−0.06	0.01	0.06	−0.22	−0.13	−0.13	−0.12
	(0.32)	(0.35)	(0.41)	(0.45)	(0.37)	(0.41)	(0.48)	(0.52)
N (left)	1684	1224	759	599	1735	1258	770	604
N (right)	1061	847	612	497	1074	863	624	501
	Log sales per employee				Log labour productivity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.09	−0.07	−0.18	−0.20	−0.14	−0.15	−0.19	−0.16
	(0.12)	(0.13)	(0.16)	(0.17)	(0.09)	(0.09)	(0.13)	(0.14)
N (left)	1659	1205	750	592	1601	1166	721	564
N (right)	1047	837	602	488	995	808	581	470
	Firm age				Foreign-owned (0/1)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.62	−0.60	−0.98	−0.87	−0.02	−0.03	−0.07	−0.06
	(0.96)	(1.05)	(1.36)	(1.51)	(0.08)	(0.09)	(0.11)	(0.12)
N (left)	1768	1276	782	611	1768	1276	782	611
N (right)	1097	877	637	512	1097	877	637	512
	Joint-stock (1/0)				Manufacturing (1/0)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.07	0.02	0.06	0.11	0.13	0.12	0.10	0.12
	(0.10)	(0.11)	(0.14)	(0.15)	(0.09)	(0.09)	(0.12)	(0.14)
N (left)	1768	1276	782	611	1768	1276	782	611
N (right)	1097	877	637	512	1097	877	637	512
	Prague (0/1)				Number of project participants			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.04	−0.05	−0.03	−0.03	0.41*	0.39	0.36	0.28
	(0.06)	(0.07)	(0.11)	(0.12)	(0.22)	(0.25)	(0.36)	(0.40)
N (left)	1768	1276	782	611	1768	1276	782	611
N (right)	1097	877	637	512	1097	877	637	512
	Cooperation with a research organisation							
	(1)	(2)	(3)	(4)				
Estimate	0.02	0.04	0.05*	0.02				
	(0.03)	(0.03)	(0.02)	(0.02)				
N (left)	1768	1276	782	611				
N (right)	1097	877	637	512				

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 Eq. (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 year and call fixed effects. Standard errors are clustered at the firm level.

private co-financing) in call 1, TA CR cut subsidies offered to all projects in call 2 by 10%. Second, for political reasons, the first two calls of ALFA overlapped with the last two calls of a similar subsidy programme, TIP, administered by the Ministry of Industry and Trade (MIT). This overlap had a far more disruptive effect on call 2 because call 1 announced results and started funding several months before TIP, but call 2 and the last call of TIP announced results

4. The figure shows no evidence of discontinuity in the density around the cut-off for these projects.

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 76 placebo tests, using 19 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 8 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 3 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. We also conduct corresponding placebo tests separately for SMEs and large firms (see Appendix Tables A.2 and Table A.3). For SMEs, we find 4 of 76 placebo tests to be significant at the 10% level and none at the 5% level. For large firms, we find 4 of 76 placebo tests significant at the 5% level and none at the 1% level. As with the placebo tests conducted for the full sample, the number of statistically significant placebo tests for either group is similar or smaller than what could be expected based on pure luck.

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 Figs. 2 and 3 and reported in Tables 4 and 5. Fig. 2 and Table 4 present the results of the RD estimation separately for the period before ($t_0 - 3$ to t_0) and during ($t_0 + 1$ to t_T) the subsidy. Fig. 3 and Table 5 present the results for the period after the subsidy ($t_T + 1$ to $t_T + 4$) and the combined period during and after the subsidy ($t_0 + 1$ to $t_T + 4$) the subsidy. Each figure and table separately presents findings for the full sample (Panel (a)), SMEs (Panel (b)) and large firms (Panel (c)).

The figures compare 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 Fig. 2, based on the full sample of firms, confirms no of pre-treatment differences between firms just below and just above the cutoff (left graph) but indicates somewhat larger R&D expenditure during the subsidy for firms above the cutoff (right graph). Panel (a) of Fig. 3 similarly indicates larger R&D expenditure for firms above the cutoff after the subsidy (left graph) and during the combined period during and after the subsidy (right graph).

5.2. Effects on R&D expenditure by firm size

These findings are elaborated in the upper half of panel (a) in Tables 4 and 5, 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). The point estimates are quite consistent across the different bandwidths (with the exception of the effects after the subsidy using the infinite bandwidth) and imply that participation in ALFA increased firms' total R&D expenditure by about 19% on average during the subsidy and 39% after the subsidy.[29] They are, however, not statistically significant at conventional levels.

The lower half of panel (a) in each table documents effects of the programme on privately funded R&D expenditure and, thus, directly tests the *crowding-in* and *crowding-out* hypotheses. It again confirms no pre-treatment differences, and it indicates positive effects of the programme on privately funded R&D expenditure, which are statistically significant using most bandwidths for the period after the subsidy and for the combined period during and after subsidy, although not for the period during the subsidy. It thus presents evidence that the ALFA programme led to *crowding in* of 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.4). The point estimates are similar across all these alternative specifications.[30]

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. Doing so is motivated by the fact that SMEs and large 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 Fig. 2 and Fig. 3 document the results for SMEs and large firms, respectively. The figures for SMEs again confirm no differences before the subsidy and show a substantially larger R&D expenditure above the cutoff both during and after the subsidy, but the difference is greater and clearer than in the full sample (panel (a)). In contrast, the results for large firms do not show any clear difference above and below the cutoff.

and started funding days from each other. Both the across-the-board budget cut and a close overlap with a directly competing programme were unique to call 2 of ALFA.

As a result of these two factors, unusually many successful applicants in call 2 withdrew their proposals. In Subprogramme 1, 15 projects were withdrawn in call 2, compared to only 4 projects in call 1, 3 projects in call 3 and 5 projects in call 4. Due to the high number of withdrawn projects, extra funding in call 2 had to be re-allocated to projects further down the rankings. We believe that a potential explanation for Subprogramme 1 failing the McCrary test in call 2 is that TA CR administrators were worried that using too much of the freed up funding to support additional projects in Subprogramme 1 would pull the cutoff score too low, and they arbitrarily drew the new cutoff where they saw a drop – itself randomly occurring – in the density of projects along the score distribution.

[29] $e^{0.18} - 1 \approx 19\%$ and $e^{0.33} - 1 \approx 39\%$.

[30] 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.

