Working Paper

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Abstract. Direct public support for business R&D is a well-established remedy to market failures, yet empirical evidence on its effectiveness yields conflicting results. The paper investigates the impact of the first European public R&D grant program targeting small and medium enterprises (i.e. the SME Instrument) on a wide range of firm outcomes. We leverage the assignment mechanisms of the policy and employ a sharp regression discontinuity design to provide the broadest quasi-experimental evidence on R&D grants over both geographical and sectoral scopes. Results show that grants trigger sizable impacts. They increase investment, notably in intangibles, and innovation outcomes as measured by cite-weighted patents; they trigger faster growth in assets, employment and revenues; they lead to higher likelihood of receiving follow-on equity financing and lower failure chances. These effects tend to be larger for firms that are smaller and younger, or operating in sectors characterized by higher financial frictions. Furthermore, responses are stronger in countries and regions with lower economic development. The paper provides extensive evidence that the beneficial effects of R&D grants materialize through funding rather than certification effects.

Keywords: Regression discontinuity design · Research and development · Innovation Policy · SMEs
JEL: D22 · G24 · G32 · L53 · O31

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1 Introduction

The use of government funding to stimulate private research and development (R&D) is a broadly accepted remedy to private underinvestment in R&D due to the presence of knowledge spillovers (Nelson, 1959; Arrow, 1972) and financial constraints (Hall and Lerner, 2010). These market failures affect above all young and small innovative firms (Teece, 1986; Hall et al., 2005).[1] Among the most common policy instruments designed to overcome these frictions, R&D grants represent the most direct form of support to private innovation efforts.[2] Differently from other policy measures (e.g. R&D tax credits), R&D grants are in principle better equipped to affect both the rate and the direction of technological change and may be deployed to prioritize areas plagued by heavier market failures or to address specific societal challenges (Azoulay and Li, 2020; Van Reenen, 2020). Despite a large body of literature, the available empirical evidence does not provide a definitive answer on the effectiveness of R&D subsidies (Zúñiga-Vicente et al., 2014; Dimos and Pugh, 2016).[3] One of the reasons behind the mixed findings is the problem of identifying causal effects as grants are not randomly assigned. While earlier studies did not address this issue (David et al., 2000; Zúñiga-Vicente et al., 2014), two recent studies have used more rigorous identification strategies (Bronzini and Iachini, 2014; Howell, 2017). Yet, these still provide conflicting results on the effects of R&D grants. Hence, further robust and generalizable causal evidence is needed (Bloom et al., 2019; Hünermund and Czarnitzki, 2019).

Against this backdrop, the paper provides the broadest quasi-experimental evidence over sectoral and geographical dimensions on the impact of R&D grants available to date. More specifically, it studies the effects of the SME Instrument, the first European R&D grant program targeting innovative small and medium-sized enterprises (SMEs). Firms can apply to either Phase I or Phase II competitions. Phase I awards firms a small grant of €50,000 to conduct feasibility studies of an innovative idea, whereas Phase II awards grants of up to €2.5 million to finance R&D, demonstration and replication in a market setting. In each competition firms are ranked by external independent experts and winners are selected based solely on EU budget availability. We leverage this aspect of the policy assignment mechanism and adopt a sharp

[1] Such barriers to innovation might be particularly detrimental to aggregate economic outcomes given the prominent contribution of young-small firms to net job creation (e.g. Haltiwanger et al. 2013) and their higher propensity to introduce radical innovations (e.g. Baumol 2005).

[2] Direct support for private R&D amounts to roughly $50 billion across OECD economies according to the latest available estimates (OECD, 2017). EU-28 economies account for around 1/5 of this figure. For a recent review of policy measures to support innovation, see Bloom et al. (2019).

[3] Examples of studies reporting a positive impact on R&D subsidy recipients in terms of innovation outcomes and measures of firm performance or financing are Lerner (2000), González et al. (2005), Czarnitzki and Lopes-Bento (2014), Howell (2017), Azoulay et al. (2019) and Widmann (2020). Conversely, Wallsten (2000), Klette et al. (2000), Lach (2002), Einiö (2014), De Blasio et al. (2014), Wang et al. (2017) find no effect. Others, such as Bronzini and Iachini (2014) and Hünermund and Czarnitzki (2019), find no average impact of R&D subsidies, but detect large heterogeneous treatment effects. David et al. (2000) and Zúñiga-Vicente et al. (2014) provide systematic reviews of the literature on R&D subsidies while Dimos and Pugh (2016) provide a meta-regression analysis of the literature. A review of recent findings on the effects of R&D subsidies on firm performance is also presented in Vanino et al. (2019).

regression discontinuity (RD) to accurately identify the causal effect of R&D subsidies (Lee and Lemieux, 2010).

The results indicate that the small grants awarded for business concept development (Phase I) have generally no statistically significant impact on firm-level outcomes. Conversely, product development grants (Phase II) - representing the bulk of the program - have sizable effects on a wide range of firm-level outcomes. More specifically, Phase II triggers an increase in subsequent firm investment with effects that are particularly strong for intangibles. The grant also induces an increase between 15 and 31% in innovation output as measured by cite-weighted patents. This additional amount of patents is due to both intensive and extensive margins. In other words, the effects of R&D grants are not limited to firms already engaged in innovative activities but extend to firms' selection into patenting. The grants have a strong policy impact on growth in both assets (46-96%) and employment (20-45%). Positive (albeit noisy) results are also documented on firm revenue growth. Interestingly, and most importantly from an entrepreneurial policy viewpoint, R&D grants also represent a catalyst for follow-on equity investments: award-winning firms experience a higher likelihood of receiving private equity (over 100% increase), and this is associated with larger amounts and a higher number of deals. The overall improvement in innovation outcomes, balance-sheet variables and external financing is reflected in a lower chance of failure by awarded firms (over 100% decrease). Taken together, the results suggest that public direct R&D support does not trigger 'crowding-out' effects, but rather induces superior performances and lays the foundations for future growth through follow-on private investment.

The unique variety of applicants present in our data allows us to explore heterogeneous effects over several dimensions. Firstly, in line with the conjecture that R&D grants ease financial constraints, we report larger effects for younger and smaller businesses and for firms that operate in sector with higher financial vulnerability. Secondly, we observe larger benefits for firms located in countries with lower economic and financial development. We also test whether R&D grants trigger differential effects depending on regional economic development and find that firms located in relatively poorer regions tend to benefit more than their counterparts in more advanced economies. These findings suggest that R&D grants constitute a useful policy instrument to reduce market frictions and promote innovative capabilities especially in laggards regions.

Finally, we provide evidence on the mechanisms driving the results. The effects of R&D grants might accrue through i) certification effects (i.e. the grant signals firms' high-quality to the market) (Lerner, 2000; Feldman and Kelley, 2006; Meuleman and De Maeseneire, 2012) or ii) funding effects (i.e. the grant is used to demonstrate the viability of a technology thus decreasing risk for the investor and mitigating information asymmetry) (Howell, 2017). Our estimates indicate that it is the latter that explains the results. To generate this finding, we exploit a unique institutional feature of the program: firms which are not awarded the grant only because of EU budget availability are given a "Seal of Excellence", i.e. a certificate designed to signal to external public and private investors the high-quality of the innovation project proposed by the firm. We find that grant winners significantly outperform firms awarded the "Seal of Excellence". Moreover, "Seal of Excellence" firms do not appear to perform better than the rest of unsuccessful firms, indicating that certification alone does not seem to trigger any positive impact on firm performance. It is possible that the "Seal of Excellence" certification effect is limited to "second-tier signaling". We further show that certification does not appear to be the main channel by documenting that the increase in the probability of receiving follow-on equity is mainly driven firms patenting after the competition. This arguably indicates that the grant money allows firms to invest in R&D, develop a technology that is ultimately patented. If anything, the certification effect at work is the one conveyed through the patent to external investors. Additional tests confirm that funding effects are overall much more important than certification effects.

The paper makes several contributions to the literature. First of all, only a very limited number of prior studies were able to exploit applications data and use an RD design to evaluate the causal effects of R&D subsidies.[4] The ones that do focus exclusively on sector-specific (Howell, 2017) or region-specific programs (Bronzini and Iachini, 2014; Bronzini and Piselli, 2016), thus limiting external validity and making the generalization of results quite difficult.[5] Our paper leverages a much broader policy intervention in terms of both sectoral and geographical scope. The SME Instrument receives applications from firms located in more than 40 different countries and operating in a large variety of industries since eligibility criteria do not restrict participation to particular sectors. Results from our study complement and support the positive role played by R&D grants also found in Howell (2017). Furthermore, the unique variety in terms of applicants' characteristics allows us to test for heterogeneous effects over more dimensions (i.e. sectors, countries and regions) than usually explored in the literature.

Second, most studies addressing the impact of R&D subsidies focus on innovation inputs whereas less attention has been paid to the effects on innovation outputs and measures of firm performance (see the discussion in Bronzini and Piselli (2016) and Vanino et al. (2019)). Most importantly, very few studies evaluate the impact of grants on more than one aspect of the in-

[4] To the best of our knowledge, only Meuleman and De Maeseneire (2012), Bronzini and Iachini (2014); Bronzini and Piselli (2016), Howell (2017) and Hünermund and Czarnitzki (2019) use applicants data. Conversely, in most cases researchers only observe treated firms and address self-selection by building control groups with matching techniques based on pre-treatment observable features (Lerner, 2000). Although this allows the comparison between observationally similar firms, it does not take into account the potential unobserved behavioural factors leading to the application decision including the availability of an innovative idea, the orientation to grow, the cost of application, the availability of other funding opportunities (Hünermund and Czarnitzki, 2019). Our data on applicant firms and the RD identification strategy alleviate this concern.

[5] Howell (2017) examines the US SBIR program administered by the Department of Energy (DOE). In particular, data refer only to DOE's Fossil Energy and Energy Efficiency and Renewable Energy offices. Hence, applicants mainly operate in related technology areas. Even if data accounted for the entire SBIR program of the DOE, this would still represent only around 8% of total SBIR budget allocation (SBA, 2017). Bronzini and Iachini (2014) and Bronzini and Piselli (2016) study a R&D subsidy policy implemented by the Emilia-Romagna region in Italy. Howell (2017) reports sizable positive effects on different firm performance measures, Bronzini and Iachini (2014) find no overall effect on investment, while Bronzini and Piselli (2016) report positive effects on patenting.

novation chain, from increased R&D spending, through innovation outcomes, to improved firm performance and the attraction of follow-on equity financing.[6] Differently from such approach, we investigate the effects on a range of firm performance measures (i.e. firm-level investment, innovation outputs, growth, survival likelihood, and private equity financing) to offer a more comprehensive understanding of the role of R&D subsidies in promoting firm growth. We show that the positive effects on innovation outcomes and follow-on private financing that were documented by Howell (2017) are also accompanied by an increase in firms' investment and superior firm growth as measured by total assets, employees and revenues.

Third, the SME Instrument represents an interesting case study above and beyond identifications aspects. Until the introduction of the SME Instrument there was no dedicated policy tool at the pan-European level designed to support directly the innovative efforts of individual SMEs. EU innovation policies had been traditionally much more focused on cooperative R&D projects bringing together science and businesses to promote cross-border technological innovation. In such framework, SMEs could indirectly benefit from policy support only as part of larger consortia.[7] On the contrary, the SME Instrument allows individual SMEs to apply for support alone.

Moreover, the SME Instrument is an interesting case of cross-national policy transfer. The program is modelled after the US Small Business Innovation Research (SBIR), which over the years has played a significant role in the US innovation system by providing early-stage finance to highly innovative small and young firms before they could be of interest to private investors (Block and Keller, 2015).[8] This study provides the first quasi-experimental evidence on the impact of SBIR-type policies. Similar programs have been implemented in OECD countries (e.g. UK and The Netherlands) and in some others are about to be launched (e.g. Australia and Canada). Hence, the analysis is highly relevant for practitioners and policy-makers managing or considering this kind of scheme in other countries. Assessing the effectiveness of R&D grants in European countries is of utmost importance given that Europe has traditionally lagged behind the US in terms of funding opportunities for start-ups and small firms with more radical

[6] For instance, Howell (2017), who study the effects on several outcomes using a RD approach, does not provide systematic evidence on balance-sheet variables. Bronzini and Iachini (2014) and Bronzini and Piselli (2016) do not offer evidence on follow-up financing, survival, successful exit and balance-sheet outcomes.

[7] Examples of this policy approach are the Fast-Track to Innovation (FTI) and the Eurostar II programs. The FTI, as the SME Instrument, offers close-to-market support to speed up market delivery of innovation. Unlike the SME Instrument, the FTI does not target exclusively SMEs; nor does it allow single applicants to submit proposals, but it is addressed to consortia of limited size. The Eurostar II scheme (Hünermund and Czarnitzki, 2019), differently from the SME Instrument, provides funding for transnational, collaborative projects led by R&D performing SMEs in participating EUREKA countries. Hence, it is not targeted at individual SMEs. See Section 2.2. in Di Minin et al. (2016) where the SME Instrument is put in historical perspective within the European innovation policy.

[8] Block and Keller (2015) document that 77 out of 88 among the most important innovations rated by R&D Magazine's annual awards were heavily funded by the federal government during the period 1977-2006. SBIR-funded innovations represented roughly 25% of total award winners each year.

projects (O'Sullivan, 2005).[9] This funding gap is arguably one of the factors behind the so-called "European paradox", namely, the difficulty of European countries in translating scientific advances into marketable innovations, growth, and jobs. To alleviate these frictions, the creation of a European SBIR equivalent has been the object of long-standing debates among scholars and policy-makers (Encaoua, 2009; Connell, 2006; Mazzucato, 2015). The SME Instrument represents the EU's attempt to bridge this gap and the evidence is that it is effective in helping start-ups and small firms to bring new ideas to market.

The paper also has implications for the literature that focuses on the role of financial frictions for small and young innovative firms (Hall and Lerner, 2010; Kerr and Nanda, 2015). In this area most studies have relied on the sensitivity of R&D investment to cash-flow (Brown et al., 2009; Cincera et al., 2016; Hall et al., 2016) whereas quasi-experimental evidence specifically addressing innovative SMEs is rare, and even rarer for Europe. In relation to this research stream we provide evidence that i) pure certification effects not attached to funding play a negligible role in attracting further investment and ii) when financial constraints are relaxed for high-risk high-quality investments, young and small innovative firms are indeed fundamental sources of value creation and growth (Haltiwanger et al., 2013; Pugsley and Hurst, 2011; Shane, 2009).

The remainder of this paper is organized as follows. In Section 2 we detail the key institutional features of the SME Instrument and provide an overview of the data. Section 3 describes the empirical strategy and presents tests of the validity of the RD design. Section 4 contains the estimation results. Section 5 reports heterogeneous treatment effects and Section 6 explores the specific mechanisms behind the effects of the policy. Robustness checks are contained in Section 7 while Section 8 bring the paper to a close.

2 Institutional setting

2.1 The SME Instrument

The SME Instrument was established in 2014 and was rolled over by the Executive Agency for Small and Medium-sized Enterprises (EASME) with the aim to provide business innovation support to SMEs. With around €3 billion in funding over 2014-2020, its goal has been the selection and support of companies with the most innovative ideas and highest growth potential.

The SME Instrument allows firms to submit their proposals during 4 cut-off dates a year per phase. Firms apply to competitions that are sector-specific and organized in 13 different topics.[10] A proposal will be considered eligible if all three of the following conditions are met: the

[9] Hall et al. (2016) document a clear negative relationship between financial constraints and R&D investment among innovative European firms. Cincera et al. (2016) show that European innovators are more financially constrained than their US counterparts, and this effect is stronger among young leading innovators.

[10] Note that the application procedure structured around pre-defined sectoral topics was implemented until the end of 2017. Starting from 2018, all proposals have been competing with each other following a bottom-up approach. Our data refer to the period 2014-2017. Descriptive statistics for applicants across topics are reported in Table A6.

applicant is a for-profit SME[11], including newly created companies and start-ups; the applicant is established in a EU Member State or a Horizon2020 associated country[12]; the applicant is not found in a situation of concurrent submission or implementation with another SME Instrument proposal.

The SME Instrument was designed after the US SBIR program and shares many similarities with it.[13] As the SBIR, it is structured in two main phases, articulated as follows: concept and feasibility assessment; demonstration and market replication R&D.[14] Despite the names given to the different phases, the SME Instrument is not strictly linear and the phases are not sequential. Depending on the stage of development of the project to be proposed, SMEs can apply directly to the Phase II if they want to bypass Phase I.

Phase I provides SMEs with proof-of-concept grants. Firms may apply to Phase I by submitting a short business plan (about 10 pages long). They describe the innovativeness and excellence of their idea, its potential impact and the proposed implementation strategy. Roughly 10% of SME Instrument budget is allocated to this phase, and each winning project is awarded a lump sum of €50,000. Funds are employed for technical feasibility and commercial assessments of innovations that SMEs need to bring to market. Fundable activities include risk assessment, market analysis and design, exploration of intellectual property regimes and strategies, development of pilot applications. Phase I grants last a maximum of 6 months and their main expected output is a feasibility study that includes a well-articulated business plan.

Phase II consists of product development grants. SMEs apply with a 30-page proposal that should include a business plan and a description of the proposed activities. Fundable activities encompass prototyping, testing, design, performance evaluation, monitoring, demonstration, piloting, validation for market duplication, scaling-up and application development. The amount of the grant ranges between a minimum of €0.5mln and a maximum of €2.5 mln. This can cover up to 70% of eligible costs.[15] Phase II projects last between 12 months and 2 years. The expected result of Phase II is a product, a process or a service that is ready to compete on the market. Awardees are also required to prepare an "investor-ready business plan", which includes a detailed commercialisation strategy, and an investment plan for the potential market launch.

[11] SMEs are defined by the European Commission as having less than 250 persons employed, an annual turnover of up to €50 mln, or a balance-sheet total of no more than €43 mln.

[12] Online Appendix Table A5 contains further details on applicants' country.

[13] See Di Minin et al. (2016) for a comparison between the two programs along with an assessment of the SME Instrument from the perspective of European innovation policies.

[14] Beyond the financial subsidy, the SME Instrument also provides coaching support. The coaches are international business experts and these activities take place in Brussels where coaches offer their experience to awardees over 3 days for Phase I and 12 days in Phase II. During this time, firm managers work with coaches to develop strategies and enhance market potential. Note that, as the SBIR, the SME Instrument also has a Phase III that focuses on commercialization. To the best of our knowledge, however, this has not been launched yet.

[15] The grant is up to €5 million in health-related topics.

After each cut-off date all eligible proposals are evaluated by a committee of four independent experts appointed by EASME.[16] The evaluation process attributes a score to three aspects of the project: i) impact, ii) excellence, and iii) quality & efficiency of implementation (scale 0 to 5). The final score for each project is calculated by adding up the median scores on all three criteria. The projects are then ranked based on these scores. Those projects that are above a minimum threshold (usually 12 points for Phase I and 13 points for Phase II) can be considered eligible for the grant. However, the effective number of grants is decided based on EU budgetary constraints.[17]

The evaluation procedure is conducted remotely. Each evaluator works independently as there are no contacts between the four experts. Hence, individual experts do not know the score given by their peers. Also, experts do not know the effective number of grants that will be granted in the competition ex-ante.

The projects that are considered eligible for the award but do not receive the grant because of insufficient budget receive the "Seal of Excellence". This certificate represents a 'quality label' recognising the value of the proposal. This may facilitate applications to other European or national public competitions, and provide companies with more visibility with respect to private investors.

During the 2014 - 2017 period around 3,200 firms received funding under the SME Instrument for a total investment of €1,318 mln. The SME Instrument is highly competitive and after four years, the overall success rate is 8.0% for Phase 1 and 4.8% for Phase 2. To have a benchmark, the US SBIR features approval rates that tend to be almost double this figure.

2.2 Data and summary statistics

We have access to confidential data concerning all SME Instrument competitions organized by the EASME from 2014 to 2017. While the list of winners for each competition is public, the information concerning competitions' applicants and rankings is not. These confidential data include information on the applicant's firm name, country, funded status, requested funding amount, number of proposal, phase, competition and final ranking.

Table 1 reports summary statistics concerning competitions. On average the number of applicants is 163 for Phase I competitions and 85 for Phase II competitions. The number of winners is rather low: the average is 13 for Phase I and 4 for Phase II. Around 50% of all firm-applications are first-time applicants. Concerning Phase II, around 15% of firms that apply to this stage have won a Phase I award (Tables A1 and A2).

[16] A yearly rotation of 20% of experts ensures an impartial treatment of the projects submitted. Experts can apply to be evaluators through a call for expressions of interest. As a general rule, expert evaluators coming from the same country as the application will not be assigned to its assessment.

[17] Note that the assignment mechanism of the SME Instrument could allow, in principle, the use of a fuzzy RD design (Lee and Lemieux, 2010) since firms that are above the eligibility threshold do not automatically win the award. However, in this scenario we would need to use as a running variable the scores and not ranks. Unfortunately, since we do not have the underlying scores that map into ranks, it is not possible to use this approach.

We employ the ORBIS Bureau van Dijk's (BvD) company database to link applicants data with firm-level outcomes. Absent the possibility to access country-specific business register data, ORBIS represents the best available source for comparable cross-national firm-level data (Dorn et al., 2020; Bajgar et al., 2020). Based on probabilistic matching on firm name and country, we retrieved longitudinal information concerning applicants to SME Instrument calls for the period 2014-2017[18]. After the exclusion of 22 firms with revenues and/or employees not complying with the SME Instrument eligibility criteria, and discarding all firms with missing patent data, we are able to successfully match 68% of all firm-applications. Table A3 provides a comparison between the number of unique firms and number of firm-applications between the raw data and the linked ORBIS data after cleaning. We are able to match around 64% of all firm-applications for Phase I and 74% for Phase II. We do not find any meaningful variation between the applicants population and the matched sample.[19]

In order to assess the impact of the policy on innovation outcomes we use the ORBIS Intellectual Property database[20] to retrieve information regarding all patent applications and their forward citations up to 2019.[21] Instead of resorting to a simple patent count, which would neglect their heterogeneity, we weight each patent by its forward citations to better assess its impact and commercial potential. In doing so we follow a well-established approach: forward patent citations are a good indicator of the 'quality' of the innovation (Trajtenberg, 1990) a predictor of both patents and firms market value (Harhoff et al., 1999; Kogan et al., 2017; Hall et al., 2005) and are correlated with product innovations (Argente et al., 2020).[22] ORBIS Zephyr database is used to retrieve private financing data (time-span 1997-2019). Furthermore, the availability of balance-sheet data allows us to access longitudinal records in terms of investment, total assets, employment and revenues. We also link firm-applications with data regarding the status of the firm at the beginning of 2019. This information allows us to assess whether each

[18] Note that we exclude 2019 competitions because we need at least one post-treatment year. Also, we exclude 2018 competitions since changes were introduced to the SME Instrument in the 2018-2020 work program (since 2018 the SME Instrument has no topics, so all proposals are in competition with each other, and interviews between experts and Phase II applicants have been introduced as a last screening step of the evaluation procedure.

[19] While ORBIS coverage has been improving during recent years, it does still not provide an optimal representativeness of younger and smaller firms (Kalemli-Ozcan et al., 2015). Table A4 in the Appendix reports descriptive statistics for the population of applicants compared with the BvD-matched sample. We also compute standardized mean differences between the population and the estimation sample to assess their comparability (Austin, 2009). Results indicate that most variables feature standardized differences below the conservative threshold of 0.10 whereas the remaining ones are all below the 0.25 threshold. Overall, this reassures us on the absence of systematic differences generated by linking EASME data with ORBIS.

[20] It contains information on over 115 million patents worldwide. The information source is the PATSTAT database, established and maintained by the European Patent Office (EPO). The match between ORBIS and PATSTAT is carried out by Bureau van Dijk under a mutual agreement with the OECD (Organisation for Economic Cooperation and Development). Squicciarini and Dernis (2013) show that the share of successfully matched patents between PATSTAT and ORBIS is above 90% for selected OECD countries.

[21] We choose to use patent applications in compliance with most of the innovation literature. Also, given that the procedure to grant a patent requires additional time, we use patent applications because of the short post-treatment time window that characterises our sample. However, we re-run the entire analysis using granted patents and find qualitatively similar results.

[22] We do not normalize patent counts by year or technology class because our models include competition fixed effects which control for time and sectors, as in Howell (2017).

firm is still active or has exited due to failure or by initial public offering (IPO) or merger and acquisition (M&A). To mitigate the influence of outliers, all balance-sheet variables are winsorized at the 2% on both tails of the distribution whereas patenting variables are winsorized at the 98th percentile.

Descriptive statistics of R&D grant competitions and firm-level variables are reported in Table 1. Firms applying to SME Instrument competitions tend to be young, with a median age of 3 years old for Phase I and 5 years old for Phase II. They also tend to be small with a median number of employees of 8 for Phase I and 11 for Phase II. Roughly 50% operate in medium or high-tech manufacturing or high-tech knowledge intensive services.[23] The median firm is not patent-active and a very small share of applicants has received some external private financing. Finally, around 6-8% of all applicants have failed by 2019 whereas IPO events are extremely rare for both Phase I and Phase II competitions.

Table 1: Descriptive statistics on SME Instrument competitions and applicants

	Phase I				Phase II			
	Mean	SD	p50	N	Mean	SD	p50	N
Panel A: competitions								
# firms	162.99	130.07	163	173	84.68	74.35	68	176
# winning firms	13.32	10.05	11	173	4.09	3.08	3	176
Panel B: competitions								
# firms	104.14	81.76	102	173	63.06	56.98	50	176
# winning firms	7.34	5.53	6	173	2.66	2.17	2	176
Panel C: applicants								
Patents^{Pre}	1.39	4.51	0	18012	4.03	8.13	0	11095
Citw patents^{Pre}	9.10	44.65	0	18012	30.84	84.70	0	11095
PE^{Pre} (d)	0.01	0.09	0	15784	0.04	0.18	0	8352
Revenues^{Pre}	2090	5823	303	9753	2944	7832	554	6238
Employees^{Pre}	15.77	28.83	5	9173	19.40	29.96	8	6700
Assets^{Pre}	1991	5838	343	12125	2932	5337	994	8411
Age^{Pre}	7.16	9.66	3	18280	8.83	11.62	5	11313
High-Tech (d)	0.51	0.50	1	17881	0.57	0.50	1	11024
Failure (d)	0.08	0.27	0	18498	0.06	0.24	0	11402
IPO (d)	0.00	0.02	0	15973	0.00	0.05	0	8432

Notes: summary statistics for competitions and applicants participating to 2014-2017 SME Instrument competitions. Panel A reports summary statistics at the competition-level for the original sample. Panel B reports summary statistics at the competition-level for the estimation sample. Panel C presents summary statistics for a number of firm-level observables. Balance-sheet variables are reported in thousand euros. These are winsorized at 2% level on both sides of the distribution while patent count and cite-weighted patents are winsorized at the 98% level.

3 Empirical strategy

The ideal experiment to infer causal effects would entail the random allocation of R&D grants to firms and an assessment of whether beneficiaries have improved their performance as a result. Understandably, this is not a viable and desirable approach from the policymaker perspective.[24]

[23] These are identified at the 2-digit NACE Rev. 2 drawing on Eurostat definitions (https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf).

[24] Dalziel (2018) highlights a series of reasons behind the scarce use of randomized control trials in R&D grant evaluation: i) even if grants are randomized among highly-quality applicants, it may result in the funding of less meritorious ones, and in reduced outcomes; ii) randomisation would decrease the certification effect to investors,

Hence, the main challenge is inferring causal effects of R&D subsidies by comparing recipient with non-recipient firms. However, these might present both observed and unobserved differences that are probably correlated with the outcome of interest. In such scenario, treatment is endogenous and models that do not adequately control for this will produce biased estimates (Bronzini and Iachini, 2014). Against this backdrop, RD designs arguably represent the best alternative to experimental evidence.[25] For the purposes of our analysis, the SME Instrument scheme presents several features that allow to use RD to accurately address the endogeneity issue. The identification strategy leverages the policy's assignment mechanism: firm proposals are ranked according to experts' evaluation and funding availability is the ultimate determinant of the number of grants awarded in each competition. We exploit this discontinuity and employ a sharp RD design comparing firms around the threshold. The RD approach, first introduced by Thistlethwaite and Campbell (1960), is based on the idea that treatment assignment around the threshold is approximately random (Lee, 2008). In this context, firms that are close to the threshold on either side are supposed to be very similar, and potential differences in the post-treatment performance of beneficiaries and non-beneficiaries can be attributed to the grant.

In order to assess the causal effect of the SME Instrument, we estimate the following equation by means of ordinary least squares (OLS):

$$\begin{aligned} Y_{ic}^{Post} =& \alpha + \beta Grant_{ic} + f\left(Rank_{ic}\right) + \gamma Y_{ic}^{Pre} + \delta_c + \varepsilon_{ic} \\ & \text{where } -r \leq Rank_{ic} \leq r \end{aligned} \tag{1}$$

Y_{ic}^{Post} is the post-treatment outcome for firm i in competition c, $Rank_{ic}$ is the centered rank assigned by experts to firm i in competition c, $Grant$ is an indicator for firm i winning the competition c (i.e. $Rank_{ic} > 0$). $f\left(Rank_{ic}\right)$ is a polynomial control for centered ranks. All regressions feature competition fixed effects (δ_c). These fixed effects effectively restrict the comparison to applicants on either side of the threshold, but within the same competition, thus controlling for time and sector specific factors. Additionally, r is the bandwidth, and ε_{ic} is the idiosyncratic error term. Standard errors are robust and clustered at the competition-level to adjust for potential serial correlation in errors.

We use polynomials that are allowed to differ on either side of the threshold, as is standard in RD (Lee and Lemieux, 2010). Drawing on Gelman and Imbens (2018), we model the running

and reduce learning opportunities due to acceptance–rejection feedback. iii) since outcomes are expected to be skewed, with a handful of firms responsible for most of the impact, large samples will be required for reliable results. For a different view on the use of randomized control trials for innovation policy, see Bravo-Biosca (2020).

[25] Lee and Lemieux (2010, p.282) point out that the popularity of RD designs in economics is motivated by their "seemingly mild assumptions compared to those needed for other non-experimental approaches" and "the belief that [...] causal inferences from RD designs are potentially more credible than those from typical 'natural experiment' strategies (e.g., difference-in-differences or instrumental variables)". Recent research is consistent with this view insofar as RD designs are able to reproduce the results from randomized experiments and randomized control trials (Chaplin et al., 2018; Hyytinen et al., 2018) and that studies using RD are less prone to "p-hacking" if compared with those using difference-in-differences or instrumental variables (Brodeur et al., 2019).

variable linearly or quadratically throughout the analysis. Higher-order polynomial models may generate imprecise estimates when the sample size is small, as it is here. As suggested by Lee and Lemieux (2010), we run regressions with a variety of bandwidths. We use the entire sample (i.e. infinite bandwidth) and two different bandwidths of 10 and 5 absolute ranks around the threshold.[26]

As already mentioned, the use of centered ranks around zero is motivated by the heterogeneity across competitions in terms of number of applicants and grants. However, we might be losing information contained in the un-centered raw ranks: two firms with the same centered rank participating in two competitions that award a different number of R&D grants might indeed differ quite substantially. This could induce heterogeneous effects across competitions based on the un-centered rank of the threshold (Barrows, 2018; Howell, 2017). To address this problem we draw upon Howell (2017), who proposes to control for dummies for the firm's rank quintile within the competition.

Although RD designs do not need conditioning on baseline covariates, Lee and Lemieux (2010) suggest including pre-treatment dependent variables as they are usually correlated with post-treatment outcomes as well as because doing so can reduce sampling variability and improve precision. Therefore, in all models we include Y_{ic}^{Pre} which controls for the respective pre-assignment dependent variable.

The above model is estimated separately for the two phases of the SME Instrument. This is motivated by the fact that, as explained in Section 2.1, applicants do not need to go through Phase I to apply for Phase II.[27] In addition, one of the eligibility criteria for the SME Instrument is that the firm is not already competing for or implementing an SME Instrument project. In any case, in further robustness checks we also estimate Phase II models by inserting controls for participation or victory of Phase I and find the same results.

3.1 Validity of the RD design

The validity of the RD strategy critically rests on a series of testable assumptions. First, the grant (i.e. treatment) should not cause rank. In our case, this is not problematic given that the decision to assign the award takes place after the ranking has been compiled by the external experts. However, the presence of firms with multiple grants might induce the treatment to cause rank. Although in our data we have firms with multiple applications, only five firms won a Phase I twice, whereas there are no multiple winners in Phase II. A potential concern has to do

[26] In robustness tests we provide estimation results using three alternative approaches. In the first we vary the bandwidths between 1 and 25 in absolute ranks. The second uses automatic bandwidth selection accounting for few mass-points in the running variable around the threshold (Calonico et al., 2017). The third employs local randomization by limiting the sample to firms just below and above the threshold (i.e. firms ranked -1 or 1), a suitable approach in cases where the number of observations near the threshold is very low and the running variable is discrete (Cattaneo et al., 2015).

[27] The US SBIR examined by Howell (2017) obliges companies to participate to Phase I before applying to Phase II. However, following a recent change, the SBIR now allows firms to apply for Phase II without going through Phase I first.

with those firms that win Phase I and participate to Phase II.[28] To check whether this might be happening, we tested whether, among firms that have applied to both Phases, winning Phase I is associated with higher likelihood of winning Phase II and found no evidence of this. Further, we estimated our models for Phase II either without Phase I grant-winning firms or including a dummy variable identifying this group of firms in the regressions. There are no significant changes in the results (see Section 7).

Given that the threshold has to be exogenous to rank in a valid RD design, a second concern involves the possibility that firm ranks are manipulated around the threshold (Lee and Lemieux, 2010). In our context this might happen if experts manipulate the rank around the threshold. However, this is not likely to happen given that the evaluation procedure is conducted remotely and the individual experts do not know the score given by the other experts. Even if one had any intention to manipulate the evaluation, it would be extremely difficult for individual experts to know exactly what score would lead to a winning rank. Also, experts do not know the effective number of awards that will be granted in the competition ex-ante since this is purely a function of EU budgetary constraints. A further potential concern for manipulation might come from applicants trying to influence ranking by submitting high-quality proposals and requesting relatively small amounts of funding in order to have higher chances to secure the R&D grant given EU budgetary constraints. This might happen in Phase II competitions were the R&D grant amount varies. If this happened, we should observe award-winning firms systematically requesting lower budgets relative to losing firms. We tested for the presence of discontinuity in the amount requested by firms just below and above the threshold and found no evidence supporting this (Figure A7 in Online Appendix).

We employ different tests to check for the presence of manipulation in the running variable. Figures A1 and A2 report the density of the centered rank variable for both phases and do not show any visible discontinuity around the threshold. For a more formal test, we cannot resort to the canonical McCrary (2008) test given the discreteness of our running variable. However, we can rely on a finite sample exact binomial test proposed by Cattaneo et al. (2017) which examines whether the number of observations just above the threshold is roughly similar to the number of observations just below the threshold.[29] We run the test using the first winner and the first loser in each competition (i.e. a bandwidth of 1 on both sides) and find no evidence of "sorting" around the threshold. Additionally, we perform the test proposed by Frandsen (2017) that is consistent when the running variable is discrete. Even in this case we can reject the null of discontinuity.[30]

To obtain evidence against differential sorting across the threshold, we also rely on balancing property tests. In particular, we assess whether firms winning the grant are different in terms

[28] Approximately 12% of all Phase II applicants have won Phase I.
[29] The intuition behind it is that, if firms cannot manipulate their ranks, they should be as likely to receive a rank value just above the threshold as they are to receive a rank value just below it.
[30] Those tests are performed for the ranking variable using the raw data as well as ranks without firms missing variables for patents and private equity.

Table 2: Balancing tests of baseline observables and pre-award outcomes - Phase I & II

	Phase I			Phase II		
	All	±10	±5	All	±10	±5
Citw patents^{Pre}	0.19**	-0.12	-0.026	0.13	-0.12	-0.12
	(0.076)	(0.14)	(0.20)	(0.15)	(0.20)	(0.28)
PE^{Pre}	0.00065	-0.025**	-0.013	-0.028	0.0047	-0.028
	(0.0049)	(0.012)	(0.010)	(0.023)	(0.024)	(0.030)
Revenues^{Pre}	0.26**	-0.36	0.64	-0.44	-0.077	-0.45
	(0.11)	(0.30)	(0.44)	(0.25)	(0.30)	(0.43)
Assets^{Pre}	0.23**	-0.40	0.081	-0.047	-0.19	-0.52**
	(0.10)	(0.23)	(0.33)	(0.16)	(0.18)	(0.25)
Employees^{Pre}	0.045	-0.27	0.44	0.0068	0.014	-0.11
	(0.078)	(0.17)	(0.24)	(0.13)	(0.17)	(0.22)
Age^{Pre}	0.11**	0.012	0.21	-0.067	-0.078	-0.16
	(0.044)	(0.098)	(0.15)	(0.074)	(0.097)	(0.14)
Cash-flow^{Pre}	0.012	-0.011	0.021	0.017	0.069	0.037
	(0.017)	(0.040)	(0.064)	(0.030)	(0.040)	(0.069)
Profit margin^{Pre}	-0.16	1.83	7.55	5.29	5.54	6.28
	(1.87)	(4.22)	(6.91)	(3.46)	(4.65)	(7.93)
High-tech	0.049**	0.071	0.092	-0.063	-0.076	-0.058
	(0.022)	(0.050)	(0.068)	(0.039)	(0.051)	(0.068)
South	-0.0051	-0.023	-0.069	0.016	-0.046	-0.056
	(0.018)	(0.038)	(0.059)	(0.033)	(0.043)	(0.059)
VC Hub	-0.00096	-0.10**	-0.092	-0.027	-0.015	0.036
	(0.021)	(0.042)	(0.062)	(0.038)	(0.048)	(0.065)

Notes: results obtained estimating our baseline RDD equation by means of OLS with predetermined observables as dependent variables: $Y_{ic}^{Pre} = \alpha + \beta\gamma Grant_{ic} + f\left(Rank_{ic}\right) + \delta_c + \varepsilon_{ic}$. Estimates are obtained using different bandwidths around the threshold: an infinite bandwidth (i.e. all firms), and bandwidths of 10 and 5 absolute ranks around the threshold. All regressions include linear controls for centered ranks on both sides of the threshold and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

of their pre-assignment observables and pre-assignment outcome variables. We provide evidence of continuity both from a graphical perspective (see Online Appendix Figures A5 and A6) and by running models where the pre-treatment firm outcome (Y_{ic}^{Pre}) is regressed against $Grant_{ic}$, linear ranks on both sides of the threshold and competition fixed effects. We estimate separate regressions for each dependent variable using different bandwidths and report the results in Table 2. Point estimates tend to be small in magnitude and not statistically significant across both pre-assignment baseline covariates (e.g. age, high-tech) and pre-assignment outcomes (e.g. private equity, assets, revenues). For Phase I applicants covariate balancing appears to be reached when bandwidths are closer to the cut-off. Conversely, for Phase II balancing is already achieved when using all observations (i.e. infinite bandwidth). In sum, the absence of systematic differences across treated and untreated groups reassures on the validity of the RD design. Finally, it is important to note that, even if the validity of the RD design holds, this approach allows for the estimation of local average treatment effects (LATE). These apply to the subpopulation of firms with ranks near the threshold. Hence, while the RD enables the estimation of causal effects, it does not allow to draw conclusions about the average treatment effects (ATE) induced by the policy for the whole population of applicants (Imbens and Lemieux, 2008).

4 Results

In this section we examine the effects of R&D grants on a wide number of firm-level outcomes encompassing several aspects of the innovation-to-market process. We start by providing evidence on whether the SME Instrument causes an increase in firm-level investment with an emphasis on intangible capital. We then study potential effects on innovation outcomes and we then move to the impact on firm growth and survival. We conclude by testing whether R&D grants act as catalysts of follow-on equity financing. Before reporting the econometric results, we show graphical evidence of discontinuity in post-grant outcome variables. Plots for Phase I and II are reported in Figure 1 using a bandwidth of -10 and 5 with a linear polynomial fit on both sides of the threshold. The graphs suggest a positive discontinuity for cite-weighted patents, private equity, assets, employees and revenues for Phase II. Finally, a negative discontinuity is present for firm failure in both phases of the SME Instrument.