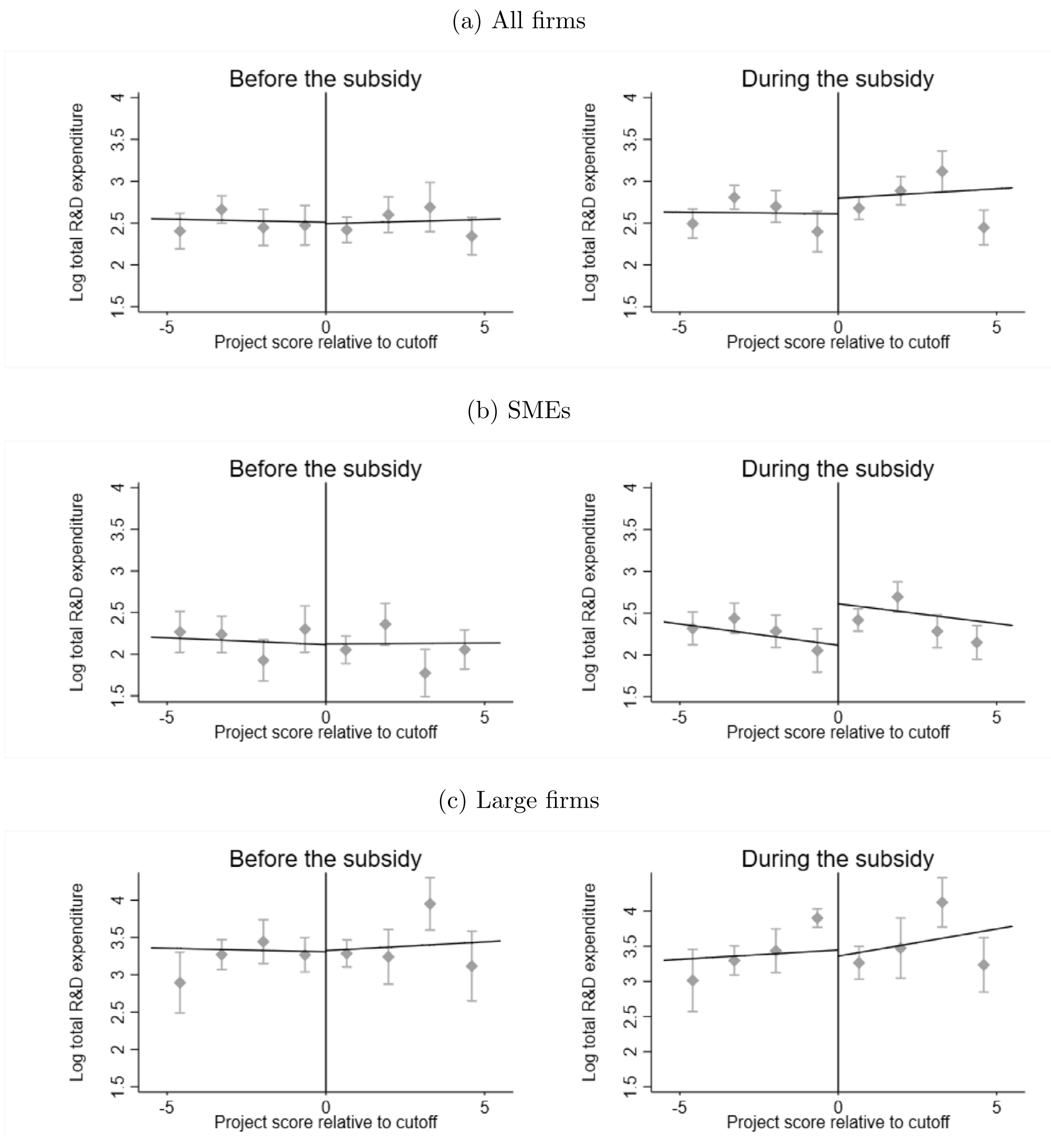

Fig. 2. Effects on total R&D expenditure before and during the subsidy.
Notes: The figures show RD plots comparing the log total R&D expenditure below and above the cutoff, separately before the subsidy ($t_0 - 3$ to t_0) and during the subsidy ($t_0 + 1$ to t_T). The results are based on estimating Eq. (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. 95% confidence intervals for values in each bin are reported.

Again, corresponding results for the different bandwidths are shown in panels (b) and (c) of Table 4 and Fig. 3. The estimates for SMEs are stronger than those for the full sample and statistically significant using all bandwidths. Using the baseline bandwidth, they imply that the ALFA programme increased the total R&D expenditure of the supported SMEs by about 71% on average during the subsidy and 211% after the subsidy.[31] These results imply that, during the subsidy, 1 unit of a subsidy generated roughly 2.3 units of additional R&D spending.[32] The estimated effects on the privately funded R&D expenditure of SMEs are also positive and large. Together, these results represent strong evidence of the subsidies crowding in private R&D investment in the case of SMEs. In Appendix Table A.6, we show that the results for SMEs are robust to a range of alternative specifications.[33]

In contrast, there is no evidence that the subsidies stimulated R&D expenditure in large firms, either during or after the subsidy. The point estimates for total R&D expenditure are not statistically significant and close to zero or negative.[34] Importantly, for privately funded R&D expenditure during the subsidy, we find statistically significant

[31] $e^{0.54} - 1 \approx 71\%$ and $e^{1.05} - 1 \approx 186\%$.

[32] 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 0.30 (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). This leads to $\frac{dR}{dG} = \frac{71\%}{30\%} = 2.35$.

[33] In Appendix Table A.7, we further show that the results are robust to dropping firms with multiple project applications in the same call and to dropping firms which re-applied in a later call of the ALFA programme.

[34] In Appendix Table A.8, across the robustness checks, we consistently estimate effects that are close to zero and insignificant. The only exception