4.1 The effects on investment

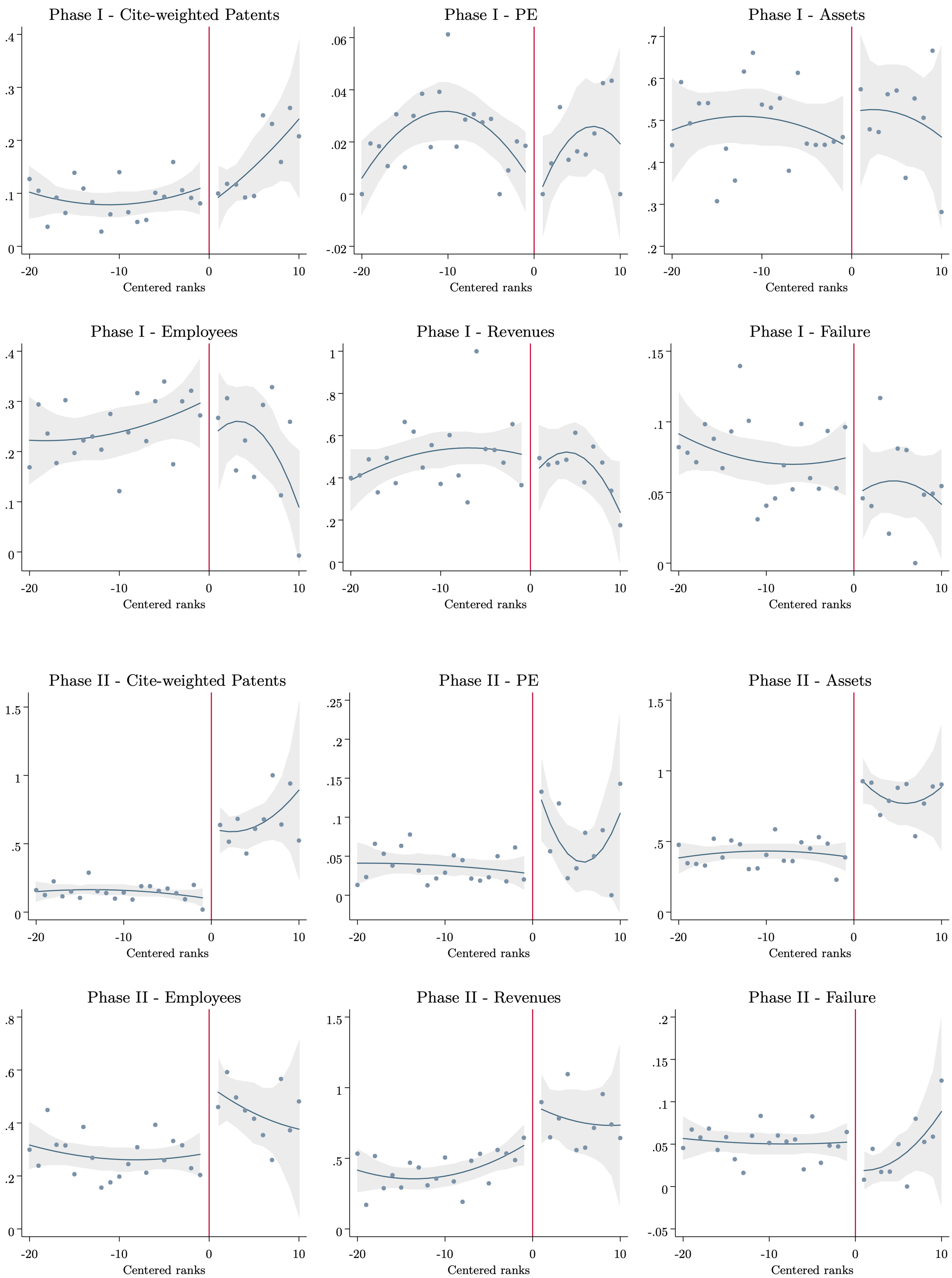
The R&D subsidy evaluation literature has traditionally focused on the effects on subsequent private R&D spending to test for the presence of 'crowding-out' or 'crowding-in' effects. Unfortunately, our data do not contain information on R&D expenditures, which prevents us from testing whether R&D grants trigger input additionality in firm-financed R&D. Hence, as in Bronzini and Iachini, 2014, we examine the effects of public direct R&D funding on firm investment. Firm investment is defined as the annual variation in fixed assets net of depreciation. We cumulate firm investment at time t (i.e. the year of the competition) and $t+1$ and scale it by total assets. To prevent potential endogeneity concerns we use the pre-grant total assets.[31]

Results are shown in Table 3 where Panel A refers to Phase I and Panel B reports results concerning Phase II. Columns 1 to 3 contain OLS specifications using infinite bandwidths (i.e. all firms) whereas columns 4 to 7 use bandwidths of 10 and 5 centered ranks (i.e. firms close to the threshold). We use both linear and quadratic interpolations of the running variable separately on both sides of the threshold. In order to select the most appropriate polynomial order, we report the Akaike information criterion (AIC) and select the models with the minimum value as the preferred specifications within a specific bandwidth (Lee and Lemieux, 2010). We include in all regressions the pre-assignment dependent variable and competition fixed effects.

The effects of Phase I are not statistically different from zero. Conversely, Phase II triggers a positive and statistically significant increase in firm investment. More in detail, considering an average investment of 0.25, the point estimates selected by the AIC (ranging from 0.37 to 0.87)

[31] We obtain similar results when using only investment at time $t+1$ or employing a different scale variable (e.g. revenues).

Fig. 1: Graphical evidence of discontinuity in firm-level outcomes (Phase I & II)



Notes: the figure reports RD plots for both Phase I (top) and Phase II (bottom). Circles represent rank-level means of the firm-level outcomes. The sample includes firms with centered ranks between -20 and 10. Fitted lines from local polynomial regressions with a quadratic fit together with 95% confidence intervals.

Table 3: The effects on investment

Panel A: Phase I	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Grant	0.046	0.034	0.003	0.033	-0.132	-0.105	-0.063
	(0.039)	(0.053)	(0.032)	(0.094)	(0.180)	(0.175)	(0.380)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
N	7594	7594	7594	954	954	482	482
R-squared	0.04	0.04	0.04	0.21	0.21	0.31	0.31
AIC	13797.59	13800.65	13803.71	1541.03	1542.23	715.37	717.92
Panel B: Phase II	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Grant	0.354***	0.395***	0.258***	0.373***	0.331*	0.387**	0.874**
	(0.094)	(0.143)	(0.057)	(0.115)	(0.195)	(0.154)	(0.356)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
N	5326	5326	5326	962	962	529	529
R-squared	0.07	0.07	0.07	0.26	0.26	0.38	0.38
AIC	9353.57	9351.01	9353.67	1826.59	1829.88	982.72	982.38

Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is the cumulated investments during time t and $t+1$ scaled by total assets at $t-1$. Regressions include total assets at $t-1$. Both variables are winsorized at the 2% and 98% of the distribution over the whole sample. Columns 1 to 3 report estimates using infinite bandwidths (i.e. all firms). Columns 4-5 and 6-7 report estimates obtained using bandwidths of, respectively, 10 and 5 ranks around the cut-off. All regressions include the pre-grant dependent variable (log of fixed assets at time $t-1$) and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

imply a sizable effect of the policy.[32] In sum, results indicate that Phase II grant-winning firms invest more than losing firms, thus providing evidence against the 'crowding-out' hypothesis.

A further test concerns the impact of R&D grants on investment in tangible as opposed to intangible (fixed) assets. In particular, investment in intangible capital is considered relatively more difficult to finance given its low redeployability, non-exclusiveness, and low liquidity (Sun and Xiaolan, 2019). Moreover, the intrinsically uncertain nature of intangible investments exacerbates asymmetric information leading to financial constraints (Hall and Lerner, 2010; Bronzini and Iachini, 2014). Hence, one might expect investments in intangibles to be particularly sensitive to R&D grants. To examine whether R&D grants are particularly beneficial to this kind of investment, we run separate regressions for tangible and intangible investment baseline models. Results document that the effects on intangible investment appear to be systematically larger if compared with the effects on tangible investment (see Table A8 and Table A9 in Online Appendix).

[32] Note that these models might only partially capture the effect induced by the grants given that Phase II projects might last up until two years. Therefore, we also run the same regression using as dependent variable the cumulated investment including $t+2$ scaled by pre-assignment total assets. Estimations are based only on firms applying during 2014, 2015 and 2016 since they feature enough post-treatment observations. Results indicate substantially larger treatment effects (Table A7).

4.2 The effects on innovation and external finance

In this section we report estimation results on the causal impact of the SME Instrument on subsequent innovation and external finance. To assess the effects on innovation outcomes, we employ patent data, which are one of the most common proxies to capture firms' innovative behaviour. We use a quality-adjusted patenting measure that is obtained by weighting patents with their subsequent citations.[33]

We run Equation (1) using as dependent variable the log of cite-weighted patents plus one after the competition.[34] To be conservative, the dependent variable considers all cite-weighted patents starting from $t+1$ (i.e. the year after the competition) and not t (i.e. the year of the competition) since this could lead to overestimate treatment effects by considering innovation outcomes that would unlikely be stemming from the grant.

Table 4: The effects on cite-weighted patents

Panel A: Phase I	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Grant	0.073**	0.071*	0.061**	-0.033	-0.056	-0.032	0.064
	(0.031)	(0.041)	(0.024)	(0.072)	(0.125)	(0.100)	(0.203)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
N	18012	18012	18012	2026	2026	1090	1090
R-squared	0.23	0.23	0.23	0.31	0.31	0.38	0.38
AIC	29068.99	29064.20	29055.06	4150.55	4154.46	2073.61	2076.90
Panel B: Phase II	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Grant	0.203***	0.282**	0.148***	0.147*	0.236*	0.314***	0.390*
	(0.068)	(0.117)	(0.051)	(0.085)	(0.138)	(0.113)	(0.230)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
N	11095	11095	11095	1822	1822	1050	1050
R-squared	0.36	0.36	0.36	0.45	0.45	0.51	0.51
AIC	23473.47	23472.94	23465.43	4198.99	4201.34	2299.14	2302.92

Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is the log of cite-weighted patents applications plus one filed starting from the year after the competition. Columns 1 to 3 report estimates using infinite bandwidths (i.e. all firms). Columns 4-5 and 6-7 report estimates obtained using bandwidths of, respectively, 10 and 5 ranks around the cut-off. All regressions include the pre-grant dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Results are shown in Table 4 and highlight that Phase I of the SME Instrument has a positive and statistically significant effect on firm-level innovation outcomes when using an infinite bandwidth, whereas this does not hold when employing bandwidths closer to the threshold. Conversely, Phase II appears to have sizable positive effects. More specifically, Phase II grant-

[33] While patent data are widely used in the literature, we have to bear in mind that they they represent a partial and often noisy proxy for firm-level innovation outcomes. There are no obvious alternatives to their use in large cross-country firm-level analyses, but this should be taken into account when interpreting our findings.

[34] We avoid running these models using the variation in the number of quality-adjusted patents because it would consider firms with one patent pre- and post-grant as having zero patents.

winning firms experience an increase in log cite-weighted patents across all specifications. Point estimates indicate an increase within the range of 15 to 31% depending on the bandwidth employed. Models using the sheer (log) number of patents yield similar results (see Table A11 in Online Appendix).

The reported increase in cite-weighted patents could be ascribed to firms that would not have filed any patent application without the grant (i.e. extensive margin) and/or to firms that would have filed patent applications but in smaller numbers absent the grant (i.e. intensive margin). To test for the presence of extensive margin effects, we estimate our baseline models using a simple dummy variable for patent applications. Estimates show that the policy increases by 8-15 percentage points the probability to apply for a patent. Relative to an 8% mean, this effect translates into an over 100% increase (Table A10 in Online Appendix). We estimate the same model by splitting the sample according to pre-competition patenting activity. While firms with patents before the grant experience larger treatment effects, these are not statistically different from those of non-patent active firms (Table A13). This indicates that the policy operates through both intensive and extensive margins. In other words, R&D grants benefit firms that have engaged in innovation activities in the past but also increase the probability of first-time patenting. The latter effect is particularly important because it indicates behavioural change of great significance for the future growth prospect of the firm. In the interest of coherence, these results have been obtained by means of OLS even though OLS are not the ideal approach for count data. Results obtained by using negative binomial models are, however, also positive and statistically significant for Phase II (see Table A12 in Online Appendix).

Next, we examine the effects of R&D grants on follow-on external finance. One of the intended outcomes of the SME Instrument is the reduction of information asymmetries between potential external investors and innovative firms. Receiving R&D grants should diminish the risk perceived by potential investors, who in turn will have greater propensity to invest. Testing whether R&D grants enhance the prospect of further external financing also indicates if grant-winning firms represent privately profitable opportunities and constitute a measure of early-stage entrepreneurial success (Howell, 2017).

We start by estimating Equation (1) where the dependent variable is a dummy indicating whether or not a firm has received private equity investment following the competition. Phase II grant-winning firms are more likely to receive private equity (Table 5). More precisely, estimates indicate that winning the grant increases the probability of receiving external equity by about 11.7 and 12.6 percentage points, relative to a 4% mean. Hence, the receipt of R&D grants triggers roughly a threefold increase in the likelihood of receiving follow-on equity investments.

To examine whether R&D subsidies help companies to raise more funding, we also estimate the models using the log of equity amount received. We find that the SME Instrument triggers

Table 5: The effects on private equity receipt

Panel A: Phase I	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Grant	-0.008	0.002	-0.001	0.006	-0.023	-0.011	-0.068**
	(0.009)	(0.011)	(0.005)	(0.011)	(0.021)	(0.017)	(0.033)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
N	15784	15784	15784	1666	1666	897	897
R-squared	0.03	0.03	0.03	0.12	0.13	0.24	0.24
AIC	-27026.99	-27039.09	-27014.08	-1910.25	-1908.94	-1502.12	-1503.44
Panel B: Phase II	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Grant	0.070**	0.126***	0.036**	0.080***	0.123***	0.117***	0.157*
	(0.028)	(0.045)	(0.015)	(0.027)	(0.047)	(0.039)	(0.085)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
N	8352	8352	8352	1358	1358	784	784
R-squared	0.07	0.07	0.07	0.17	0.17	0.27	0.27
AIC	-5105.58	-5113.51	-5100.54	-621.06	-619.83	-355.78	-352.28

Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is a dummy variable indicating whether a firm has received private equity financing after the competition. Columns 1 to 3 report estimates using infinite bandwidths (i.e. all firms). Columns 4-5 and 6-7 report estimates obtained using bandwidths of, respectively, 10 and 5 ranks around the cut-off. All regressions include the pre-grant dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

a sizable increase between 46 and 97% in the amount of private equity (Table A14) and around 17 percentage points increase in the number of deals (Table A15).[35]

4.3 The effects on firm growth and survival

The availability of data on firm balance-sheets make it possible to examine indirect effects of R&D grants on firm performance. In this section we investigate whether the SME Instrument triggers an increase in the growth rates of total assets, employees and revenues. All dependent variables in these models are computed as the log difference between outcomes at $t + 1$ (i.e. one year after the competition) and $t - 1$ (i.e. the year before the competition).[36] Additionally, we insert in all models the pre-assignment log level of the dependent variable.

We start by examining whether the SME Instrument induces an effect on assets and employment growth. As for investment and patents, we cannot detect any effect of Phase I on firm balance-sheets. On the contrary, Phase II positively affects firm growth in total assets and

[35] In principle, the positive effects on equity could be materializing via negative spillovers. That is, the award increases the probability of receiving private financing by reducing those of losing firms. Following Howell (2017), we exploit the fact that equity funds tend to invest close to their location and test whether the effects of the grant change for firms in the same NUTS-3 region. We do not detect any statistically significant difference.

[36] In robustness checks, we also estimated the models using dependent variables in log levels or computing them as averages in the two years preceding and following the competition. Results for the former specification are reported in the Appendix in Tables A16, A17 and A18. Similar results are obtained using growth rates computed as in Haltiwanger et al. (2013).

Table 6: The effects on asset growth

Panel A: Phase I	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Grant	0.093*	0.022	0.053	0.029	-0.022	0.046	0.138
	(0.047)	(0.065)	(0.038)	(0.100)	(0.187)	(0.163)	(0.310)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
N	10702	10702	10702	1315	1315	701	701
R-squared	0.16	0.16	0.16	0.30	0.30	0.37	0.37
AIC	25333.83	25314.69	25308.11	2937.59	2940.07	1500.17	1503.79
Panel B: Phase II	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Grant	0.518***	0.569***	0.402***	0.456***	0.569***	0.556***	0.966***
	(0.062)	(0.096)	(0.044)	(0.088)	(0.136)	(0.125)	(0.269)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
N	7306	7306	7306	1311	1311	743	743
R-squared	0.16	0.16	0.16	0.37	0.37	0.45	0.45
AIC	16122.35	16122.65	16107.71	2677.11	2679.75	1462.10	1461.56

Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is the log differences of assets between time $t-1$ (i.e. the year preceding the competition) and time $t+1$ (i.e. the year after the competition). Both variables are winsorized at the 2% and 98% of the distribution over the whole sample. Columns 1 to 3 report estimates using infinite bandwidths (i.e. all firms). Columns 4-5 and 6-7 report estimates obtained using bandwidths of, respectively, 10 and 5 ranks around the cut-off. All regressions include the pre-grant dependent variable (log of assets at time $t-1$) and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

number of employees. Results indicate that Phase II causes an increase in assets growth between 46 and 96% (Table 6) whereas the effect on employment growth is within the 21 to 30% range (Table 7).

Positive (albeit noisy) effects are documented also in the case of firm revenues with an approximate 20-45% increase (Table 8). In particular, results obtained using firms closer to the threshold show coefficients with similar magnitudes but estimated with less precision. The weaker evidence concerning revenues is plausible given that these ventures, while benefiting on several levels from the receipt of the R&D grant, might take a long time to reach commercial maturity. This can arguably be attributed to the fact that revenue growth depends on the market introduction and diffusion of the product they were developing through the R&D grants and this may take years, especially in some high-tech industries.[37]

The overall improvement in innovation outcomes, balance-sheet variables and financing might also reflect on lower probability of failure among the grant recipients. We therefore examine whether the policy decreases firm failure, namely, exit through bankruptcy, dissolution, liquidation or insolvency by 2019. Results show a decrease in the likelihood of failure that is around 4 to 12 percentage points (Table 9). This represents a substantial impact in economic terms since the mean of the dependent variable is 6.1%. This is not an obvious finding. Prior studies

[37] Gilbert et al. (2006) argue that for these reasons employment is a better indicator of growth performance for these firms.

Table 7: The effects on employment growth

Panel A: Phase I	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Grant	-0.017	0.021	-0.012	-0.052	-0.001	0.107	-0.050
	(0.037)	(0.049)	(0.028)	(0.068)	(0.122)	(0.117)	(0.234)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
N	7614	7614	7614	968	968	483	483
R-squared	0.11	0.11	0.11	0.28	0.28	0.41	0.41
AIC	11099.24	11098.99	11093.61	1192.55	1195.85	514.73	517.95
Panel B: Phase II	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Grant	0.299***	0.222***	0.195***	0.251***	0.271**	0.211*	0.204
	(0.053)	(0.081)	(0.033)	(0.071)	(0.123)	(0.112)	(0.206)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
N	5493	5493	5493	962	962	548	548
R-squared	0.14	0.14	0.14	0.33	0.33	0.46	0.46
AIC	7890.43	7892.21	7892.34	1286.54	1289.41	625.87	629.86

Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is the log differences of employees between time $t-1$ (i.e. the year preceding the competition) and time $t+1$ (i.e. the year after the competition). Both variables are winsorized at the 2% and 98% of the distribution over the whole sample. Columns 1 to 3 report estimates using infinite bandwidths (i.e. all firms). Columns 4-5 and 6-7 report estimates obtained using bandwidths of, respectively, 10 and 5 ranks around the cut-off. All regressions include the pre-grant dependent variable (log of employees at time $t-1$) and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

have, in fact, shown that new ventures with high innovation potential display higher failure rates relative to their non-innovative counterparts (Hyytinen et al., 2015). The effect of R&D subsidies in reducing the probability of failure is important because these firms, in the absence of an appropriate policy, would be likely to exit even though they have good innovative potential. The result is also desirable from a policy perspective because the positive impact of the scheme on other firm outcomes could in theory be counterbalanced by decreased or unchanged survival chances among awarded firms, which might indicate a dispersion of public resources. This is, however, not the case.

Finally, we examine whether R&D subsidies have an impact on the probability of experiencing successful exits and estimate the effect of the SME Instrument on IPO or M&A events. Estimation results reported in the Appendix (Tables A19 and A20) document that the effect is not statistically different from zero (this is not entirely surprising given the very low number of IPO and M&A observed after 2014).

5 Heterogeneous effects

In the absence of market failures, R&D grants should have no effect on firm-level outcomes. In such scenario firms undertake innovative projects based solely on whether the expected returns are higher than market returns (Hall and Lerner, 2010). Firms without good investment oppor-

Table 8: The effects on revenue growth

Panel A: Phase I	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Grant	0.017	-0.006	0.010	-0.081	0.010	0.080	0.489
	(0.053)	(0.068)	(0.046)	(0.114)	(0.184)	(0.176)	(0.412)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
$Rank^2$ × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
N	8124	8124	8124	958	958	486	486
R-squared	0.19	0.19	0.20	0.37	0.38	0.47	0.47
AIC	20041.56	20028.09	20018.13	2149.04	2149.72	1028.60	1029.26
Panel B: Phase II	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Grant	0.451***	0.587***	0.340***	0.248**	0.141	0.154	0.172
	(0.117)	(0.165)	(0.069)	(0.121)	(0.205)	(0.177)	(0.376)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
$Rank^2$ × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
N	5119	5119	5119	867	867	480	480
R-squared	0.19	0.19	0.19	0.42	0.42	0.55	0.55
AIC	12887.24	12886.09	12878.85	2007.78	2010.42	1003.01	1007.00

Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is the log differences of revenues between time $t-1$ (i.e. the year preceding the competition) and time $t+1$ (i.e. the year after the competition). Both variables are winsorized at the 2% and 98% of the distribution over the whole sample. Columns 1 to 3 report estimates using infinite bandwidths (i.e. all firms). Columns 4-5 and 6-7 report estimates obtained using bandwidths of, respectively, 10 and 5 ranks around the cut-off. All regressions include the pre-grant dependent variable (log of revenues at time $t-1$) and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

tunities would pass the additional cash received with the R&D grant to shareholders and firms with good investment prospects would invest with or without the grant. Because we have shown that Phase II does have a causal effect on a wide range of firm activities, then we have to infer that some kind of friction is deterring the investment in innovative projects without the grant.

A large literature has documented that financial constraints are particularly problematic for innovative firms (for a survey, see Hall and Lerner (2010)). This is one of the reasons why governments subsidize R&D, that is, to help financially vulnerable firms to conduct research projects they otherwise would not be able to pursue. If the effect of R&D grants on firm performance takes place by reducing market failures, the additionality has greater social desirability. In this section we explore whether the policy alleviates financial frictions using proxies at different aggregation levels (i.e. firm, sector, country). The unusual variety in our data in terms of both sectors and countries of origin of applicants allows us to explore interesting heterogeneous effects which are new to this literature.