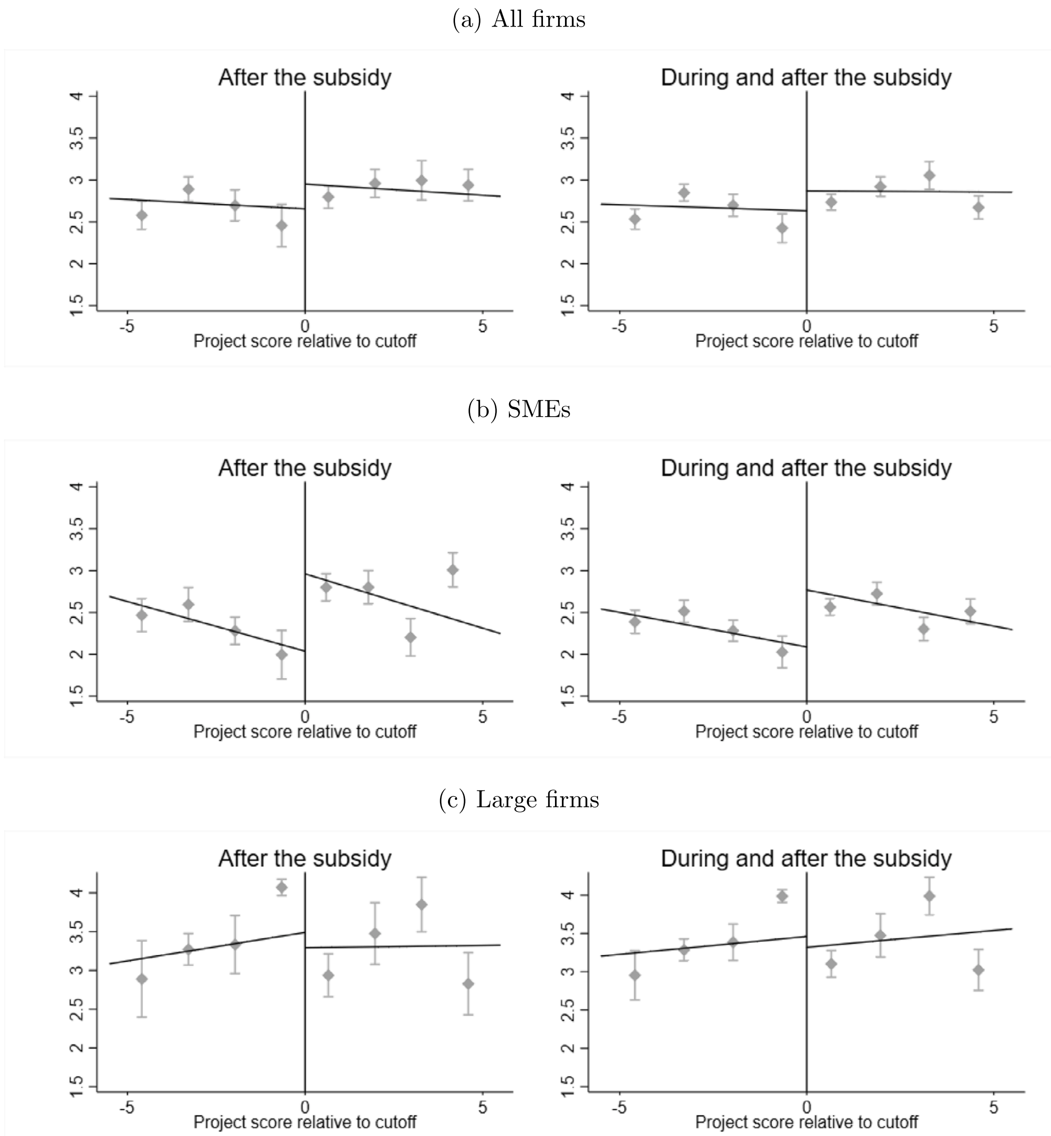

Fig. 3. Longer-term effects on total R&D expenditure.
Notes: The figures show RD plots comparing the log total R&D expenditure below and above the cutoff, after the subsidy ($t_T + 1$ to $t_T + 4$) and combining the period during and after the subsidy ($t_0 + 1$ to $t_T + 4$). The results are based on estimating Eq. (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. 95% confidence intervals for values in each bin are reported.

negative effects, which represents evidence that, among large firms, the subsidies crowded out private investment.

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 6. 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 (average across years $t_0 - 3$ to $t_0 - 1$). Specifically, we split the supported firms into those above and below the median of the subsidy-to-R&D ratio. Both during and after the subsidy, we indeed find much larger effects for firms that received more sizeable subsidies relative to their initial R&D expenditure.

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

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.

Table 4
Effects on R&D expenditure before and during the subsidy.

Band	Before the subsidy				During the subsidy			
	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	−0.02 (0.06)	−0.04 (0.06)	−0.01 (0.08)	0.02 (0.09)	0.21 (0.13)	0.21 (0.15)	0.18 (0.19)	0.17 (0.21)
N (left) N (right)	1553 982	1142 797	712 568	562 465	1440 925	1077 749	681 538	539 444
	Outcome: Log privately funded R&D expenditure							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.03 (0.06)	0.01 (0.07)	0.02 (0.08)	0.03 (0.09)	0.15 (0.14)	0.19 (0.16)	0.36 (0.24)	0.34 (0.26)
N (left) N (right)	1553 982	1142 797	712 568	562 465	1440 925	1077 749	681 538	539 444
	(b) SMEs Outcome: Log total R&D expenditure							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.03 (0.06)	−0.01 (0.07)	0.02 (0.10)	0.05 (0.11)	0.32* (0.17)	0.39** (0.18)	0.54** (0.24)	0.59** (0.26)
N (left) N (right)	1110 708	809 568	486 391	369 316	1010 664	742 531	451 369	345 301
	Outcome: Log privately funded R&D expenditure							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.04 (0.07)	0.03 (0.07)	0.07 (0.10)	0.07 (0.10)	0.22 (0.15)	0.41** (0.19)	0.94*** (0.29)	1.03*** (0.31)
N (left) N (right)	1110 708	809 568	486 391	369 316	1010 664	742 531	451 369	345 301
	(c) Large firms Outcome: Log total R&D expenditure							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.05 (0.11)	−0.15 (0.12)	0.06 (0.11)	0.06 (0.11)	−0.03 (0.18)	−0.10 (0.16)	−0.13 (0.17)	−0.13 (0.18)
N (left) N (right)	443 274	333 229	226 177	193 149	430 261	335 218	230 169	194 143
	Outcome: Log privately funded R&D expenditure							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.04 (0.12)	−0.10 (0.12)	0.04 (0.12)	0.03 (0.12)	−0.12 (0.25)	−0.29 (0.22)	−0.48** (0.22)	−0.45** (0.21)
N (left) N (right)	443 274	333 229	226 177	193 149	430 261	335 218	230 169	194 143

Notes: *** 1%, ** 5%, * 10%. The table reports RD estimates of the effect of the subsidies on total and privately funded R&D expenditure, separately before the subsidy ($t_0 - 3$ to t_0) and during the subsidy ($t_0 + 1$ to t_T) and separately for all firms, SMEs and large firms. The results are based on estimating Eq. (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.

indirect support for business R&D on financially constrained firms.[35] 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 at the time of applying to ALFA (t_0). For this reason, results for young firms are based on a very small number of observations and need to be treated with extreme caution. We nevertheless show separate results for young and old firms in panel (b) of Table 6. They indeed suggest much stronger effects for younger firms.

[35] 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
Longer-term effects on R&D expenditure.

Band	After the subsidy				During and after the subsidy			
	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	0.12 (0.18)	0.27 (0.19)	0.33 (0.24)	0.37 (0.26)	0.17 (0.14)	0.23 (0.15)	0.25 (0.20)	0.27 (0.22)
N (left) N (right)	1276 855	959 678	617 493	489 414	2716 1780	2036 1427	1298 1031	1028 858
	Outcome: Log privately funded R&D expenditure							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.21 (0.20)	0.44* (0.23)	0.62* (0.35)	0.71* (0.38)	0.17 (0.15)	0.30* (0.18)	0.49* (0.27)	0.51* (0.29)
N (left) N (right)	1276 855	959 678	617 493	489 414	2716 1780	2036 1427	1298 1031	1028 858
	(b) SMEs Outcome: Log total R&D expenditure							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.38* (0.21)	0.70*** (0.22)	1.05*** (0.30)	1.23*** (0.33)	0.34** (0.17)	0.51*** (0.18)	0.76*** (0.24)	0.87*** (0.26)
N (left) N (right)	883 589	648 458	395 323	301 272	1893 1253	1390 989	846 692	646 573
	Outcome: Log privately funded R&D expenditure							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.38 (0.25)	0.83*** (0.29)	1.44*** (0.44)	1.73*** (0.48)	0.29 (0.18)	0.57*** (0.22)	1.16*** (0.33)	1.32*** (0.35)
N (left) N (right)	883 589	648 458	395 323	301 272	1893 1253	1390 989	846 692	646 573
	(c) Large firms Outcome: Log total R&D expenditure							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.15 (0.27)	−0.09 (0.23)	−0.28 (0.27)	−0.17 (0.24)	−0.11 (0.20)	−0.10 (0.18)	−0.20 (0.20)	−0.18 (0.20)
N (left) N (right)	393 266	311 220	222 170	188 142	823 527	646 438	452 339	382 285
	Outcome: Log privately funded R&D expenditure							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.08 (0.32)	−0.09 (0.28)	−0.38 (0.30)	−0.11 (0.28)	−0.14 (0.26)	−0.20 (0.23)	−0.43* (0.24)	−0.36 (0.22)
N (left) N (right)	393 266	311 220	222 170	188 142	823 527	646 438	452 339	382 285