First, we investigate whether the effect of the SME Instrument varies according to the most commonly used proxies for financial vulnerability, namely, firm age and firm size. Both size and age are considered firm characteristics that are associated with the likelihood of facing constraints (Hadlock and Pierce, 2010). Small firms suffer from information asymmetries, often lack sufficient collateral and feature more volatile revenues since they are less diversified. These

Table 9: The effects on firm failure

Panel A: Phase I	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Grant	-0.014	-0.019	-0.005	-0.028	-0.034	-0.045	-0.065
	(0.011)	(0.014)	(0.008)	(0.026)	(0.043)	(0.039)	(0.081)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
N	18498	18498	18498	1962	1962	1040	1040
R-squared	0.02	0.02	0.02	0.11	0.11	0.11	0.11
AIC	3317.70	3321.20	3318.42	-306.17	-302.71	-116.97	-113.07
Panel B: Phase II	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Grant	-0.044***	-0.055***	-0.020**	-0.048***	-0.058*	-0.067**	-0.129**
	(0.012)	(0.012)	(0.009)	(0.017)	(0.031)	(0.031)	(0.057)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
N	11402	11402	11402	1787	1787	1011	1011
R-squared	0.03	0.03	0.04	0.10	0.10	0.14	0.15
AIC	-457.80	-454.15	-458.75	-798.52	-795.33	-449.66	-450.77

Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is a dummy indicating a firm has failed in the years after the competition (as of March 2019). Columns 1 to 3 report estimates using infinite bandwidths (i.e. all firms). Columns 4-5 and 6-7 report estimates obtained using bandwidths of, respectively, 10 and 5 ranks around the cut-off. All regressions include competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

aspects make them more dependent from external finance but less able than larger businesses to secure it. A voluminous literature finds a negative correlation between firm size and the cost of finance (Carpenter and Petersen, 2002). Young firms are considered to be more financially vulnerable because of their weaker reputation and higher likelihood of experiencing bankruptcies. Additionally, young firms might suffer from lower cash-flows that might not be sufficient to finance subsequent investment via internal resources, and if they are developing innovation projects, they are less likely to receive bank finance due to well-known asymmetric information problems.[38] The above aspects tend to be even more binding for small and young firms undertaking innovative efforts given the highly risky nature of innovation activities.[39] Given that financial frictions are amplified for small and young innovative firms, the impact of innovation subsidies might be inversely related to both firm size and age.

To assess whether R&D subsidies are especially beneficial to businesses that are more prone to financial constraints, we estimate Equation (1) by inserting a dummy variable for above-median age or firm assets (as a proxy for firm size). The coefficient of interest, on the interaction between the treatment variable and the dummy variables, is interpreted as the differential effect of the R&D grants on firm-level outcomes for older (larger) firms, relative to younger (smaller)

[38] Robb and Robinson (2014), using US data on start-ups, document their heavy reliance on external sources of finance.

[39] This view is supported by studies such as Brown et al. (2009), Hall and Lerner (2010), and Czarnitzki and Hottenrott (2011). Brown et al. (2009) document that financial constraints negatively affect R&D investment of younger firms, whereas no effect is detected for mature firms.

firms. Results are reported in Table 10 and suggest that older or larger firms systematically experience treatment effects of lower magnitude if compared with younger or smaller firms. This suggests that R&D subsidies trigger a stronger impact for firms that are much more likely to suffer from financial constraints.

Table 10: Heterogeneous effects across firm-level proxies of financial constraints (Phase II)

	(1) Patents^{Post}	(2) PE^{Post}	(3) Investment^{Post}	(4) Assets^{Post}	(5) Employees^{Post}	(6) Revenues^{Post}	(7) Failure^{Post}
Grant	0.260***	0.097***	0.546***	0.755***	0.406***	0.592***	-0.055***
	(0.080)	(0.033)	(0.134)	(0.079)	(0.072)	(0.167)	(0.013)
Age > p50	-0.084***	-0.019***	-0.313***	-0.259***	-0.182***	-0.194***	-0.022***
	(0.013)	(0.003)	(0.019)	(0.020)	(0.018)	(0.032)	(0.005)
Grant × Age > p50	-0.117	-0.049*	-0.351***	-0.441***	-0.180***	-0.258*	0.020
	(0.081)	(0.029)	(0.112)	(0.070)	(0.059)	(0.152)	(0.013)
N	11003	8352	5324	7304	5491	5117	11313
R-squared	0.36	0.07	0.13	0.18	0.16	0.20	0.04
	(1) Patents^{Post}	(2) PE^{Post}	(3) Investment^{Post}	(4) Assets^{Post}	(5) Employees^{Post}	(6) Revenues^{Post}	(7) Failure^{Post}
Grant	0.287***	0.089***	0.711***	0.849***	0.452***	0.696***	-0.059***
	(0.086)	(0.030)	(0.144)	(0.075)	(0.070)	(0.134)	(0.018)
Size > p50	0.049***	0.018***	-0.235***	0.076**	0.134***	0.427***	-0.015***
	(0.018)	(0.005)	(0.021)	(0.035)	(0.024)	(0.041)	(0.004)
Grant × Size > p50	-0.087	-0.003	-0.587***	-0.658***	-0.288***	-0.529***	0.033**
	(0.080)	(0.030)	(0.131)	(0.073)	(0.064)	(0.136)	(0.016)
N	8121	6217	5326	7306	5249	5029	8339
R-squared	0.36	0.08	0.11	0.16	0.16	0.22	0.05

Notes: results obtained using equation (1) augmented with a firm-level financial constraint proxy. Age is a dummy variable taking the value of 1 if a firm is above the median age, and 0 otherwise.. Size is a dummy variable taking the value of 1 if a firm is above the median pre-determined assets, and 0 otherwise. All regressions include linear ranks on both sides of the thresholds, pre-grant dependent variables and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Second, we examine the differential effect of R&D grants across sectoral-level measures of financial frictions. For example, firms operating in sectors with more tangible assets can pledge more collateral and might find it easier to secure external finance (Braun and Larrain, 2005), thus experiencing a lower sensitivity to the receipt of R&D grants. Likewise, sectors featuring the ability to generate more cash-flow might be find it easier to self-finance their investment and display a lower responsiveness to the receipt of R&D grants (Brown et al., 2009). We use two proxies for a sector's financial vulnerability: asset tangibility and liquidity. We compute these proxies using firm-level balance-sheet data for the period preceding the competition, so that the effects of the grant do not contaminate the sectoral proxies. We first calculate asset tangibility (i.e. tangible assets over total assets) and liquidity (cash-flow over total assets) at the firm-level and use the median value across all firms within a 2-digit NACE rev. 2 sector. We then group the sectors depending on whether they are above or below the corresponding median. We report estimation results in Table 11 and show that firms operating in sectors that are financially stronger (i.e. characterized by higher asset tangibility and liquidity) display smaller treatment effects with respect to firms active in financially weaker sectors.

Table 11: Heterogeneous effects across sector-level proxies of financial constraints (Phase II)

	(1) Patents^{Post}	(2) PE^{Post}	(3) Investment^{Post}	(4) Assets^{Post}	(5) Employees^{Post}	(6) Revenues^{Post}	(7) Failure^{Post}
Grant	0.226***	0.098***	0.451***	0.661***	0.420***	0.535***	-0.053***
	(0.077)	(0.035)	(0.123)	(0.083)	(0.064)	(0.165)	(0.016)
CFA > p50	-0.040***	-0.012***	-0.080***	-0.008	0.076***	0.088***	-0.034***
	(0.014)	(0.004)	(0.020)	(0.020)	(0.014)	(0.028)	(0.005)
Grant × CFA > p50	-0.083	-0.049*	-0.250**	-0.292***	-0.204***	-0.146	0.013
	(0.081)	(0.029)	(0.119)	(0.086)	(0.067)	(0.136)	(0.018)
Rank × Award	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	10580	7927	5100	6971	5263	4885	10874
R-squared	0.36	0.07	0.07	0.16	0.14	0.19	0.04
	(1) Patents^{Post}	(2) PE^{Post}	(3) Investment^{Post}	(4) Assets^{Post}	(5) Employees^{Post}	(6) Revenues^{Post}	(7) Failure^{Post}
Grant	0.204**	0.073**	0.416***	0.578***	0.333***	0.498***	-0.041***
	(0.080)	(0.031)	(0.113)	(0.074)	(0.059)	(0.131)	(0.014)
TNG > p50	-0.054***	-0.008*	-0.087***	-0.049**	-0.008	0.044	0.001
	(0.019)	(0.005)	(0.019)	(0.024)	(0.015)	(0.031)	(0.007)
Grant × TNG > p50	-0.061	0.010	-0.227**	-0.258***	-0.106*	-0.177	-0.012
	(0.108)	(0.034)	(0.099)	(0.078)	(0.063)	(0.138)	(0.017)
Rank × Award	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	10580	7927	5100	6971	5263	4885	10874
R-squared	0.36	0.07	0.07	0.16	0.14	0.19	0.04

Notes: results obtained using equation (1) augmented with a sectoral-level financial constraint proxy. We compute the sectoral-level measures of financial constraints using pre-determined firm-level variables and then taking the median only for those 2-digit NACE rev. 2 sector with at least 50 observations. CFA is a dummy variable taking the value of 1 if a sector is above the median level of cash-flow over total assets, and 0 otherwise. TNG is a dummy variable taking the value of 1 if a sector is above the median level of tangible assets over total assets, and 0 otherwise. All regressions include the pre-grant dependent variables and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Third, we investigate potential heterogeneous effects across countries. In particular, we examine whether the impact of R&D grant varies according to the economic development of the recipients' country. We use GDP per-capita and divide countries in two groups using the corresponding median value[40]. Estimates reported in Table 12 suggest that the effects of R&D grants generally decline with levels of economic development. Next, we investigate the heterogeneous response across different levels of financial development. If R&D grants alleviate financial constraints, one might expect to find larger treatment effects for those firms located in countries with lower availability of credit. To do so we employ country-level data on the ratio of domestic credit to the private sector to GDP and divide the sample based on the corresponding median level (Beck et al., 2000).[41] Results suggest a negative relationship between financial development levels and treatment effects for most outcomes. In other words, firms in countries with lower credit availability tend to reap larger benefits from R&D grants. The only exception for both economic and financial development is private equity: countries with the highest economic and

[40] GDP per-capita data refer to 2013 and are in constant 2010 US dollars. They are drawn from the World Bank Development Indicators.

[41] Data are drawn from the World Bank Global Financial Development Database. Data refer to 2013. While financial development is linked with economic development, the samples slightly differ from each other (i.e. five countries change quantile).

financial development feature the largest treatment effects. One potential explanation for this is related to the supply-side: private equity plays a bigger role in countries with highly developed capital markets (Brown et al., 2009) and private equity firms, which are more abundant in such countries, tend to invest in firms that are closer to them.

Table 12: Heterogeneous effects across country-level economic and financial development (Phase II)

	(1) Patents^{Post}	(2) PE^{Post}	(3) Investment^{Post}	(4) Assets^{Post}	(5) Employees^{Post}	(6) Revenues^{Post}	(7) Failure^{Post}
Grant	0.147*	0.010	0.718**	0.939***	0.543***	0.874***	0.009
	(0.088)	(0.021)	(0.336)	(0.159)	(0.087)	(0.209)	(0.035)
GDP > p50	0.140***	0.025***	0.054**	0.119***	0.137***	0.198***	0.039***
	(0.016)	(0.003)	(0.027)	(0.028)	(0.019)	(0.034)	(0.007)
Grant × GDP > p50	0.063	0.067***	-0.400	-0.470***	-0.281***	-0.500***	-0.060
	(0.105)	(0.017)	(0.330)	(0.156)	(0.085)	(0.190)	(0.036)
N	11095	8352	5326	7306	5493	5119	11402
R-squared	0.36	0.07	0.07	0.16	0.15	0.20	0.04
	(1) Patents^{Post}	(2) PE^{Post}	(3) Investment^{Post}	(4) Assets^{Post}	(5) Employees^{Post}	(6) Revenues^{Post}	(7) Failure^{Post}
Grant	0.098	0.024	0.814**	0.959***	0.575***	0.966***	0.000
	(0.097)	(0.030)	(0.332)	(0.166)	(0.090)	(0.221)	(0.029)
FIN > p50	-0.017	0.011***	0.078***	0.119***	0.137***	0.195***	0.037***
	(0.018)	(0.004)	(0.024)	(0.029)	(0.018)	(0.038)	(0.005)
Grant × FIN > p50	0.114	0.054**	-0.484	-0.475***	-0.289***	-0.593***	-0.052*
	(0.111)	(0.026)	(0.322)	(0.162)	(0.081)	(0.193)	(0.030)
N	11055	8319	5300	7268	5468	5089	11360
R-squared	0.36	0.07	0.07	0.16	0.15	0.20	0.04

Notes: results obtained using equation (1) augmented with a country-level proxies for economic and financial development. We compute the country-level measures of economic and financial development using, respectively, GDP-per capita and domestic credit to the private sector for 2013. GDP is a dummy variable taking the value of 1 if a country is above the median level of GDP-per capita, and 0 otherwise. FIN is a dummy variable taking the value of 1 if a country is above the median level of domestic credit to the private sector, and 0 otherwise. All regressions include linear ranks on both sides of the thresholds, pre-grant dependent variables and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

We further explore differential effects of R&D grants across levels of economic development from a more disaggregated perspective. In more detail, we test for potential heterogeneous effects across European regions (NUTS2) depending on their GDP per capita to understand whether grants spur larger effects in more disadvantaged regions. Results in Table 13 show that being located in a more economically advanced region does not lead to a statistically different effect in terms of of patenting and equity. Also, for the remaining outcomes, we observe that firms in relatively poorer regions enjoy larger effects. These findings suggest that the effects of R&D grants are generally more beneficial for firms operating in laggard regions.

6 Disentangling potential mechanisms

The positive impact of the SME Instrument could be materialising through different channels. In principle, one can think about two main mechanisms, that is, funding or certification (Lerner, 2000; Howell, 2017). Funding refers to the possibility that the R&D subsidies allow firms to successfully develop a technology and thus to decrease investment risk. Certification, instead, refers to the possibility that the grant provides a positive signal about firm (or project) quality

Table 13: Heterogeneous effects across regional economic development (Phase II)

	(1) Patents^{Post}	(2) PE^{Post}	(3) Investment^{Post}	(4) Assets^{Post}	(5) Employees^{Post}	(6) Revenues^{Post}	(7) Failure^{Post}
Grant	0.248***	0.065*	0.591***	0.708***	0.459***	0.586***	-0.003
	(0.074)	(0.034)	(0.147)	(0.087)	(0.064)	(0.154)	(0.023)
REG > p50	0.110***	0.022***	0.044**	0.101***	0.102***	0.165***	0.029***
	(0.014)	(0.004)	(0.022)	(0.019)	(0.014)	(0.027)	(0.006)
Grant × REG > p50	-0.049	0.006	-0.307**	-0.251***	-0.222***	-0.219*	-0.050**
	(0.085)	(0.030)	(0.143)	(0.081)	(0.063)	(0.129)	(0.023)
N	10130	7879	5198	7112	5281	4982	10419
R-squared	0.36	0.07	0.07	0.16	0.15	0.20	0.04

Notes: results obtained using equation (1) augmented with a region-level proxy for economic development. We compute the region-level measure of economic development using the NUTS2 GDP-per capita for 2013. REG is a dummy variable taking the value of 1 if a NUTS2 region is above the median level of GDP per capita, and 0 otherwise. All regressions include linear ranks on both sides of the thresholds, pre-grant dependent variables and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

to the market (Takalo and Tanayama, 2010) that decreases information asymmetries about the quality of the investment proposition. In order to test which of the above mechanisms may be at work, we run further tests.

First, we exploit information on those firms that are considered eligible for the grant but are eventually discarded due to the scheme's budgetary constraints. EASME awards the so-called "Seal of Excellence" (SOE) certificate with the specific aim to signal firm quality to other public institutions and private investors, and to help unsuccessful firms to secure alternative funding. We leverage these data and re-run our models limiting the sample to competitions with at least one SOE attributed to a non-winning firm. If certification is the main mechanisms behind the positive effects of the scheme, differences between grant-winning firms and SOE-winning firms should be smaller compared with baseline estimates.[42] Although in some cases point estimates tend to be slightly smaller, all results tend to be strongly confirmed, thus indicating that certification is not the mechanism that drives our findings (Table A22).

Second, we re-run our models using only firms that received the SOE and the rest of unsuccessful firms. This test is based on the idea that, if the certification channel is at work, this would imply the presence of statistically significant differences in post-grant outcomes between the winners of the SOE and all the other firms that neither win the grant nor the SOE. In this case our treatment variable is the SOE itself and the re-centered threshold lies between the last SOE winning firm and the first SOE losing firm. Results reported in Table 14 document an absence of statistically significant differences for all firm-level outcomes (the only exception is revenues, although this is not confirmed when we vary the bandwidth). Even in this case, our tests do not provide support in favour of the certification channel.

Third, another potential explanation for the absence of certification is the possibility that the effect is present only for first-time recipients. The intuition is that certification is beneficial at first but repeated certifications are redundant and might even be detrimental to firm performance

[42] Note that this tests also represents an ideal robustness check given that, for such competitions, randomization of treatment assignment should be particularly strong.

Table 14: SOE-winning firms vs rest of losing firms (Phase II)

	Patents^{Post}		PE^{Post}		Assets^{Post}	
	(1) All	(2) ±10	(3) All	(4) ±10	(5) All	(6) ±10
Seal	0.025	0.037	-0.001	-0.006	0.033	-0.006
	(0.023)	(0.066)	(0.007)	(0.016)	(0.030)	(0.093)
N	10528	2386	7768	1766	6892	1636
R-squared	0.35	0.39	0.07	0.11	0.11	0.20
	Employees^{Post}		Revenues^{Post}		Failure^{Post}	
	(1) All	(2) ±10	(3) All	(4) ±10	(5) All	(6) ±10
Seal	0.017	0.075	0.085**	0.088	-0.011*	-0.030
	(0.022)	(0.073)	(0.038)	(0.126)	(0.007)	(0.019)
N	5191	1255	4844	1138	10819	2460
R-squared	0.12	0.23	0.16	0.22	0.03	0.09

Notes: results obtained using different specifications of equation (1) by means of OLS. The treatment variable (Seal) is a dummy variable indicating whether a firm has received the Seal of Excellence. Ranks are re-centered so that 0 lies between the last SOE-winning firms and the first SOE-losing firm. All regressions include the pre-grant dependent variable, linear controls for ranks on both sides of the threshold, and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

(Lanahan and Armanios, 2018). Results for the tests discussed above could also be influenced by a small share of firms that receive the SOE multiple times. To rule this out, we find no clear-cut evidence of certification when we include only first-time applicants or first-time SOE winners.

Fourth, it might be that the certification effects stemming from the SOE entail a weaker signal to the market than the one contained in the receipt of the grant. While the results on private financing are consistent, in principle, with certification effects, the results on patenting and the remaining outcomes are not directly ascribable to this channel. If certification is at work, the effects on patenting should work through the receipt of private equity after the competition. That is, only those firms receiving private equity thanks to the certification effect of the grant should witness an increase in patenting. To check if the effects on patenting are due to equity financing, we re-run our models by splitting the sample into firms that do or do not receive private equity after the grant. Results show that the increase in patenting is mainly driven by those firms not receiving private equity (Table 15).

On the contrary, the effect on private equity can be explained by post-competition patenting. Indeed, those firms filing patent applications after the receipt of the grant have higher probabilities of receiving private equity than those that do not patent (see Table 16). This is consistent with the funding channel: grants are used by firms to perform R&D activities that result in a patentable technology; this, in turn, provides a quality 'stamp' that attracts private finance. Hence, if anything, certification effects (stemming from patents) are at work via funding effects.

Fifth, if funding is the main mechanism we should observe that firms that receive larger grants enjoy greater performance premia (Lerner, 2000). On the contrary, if certification were the main one, a large subsidy would yield a similar effect to a small one. To explore this, we

Table 15: The effects on patents for firms (not) receiving private equity (Phase II)

	Patents^{Post}			
	(1) w/ PE^{Post}	(2) w/o PE^{Post}	(3) w/ PE^{Post}	(4) w/o PE^{Post}
Grant	0.063	0.233***	-0.247	0.266**
	(0.365)	(0.071)	(0.521)	(0.132)
Rank × Grant	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	No	Yes	Yes
N	242	7921	242	7921
R-squared	0.69	0.40	0.70	0.40

Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is the log of cite-weighted patents plus one. Odd columns reports estimations using only firms with post-grant private equity. Even columns use only firms without post-grant private equity. All regressions include the pre-grant dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 16: The effects on private equity for firms (not) patenting (Phase II)

	PE^{Post}			
	(1) w/o Pat^{Post}	(2) w/ Pat^{Post}	(3) w/o Pat^{Post}	(4) w/ Pat^{Post}
Grant	0.040	0.099**	0.054	0.200***
	(0.031)	(0.047)	(0.056)	(0.063)
Rank × Grant	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	No	Yes	Yes
N	6424	1911	6424	1911
R-squared	0.06	0.13	0.06	0.13

Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is a dummy variable indicating whether a firm has received private equity financing after the competition. Odd columns limit the sample to firms without post-grant patenting activities while even columns include only firms with post-grant patenting activities. All regressions include the pre-grant dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

exploit variation in R&D grant size in Phase II (the amount varies from 0.5 up to 2.5 million). We run our baseline models letting the $Grant_{ic}$ coefficient vary depending on whether the winning firm gets an above-median or below-median grant. Although coefficients of these two interactions are not always statistically different between each other, we can observe that firms getting larger amount of subsidies systematically drive the overall results (Table A21). Although we cannot exclude altogether that larger grants represent themselves stronger signals to investors when seeking financing, we interpret this as further evidence that certification is not the main mechanisms through which the SME Instrument generates its outcomes.