Notes: *** 1%, ** 5%, * 10%. The table reports RD estimates of the effect of the subsidies on total and privately funded R&D expenditure, after the subsidy (t_T+1 to t_T+4) and combining the period during and after the subsidy (t_0+1 to t_T+4), and separately for all firms, SMEs and large firms. The results are based on estimating Eq. (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.

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 to find it very difficult, or costly, to borrow in the credit markets.[36] 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.[37] We report the results in panel (c) of Table 6. We estimate large and statistically significant effects of ALFA for firms with relatively low values of the Altman Z-score. In contrast,

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

[37] 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 equity to total liabilities and E by the ratio of sales to total assets.

Table 6
The role of relative subsidy size and credit constraints.

Band	Outcome: Log total R&D expenditure							
	During the subsidy				After the subsidy			
	Infinite	Wide	Baseline	Narrow	Infinite	Wide	Baseline	Narrow
	(a) By subsidy size relative to initial R&D expenditure Large (above-median)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.34** (0.15)	0.30* (0.16)	0.26 (0.20)	0.21 (0.21)	0.31 (0.22)	0.42* (0.24)	0.45 (0.28)	0.44 (0.31)
N (left) N (right)	1440 440	1077 337	681 231	539 185	1276 368	959 268	617 183	489 149
	Small (below-median)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.06 (0.15)	0.09 (0.16)	0.06 (0.22)	0.09 (0.24)	0.04 (0.20)	0.22 (0.21)	0.27 (0.27)	0.35 (0.28)
N (left) N (right)	1440 485	1077 412	681 307	539 259	1276 487	959 410	617 310	489 265
	(b) By firm age Young (5 years or younger)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.25*** (0.00)	0.30 (0.31)	1.46** (0.68)	1.11*** (0.40)	−0.07*** (0.00)	0.21 (0.37)	0.25 (0.17)	1.18*** (0.34)
N (left) N (right)	46 41	31 31	17 23	13 19	42 44	28 32	16 24	12 20
	Old (older than 5 years)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.22 (0.14)	0.19 (0.15)	0.16 (0.20)	0.14 (0.22)	0.09 (0.18)	0.22 (0.20)	0.31 (0.25)	0.36 (0.27)
N (left) N (right)	1394 884	1046 718	664 515	526 425	1234 811	931 646	601 469	477 394
	(c) By Altman Z-score Low (below median)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.37** (0.17)	0.36** (0.17)	0.57*** (0.22)	0.70*** (0.22)	0.42 (0.27)	0.46* (0.27)	0.68* (0.35)	0.74** (0.37)
N (left) N (right)	692 392	511 327	304 247	240 211	610 380	447 314	271 247	214 209
	High (above median)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.15 (0.14)	0.22 (0.16)	0.17 (0.20)	0.04 (0.20)	−0.13 (0.19)	0.05 (0.19)	0.12 (0.21)	0.03 (0.23)
N (left) N (right)	679 466	517 380	340 268	268 214	620 420	478 331	320 227	251 191

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 Eq. (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.

the estimates for firms with relatively high Z-scores are smaller and statistically insignificant at the conventional levels.

Overall, the evidence presented here indicates that both relative subsidy intensity and financing constraints play an important role in the observed effect heterogeneity between SMEs and large firms.

5.3. Short-term vs. long-term effects

The results in Table 5 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 Fig. 4. Its panel (a) shows estimates of the effect on total R&D expenditure separately for each post-treatment year (using the baseline bandwidth). It indicates somewhat weaker effects in the first two years.[38] Panel (b) reveals that these are due to strong crowding out of other sources of direct public funding. This is consistent with the idea that some firms sought public funding for the same R&D

[38] 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).

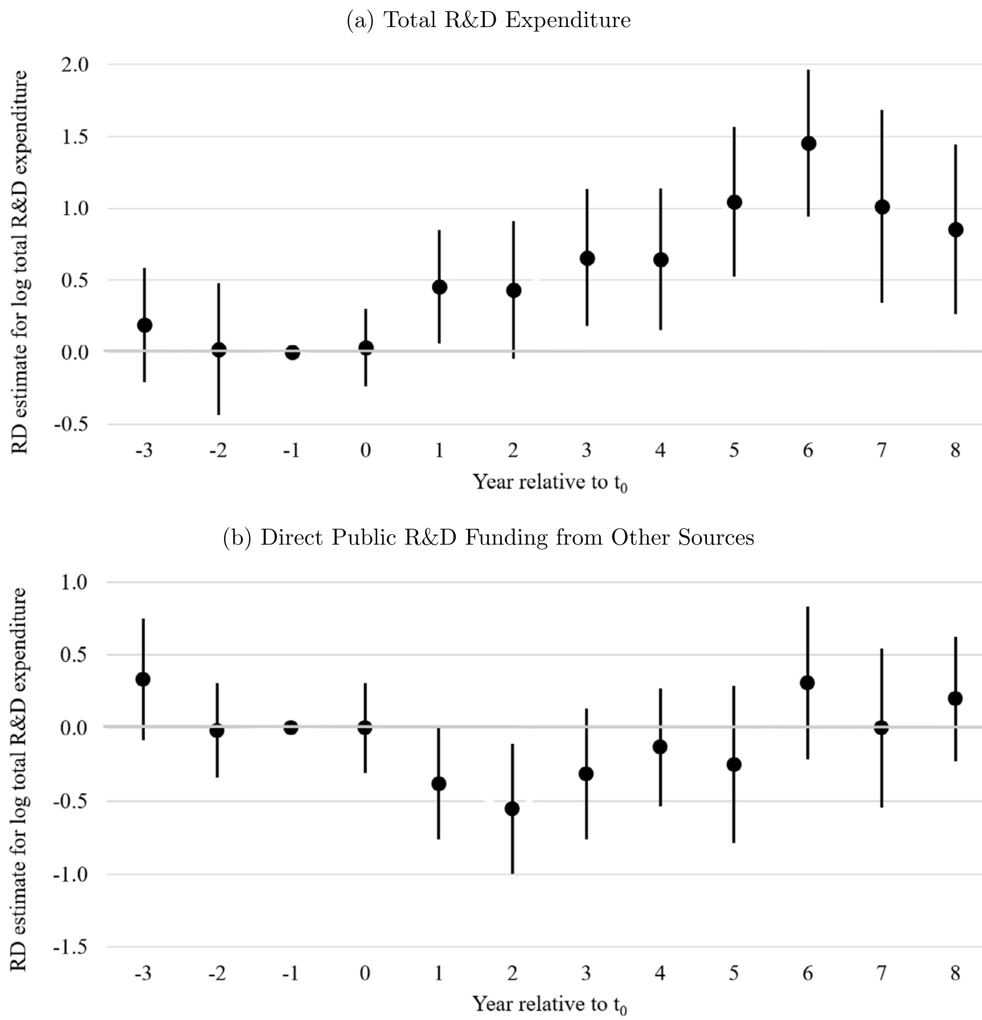

Fig. 4. Effects on R&D expenditure by year relative to t_0 (SMEs).
Notes: The figure displays results of RD estimates of the effect of the subsidies on total R&D expenditure separately for each year relative to t_0, together with their 95% confidence intervals based on standard errors clustered at the firm level. The results are based on estimating Eq. (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.

project from multiple sources, and when they succeeded in the ALFA programme, they turned the alternative sources down.

After the first two years, panel (a) of Fig. 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 7, where we split total R&D expenditure of SMEs by type of costs into current expenditure and capital investment. 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 7, 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.[39] 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 subsidised 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 7) indicates that the increased probability of subsequent public funding is specific to the relationships between the TA CR and the supported firms.

[39] 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).

Table 7
Effects on components of R&D expenditure (SMEs).

Band	During the subsidy				After the subsidy			
	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	0.23*	0.29**	0.33*	0.35**	0.35**	0.57***	0.81***	0.95***
	(0.13)	(0.14)	(0.17)	(0.18)	(0.17)	(0.18)	(0.23)	(0.25)
N (left)	1010	742	451	345	883	648	395	301
N (right)	664	531	369	301	589	458	323	272
	Outcome: Log capital R&D expenditure							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.08	−0.12	−0.14	−0.07	−0.13	−0.02	−0.21	−0.27
	(0.17)	(0.19)	(0.22)	(0.22)	(0.21)	(0.24)	(0.29)	(0.29)
N (left)	1010	742	451	345	883	648	395	301
N (right)	664	531	369	301	589	458	323	272
	(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	0.90***	1.13***	1.25***	1.15***	0.29	0.67***	1.19***	1.37***
	(0.20)	(0.22)	(0.28)	(0.31)	(0.23)	(0.24)	(0.30)	(0.34)
N (left)	1010	742	451	345	883	648	395	301
N (right)	664	531	369	301	589	458	323	272
	Outcome: Log direct public R&D funding from other sources							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.04	−0.06	−0.38*	−0.38*	0.17	0.22	0.04	0.11
	(0.15)	(0.17)	(0.20)	(0.22)	(0.17)	(0.18)	(0.23)	(0.25)
N (left)	1010	742	451	345	883	648	395	301
N (right)	664	531	369	301	589	458	323	272
	Outcome: Log R&D tax relief							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.11	−0.18	−0.43	−0.35	−0.18	−0.12	−0.31	−0.40
	(0.25)	(0.30)	(0.48)	(0.52)	(0.25)	(0.33)	(0.54)	(0.61)
N (left)	1010	742	451	345	883	648	395	301
N (right)	664	531	369	301	589	458	323	272

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 Eq. (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 8
Effects on patenting and economic performance (SMEs).

Band	During the subsidy				After the subsidy			
	Infinite	Wide	Baseline	Narrow	Infinite	Wide	Baseline	Narrow
	Outcome: Log patent applications							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.01	0.02	−0.04	−0.03	−0.04	−0.00	−0.02	−0.00
	(0.06)	(0.06)	(0.07)	(0.08)	(0.04)	(0.04)	(0.06)	(0.06)
N (left)	1010	742	451	345	883	648	395	301
N (right)	664	531	369	301	589	458	323	272
	Outcome: Log sales							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.08	0.13	0.20	0.27*	−0.03	0.09	0.02	0.00
	(0.09)	(0.10)	(0.13)	(0.14)	(0.12)	(0.14)	(0.20)	(0.21)
N (left)	994	729	448	342	851	622	379	289
N (right)	641	522	360	292	559	441	310	259
	Outcome: Log sales per employee							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.06	0.13**	0.17**	0.17**	0.01	0.05	−0.02	−0.09
	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.09)	(0.09)
N (left)	972	713	437	332	744	540	334	261
N (right)	612	499	344	282	505	393	267	223
	Outcome: Log labour productivity							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.06	0.08	0.09	0.09	0.04	0.03	−0.10	−0.10
	(0.07)	(0.08)	(0.11)	(0.12)	(0.06)	(0.07)	(0.09)	(0.10)
N (left)	975	719	432	329	747	543	336	261
N (right)	633	511	352	284	490	381	264	219
	Outcome: Log employment							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.04	0.00	−0.03	−0.00	−0.02	0.01	−0.01	0.04
	(0.05)	(0.06)	(0.07)	(0.08)	(0.07)	(0.07)	(0.10)	(0.10)
N (left)	981	725	441	335	721	523	323	250
N (right)	622	509	348	283	493	382	257	217

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 Eq. (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.

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, sales per employee, labour productivity and employment of SMEs in Table 8.[40]

We do not find any effect of ALFA on patenting. This is in line with the fact that reported outputs across the 961 projects supported in all subprogrammes and calls of ALFA include only 269 patents, i.e. 0.28 patents per project and 0.07 patent per project year (Office of the Government of the Czech Republic, 2025), and even these numbers likely represent an upper bound on the causal effect of the programme on patenting, as some of the patents reported as projects outputs would likely be filed even in the absence of support. Instead, a vast majority of reported project outputs are incremental innovation outputs less demanding in terms of technological novelty, including 873 utility models ("lesser" patents), 525 prototypes, 1537 functional samples, 502 verified technologies and 758 pieces of software.

In line with the limited novelty of project outputs, we find evidence of positive effects of ALFA on economic performance in the short run but not in the longer term. In particular, we find that ALFA increased the sales per employee of the supported SMEs during the subsidy by about 18%, and the effects were statistically significant at the 5% level for all but the infinite bandwidth. The point estimates for sales are similar to those for sales per employee, but larger standard errors mean that they are statistically significant only for the narrow bandwidth. The point estimates for labour productivity are also positive but not statistically significant. The estimates imply relatively high annual private rates of return of the additionally induced R&D expenditure around 76%.[41] However, the effects appear to be short-lived, as we do not find any effects of ALFA on economic performance after the end of the subsidy. We also do not find any effects of ALFA on the employment of the supported SMEs, either in the short or the longer term.