Sixth, as already mentioned, the positive effects of R&D grants on private equity are consistent with the certification hypothesis. In this scenario, the quality signal generated by the grant is expected to benefit winners as soon as the competition results are announced. Hence, the impact of certification is expected to materialize immediately after competitions. We therefore estimate treatment effects over time (i.e. from time t to time $t + 2$). Results show that the positive effects of the grant emerge only at time $t + 2$ (see FigureA3). This delay constitutes evidence against the certification effect.

Seventh, we check whether ranks are correlated with outcomes conditional on receiving the R&D grant. This is informative because private investors observe winners (and SOE-winning firms) within each competition and this could be perceived as a signal of firms' quality. We explore this by examining the coefficients on ranks in all our models for private equity financing and find no statistically significant relationship. Also, we examined whether ranks are predictive of future private equity financing when the sample is composed only by grant-winning and SOE-winning firms. In this scenario, both groups of firms receive some form of certification and we could expect ranks to be correlated with obtaining subsequent finance on both sides of the threshold. However, ranks have relatively small explanatory power and we do not detect any statistically significant association.

Eighth, we exploit balance-sheet data to study whether R&D grants affect the amount and composition of firms' debt. This is interesting since certification effects would arguably increase the chances for grant-winning firms to receive external debt by banks (Meuleman and De Maeseneire, 2012). The signal about firm quality contained in the grant may help lenders in their evaluation of borrowers by reducing asymmetries of information and the perceived risk of innovative projects. Moreover, certification might entail an effect on the type of debt: banks might be more willing to provide long-term debt to firms that already received a positive screening by government agencies. Hence, for certification to be the main channel, these conjectures should be reflected into i) an increase in the amount of debt and ii) a re-balancing towards long-term debt. We begin by testing whether R&D grants cause an increase in total debt over total assets. Results indicate that the effects are negative but generally not statistically significant, thus rejecting the certification effect (Table A23). Next, we examine the effects of the R&D grants on the ratio between long-term debt over total debt. Point estimates are positive but small in magnitude and never statistically significant (Table A24). In sum, these tests indicate the absence of any strong evidence in support of the role of certification in driving the effects of the policy scheme. Note that this does not mean that the SOE could or should not be used to allocate further funding that may become available from other agencies. It only means that in order to make a difference to firm performance, the quality assessment - which appears to be able to select valuable projects - must be associated with funding.[43]

7 Robustness and falsification tests

In this section we report a number of robustness tests and falsification tests to check the sensitivity of the results. We perform falsification tests with placebo thresholds; we employ alternative

[43] There exist additional mechanisms that could be potentially at play but we are unable to test. One example is business coaching. As already mentioned, the EU hosts the winners for approximately 12 days during the first year of Phase II. While helpful in enhancing applicants' organisational capabilities, management practices and possibly improve firms' networking this is unlikely to make a difference that is separable from funding.

criteria to select bandwidths; we estimate our models using different estimation techniques such as difference-in-difference, local polynomial models with triangular kernel and a local randomization approach. Finally, we test the sensitivity of results to different samples, error clustering and fixed effects structures.

Placebo tests - we investigate the presence of discontinuities in our firm-level outcome variables away from the true threshold that assigns treatment. Obtaining significant estimates in correspondence of placebo thresholds would cast doubts on the 'smoothness' assumption which lies behind the RD design thus suggesting spurious results. We vary the threshold arbitrarily to test whether the effects are actually determined by the grant. Instead of considering the centered rank threshold at 0, we use a placebo threshold between ranks 1 and 2 or, alternatively, between rank -2 and -1. To avoid "contamination" from real treatment effects, we respectively restrict observations to treated (untreated) firms for the artificial threshold above (below) the actual cut-off (Cattaneo et al., 2019). We run these models for all firm outcomes and find no systematic relationship between the placebo thresholds and firm outcomes (Table 17).

Alternative bandwidths - the baseline approach uses two different bandwidths around the threshold. To test the sensitivity of our results to bandwidth choice we run the models for Phase II varying the bandwidth between 1 and 25 on both sides of the thresholds. Results are displayed in Figure A4 and show that point estimates are consistently above zero for all firm outcomes variables but revenues, which is reassuring of the robustness of our main findings.

Alternative fixed effects and standard error clustering - in our benchmark estimation approach we include competition fixed effects which control for differences across sectoral topics. Yet, this approach might fail to capture more granular differences across sectors. In order to test the sensitivity of our results, we augment the models including a larger number of fixed effects such as competition, sector (two-digit NACE), cohort, and country dummies. We also included dummies for firms with multiple applications and a dummy for those firms winning Phase I and participating to Phase II. Results shown in Online Appendix Table A25 are largely unaltered. Furthermore, we also tested the robustness of our results to alternative standard errors clustering choices. Lee and Card (2008) argue that in presence of a discrete running variable one should use standard errors that are clustered at each of the different values taken by the rank. However, Kolesár and Rothe (2018) recommend against using confidence intervals based on standard errors clustered at the rank-level by providing theoretical and empirical evidence showing that they do not guard against model misspecification and that they have poor coverage properties. Instead, they argue that Eicker-Huber-White heteroskedasticity-robust standard error generally have better coverage properties. Following their indication we employ Eicker-Huber-White heteroskedasticity-robust standard errors and obtain similar patterns of statistical significance (Table A26). We also use standard errors clustered at the rank-level or at the firm-level which confirm our findings.

Table 17: Placebo tests for Phase II

	Patents^{Post}				PE^{Post}			
	(1) 0;10	(2) -10;0	(3) 0;5	(4) -5;0	(5) 0;10	(6) -10;0	(7) 0;5	(8) -5;0
Placebo Grant (2)	-0.391 (0.253)		-0.204 (0.198)		-0.045 (0.049)		-0.028 (0.080)	
Placebo Grant (-2)		-0.044 (0.086)		-0.032 (0.123)		-0.038* (0.020)		-0.036 (0.035)
N	418	1362	317	685	326	989	242	479
R-squared	0.58	0.47	0.60	0.58	0.35	0.18	0.40	0.30
	Assets^{Post}				Employees^{Post}			
	(1) 0;10	(2) -10;0	(3) 0;5	(4) -5;0	(5) 0;10	(6) -10;0	(7) 0;5	(8) -5;0
Placebo Grant (2)	0.126 (0.251)		0.130 (0.436)		0.103 (0.112)		-0.041 (0.174)	
Placebo Grant (-2)		0.051 (0.141)		-0.055 (0.258)		-0.036 (0.082)		0.094 (0.154)
N	180	636	122	285	205	704	143	323
R-squared	0.65	0.43	0.69	0.57	0.65	0.29	0.69	0.47
	Revenues^{Post}				Failure^{Post}			
	(1) 0;10	(2) -10;0	(3) 0;5	(4) -5;0	(5) 0;10	(6) -10;0	(7) 0;5	(8) -5;0
Placebo Grant (2)	-0.031 (0.131)		-0.248 (0.212)		0.003 (0.028)		0.010 (0.044)	
Placebo Grant (-2)		-0.059 (0.105)		0.090 (0.175)		0.020 (0.025)		0.029 (0.039)
N	291	968	202	465	427	1401	324	704
R-squared	0.67	0.29	0.71	0.39	0.27	0.13	0.36	0.21

Notes: results obtained using a placebo threshold between ranks -2 and -1 or, alternatively, between rank 1 and 2. For the placebo threshold above the actual one, estimates are obtained using bandwidths from centered ranks 0 to 10 (or 0 to 5). For the placebo threshold below the actual one, estimates are obtained using bandwidths from centered ranks -10 to 0 (or -5 to 0). All regressions include linear ranks on both sides of the threshold, the pre-grant dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Non-parametric estimations - our main findings are obtained by means of a parametric approach. However, in case the model is misspecified, parametric estimates might be inconsistent. We provide results obtained using a non-parametric approach and re-run our models using a triangular kernel. Point estimates show similar patterns in both magnitudes and statistical significance (Table A27).

Bias-corrected estimations with data-driven bandwidths - we resort to the recent developments by Calonico et al. (2015, 2017) that allow us to obtain local polynomial RD estimates with bias-correction, robust inference and data-driven bandwidth selection. Additionally, the estimation procedure adjusts for the presence of few mass points around the threshold as it is here. We test for different specifications using either linear or quadratic interpolation of the running variable and two bandwidth selectors: a common MSE-optimal or two different MSE-optimal bandwidth below and above the threshold. Results are reported in Online Appendix Table A28 and Table A29 and are consistent with our baseline findings.

External validity - our econometric strategy allows to infer local average treatment effects (LATE) and not average treatment effects (ATE) that can be generalized to the entire population of interest. In other words, the causal impact is obtained by comparing firms near the threshold but do not necessarily refer to the entire number of applicants. Therefore, we test the stability of our RD estimates in order to understand whether the estimated effects can be potentially extended to firms that are marginally away from the threshold. To do so we follow Dong and Lewbel (2015) and Cerulli et al. (2017) and compute the treatment effects derivative (TED). The TED is the derivative of the RD treatment effect with respect to the running variable. If TED is statistically significant and large in magnitude, this is evidence of instability and hence a potential lack of external validity. In contrast, having TED near-zero provides evidence in support of the stability of RD estimates. We report the TED for our baseline models in Online Appendix Table A30 and show that point estimates are not significant and small in magnitude, thus reassuring us on the stability and external validity of the results.

Local randomization approach - A natural alternative to analyzing an RD design with a discrete running variable is a local randomization approach. This method allows the researcher to use finite-sample exact randomization inference tools, which are particularly appealing in applications where the number of observations near the threshold is small (Cattaneo et al., 2015). This approach changes the parameter of interest from the RD treatment effect at the threshold to the RD treatment effect in the neighborhood around the threshold where local randomization is assumed to hold. A key advantage of this alternative conceptual framework is that, unlike the standard continuity-based approach of the RD, it can be used even when there are very few mass points in the running variable (Cattaneo et al., 2015). Indeed, it can be used with as few as two mass points, as it is here, if we assume that the first unsuccessful firm and first winner is where the randomization is at its peak. In other words, with a discrete running variable we know the exact location of the minimum window around the threshold: this window is the interval of the running variable that contains the two mass points, one on each side of the threshold, that are immediately consecutive to the threshold value. In our case, we take firms ranked -1 and 1 and run our local randomization approach. A valid local randomization requires the absence of any systematic difference in predetermined covariates between treated and untreated firms. Online Appendix Table A31 shows that the difference-in-means between firms ranked -1 and 1 for each covariate is indistinguishable from zero thus confirming the validity of the approach. Results are reported in Online Appendix Table A32 and largely corroborate our main findings.

Difference-in-differences - the availability of a longitudinal data gives us the possibility to test whether our results hold when combining a difference-in-differences (DID) with the RD design (Frandsen, 2014). This is useful in several ways. First of all, the larger number of observations generates an increase in statistical power. Second, the DID allows us to control for group-specific unobserved characteristics or, alternatively, for firm unobserved heterogeneity. This is important especially for the innovation outcomes because of the well-known persistence of innovative activities. DID controls for potential heterogeneity in the performances of treated and untreated firms before the program. This is relevant because there is evidence that studies assessing the impact of R&D subsidies on firm outcomes tend to yield larger program effects when methods do not control for firm unobservable factors (Dimos and Pugh, 2016). We run the following equation using all firms (i.e. infinite bandwidth) as well as those closer to the threshold (i.e. bandwidth of 10 and 5):

$$Y_{i,c,t} = \gamma Grant_{i,c} + \delta Post_{i,c,t} + \beta Grant_{i,c} \times Post_{i,c,t} + f\left(Rank_{i,c}\right) + X_{ic}\mathit{\Gamma} + \varepsilon_{i,c,t} \qquad (2)$$

where $Y_{i,c,t}$ is an outcome variable for firm i, in competition c, at time t. $Grant_{i,c}$ is a time-invariant dummy variable indicating whether firm i wins competition c, $Post_{i,c,t}$ is an indicator variable for the post-program period, and $Grant_{i,c} \times Post_{i,c,t}$ is equal to 1 for those observations in the treatment group in the post-program period and represents the coefficient of interest. All regressions control for linear polynomials of the running variable separately on each side of the threshold. Additionally, X_i is a vector of firm-level covariates encompassing competition, country, sector (2-digit NACE rev. 2), cohort, and time fixed effects. We also run different specifications including firm-by-application fixed effects, which control for unobserved firm heterogeneity.[44] Standard errors are clustered at the competition-level, though results hold when using either firm or rank clustering. Tables A33 and A34 report the results. Point estimates are positive and significant for assets, employees, revenues, as well as for the number of cite-weighted patents and the amount of private equity received. Hence, this represents corroboratory evidence and indicate that time-invariant firm differences do not drive the findings from the previous sections.

Sample selection - we re-run our main baseline models using only first-time applicants and found similar results. Additionally, we repeated the analysis excluding the five competitions with the largest number of participants. Moreover, given that competitions in health-related topics award more generous R&D grants (i.e. up to €5 million), we dropped these competitions and obtained unaltered results.

8 Conclusions

Governments around the world use R&D grants to affect both the rate and the direction of technological change by prioritizing technological areas that may be affected by the most serious market failures, may trigger the strongest positive externalities, and/or may yield the highest expected social returns. Yet, the empirical literature has not provided conclusive results on their

[44] This is done to accommodate firms that may apply more than once, and it amounts to consider each application made by a firm as a different unit following Cellini et al. (2010) and Hvide and Meling (2019).

effectiveness. Together with the view that governments should avoid ‘picking winners’ (Lerner, 2009), this is arguably one of the main reasons behind the shift towards more indirect and ‘technology neutral’ forms of support (i.e. R&D tax credits) observed in several OECD countries over the last twenty years (Appelt et al., 2019). More recently, however, there has been renewed interest in the use of more direct forms of support, often inspired by the funding activities of the US Federal Agencies (Mazzucato, 2015; Bloom et al., 2019). In this study we exploit confidential data on the applicants of a large-scale R&D grants European program modelled after the US SBIR program. We leverage the availability of rankings to adopt a sharp RD design, thus providing the broadest quasi-experimental evidence on the effects of public R&D support across sectors and countries. First, our results indicate that R&D grants to small and young innovative firms have large and positive effects on cite-weighted patents, investment, firm growth, the probability of receiving external equity and on firm survival. Overall these findings suggest the absence of ‘crowding-out’ effects stemming from public direct R&D support. Second, the paper uses the wide variety in terms of applicants’ characteristics to explore heterogeneous effects over several dimensions. The evidence points to the role of R&D grants in alleviating financial constraints that typically hamper innovation. We document that R&D grants are especially beneficial for firms operating in countries as well as regions that are relatively less developed. Third, the mechanism behind the positive results appears to be funding, rather than pure certification, because it makes it possible for firms to pursue early-stage technology development, prove its viability, decrease technical and market uncertainty, and increase the likelihood of further external investments.

From a broader perspective, our findings join a recent stream of literature using clearer causal identification strategies on the effects of R&D grants (Howell, 2017), R&D procurement (Moretti et al., 2019) and R&D tax credits (Dechezleprêtre et al., 2019) which constitute a robust empirical base documenting the effectiveness of government support for private innovative investment.

In terms of policy implications, the results reveal a considerable success for the program, in spite of its relatively young age and short period over which we detect positive outcomes. This indicates that small and young European firms are highly receptive to policy initiatives designed to support their riskier activities and that the funding agency has been rather effective in doing so. Furthermore, the study suggests that adopting SBIR-type policies can produce positive results in contexts other than the US. It is worth noticing that the positive effects generated by the SME Instrument have been so far achieved with a budget that is still way below the current US SBIR budget (roughly 1/5) and European policy-makers might therefore consider allocating an even larger budget to this form of support.

Results concerning Phase I grants are less positive. Phase I does not appear to generate quantifiable benefits. One possibility, which we leave for future research, is that results stemming for this early-stage (smaller) grants might materialize over a longer time span than the one considered here. Furthermore, the absence of a positive impact of Phase I might also indicate that European innovative SMEs might be facing higher barriers when it comes to securing external funds for R&D rather than for proof-of-concept activities.

There is obviously no shortage of extensions and new questions for further research on this topic. We highlight two. The first one is the long-term effects of the program. The second one concerns the nature and extent of spillovers that could further amplify across firms, and perhaps cluster within regions, the positive effects of R&D grants.

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9 Online Appendix

Table A1: Descriptive statistics on SMEi competitions (2014-2017) - raw sample

	Mean	SD	Median	N
Panel A: Phase I				
mean # firms	162.99	130.07	163	173
mean # grant-winning firms	13.32	10.05	11	173
% grant-winning firms	0.10	0.06	0	173
% first applicants	0.65	0.14	1	173
% firms in consortium	0.06	0.03	0	173
% firms below available budget	0.09	0.07	0	173
	Mean	SD	Median	N
Panel B: Phase II				
mean # firms	84.68	74.35	68	176
mean # grant-winning firms	4.09	3.08	3	176
% grant-winning firms	0.07	0.07	0	176
% first applicants	0.59	0.20	1	176
% firms in consortium	0.18	0.09	0	176
% firms that won Phase I	0.12	0.08	0	176
% firms below available budget	0.36	0.16	0	176

Table A2: Descriptive statistics on SMEi competitions (2014-2017) - cleaned sample

	Mean	SD	Median	N
Panel A: Phase I				
mean # firms	104.14	81.76	102	173
mean # grant-winning firms	7.34	5.53	6	173
% grant-winning firms	0.08	0.05	0	173
% first applicants	0.49	0.18	0	173
% firms in consortium	0.06	0.04	0	173
% firms below available budget	0.10	0.08	0	173
	Mean	SD	Median	N
Panel B: Phase II				
mean # firms	63.06	56.98	50	176
mean # grant-winning firms	2.66	2.17	2	176
% grant-winning firms	0.06	0.07	0	176
% first applicants	0.48	0.25	0	176
% firms in consortium	0.18	0.10	0	176
% firms that won Phase I	0.15	0.10	0	176
% firms below available budget	0.40	0.17	0	176

Table A3: Descriptive statistics on SMEi applications (2014-2017)

	Phase I	Phase II
Panel A: raw data		
# unique firms	18564	8052
# firm-applications	28198	14904
	Phase I	Phase II
Panel B: cleaned data		
# unique firms	8726	4528
# firm-applications	18012	11095

Fig. A1: Applicants by centered ranks - raw data

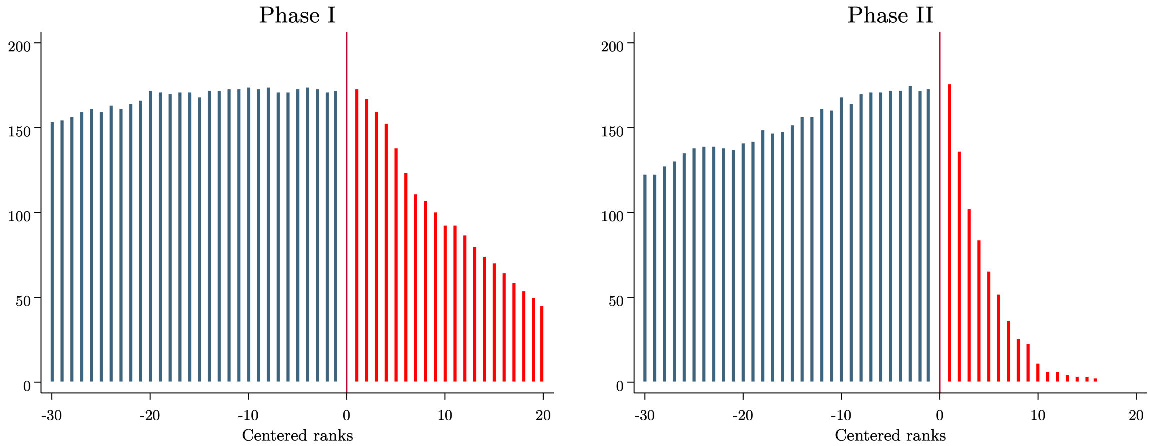


Fig. A2: Applicants by centered ranks - cleaned data

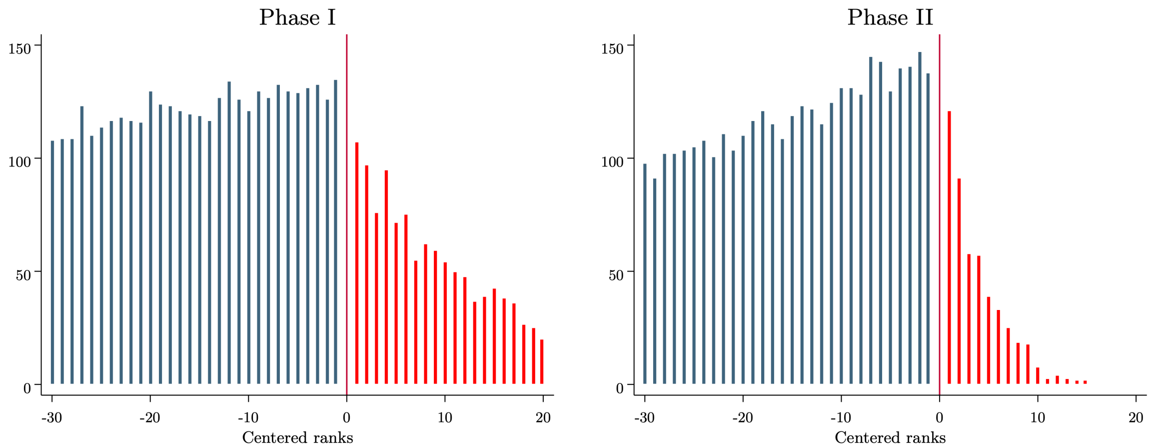


Table A4: Comparison between applicants population and sample

	Phase I			Phase II		
	(1)	(2)	Std. Diff.	(1)	(2)	Std. Diff.
Applicants	133.59	138.20	-0.102	75.29	78.03	-0.152
Partners	1.07	1.07	-0.003	1.23	1.22	0.043
Uncentered ranks	134.48	125.96	0.184	76.13	73.47	0.140
Grant (%)	0.08	0.07	0.112	0.05	0.04	0.105
Local10 (%)	0.11	0.11	0.046	0.16	0.16	0.035
Local5 (%)	0.06	0.06	0.027	0.10	0.09	0.005
Firms in consortium (%)	0.05	0.05	0.003	0.16	0.15	0.032
North (%)	0.12	0.13	0.042	0.17	0.17	0.055
South (%)	0.39	0.42	0.173	0.33	0.35	0.137
East (%)	0.18	0.15	0.179	0.10	0.09	0.114
West (%)	0.26	0.26	0.030	0.34	0.33	0.052
Other (%)	0.05	0.04	0.176	0.06	0.06	0.092
Application year	2015.75	2015.82	0.192	2016.03	2016.09	0.249
Cut-off date	2.56	2.57	0.035	2.62	2.65	0.101
Grant amount (th. euros)				1638.79	1632.74	0.023
N	28198	18012		14904	11095	

Notes: columns 1 contain means for the population of applicants. Columns 2 uses the sample of firms without missing variables for patents. Columns 3 reports mean standardized differences betweeen these two samples. All variables can be interpreted as percentages except for applicants, partners, uncentered ranks, application year, cut-off date and grant amount. Applicants refer to the number of participating firms; partners refer to the number of firms participating in the same application; uncentered ranks is the average raw rank. Grant indicates the percentage of winning firms; Seal the percentage of firms awarded with the "Seal of Excellence"; Losers refer to the remaining applicants; Grant amount is the amount received by winning firms and it is reported for Phase II only since there is no variation in grant amount in Phase I.