Overall, the results in this section suggest that, among projects just above the funding threshold, ALFA led to rather incremental innovations that translated into increased SME sales in the short term but not sustained productivity and employment growth in the longer run.

6. Conclusion

Governments use grants to subsidise business R&D because private funding of R&D falls short of what is socially desirable. Yet, some essential questions about the effects of such grants still wait for answers. Firstly, previous studies using the RD design to identify the causal effects of business R&D subsidies lacked information on R&D expenditure, and thus could not directly test whether the subsidies crowded in or crowded out private R&D spending. Second, even if direct 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. Overall, 1 unit of subsidy is associated with 2.3 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 at least partly related to the ability of these firms to gain subsequent support from the same funding provider. We also find evidence that, in the short term, ALFA increased sales per employee of the supported SMEs but, at least in the case of projects just above the funding cutoff, ALFA does not appear to have led to more patenting or sustained increase in economic performance in the long term. In contrast to SMEs, we do not find any positive effects of the programme on large firms, and we present evidence that ALFA actually crowded out private R&D expenditure in large firms. We show that financing constraints play an important role in explaining the effect heterogeneity.

One important qualification to our analysis that we would like to emphasise is that our RD approach identifies local average treatment effects around the funding cutoff, which need to be interpreted as the impact of marginally supported projects. For example, it is possible that ALFA had more sustained, transformative economic effects in the case of highly rated projects scoring far above the funding cutoff. In this sense, our analysis is complementary to earlier studies employing difference-in-differences and matching designs, which have the capacity to estimate (global) average treatment effects or average treatment effects on the treated, but at the expense of stronger identifying assumptions.

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 (TACR, 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 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 SMEs.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. Additional tables

See Tables A.1–A.8.

Data availability

Some of the firm-level data that has been used is confidential. The code and the non-confidential part of the data will be made available on request.

[40] To prevent the results for economic performance from being driven by outliers, we exclude from the regressions for each economic outcome observations with 1% largest or smallest changes in that economic outcome relative to $t_0 - 1$.

[41] An average ratio of an annual subsidy to pre-treatment sales among supported SMEs (winsorised at the 98% percentile) is 10.1%. Writing dS and ΔS for absolute and proportional changes in sales (keeping employment constant), respectively, $\frac{dS}{dR} = \frac{dS}{dG} / \frac{dR}{dG} = \frac{\Delta S}{\frac{dG}{S}} / \frac{\Delta R}{\frac{dG}{R}} = \frac{18\%}{10.1\%} / \frac{71\%}{30\%} = 76\%$.

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 the Czech Republic 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)
Sales per employee	Sales per employee (thousands CZK)
Labour productivity	Value added per employee (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
RD estimates before the treatment (SMEs, $t_0 - 3$ to t_0).

Band	Before the subsidy							
	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	−0.17	0.01	0.07	0.02	−0.15	0.09	0.05	−0.05
	(0.26)	(0.28)	(0.36)	(0.40)	(0.26)	(0.28)	(0.36)	(0.41)
N (left)	1313	934	549	412	1313	934	549	412
N (right)	808	641	453	359	808	641	453	359
	Log direct public funding from TACR				Log direct public funding from other sources			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.09	0.18	0.26	0.32*	−0.21	−0.11	−0.02	−0.05
	(0.12)	(0.14)	(0.17)	(0.18)	(0.23)	(0.24)	(0.30)	(0.33)
N (left)	1313	934	549	412	1313	934	549	412
N (right)	808	641	453	359	808	641	453	359
	Log R&D tax relief				Log current R&D expenditure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.16	−0.31	−0.45	−0.48	−0.18	−0.07	−0.04	−0.08
	(0.23)	(0.27)	(0.36)	(0.40)	(0.21)	(0.22)	(0.28)	(0.32)
N (left)	1313	934	549	412	1313	934	549	412
N (right)	808	641	453	359	808	641	453	359
	Log capital R&D expenditure				Log patent applications			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.04	0.08	−0.05	−0.30	0.02	0.06	0.06	0.02
	(0.24)	(0.25)	(0.30)	(0.34)	(0.06)	(0.06)	(0.06)	(0.07)
N (left)	1313	934	549	412	1313	934	549	412
N (right)	808	641	453	359	808	641	453	359
	Log employment				Log sales			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.10	−0.04	−0.27	−0.37	−0.24	−0.18	−0.46	−0.57
	(0.20)	(0.22)	(0.28)	(0.31)	(0.26)	(0.28)	(0.34)	(0.36)
N (left)	1230	883	526	400	1285	920	539	407
N (right)	775	612	429	344	789	628	441	348
	Log sales per employee				Log labour productivity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.09	−0.10	−0.21	−0.20	−0.15	−0.18	−0.23	−0.14
	(0.12)	(0.13)	(0.19)	(0.21)	(0.11)	(0.12)	(0.16)	(0.18)
N (left)	1210	868	519	395	1165	839	499	376
N (right)	763	603	420	335	722	581	405	322
	Firm age				Foreign-owned (0/1)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.62	−0.48	−1.01	−1.19	0.05	0.07	0.07	0.05
	(1.04)	(1.13)	(1.48)	(1.67)	(0.09)	(0.09)	(0.12)	(0.14)
N (left)	1313	934	549	412	1313	934	549	412
N (right)	808	641	453	359	808	641	453	359
	Joint-stock (1/0)				Manufacturing (1/0)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.15	−0.11	−0.14	−0.10	0.18*	0.16	0.13	0.13
	(0.10)	(0.11)	(0.15)	(0.18)	(0.10)	(0.11)	(0.15)	(0.17)
N (left)	1313	934	549	412	1313	934	549	412
N (right)	808	641	453	359	808	641	453	359
	Prague (0/1)				Number of project participants			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.07	−0.09	−0.07	−0.07	0.43*	0.36	0.36	0.19
	(0.08)	(0.09)	(0.13)	(0.15)	(0.23)	(0.27)	(0.42)	(0.47)
N (left)	1313	934	549	412	1313	934	549	412
N (right)	808	641	453	359	808	641	453	359
	Cooperation with a research organisation							
	(1)	(2)	(3)	(4)				
Estimate	0.02	0.04	0.05*	0.01				
	(0.03)	(0.03)	(0.03)	(0.02)				
N (left)	1313	934	549	412				
N (right)	808	641	453	359				

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 for SMEs. It estimates Eq. (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.

Table A.3
RD estimates before the treatment (Large firms, $t_0 - 3$ to t_0).

Band	Before the subsidy							
	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	0.24	−0.23	−0.20	−0.15	0.17	−0.23	−0.23	−0.19
	(0.36)	(0.35)	(0.29)	(0.28)	(0.36)	(0.37)	(0.33)	(0.31)
N (left)	455	342	233	199	455	342	233	199
N (right)	289	236	184	153	289	236	184	153
	Log direct public funding from TACR				Log direct public funding from other sources			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.33	−0.37	−0.29	−0.35	0.48	0.36	0.35	0.24
	(0.22)	(0.25)	(0.28)	(0.28)	(0.42)	(0.44)	(0.47)	(0.48)
N (left)	455	342	233	199	455	342	233	199
N (right)	289	236	184	153	289	236	184	153
	Log R&D tax relief				Log current R&D expenditure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.45	−1.00	−0.92	−1.19	0.32	−0.03	−0.04	−0.05
	(0.68)	(0.71)	(0.82)	(0.83)	(0.33)	(0.32)	(0.27)	(0.27)
N (left)	455	342	233	199	455	342	233	199
N (right)	289	236	184	153	289	236	184	153
	Log capital R&D expenditure				Log patent applications			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.27	−0.75	−0.73	−0.70	−0.24	−0.29	−0.27	−0.28
	(0.49)	(0.52)	(0.63)	(0.65)	(0.18)	(0.21)	(0.22)	(0.22)
N (left)	455	342	233	199	455	342	233	199
N (right)	289	236	184	153	289	236	184	153
	Log employment				Log sales			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.36	0.34	0.44	0.45	0.29	0.39	0.30	0.17
	(0.35)	(0.38)	(0.42)	(0.42)	(0.49)	(0.51)	(0.56)	(0.57)
N (left)	454	341	233	199	450	338	231	197
N (right)	286	235	183	153	285	235	183	153
	Log sales per employee				Log labour productivity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.06	0.06	−0.13	−0.28	−0.11	−0.08	−0.16	−0.27
	(0.26)	(0.26)	(0.25)	(0.24)	(0.15)	(0.16)	(0.18)	(0.17)
N (left)	449	337	231	197	436	327	222	188
N (right)	284	234	182	153	273	227	176	148
	Firm age				Foreign-owned (0/1)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.96	−1.00	−1.24	−0.66	−0.18	−0.26	−0.38**	−0.32
	(2.23)	(2.37)	(2.88)	(2.95)	(0.17)	(0.17)	(0.19)	(0.20)
N (left)	455	342	233	199	455	342	233	199
N (right)	289	236	184	153	289	236	184	153
	Joint-stock (1/0)				Manufacturing (1/0)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.20	0.37**	0.46**	0.43**	0.06	0.03	−0.07	−0.07
	(0.16)	(0.18)	(0.20)	(0.21)	(0.06)	(0.06)	(0.04)	(0.05)
N (left)	455	342	233	199	455	342	233	199
N (right)	289	236	184	153	289	236	184	153
	Prague (0/1)				Number of project participants			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.02	0.02	0.11	0.11	0.32	0.31	0.10	0.22
	(0.06)	(0.07)	(0.07)	(0.07)	(0.49)	(0.56)	(0.65)	(0.70)
N (left)	455	342	233	199	455	342	233	199
N (right)	289	236	184	153	289	236	184	153
	Cooperation with a research organisation							
	(1)	(2)	(3)	(4)				
Estimate	0.04	0.05	0.04	0.02				
	(0.05)	(0.06)	(0.06)	(0.06)				
N (left)	455	342	233	199				
N (right)	289	236	184	153				

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 for large firms. It estimates Eq. (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.

Table A.4
Robustness checks (All firms).

Band	During the subsidy				After the subsidy			
	Infinite	Wide	Baseline	Narrow	Infinite	Wide	Baseline	Narrow
	Baseline							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.21	0.21	0.18	0.17	0.12	0.27	0.33	0.37
	(0.13)	(0.15)	(0.19)	(0.21)	(0.18)	(0.19)	(0.24)	(0.26)
N (left)	1440	1077	681	539	1276	959	617	489
N (right)	925	749	538	444	855	678	493	414
	Zero-degree polynomial							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.19**	0.19*	0.18	0.15	0.17	0.16	0.26	0.23
	(0.10)	(0.11)	(0.13)	(0.14)	(0.13)	(0.14)	(0.17)	(0.18)
N (left)	1440	1077	681	539	1276	959	617	489
N (right)	925	749	538	444	855	678	493	414
	Quadratic polynomial							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.19	0.18	0.26	0.32	0.25	0.38	0.51*	0.57*
	(0.17)	(0.20)	(0.25)	(0.27)	(0.22)	(0.25)	(0.30)	(0.31)
N (left)	1440	1077	681	539	1276	959	617	489
N (right)	925	749	538	444	855	678	493	414
	Uniform kernel							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.22	0.21	0.20	0.09	0.11	0.15	0.40*	0.19
	(0.13)	(0.13)	(0.18)	(0.21)	(0.18)	(0.18)	(0.24)	(0.27)
N (left)	1440	1102	699	569	1276	982	629	508
N (right)	925	771	552	467	855	702	502	439
	During = 4 years							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.19	0.20	0.16	0.15	0.12	0.26	0.33	0.37
	(0.14)	(0.15)	(0.20)	(0.22)	(0.18)	(0.19)	(0.24)	(0.26)
N (left)	1440	1077	681	539	1276	959	617	489
N (right)	986	790	568	469	841	667	484	406
	Outliers kept							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.22	0.20	0.18	0.17	0.12	0.27	0.30	0.37
	(0.13)	(0.15)	(0.19)	(0.21)	(0.18)	(0.19)	(0.24)	(0.26)
N (left)	1453	1086	686	539	1288	969	623	489
N (right)	925	749	538	444	855	678	493	414

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 Eq. (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.

Band	During the subsidy				After the subsidy			
	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	0.21	0.21	0.18	0.18	0.13	0.29	0.35	0.41
	(0.13)	(0.15)	(0.19)	(0.21)	(0.18)	(0.19)	(0.24)	(0.26)
N (left)	1440	1077	681	539	1276	959	617	489
N (right)	942	762	551	456	867	688	503	424
	Outcome: Log privately funded R&D expenditure							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.14	0.19	0.36	0.34	0.22	0.45*	0.64*	0.74**
	(0.13)	(0.16)	(0.24)	(0.25)	(0.20)	(0.23)	(0.35)	(0.38)
N (left)	1440	1077	681	539	1276	959	617	489
N (right)	942	762	551	456	867	688	503	424
	(b) SMEs Outcome: Log total R&D expenditure							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.32*	0.39**	0.54**	0.59**	0.39*	0.70***	1.05***	1.23***
	(0.17)	(0.18)	(0.24)	(0.26)	(0.21)	(0.22)	(0.30)	(0.33)
N (left)	1010	742	451	345	883	648	395	301
N (right)	669	532	370	301	591	458	323	272
	Outcome: Log privately funded R&D expenditure							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.22	0.41**	0.94***	1.03***	0.40	0.83***	1.44***	1.73***
	(0.15)	(0.19)	(0.29)	(0.31)	(0.25)	(0.29)	(0.44)	(0.48)
N (left)	1010	742	451	345	883	648	395	301
N (right)	669	532	370	301	591	458	323	272
	(c) Large firms Outcome: Log total R&D expenditure							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.04	−0.11	−0.15	−0.18	−0.17	−0.10	−0.30	−0.28
	(0.17)	(0.16)	(0.18)	(0.18)	(0.26)	(0.24)	(0.28)	(0.26)
N (left)	430	335	230	194	393	311	222	188
N (right)	273	230	181	155	276	230	180	152
	Outcome: Log privately funded R&D expenditure							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.13	−0.31	−0.50**	−0.47**	−0.12	−0.11	−0.41	−0.22
	(0.24)	(0.21)	(0.22)	(0.21)	(0.31)	(0.27)	(0.31)	(0.29)
N (left)	430	335	230	194	393	311	222	188
N (right)	273	230	181	155	276	230	180	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 Eq. (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
Robustness checks (SMEs).