Table A5: Applicants' countries

	ISO	Type	GDP	Population		Sample	
				N	%	N	%
Anguilla (UK)	AI	OCT	.	10	0.0		
Albania	AL	H2020	Q1	13	0.0	7	0.0
Armenia	AM	H2020	Q1	12	0.0		
Austria	AT	EU-28	Q2	580	1.3	385	1.3
Bosnia and Herzegovina	BA	H2020	Q1	24	0.1	10	0.0
Belgium	BE	EU-28	Q2	576	1.3	451	1.5
Bulgaria	BG	EU-28	Q1	771	1.8	346	1.2
Switzerland	CH	H2020	Q2	261	0.6	179	0.6
Cyprus	CY	EU-28	Q2	147	0.3	103	0.4
Czech Republic	CZ	EU-28	Q1	350	0.8	240	0.8
Germany	DE	EU-28	Q2	2521	5.8	1709	5.9
Denmark	DK	EU-28	Q2	1045	2.4	766	2.6
Estonia	EE	EU-28	Q1	538	1.2	364	1.3
Greece	EL	EU-28	Q1	627	1.5	135	0.5
Spain	ES	EU-28	Q2	6863	15.9	5314	18.3
Finland	FI	EU-28	Q2	1327	3.1	976	3.4
Faroer Islands (Denmark)	FO	H2020	Q2	20	0.0	12	0.0
France	FR	EU-28	Q2	2322	5.4	1327	4.6
Georgia	GE	H2020	Q1	6	0.0		
Greenland (Denmark)	GL	OCT	Q2	1	0.0	1	0.0
Croatia	HR	EU-28	Q1	291	0.7	136	0.5
Hungary	HU	EU-28	Q1	1388	3.2	804	2.8
Ireland	IE	EU-28	Q2	687	1.6	499	1.7
Israel	IL	H2020	Q2	1501	3.5	1041	3.6
Iceland	IS	H2020	Q2	221	0.5	145	0.5
Italy	IT	EU-28	Q2	7457	17.3	5234	18.0
Lithuania	LT	EU-28	Q1	264	0.6	179	0.6
Luxembourg	LU	EU-28	Q2	58	0.1	42	0.1
Latvia	LV	EU-28	Q1	373	0.9	281	1.0
Moldova	MD	H2020	Q1	45	0.1	11	0.0
Montenegro	ME	H2020	Q1	11	0.0	3	0.0
Macedonia	MK	H2020	Q1	42	0.1	7	0.0
Malta	MT	EU-28	Q2	74	0.2	44	0.2
Netherlands	NL	EU-28	Q2	1543	3.6	1118	3.8
Norway	NO	H2020	Q2	783	1.8	546	1.9
Poland	PL	EU-28	Q1	1498	3.5	894	3.1
Portugal	PT	EU-28	Q1	881	2.0	669	2.3
Romania	RO	EU-28	Q1	341	0.8	232	0.8
Serbia	RS	H2020	Q1	176	0.4	82	0.3
Sweden	SE	EU-28	Q2	1346	3.1	920	3.2
Slovenia	SI	EU-28	Q2	883	2.0	635	2.2
Slovakia	SK	EU-28	Q1	389	0.9	277	1.0
Turkey	TR	H2020	Q1	859	2.0	237	0.8
Ukraine	UA	H2020	Q1	198	0.5	36	0.1
United Kingdom	UK	EU-28	Q2	3773	8.8	2710	9.3
Virgin Islands (UK)	VG	OCT	.	6	0.0		
Total				43102	100.0	29107	100.0

Notes: elaboration based on EASME data for 2014-2017 SME Instrument competitions. Type indicates whether the country is part of the European Union or an Horizon2020 associated country. Anguilla, Greenland and Virgin Islands are Overseas Countries and Territories (OCT) linked to the EU Member States. Area indicates the geographic area of the country. GDP indicates the quantile of GDP-per capital level (i.e. Q1 for low economic development, Q2 for high economic development). Data for GDP are drawn from the World Bank Development Indicators. Empty cells indicate missing obervations.

Table A6: Competition topics

	Population		Sample	
	N	%	N	%
Open Disruptive Innovation Scheme	10893	25.3	7228	24.8
Nanotechnologies	4157	9.6	2805	9.6
Biotechnology	1226	2.8	878	3.0
Space research and development	714	1.7	488	1.7
Healthcare biotechnology	1188	2.8	871	3.0
ICT solutions for health, well-being and ageing well	4200	9.7	2856	9.8
Sustainable agriculture, forestry, agri-food and bio-based sectors	3228	7.5	2234	7.7
Innovative solutions for blue growth	633	1.5	439	1.5
Low carbon and efficient energy system	4595	10.7	3138	10.8
Transport and Smart Cities Mobility	3895	9.0	2506	8.6
Climate action, environment, resource efficiency and raw materials	3908	9.1	2594	8.9
New business models for inclusive, innovative and reflective societies	2869	6.7	1957	6.7
Security research and development	1596	3.7	1113	3.8
Total	43102	100.0	29107	100.0

Notes: elaboration based on EASME data for competition taking place during the period 2014-2017.

Table A7: The effects on investment over longer time span

	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel A: Phase I							
Grant	0.023	-0.011	-0.014	-0.028	-0.384	-0.457	0.059
	(0.074)	(0.104)	(0.059)	(0.188)	(0.402)	(0.378)	(0.873)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4951	4951	4951	635	635	311	311
# competitions	125	125	125	122	122	97	97
R-squared	0.06	0.06	0.06	0.21	0.22	0.31	0.32
AIC	13546.06	13549.58	13561.43	1676.60	1676.18	748.02	750.39
	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel B: Phase II							
Grant	0.640***	0.808**	0.329***	0.688**	1.178**	1.130***	1.746**
	(0.199)	(0.317)	(0.121)	(0.273)	(0.460)	(0.380)	(0.766)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2796	2796	2796	614	614	347	347
# competitions	119	119	119	117	117	101	101
R-squared	0.09	0.09	0.09	0.26	0.27	0.39	0.40
AIC	7829.43	7830.79	7831.52	1871.52	1871.85	1053.47	1056.10

Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is the cumulated investments during time t, $t+1$ and $t+2$ scaled by total assets at $t-1$. Regressions include total assets at $t-1$. Both variables are winsorized at the 2% and 98% of the distribution over the whole sample. Columns 1 to 3 report estimates using infinite bandwidths (i.e. all firms). Columns 4-5 and 6-7 report estimates obtained using bandwidths of, respectively, 10 and 5 ranks around the cut-off. All regressions include the pre-grant dependent variable (log of assets at time $t-1$) and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: The effects on investment in tangibles

	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel A: Phase I							
Grant	-0.021	-0.019	0.001	0.001	0.020	0.060	0.079
	(0.013)	(0.017)	(0.010)	(0.029)	(0.046)	(0.045)	(0.094)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
$Rank^2$ × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	9803	9803	9803	1206	1206	638	638
# competitions	173	173	173	173	173	161	161
R-squared	0.03	0.03	0.03	0.15	0.15	0.25	0.25
AIC	1734.83	1738.29	1741.08	-353.35	-351.03	-259.58	-255.80
	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel B: Phase II							
Grant	0.077***	0.072*	0.061***	0.066*	0.109*	0.121**	0.280**
	(0.027)	(0.041)	(0.019)	(0.036)	(0.062)	(0.059)	(0.116)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
$Rank^2$ × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6790	6790	6790	1224	1224	689	689
# competitions	173	173	173	173	173	163	163
R-squared	0.04	0.04	0.04	0.19	0.19	0.26	0.26
AIC	-202.26	-201.87	-202.66	11.79	14.28	26.10	25.71

Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is the cumulated investments in tangibles during time t and $t+1$ scaled by total assets at $t-1$. Regressions include total assets at $t-1$. Both variables are winsorized at the 2% and 98% of the distribution over the whole sample. Columns 1 to 3 report estimates using infinite bandwidths (i.e. all firms). Columns 4-5 and 6-7 report estimates obtained using bandwidths of, respectively, 10 and 5 ranks around the cut-off. All regressions include the pre-grant dependent variable (log of assets at time $t-1$) and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: The effects on investment in intangibles

	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel A: Phase I							
Grant	0.037	0.018	-0.017	0.048	-0.059	-0.005	-0.088
	(0.042)	(0.053)	(0.033)	(0.084)	(0.156)	(0.146)	(0.290)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
$\text{Rank}^2\times$ Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	9803	9803	9803	1208	1208	639	639
# competitions	173	173	173	173	173	161	161
R-squared	0.04	0.04	0.04	0.17	0.17	0.27	0.27
AIC	20399.42	20395.52	20395.34	2338.67	2341.47	1090.90	1094.67
	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel B: Phase II							
Grant	0.228**	0.213	0.235***	0.238**	0.230	0.350**	0.860***
	(0.088)	(0.139)	(0.061)	(0.103)	(0.178)	(0.145)	(0.322)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
$\text{Rank}^2\times$ Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6782	6782	6782	1221	1221	688	688
# competitions	173	173	173	173	173	163	163
R-squared	0.06	0.06	0.06	0.21	0.22	0.30	0.30
AIC	13328.99	13324.93	13323.01	2596.36	2593.83	1442.77	1441.46

Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is the cumulated investments in intangibles during time t and $t+1$ scaled by total assets at $t-1$. Regressions include total assets at $t-1$. Both variables are winsorized at the 2% and 98% of the distribution over the whole sample. Columns 1 to 3 report estimates using infinite bandwidths (i.e. all firms). Columns 4-5 and 6-7 report estimates obtained using bandwidths of, respectively, 10 and 5 ranks around the cut-off. All regressions include the pre-grant dependent variable (log of assets at time $t-1$) and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: The effects on patents (dummy)

	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel A: Phase I							
Grant	0.049***	0.034	0.034**	-0.019	-0.092	-0.054	-0.113
	(0.018)	(0.025)	(0.013)	(0.041)	(0.065)	(0.054)	(0.116)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
$\text{Rank}^2 \times$ Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	18012	18012	18012	2026	2026	1090	1090
# competitions	173	173	173	173	173	173	173
R-squared	0.17	0.17	0.17	0.23	0.23	0.31	0.31
AIC	10402.00	10383.97	10370.64	1769.34	1770.97	826.39	829.78
	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel B: Phase II							
Grant	0.105***	0.142***	0.079***	0.086*	0.160**	0.185***	0.222*
	(0.033)	(0.054)	(0.025)	(0.044)	(0.073)	(0.061)	(0.128)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
$\text{Rank}^2 \times$ Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11095	11095	11095	1822	1822	1050	1050
# competitions	176	176	176	176	176	175	175
R-squared	0.24	0.24	0.24	0.33	0.33	0.38	0.38
AIC	10186.57	10186.62	10173.11	1750.68	1752.27	940.73	944.04

Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is a dummy indicating with 1 if a firm has applied for a patent starting from the year after the competition, and 0 otherwise. Columns 1 to 3 report estimates using infinite bandwidths (i.e. all firms). Columns 4-5 and 6-7 report estimates obtained using bandwidths of, respectively, 10 and 5 ranks around the cut-off. All regressions include the pre-grant dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: The effects on patents (count)

	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel A: Phase I							
Grant	0.071**	0.064*	0.053**	-0.015	-0.034	-0.007	0.009
	(0.028)	(0.037)	(0.021)	(0.066)	(0.109)	(0.088)	(0.180)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
$\text{Rank}^2 \times$ Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	18012	18012	18012	2026	2026	1090	1090
# competitions	173	173	173	173	173	173	173
R-squared	0.23	0.23	0.23	0.30	0.30	0.38	0.38
AIC	25151.58	25146.18	25139.21	3629.76	3633.70	1790.04	1793.14
	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel B: Phase II							
Grant	0.215***	0.301***	0.146***	0.159**	0.243*	0.307***	0.328
	(0.061)	(0.105)	(0.045)	(0.077)	(0.124)	(0.102)	(0.212)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
$\text{Rank}^2 \times$ Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11095	11095	11095	1822	1822	1050	1050
# competitions	176	176	176	176	176	175	175
R-squared	0.35	0.35	0.35	0.44	0.44	0.50	0.50
AIC	21048.00	21046.02	21038.95	3788.70	3790.62	2085.63	2089.29

Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is the (log) number of patent applications plus one starting from the year after the competition, and 0 otherwise. Columns 1 to 3 report estimates using infinite bandwidths (i.e. all firms). Columns 4-5 and 6-7 report estimates obtained using bandwidths of, respectively, 10 and 5 ranks around the cut-off. All regressions include the pre-grant dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A12: The effects on cite-weighted patents (negative binomial models)

	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel A: Phase I							
Grant	0.228	0.293	0.140	-0.058	-0.058	-0.485	-0.485
	(0.172)	(0.245)	(0.138)	(0.406)	(0.406)	(0.572)	(0.572)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	Yes	No	No	No	No	No
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	18012	18012	18012	2026	2026	1090	1090
# competitions	173	173	173	173	173	173	173
Pseudo R-squared	0.07	0.07	0.06	0.11	0.11	0.16	0.16
AIC	26518.68	26520.57	26535.54	4440.68	4440.68	2464.50	2464.50
	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel B: Phase II							
Grant	0.526**	0.918***	0.400**	0.462*	0.492	0.780**	0.624
	(0.235)	(0.353)	(0.185)	(0.260)	(0.406)	(0.329)	(0.711)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11095	11095	11095	1822	1822	1051	1051
# competitions	176	176	176	176	176	176	176
Pseudo R-squared	0.07	0.07	0.07	0.11	0.11	0.14	0.14
AIC	27270.65	27114.88	27113.88	5694.81	5667.84	3446.41	3456.04

Notes: results obtained using different specifications of equation (1) using negative binomial models. The dependent variable is the number of cite-weighted patents after the competition. Columns 1 to 3 report estimates using infinite bandwidths (i.e. all firms). Columns 4-5 and 6-7 report estimates obtained using bandwidths of, respectively, 10 and 5 ranks around the cut-off. All regressions include the pre-grant dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A13: The effects on the extensive margin for patents (Phase II)

	Patents^{Post} (d)							
	w/o Patents^{Pre}				w/ Patents^{Pre}			
	(1) All	(2) All	(3) ±10	(4) ±10	(5) All	(6) All	(7) ±10	(8) ±10
Grant	0.096**	0.108	0.113**	0.129	0.130***	0.181**	0.095	0.256**
	(0.042)	(0.073)	(0.054)	(0.092)	(0.045)	(0.070)	(0.072)	(0.124)
Rank × Grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	Yes	No	Yes	No	Yes	No	Yes
N	7005	7005	999	999	4080	4080	803	803
R-squared	0.09	0.09	0.28	0.28	0.10	0.10	0.26	0.26
AIC	3390.47	3390.71	538.03	541.84	5499.56	5502.67	906.89	906.09

Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is a dummy indicating with 1 if a firm has applied for a patent starting from the year after the competition, and 0 otherwise. Columns 1 to 4 report different specifications using the sample of firms without pre-competition patents. Columns 5 to 8 report different specifications using the sample of firms wit pre-competition patents. All regressions include competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A14: The effects on private equity amount

	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel A: Phase I							
Grant	-0.021	0.049	0.021	0.080	-0.112	-0.099	-0.380*
	(0.056)	(0.069)	(0.035)	(0.079)	(0.127)	(0.086)	(0.217)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
$\text{Rank}^2 \times$ Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15784	15784	15784	1666	1666	897	897
# competitions	173	173	173	173	173	172	172
R-squared	0.03	0.03	0.03	0.11	0.11	0.19	0.20
AIC	32509.49	32498.24	32522.02	4544.19	4546.21	1858.79	1860.73
	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel B: Phase II							
Grant	0.386	0.969***	0.200	0.464**	0.766**	0.731**	1.391**
	(0.236)	(0.369)	(0.123)	(0.228)	(0.366)	(0.302)	(0.660)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
$\text{Rank}^2 \times$ Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8352	8352	8352	1358	1358	784	784
# competitions	176	176	176	176	176	168	168
R-squared	0.06	0.06	0.06	0.16	0.16	0.28	0.28
AIC	29029.25	29013.26	29034.37	4919.97	4920.19	2833.94	2835.67

Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is the (log) of one plus the private equity amount received after the competition. Columns 1 to 3 report estimates using infinite bandwidths (i.e. all firms). Columns 4-5 and 6-7 report estimates obtained using bandwidths of, respectively, 10 and 5 ranks around the cut-off. All regressions include the pre-grant dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A15: The effects on private equity deals

	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel A: Phase I							
Grant	-0.004	0.004	-0.002	0.012	-0.026	-0.016	-0.109**
	(0.011)	(0.013)	(0.008)	(0.016)	(0.028)	(0.023)	(0.052)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2× Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15784	15784	15784	1666	1666	897	897
# competitions	173	173	173	173	173	172	172
R-squared	0.02	0.02	0.02	0.12	0.12	0.22	0.23
AIC	-18332.28	-18342.69	-18330.20	-380.70	-378.63	-793.62	-794.21
	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel B: Phase II							
Grant	0.082**	0.158***	0.037*	0.093**	0.183***	0.156***	0.235**
	(0.035)	(0.054)	(0.019)	(0.037)	(0.062)	(0.050)	(0.109)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2× Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8352	8352	8352	1358	1358	784	784
# competitions	176	176	176	176	176	168	168
R-squared	0.07	0.07	0.07	0.20	0.20	0.30	0.30
AIC	-1213.95	-1222.69	-1201.09	-7.26	-9.62	10.15	12.68

Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is the (log) of one plus the number of private equity deals after the competition. Columns 1 to 3 report estimates using infinite bandwidths (i.e. all firms). Columns 4-5 and 6-7 report estimates obtained using bandwidths of, respectively, 10 and 5 ranks around the cut-off. All regressions include the pre-grant dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A16: The effects on assets (levels)

	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel A: Phase I							
Grant	0.070	-0.030	0.022	0.099	0.133	0.313	0.582
	(0.062)	(0.083)	(0.051)	(0.129)	(0.229)	(0.208)	(0.391)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
$\text{Rank}^2\times$ Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7662	7662	7662	985	985	513	513
# competitions	139	139	139	125	125	118	118
R-squared	0.81	0.81	0.81	0.84	0.84	0.85	0.85
AIC	20274.95	20258.23	20255.92	2403.12	2404.16	1182.24	1185.08
	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel B: Phase II							
Grant	0.502***	0.602***	0.363***	0.476***	0.533***	0.539***	0.584*
	(0.078)	(0.123)	(0.069)	(0.110)	(0.172)	(0.160)	(0.345)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
$\text{Rank}^2\times$ Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4438	4438	4438	926	926	553	553
# competitions	145	145	145	123	123	119	119
R-squared	0.79	0.79	0.79	0.75	0.75	0.75	0.75
AIC	11027.56	11030.53	11019.18	2290.52	2294.30	1410.88	1413.84

Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is (log) assets at time $t + 1$ (with t being the year of the competition). The pre-award variable is the (log) assets at time $t - 1$. Both variables are winsorized at the 2% and 98% of the distribution over the whole sample. Columns 1 to 3 report estimates using infinite bandwidths (i.e. all firms). Columns 4-5 and 6-7 report estimates obtained using bandwidths of, respectively, 10 and 5 ranks around the cut-off. All regressions include the pre-grant dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A17: The effects on employment (levels)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	All	All	±10	±10	±5	±5
Panel A: Phase I							
Grant	-0.029	-0.004	-0.033	-0.065	0.028	0.035	-0.142
	(0.050)	(0.060)	(0.036)	(0.098)	(0.174)	(0.161)	(0.293)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
$\text{Rank}^2 \times$ Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5515	5515	5515	707	707	337	337
# competitions	167	167	167	136	136	108	108
R-squared	0.84	0.84	0.84	0.85	0.85	0.88	0.88
AIC	8747.94	8742.33	8741.93	1020.99	1023.95	417.12	420.36
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	All	All	±10	±10	±5	±5
Panel B: Phase II							
Grant	0.264***	0.196*	0.158***	0.203**	0.327**	0.302**	0.090
	(0.073)	(0.107)	(0.046)	(0.090)	(0.165)	(0.144)	(0.265)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
$\text{Rank}^2 \times$ Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3227	3227	3227	657	657	396	396
# competitions	150	150	150	120	120	110	110
R-squared	0.82	0.82	0.82	0.83	0.84	0.85	0.85
AIC	5102.15	5105.43	5104.49	923.01	921.92	512.34	514.58

Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is (log) employees at time $t+1$ (with t being the year of the competition). The pre-award variable is the (log) employees at time $t-1$. Both variables are winsorized at the 2% and 98% of the distribution over the whole sample. Columns 1 to 3 report estimates using infinite bandwidths (i.e. all firms). Columns 4-5 and 6-7 report estimates obtained using bandwidths of, respectively, 10 and 5 ranks around the cut-off. All regressions include the pre-grant dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A18: The effects on revenues (levels)

	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel A: Phase I							
Grant	0.069	0.030	0.036	0.075	0.194	0.284	0.476
	(0.073)	(0.088)	(0.056)	(0.151)	(0.232)	(0.216)	(0.495)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
$Rank^2 \times$ Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5916	5916	5916	707	707	348	348
# competitions	146	146	146	126	126	106	106
R-squared	0.79	0.79	0.79	0.82	0.82	0.86	0.86
AIC	16218.37	16207.20	16181.82	1792.50	1796.19	788.70	791.64
	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel B: Phase II							
Grant	0.332**	0.596***	0.277***	0.202	0.387	0.431	0.781
	(0.157)	(0.221)	(0.100)	(0.190)	(0.328)	(0.296)	(0.501)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
$Rank^2 \times$ Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3072	3072	3072	620	620	366	366
# competitions	137	137	137	118	118	105	105
R-squared	0.77	0.77	0.77	0.80	0.80	0.85	0.85
AIC	8693.72	8693.79	8691.58	1655.73	1659.11	909.42	909.94

Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is (log) revenues at time $t+1$ (with t being the year of the competition). The pre-award variable is the (log) revenues at time $t-1$. Both variables are winsorized at the 2% and 98% of the distribution over the whole sample. Columns 1 to 3 report estimates using infinite bandwidths (i.e. all firms). Columns 4-5 and 6-7 report estimates obtained using bandwidths of, respectively, 10 and 5 ranks around the cut-off. All regressions include the pre-grant dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A19: The effects on IPO

	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel A: Phase I							
Grant	-0.002*	-0.003*	-0.001	-0.004	0.003	0.003	0.012
	(0.001)	(0.002)	(0.001)	(0.003)	(0.004)	(0.005)	(0.014)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	No	No	No	No	No	No	No
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15973	15973	15973	1684	1684	908	908
# competitions	173	173	173	173	173	172	172
R-squared	0.02	0.02	0.02	0.12	0.12	0.33	0.33
AIC	-76355.96	-76354.23	-76358.53	-5606.38	-5605.81	-2973.68	-2970.43
	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel B: Phase II							
Grant	0.005	-0.003	0.004	-0.001	-0.009	-0.002	-0.038*
	(0.007)	(0.008)	(0.005)	(0.010)	(0.011)	(0.011)	(0.022)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	No	No	No	No	No	No	No
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8432	8432	8432	1365	1365	789	789
# competitions	176	176	176	176	176	168	168
R-squared	0.02	0.02	0.02	0.09	0.09	0.16	0.16
AIC	-25320.35	-25318.38	-25318.35	-3451.33	-3447.81	-1888.68	-1887.29

Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is a dummy indicating whether a firms has exited through an IPO (as of March 2019). Columns 1 to 3 report estimates using infinite bandwidths (i.e. all firms). Columns 4-5 and 6-7 report estimates obtained using bandwidths of, respectively, 10 and 5 ranks around the cut-off. All regressions include competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A20: The effects on M&A

	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel A: Phase I							
Grant	0.003	-0.004	0.004	0.004	0.014	0.020*	-0.002
	(0.006)	(0.007)	(0.005)	(0.012)	(0.015)	(0.011)	(0.017)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	No	No	No	No	No	No	No
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15973	15973	15973	1684	1684	908	908
# competitions	173	173	173	173	173	172	172
R-squared	0.02	0.02	0.02	0.09	0.09	0.18	0.18
AIC	-32033.04	-32039.83	-32047.38	-3038.34	-3038.17	-1793.11	-1791.17
	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel B: Phase II							
Grant	-0.010	-0.027**	-0.002	-0.001	-0.022	-0.009	-0.045
	(0.012)	(0.012)	(0.010)	(0.015)	(0.022)	(0.018)	(0.038)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	No	No	No	No	No	No	No
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8432	8432	8432	1365	1365	789	789
# competitions	176	176	176	176	176	168	168
R-squared	0.03	0.03	0.03	0.14	0.14	0.15	0.15
AIC	-9002.80	-9000.62	-9001.07	-1326.66	-1327.02	-1025.69	-1023.27

Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is a dummy indicating whether a firms has exited through an acquisition. Columns 1 to 3 report estimates using infinite bandwidths (i.e. all firms). Columns 4-5 and 6-7 report estimates obtained using bandwidths of, respectively, 10 and 5 ranks around the cut-off. All regressions include competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A21: Certification vs Funding (Phase II) - Test 4

	Patents^{Post}		Late VC^{Post}		Revenues^{Post}	
	(1) All	(2) ±10	(3) All	(4) ±10	(5) All	(6) ±10
Grant × Small	0.127	0.103	0.072**	0.081***	0.318**	0.184
	(0.081)	(0.092)	(0.031)	(0.030)	(0.136)	(0.131)
Grant × Large	0.259***	0.205**	0.084***	0.086***	0.599***	0.514***
	(0.080)	(0.083)	(0.031)	(0.031)	(0.121)	(0.126)
Rank × Grant	Yes	Yes	Yes	Yes	Yes	Yes
N	11095	1822	8352	1358	5119	867
# competitions	176	176	176	176	170	162
R-squared	0.36	0.45	0.06	0.17	0.19	0.43
	Employees^{Post}		Assets^{Post}		Failure^{Post}	
	(1) All	(2) ±10	(3) All	(4) ±10	(5) All	(6) ±10
Grant × Small	0.297***	0.211***	0.560***	0.402***	-0.045***	-0.035**
	(0.063)	(0.068)	(0.078)	(0.084)	(0.017)	(0.017)
Grant × Large	0.335***	0.285***	0.563***	0.466***	-0.055***	-0.036**
	(0.059)	(0.065)	(0.069)	(0.079)	(0.014)	(0.015)
Rank × Grant	Yes	Yes	Yes	Yes	Yes	Yes
N	5493	962	7306	1311	11402	1872
# competitions	171	166	174	174	176	176
R-squared	0.14	0.33	0.15	0.37	0.03	0.12

Notes: results obtained using different specifications of equation (1) by means of OLS. The award coefficient is interacted with a dummy variable that indicates with 1 the receipt of a R&D grant that is above the median value, with 0 below the median value. All regressions include the pre-grant dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A22: Winning firms vs SOE firms (Phase II)

	Patents^{Post}				PE^{Post}			
	(1) All	(2) All	(3) ±10	(4) ±10	(5) All	(6) All	(7) ±10	(8) ±10
Grant	0.203***	0.206***	0.147*	0.177*	0.071**	0.066**	0.081***	0.079***
	(0.068)	(0.073)	(0.085)	(0.091)	(0.028)	(0.027)	(0.028)	(0.028)
N	11095	5340	1822	1632	8218	3710	1329	1170
R-squared	0.36	0.38	0.45	0.48	0.07	0.09	0.17	0.19
	Assets^{Post}				Employees^{Post}			
	(1) All	(2) All	(3) ±10	(4) ±10	(5) All	(6) All	(7) ±10	(8) ±10
Grant	0.562***	0.518***	0.491***	0.526***	0.324***	0.317***	0.278***	0.295***
	(0.067)	(0.073)	(0.100)	(0.106)	(0.062)	(0.064)	(0.081)	(0.084)
N	7306	3651	1311	1166	5493	2782	962	856
R-squared	0.14	0.17	0.34	0.36	0.14	0.18	0.32	0.33
	Revenues^{Post}				Exit^{Post}			
	(1) All	(2) All	(3) ±10	(4) ±10	(5) All	(6) All	(7) ±10	(8) ±10
Grant	0.506***	0.380**	0.309**	0.287*	-0.044***	-0.033***	-0.033**	-0.027*
	(0.141)	(0.148)	(0.151)	(0.151)	(0.012)	(0.012)	(0.016)	(0.016)
N	5119	2548	867	776	11402	5474	1872	1674
R-squared	0.17	0.24	0.40	0.41	0.03	0.04	0.12	0.11

Notes: results obtained using different specifications of equation (1) by means of OLS. The sample exclusively includes winning firms and SOE firms. Odd columns report the baseline results whereas even columns contain estimates obtained by limiting the sample to winning and SOE firms. All regressions include the pre-grant dependent variable, linear polynomials for the centered ranks separately for each side of the threshold and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A23: The effects on debt over total assets

	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel A: Phase I							
Grant	-0.072	-0.094	-0.024	0.005	0.055	0.070	0.111
	(0.047)	(0.070)	(0.040)	(0.105)	(0.194)	(0.180)	(0.385)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2× Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	10491	10491	10491	1286	1286	675	675
# competitions	173	173	173	173	173	162	162
R-squared	0.39	0.39	0.39	0.42	0.42	0.43	0.43
AIC	24122.03	24125.09	24122.93	2684.68	2688.07	1486.89	1490.80
	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel B: Phase II							
Grant	-0.092	-0.130	-0.065*	-0.125	-0.174	-0.016	-0.425*
	(0.063)	(0.088)	(0.039)	(0.089)	(0.145)	(0.135)	(0.244)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2× Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4438	4438	4438	926	926	553	553
# competitions	145	145	145	123	123	119	119
R-squared	0.79	0.79	0.79	0.75	0.75	0.75	0.75
AIC	11027.56	11030.53	11019.18	2290.52	2294.30	1410.88	1413.84

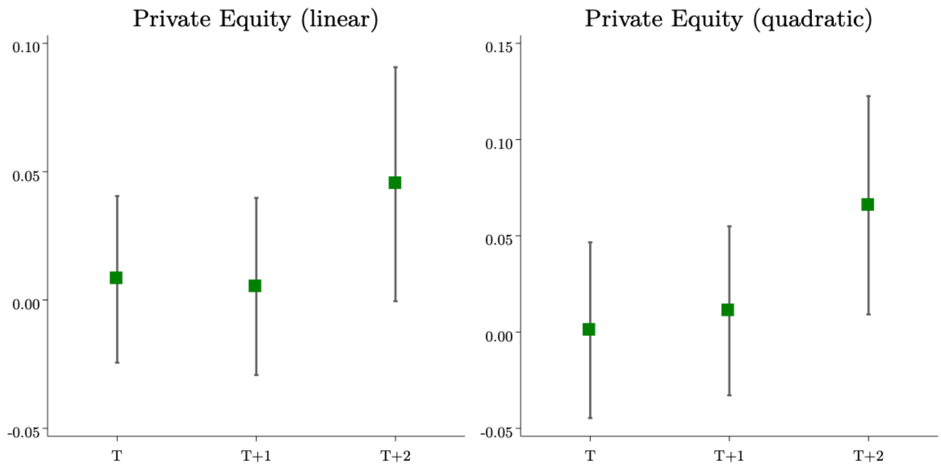
Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is the ratio between total debt and total assets at time $t + 1$ (with t being the year of the competition). The pre-award variable is the ratio between total debt and total assets at time $t - 1$. Both variables are winsorized at the 2% and 98% of the distribution over the whole sample. Columns 1 to 3 report estimates using infinite bandwidths (i.e. all firms). Columns 4-5 and 6-7 report estimates obtained using bandwidths of, respectively, 10 and 5 ranks around the cut-off. All regressions include the pre-grant dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A24: The effects on long-term debt over total debt

	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel A: Phase I							
Grant	0.020	0.007	0.007	0.000	-0.028	-0.078	0.030
	(0.019)	(0.025)	(0.015)	(0.041)	(0.073)	(0.069)	(0.145)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	No	No	No	No	No	No	No
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	9777	9777	9777	1180	1180	620	620
# competitions	173	173	173	173	173	160	160
R-squared	0.03	0.03	0.03	0.16	0.16	0.23	0.24
AIC	4014.93	4009.13	3994.95	348.46	350.56	162.46	163.58
	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel B: Phase II							
Grant	0.019	0.023	-0.021	0.008	0.039	0.027	0.052
	(0.029)	(0.044)	(0.018)	(0.042)	(0.064)	(0.058)	(0.110)
Rank × Grant	Yes	Yes	No	Yes	Yes	Yes	Yes
Rank^2 × Grant	No	Yes	No	No	Yes	No	Yes
Rank quintiles	No	No	Yes	No	No	No	No
Pre-grant	No	No	No	No	No	No	No
Competition FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6440	6440	6440	1156	1156	655	655
# competitions	174	174	174	172	172	160	160
R-squared	0.04	0.04	0.04	0.15	0.15	0.25	0.25
AIC	2369.46	2366.79	2357.45	314.42	317.87	103.61	106.80

Notes: results obtained using different specifications of equation (1) by means of OLS. The dependent variable is the ratio between long-term debt and total debt at time $t+1$ (with t being the year of the competition). The pre-award variable is the ratio between total debt and total assets at time $t-1$. Both variables are winsorized at the 2% and 98% of the distribution over the whole sample. Columns 1 to 3 report estimates using infinite bandwidths (i.e. all firms). Columns 4-5 and 6-7 report estimates obtained using bandwidths of, respectively, 10 and 5 ranks around the cut-off. All regressions include the pre-grant dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Fig. A3: Treatment effects over time for PE - Phase II



Notes: results obtained based on equation (1) with private equity (dummy) as dependent variable. Regressions include linear ranks on both sides (left), or quadratic ones (right), pre-grant dependent variable, competition fixed effects and based on firms within -10 and 10 centered ranks. Standard errors clustered at the competition-level. 95% confidence intervals reported.

Table A25: Alternative fixed effect structure

	Phase I				Phase II			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patents^{Post}	All	All	±10	±10	All	All	±10	±10
Grant	0.073**	0.066**	-0.033	-0.002	0.203***	0.221***	0.147*	0.120
	(0.031)	(0.032)	(0.072)	(0.075)	(0.068)	(0.069)	(0.085)	(0.090)
N	18012	17276	2026	1936	11095	10681	1822	1819
# FE	1	5	1	5	1	6	1	4
R-squared	0.23	0.27	0.31	0.37	0.36	0.41	0.45	0.47
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PE^{Post}	All	All	±10	±10	All	All	±10	±10
Grant	-0.008	-0.009	0.006	0.005	0.070**	0.072**	0.080***	0.074**
	(0.009)	(0.008)	(0.011)	(0.014)	(0.028)	(0.028)	(0.027)	(0.030)
N	15784	15352	1666	1608	8352	8153	1358	1308
# FE	1	5	1	5	1	6	1	6
R-squared	0.03	0.05	0.12	0.28	0.07	0.11	0.17	0.27
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Investment^{Post}	All	All	±10	±10	All	All	±10	±10
Grant	0.046	0.031	0.033	-0.062	0.354***	0.326***	0.373***	0.340***
	(0.039)	(0.037)	(0.094)	(0.095)	(0.094)	(0.092)	(0.115)	(0.113)
N	7594	7579	954	945	5326	5314	962	946
# FE	1	4	1	4	1	4	1	4
R-squared	0.04	0.16	0.21	0.41	0.07	0.21	0.26	0.42
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Assets^{Post}	All	All	±10	±10	All	All	±10	±10
Grant	0.046	0.030	0.033	-0.075	0.354***	0.305***	0.373***	0.319***
	(0.039)	(0.039)	(0.094)	(0.104)	(0.094)	(0.091)	(0.115)	(0.120)
N	7594	7577	954	936	5326	5311	962	934
# FE	1	5	1	5	1	6	1	6
R-squared	0.04	0.19	0.21	0.48	0.07	0.24	0.26	0.45
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Employees^{Post}	All	All	±10	±10	All	All	±10	±10
Grant	0.093*	0.093**	0.029	0.033	0.518***	0.491***	0.456***	0.360***
	(0.047)	(0.047)	(0.100)	(0.107)	(0.062)	(0.059)	(0.088)	(0.093)
N	10702	10657	1315	1293	7306	7269	1311	1286
# FE	1	5	1	5	1	6	1	6
R-squared	0.16	0.25	0.30	0.41	0.16	0.25	0.37	0.51
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Revenues^{Post}	All	All	±10	±10	All	All	±10	±10
Grant	0.017	0.013	-0.081	-0.021	0.451***	0.412***	0.248**	0.218
	(0.053)	(0.051)	(0.114)	(0.133)	(0.117)	(0.120)	(0.121)	(0.146)
N	8124	8100	958	934	5119	5100	867	840
# FE	1	5	1	5	1	6	1	6
R-squared	0.19	0.26	0.37	0.52	0.19	0.28	0.42	0.53
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Failure^{Post}	All	All	±10	±10	All	All	±10	±10
Grant	-0.014	-0.013	-0.035	-0.022	-0.044***	-0.044***	-0.033**	-0.043**
	(0.011)	(0.012)	(0.024)	(0.025)	(0.012)	(0.012)	(0.016)	(0.017)
N	18498	17738	2086	1993	11402	10985	1872	1804
# FE	1	5	1	5	1	5	1	5
R-squared	0.02	0.08	0.08	0.21	0.03	0.11	0.12	0.21

Notes: results obtained using different fixed effects. Odd columns contain only competitions fixed effects as in our benchmark specification, whereas even columns add country, cohort, a dummy for firms with multiple applicants and sector fixed effects. For Phase II models we included a dummy for those firms that won a Phase I grant. All regressions include the pre-grant dependent variable and linear polynomials on both sides of the threshold. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A26: Alternative standard errors clustering

	Phase I				Phase II			
Patents^{Post}	(1) All	(2) All	(3) ±10	(4) ±10	(5) All	(6) All	(7) ±10	(8) ±10
Grant	0.073**	0.073**	-0.033	-0.033	0.203***	0.203***	0.147*	0.147*
	(0.031)	(0.035)	(0.072)	(0.067)	(0.068)	(0.071)	(0.085)	(0.085)
N	18012	18012	2026	2026	11095	11095	1822	1822
SE	Comp.	EHW	Comp.	EHW	Comp.	EHW	Comp.	EHW
R-squared	0.23	0.23	0.31	0.31	0.36	0.36	0.45	0.45
PE^{Post}	(1) All	(2) All	(3) ±10	(4) ±10	(5) All	(6) All	(7) ±10	(8) ±10
Grant	-0.008	-0.008	0.006	0.006	0.070**	0.070**	0.080***	0.080***
	(0.009)	(0.008)	(0.011)	(0.012)	(0.028)	(0.027)	(0.027)	(0.029)
N	15784	15784	1666	1666	8352	8352	1358	1358
SE	Comp.	EHW	Comp.	EHW	Comp.	EHW	Comp.	EHW
R-squared	0.03	0.03	0.12	0.12	0.07	0.07	0.17	0.17
Investment^{Post}	(1) All	(2) All	(3) ±10	(4) ±10	(5) All	(6) All	(7) ±10	(8) ±10
Grant	0.046	0.046	0.033	0.033	0.354***	0.354***	0.373***	0.373***
	(0.039)	(0.040)	(0.094)	(0.094)	(0.094)	(0.093)	(0.115)	(0.113)
N	7594	7594	954	954	5326	5326	962	962
SE	Comp.	EHW	Comp.	EHW	Comp.	EHW	Comp.	EHW
R-squared	0.04	0.04	0.21	0.21	0.07	0.07	0.26	0.26
Assets^{Post}	(1) All	(2) All	(3) ±10	(4) ±10	(5) All	(6) All	(7) ±10	(8) ±10
Grant	0.093*	0.093**	0.029	0.029	0.518***	0.518***	0.456***	0.456***
	(0.047)	(0.046)	(0.100)	(0.101)	(0.062)	(0.063)	(0.088)	(0.087)
N	10702	10702	1315	1315	7306	7306	1311	1311
SE	Comp.	EHW	Comp.	EHW	Comp.	EHW	Comp.	EHW
R-squared	0.16	0.16	0.30	0.30	0.16	0.16	0.37	0.37
Employees^{Post}	(1) All	(2) All	(3) ±10	(4) ±10	(5) All	(6) All	(7) ±10	(8) ±10
Grant	-0.017	-0.017	-0.052	-0.052	0.299***	0.299***	0.251***	0.251***
	(0.037)	(0.033)	(0.068)	(0.073)	(0.053)	(0.054)	(0.071)	(0.074)
N	7614	7614	968	968	5493	5493	962	962
SE	Comp.	EHW	Comp.	EHW	Comp.	EHW	Comp.	EHW
R-squared	0.11	0.11	0.28	0.28	0.14	0.14	0.33	0.33
Revenues^{Post}	(1) All	(2) All	(3) ±10	(4) ±10	(5) All	(6) All	(7) ±10	(8) ±10
Grant	0.017	0.017	-0.081	-0.081	0.451***	0.451***	0.248**	0.248*
	(0.053)	(0.053)	(0.114)	(0.119)	(0.117)	(0.108)	(0.121)	(0.128)
N	8124	8124	958	958	5119	5119	867	867
SE	Comp.	EHW	Comp.	EHW	Comp.	EHW	Comp.	EHW
R-squared	0.19	0.19	0.37	0.37	0.19	0.19	0.42	0.42
Failure^{Post}	(1) All	(2) All	(3) ±10	(4) ±10	(5) All	(6) All	(7) ±10	(8) ±10
Grant	-0.014	-0.014	-0.035	-0.035	-0.044***	-0.044***	-0.033**	-0.033*
	(0.011)	(0.011)	(0.024)	(0.023)	(0.012)	(0.012)	(0.016)	(0.018)
N	18498	18498	2086	2086	11402	11402	1872	1872
SE	Comp.	EHW	Comp.	EHW	Comp.	EHW	Comp.	EHW
R-squared	0.02	0.02	0.08	0.08	0.03	0.03	0.12	0.12