Band	During the subsidy				After the subsidy			
	Infinite	Wide	Baseline	Narrow	Infinite	Wide	Baseline	Narrow
	Baseline							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.32*	0.39**	0.54**	0.59**	0.38*	0.70***	1.05***	1.23***
	(0.17)	(0.18)	(0.24)	(0.26)	(0.21)	(0.22)	(0.30)	(0.33)
N (left)	1010	742	451	345	883	648	395	301
N (right)	664	531	369	301	589	458	323	272
	Zero-degree polynomial							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.23*	0.26*	0.36**	0.35**	0.31*	0.39**	0.64***	0.65***
	(0.13)	(0.14)	(0.16)	(0.17)	(0.16)	(0.17)	(0.19)	(0.21)
N (left)	1010	742	451	345	883	648	395	301
N (right)	664	531	369	301	589	458	323	272
	Quadratic polynomial							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.37*	0.46*	0.71**	0.72**	0.59**	1.05***	1.51***	1.42***
	(0.21)	(0.24)	(0.31)	(0.33)	(0.27)	(0.30)	(0.41)	(0.47)
N (left)	1010	742	451	345	883	648	395	301
N (right)	664	531	369	301	589	458	323	272
	Uniform kernel							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.32*	0.34*	0.43*	0.42	0.37*	0.46**	0.98***	0.92***
	(0.17)	(0.17)	(0.23)	(0.26)	(0.21)	(0.22)	(0.28)	(0.33)
N (left)	1010	756	462	367	883	659	402	314
N (right)	664	545	383	317	589	474	332	289
	During = 4 years							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.30*	0.38**	0.54**	0.60**	0.37*	0.68***	1.04***	1.22***
	(0.17)	(0.18)	(0.24)	(0.26)	(0.21)	(0.22)	(0.30)	(0.33)
N (left)	1010	742	451	345	883	648	395	301
N (right)	707	559	389	318	579	451	316	266
	Outliers kept							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.32*	0.38**	0.53**	0.59**	0.39*	0.67***	0.99***	1.22***
	(0.17)	(0.18)	(0.24)	(0.26)	(0.21)	(0.22)	(0.30)	(0.33)
N (left)	1019	751	456	345	893	658	401	301
N (right)	664	531	369	301	589	458	323	272

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 Eq. (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.7
Effects on R&D expenditure during and after the subsidy excluding firms with multiple or repeated applications (SMEs).

Outcome:	During and after the subsidy							
	Log total R&D expenditure				Log privately funded R&D expenditure			
Band	Infinite	Wide	Baseline	Narrow	Infinite	Wide	Baseline	Narrow
	(a) All firms (baseline)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.34**	0.51***	0.76***	0.87***	0.29	0.57***	1.16***	1.32***
	(0.17)	(0.18)	(0.24)	(0.26)	(0.18)	(0.22)	(0.33)	(0.35)
N (left)	1893	1390	846	646	1893	1390	846	646
N (right)	1253	989	692	573	1253	989	692	573
	(b) Excluding firms with multiple applications in a given call							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.26	0.42*	0.63**	0.79***	0.27	0.53*	0.85**	1.02***
	(0.22)	(0.24)	(0.31)	(0.30)	(0.24)	(0.28)	(0.34)	(0.34)
N (left)	852	584	404	303	852	584	404	303
N (right)	680	546	392	312	680	546	392	312
	(c) Excluding firms which re-applied in a later call							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.29	0.44**	0.62**	0.82***	0.15	0.37*	0.86***	1.12***
	(0.18)	(0.19)	(0.25)	(0.27)	(0.20)	(0.22)	(0.27)	(0.29)
N (left)	1371	1007	586	429	1371	1007	586	429
N (right)	779	700	508	405	779	700	508	405

Notes: *** 1%, ** 5%, * 10%. The table reports RD estimates of the effect of the subsidies on total and privately funded R&D expenditure, separately before the subsidy ($t_0 - 3$ to t_0) and during the subsidy ($t_0 + 1$ to t_T) 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. In Panel (b), regressions exclude firms with more than one project application in a given call. In Panel (c), regressions exclude firms which applied again in one of the later calls of ALFA.

Table A.8
Robustness checks (Large firms).

Band	During the subsidy				After the subsidy			
	Infinite	Wide	Baseline	Narrow	Infinite	Wide	Baseline	Narrow
	Baseline							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.03	−0.10	−0.13	−0.13	−0.15	−0.09	−0.28	−0.17
	(0.18)	(0.16)	(0.17)	(0.18)	(0.27)	(0.23)	(0.27)	(0.24)
N (left)	430	335	230	194	393	311	222	188
N (right)	261	218	169	143	266	220	170	142
	Zero-degree polynomial							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	0.22	0.12	0.02	0.09	0.11	0.00	0.10	0.31
	(0.14)	(0.12)	(0.13)	(0.14)	(0.21)	(0.19)	(0.19)	(0.19)
N (left)	430	335	230	194	393	311	222	188
N (right)	261	218	169	143	266	220	170	142
	Quadratic polynomial							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.25	−0.21	−0.58***	−0.39**	−0.22	−0.22	−1.02***	−0.52*
	(0.22)	(0.20)	(0.17)	(0.17)	(0.35)	(0.32)	(0.26)	(0.27)
N (left)	430	335	230	194	393	311	222	188
N (right)	261	218	169	143	266	220	170	142
	Uniform kernel							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.02	−0.11	0.02	−0.14	−0.15	−0.27	0.11	−0.40
	(0.18)	(0.18)	(0.20)	(0.20)	(0.27)	(0.26)	(0.32)	(0.32)
N (left)	430	346	237	202	393	323	227	194
N (right)	261	226	169	150	266	228	170	150
	During = 4 years							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.07	−0.11	−0.14	−0.15	−0.15	−0.08	−0.26	−0.17
	(0.18)	(0.16)	(0.17)	(0.18)	(0.27)	(0.24)	(0.27)	(0.25)
N (left)	430	335	230	194	393	311	222	188
N (right)	279	231	179	151	262	216	168	140
	Outliers kept							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimate	−0.03	−0.10	−0.13	−0.13	−0.16	−0.07	−0.28	−0.17
	(0.18)	(0.16)	(0.17)	(0.18)	(0.27)	(0.24)	(0.27)	(0.24)
N (left)	434	335	230	194	395	311	222	188
N (right)	261	218	169	143	266	220	170	142

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 Eq. (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.

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