Notes: results obtained using different standard errors clustering. Odd columns contain estimates with standard errors clustered at the competition-level as in the baseline models. Even columns report results obtained using Eicker-Huber-White heteroskedasticity-robust standard errors. All regressions include the pre-grant dependent variable and linear polynomials on both sides of the threshold. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A27: Non-parametric estimations

	Patents^{Post}		PE^{Post}		Assets^{Post}	
	(1) ±10	(2) ±5	(3) ±10	(4) ±5	(5) ±10	(6) ±5
Panel A: Phase I						
Grant	-0.055	-0.029	-0.008	-0.034*	-0.009	-0.085
	(0.085)	(0.126)	(0.013)	(0.018)	(0.120)	(0.252)
Rank × Grant	Yes	Yes	Yes	Yes	Yes	Yes
N	1853	891	1522	731	867	386
R-squared	0.34	0.41	0.14	0.26	0.27	0.43
	Employees^{Post}		Revenues^{Post}		Failure^{Post}	
	(1) ±10	(2) ±5	(3) ±10	(4) ±5	(5) ±10	(6) ±5
Grant	0.012	0.036	-0.007	0.024	-0.008	0.138
	(0.123)	(0.201)	(0.083)	(0.139)	(0.123)	(0.246)
Rank × Grant	Yes	Yes	Yes	Yes	Yes	Yes
N	1208	571	879	386	875	387
R-squared	0.32	0.43	0.35	0.50	0.42	0.49
	Patents^{Post}		PE^{Post}		Assets^{Post}	
	(1) ±10	(2) ±5	(3) ±10	(4) ±5	(5) ±10	(6) ±5
Panel B: Phase II						
Grant	0.204**	0.378***	0.089***	0.118**	0.383***	0.545***
	(0.094)	(0.133)	(0.031)	(0.050)	(0.128)	(0.206)
Rank × Grant	Yes	Yes	Yes	Yes	Yes	Yes
N	1685	883	1246	664	885	434
R-squared	0.48	0.56	0.25	0.41	0.32	0.44
	Employees^{Post}		Revenues^{Post}		Failure^{Post}	
	(1) ±10	(2) ±5	(3) ±10	(4) ±5	(5) ±10	(6) ±5
Grant	0.513***	0.683***	0.245***	0.175	0.213*	0.212
	(0.098)	(0.157)	(0.082)	(0.126)	(0.127)	(0.199)
Rank × Grant	Yes	Yes	Yes	Yes	Yes	Yes
N	1205	620	886	450	797	386
R-squared	0.42	0.52	0.41	0.52	0.51	0.62

Notes: results obtained using different specifications of equation (1) using triangular kernel. All regressions include the pre-grant dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A28: Robust bias-corrected local polynomial estimates with data-driven bandwidths

	Phase I				Phase II			
Patents^{Post}	(1) MSE	(2) MSE	(3) MSE2	(4) MSE2	(5) MSE	(6) MSE	(7) MSE2	(8) MSE2
RD_Estimate	-0.016	-0.059	0.033	0.009	0.161**	0.245**	0.161***	0.242**
Robust SE	0.054	0.079	0.045	0.064	0.108	0.154	0.102	0.139
Robust p-value	0.570	0.304	0.644	0.987	0.025	0.058	0.022	0.045
N left	2746	3323	8725	11600	2304	2632	4178	7144
N right	1132	1201	1201	1235	468	468	468	468
Order Poly.	1	2	1	2	1	2	1	2
BW left	22.6	27.5	88.4	132.1	18.2	21.8	37.8	78.0
BW right	22.6	27.5	27.9	31.3	18.2	21.8	18.9	25.9
PE^{Post}	(1) MSE	(2) MSE	(3) MSE2	(4) MSE2	(5) MSE	(6) MSE	(7) MSE2	(8) MSE2
RD_Estimate	-0.006	-0.003	-0.011*	-0.018**	0.087***	0.119***	0.082***	0.121***
Robust SE	0.009	0.012	0.007	0.009	0.039	0.057	0.038	0.054
Robust p-value	0.670	0.699	0.019	0.003	0.002	0.071	0.002	0.037
N left	2068	3021	6443	9189	1689	2151	4179	5643
N right	900	1012	944	996	377	377	377	377
Order Poly.	1	2	1	2	1	2	1	2
BW left	20.9	30.1	74.3	118.7	18.2	24.1	55.2	88.4
BW right	20.9	30.1	23.5	28.4	18.2	24.1	18.9	26.3
Investment^{Post}	(1) MSE	(2) MSE	(3) MSE2	(4) MSE2	(5) MSE	(6) MSE	(7) MSE2	(8) MSE2
RD_Estimate	0.028	-0.011	0.049	0.024	0.343***	0.393***	0.338***	0.363***
Robust SE	0.076	0.107	0.059	0.077	0.127	0.213	0.123	0.205
Robust p-value	0.829	0.719	0.571	0.907	0.003	0.069	0.003	0.120
N left	1084	1292	3946	5504	1133	1367	2496	3658
N right	521	558	566	579	246	246	246	246
Order Poly.	1	2	1	2	1	2	1	2
BW left	19.1	23.6	90.2	152.0	17.8	21.6	46.1	83.0
BW right	19.1	23.6	24.0	26.9	17.8	21.6	19.6	23.4
Assets^{Post}	(1) MSE	(2) MSE	(3) MSE2	(4) MSE2	(5) MSE	(6) MSE	(7) MSE2	(8) MSE2
RD_Estimate	0.038	0.032	0.064	0.044	0.457***	0.535***	0.435***	0.497***
Robust SE	0.083	0.114	0.069	0.091	0.094	0.142	0.082	0.123
Robust p-value	0.672	0.965	0.399	0.858	0.000	0.000	0.000	0.000
N left	1520	2027	5262	6736	1307	1627	3068	4906
N right	726	809	769	827	350	350	350	350
Order Poly.	1	2	1	2	1	2	1	2
BW left	19.4	27.0	85.2	121.0	14.5	18.4	40.0	80.1
BW right	19.4	27.0	22.6	29.0	14.5	18.4	21.6	24.6

Notes: results obtained using the estimator developed by Calonico et al. (2017) which account for few mass points around the threshold. Odd columns report estimations using the mean-square error bandwidth while even columns use the asymmetric mean-square error bandwidth. All regressions include the pre-grant dependent variable. Standard errors are robust and clustered at the competition level. Asterisks denote conventional $p-values$ while robust standard errors and robust $p-values$ are reported in the table. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A29: Robust bias-corrected local polynomial estimates with data-driven bandwidths

	Phase I				Phase II			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Employees^{Post}	MSE	MSE	MSE2	MSE2	MSE	MSE	MSE2	MSE2
RD_Estimate	-0.050	-0.077	-0.011	-0.025	0.242***	0.184**	0.243***	0.172**
Robust SE	0.038	0.066	0.031	0.049	0.052	0.082	0.042	0.067
Robust p-value	0.188	0.243	0.731	0.611	0.000	0.024	0.000	0.011
N left	1380	1270	4194	5129	968	1381	2494	3936
N right	594	581	618	603	259	259	259	259
Order Poly.	1	2	1	2	1	2	1	2
BW left	25.9	23.2	99.9	135.4	14.9	21.0	45.9	91.5
BW right	25.9	23.2	28.4	26.7	14.9	21.0	16.4	25.8
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Revenues^{Post}	MSE	MSE	MSE2	MSE2	MSE	MSE	MSE2	MSE2
RD_Estimate	-0.081	-0.093	-0.077	-0.079	0.250***	0.319**	0.290***	0.399***
Robust SE	0.084	0.118	0.067	0.083	0.136	0.198	0.130	0.186
Robust p-value	0.377	0.406	0.288	0.223	0.014	0.315	0.003	0.147
N left	1205	1303	3126	5138	1049	1213	1653	3257
N right	544	557	579	579	234	234 :	234	234
Order Poly.	1	2	1	2	1	2	1	2
BW left	21.3	23.4	63.8	123.5	17.5	20.2	29.5	73.5
BW right	21.3	23.4	26.4	26.5	17.5	20.2	18.9	25.5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Failure^{Post}	MSE	MSE	MSE2	MSE2	MSE	MSE	MSE2	MSE2
RD_Estimate	-0.023	-0.039	-0.022*	-0.031*	-0.036***	-0.040**	-0.030***	-0.036***
Robust SE	0.020	0.029	0.016	0.021	0.016	0.024	0.011	0.017
Robust p-value	0.169	0.100	0.105	0.094	0.008	0.277	0.002	0.276
N left	2709	2949	8897	12008	2019	2252	4758	7424
N right	1160	1194	1246	1276	479	479	479	479
Order Poly	1	2	1	2	1	2	1	2
BW left	21.9	23.2	87.7	133.3	15.6	17.8	42.3	79.8
BW right	21.9	23.2	27.5	30.3	15.6	17.8	23.8	21.4

Notes: results obtained using the estimator developed by Calonico et al. (2017) which account for few mass points around the threshold. Odd columns report estimations using the mean-square error bandwidth while even columns use the asymmetric mean-square error bandwidth. All regressions include the pre-grant dependent variable. Standard errors are robust and clustered at the competition level. Asterisks denote conventional $p-values$ while robust standard errors and robust $p-values$ are reported in the table. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A30: Treatment effects derivatives

Patents^{Post}	(1) ±10	(2) ±10	(3) ±5	(4) ±5
TED	-0.013	-0.090	-0.073*	-0.130
	(0.021)	(0.067)	(0.038)	(0.209)
N	1822	1822	1050	1050
R-squared	0.45	0.45	0.51	0.51
PE^{Post}	(1) ±10	(2) ±10	(3) ±5	(4) ±5
TED	-0.011	-0.034	-0.020*	-0.017
	(0.007)	(0.023)	(0.012)	(0.064)
N	1358	1358	784	784
R-squared	0.17	0.17	0.27	0.27
Investment^{Post}	(1) ±10	(2) ±10	(3) ±5	(4) ±5
TED	-0.030	0.032	0.048	-0.114
	(0.023)	(0.114)	(0.054)	(0.295)
N	962	962	529	529
R-squared	0.26	0.26	0.38	0.38
Assets^{Post}	(1) ±10	(2) ±10	(3) ±5	(4) ±5
TED	-0.017	-0.007	0.018	-0.188
	(0.020)	(0.064)	(0.042)	(0.204)
N	1311	1311	743	743
R-squared	0.37	0.37	0.45	0.45
Employees^{Post}	(1) ±10	(2) ±10	(3) ±5	(4) ±5
TED	-0.018	0.031	0.015	0.005
	(0.015)	(0.059)	(0.033)	(0.171)
N	962	962	548	548
R-squared	0.33	0.33	0.46	0.46
Revenues^{Post}	(1) ±10	(2) ±10	(3) ±5	(4) ±5
TED	-0.055**	-0.119	-0.075	-0.081
	(0.028)	(0.116)	(0.068)	(0.317)
N	867	867	480	480
R-squared	0.42	0.42	0.55	0.55
Failure^{Post}	(1) ±10	(2) ±10	(3) ±5	(4) ±5
TED	0.006	-0.005	0.011	-0.046
	(0.005)	(0.015)	(0.009)	(0.047)
N	1872	1872	1077	1077
R-squared	0.12	0.12	0.19	0.19

Notes: reported coefficients are treatment effects derivatives (Dong and Lewbel, 2015; Cerulli et al., 2017). Odd columns report estimates using linear controls for centered ranks whereas even columns report estimates obtained quadratic controls for centered ranks. All regressions include the pre-grant dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A31: Local Randomization analysis for pre-determinated covariates

Panel A: Phase I	(1) Patents^{Pre}	(2) PE^{Pre}	(3) Assets^{Pre}	(4) Employees^{Pre}	(5) Revenues^{Pre}	(6) Age^{Pre}
Grant	-0.008 [0.962]	0.000 [1.000]	0.005 [0.989]	-0.025 [0.924]	0.093 [0.820]	0.007 [0.961]
N	240	196	146	106	101	229
Panel B: Phase II	(1) Patents^{Pre}	(2) PE^{Pre}	(3) Assets^{Pre}	(4) Employees^{Pre}	(5) Revenues^{Pre}	(6) Age^{Pre}
Grant	0.012 [0.966]	-0.020 [0.748]	-0.000 [0.998]	-0.076 [0.711]	-0.065 [0.871]	-0.002 [0.984]
N	257	197	184	129	120	262

Notes: results obtained using the Local Randomization approach of Cattaneo et al. (2015) to test for differences in predetermined covariates between treated and untreated firms. All firms ranking just above and below the threshold (i.e. ranks -1 and 1) are included. Tables report difference-in-means and Fisherian p-values for finite sample inference in brackets. Estimates obtained using 1000 replications. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A32: Local Randomization estimates

Panel A: Phase I	(1) Patents^{Post}	(2) PE^{Post}	(3) Assets^{Post}	(4) Employees^{Post}	(5) Revenues^{Post}	(6) Failure^{Post}
Grant	-0.036 [0.749]	-0.019 [0.520]	0.114 [0.444]	-0.005 [0.960]	0.128 [0.446]	-0.050 [0.148]
N	240	196	146	106	101	229
Panel B: Phase II	(1) Patents^{Post}	(2) PE^{Post}	(3) Assets^{Post}	(4) Employees^{Post}	(5) Revenues^{Post}	(6) Failure^{Post}
Grant	0.227* [0.085]	0.112*** [0.004]	0.539*** [0.000]	0.257*** [0.006]	0.252 [0.176]	-0.056** [0.028]
N	257	197	184	129	120	262

Notes: results obtained using the Local Randomization approach of Cattaneo et al. (2015). All firms ranking just above and below the threshold (i.e. ranks -1 and 1) are included. Tables report difference-in-means and Fisherian p-values for finite sample inference in brackets. Estimates obtained using 1000 replications. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A33: Difference-in-differences models - Phase II

	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel A: Revenues							
Grant × Post	0.375***	0.349***	0.279***	0.243**	0.225***	0.295***	0.220**
	(0.090)	(0.076)	(0.071)	(0.098)	(0.081)	(0.112)	(0.095)
Rank × Grant	Yes	Yes	No	Yes	No	Yes	No
Sector FE	No	Yes	No	Yes	No	Yes	No
Cohort FE	No	Yes	No	Yes	No	Yes	No
Competition FE	Yes	Yes	No	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	Yes	No	Yes	No
Firm-application FE	No	No	Yes	No	Yes	No	Yes
N	12281	12235	11064	2039	1852	1163	1058
# competitions	175	175	175	175	174	167	166
R-squared	0.07	0.48	0.95	0.62	0.94	0.69	0.94
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	All	All	±10	±10	5	5
Panel B: Assets							
Grant × Post	0.476***	0.438***	0.422***	0.395***	0.387***	0.390***	0.409***
	(0.053)	(0.050)	(0.049)	(0.061)	(0.053)	(0.073)	(0.062)
Rank × Grant	Yes	Yes	No	Yes	No	Yes	No
Sector FE	No	Yes	No	Yes	No	Yes	No
Cohort FE	No	Yes	No	Yes	No	Yes	No
Competition FE	Yes	Yes	No	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	Yes	No	Yes	No
Firm-application FE	No	No	Yes	No	Yes	No	Yes
N	16888	16807	15848	2913	2786	1661	1594
# competitions	176	176	175	176	175	176	175
R-squared	0.06	0.38	0.95	0.50	0.94	0.57	0.93
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	All	All	±10	±10	5	5
Panel C: Employees							
Grant × Post	0.135***	0.179***	0.177***	0.171***	0.167***	0.151***	0.192***
	(0.042)	(0.038)	(0.031)	(0.043)	(0.035)	(0.058)	(0.045)
Rank × Grant	Yes	Yes	No	Yes	No	Yes	No
Sector FE	No	Yes	No	Yes	No	Yes	No
Cohort FE	No	Yes	No	Yes	No	Yes	No
Competition FE	Yes	Yes	No	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	Yes	No	Yes	No
Firm-application FE	No	No	Yes	No	Yes	No	Yes
N	13852	13731	11950	2378	2076	1365	1204
# competitions	175	175	175	175	174	172	171
R-squared	0.05	0.37	0.96	0.51	0.96	0.58	0.96

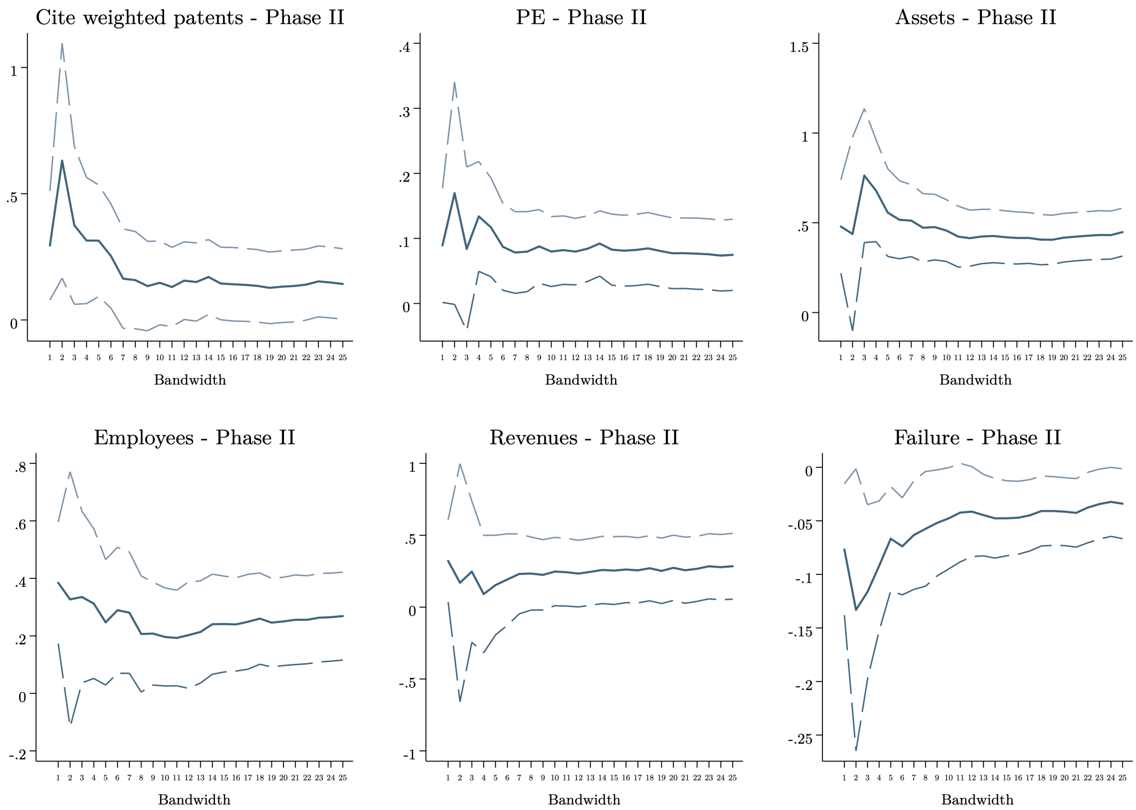
Notes: two-period DID estimations using different specifications of equation (2) by means of OLS. The dependent variables are computed as the average (log) between time $t-2$ and $t-1$ for the period preceding the treatment and the average (log) between time t and $t+1$ for the treatment period. All specifications include the standalone Grant and Post variables as well as linear controls for centered ranks on both sides of the threshold and year fixed effects. Columns 1 to 4 use infinite bandwidths whereas columns 4-5 and 6-7 employ bandwidths of 10 and 5, respectively. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A34: Difference-in-differences models - Phase II

	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel A: Patent							
Grant × Post	0.312***	0.318***	0.311***	0.182***	0.180***	0.137*	0.140**
	(0.055)	(0.056)	(0.055)	(0.062)	(0.060)	(0.070)	(0.066)
Rank × Grant	Yes	Yes	No	Yes	No	Yes	No
Sector FE	No	Yes	No	Yes	No	Yes	No
Cohort FE	No	Yes	No	Yes	No	Yes	No
Competition FE	Yes	Yes	No	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	Yes	No	Yes	No
Firm-application FE	No	No	Yes	No	Yes	No	Yes
N	22193	21375	22190	3555	3644	2051	2102
# competitions	176	176	176	176	176	176	176
R-squared	0.11	0.27	0.96	0.39	0.96	0.48	0.96
	(1) All	(2) All	(3) All	(4) ±10	(5) ±10	(6) ±5	(7) ±5
Panel B: Private Equity							
Grant × Post	0.242**	0.243**	0.242**	0.235**	0.235**	0.208	0.207
	(0.105)	(0.107)	(0.105)	(0.114)	(0.110)	(0.137)	(0.129)
Rank × Grant	Yes	Yes	No	Yes	No	Yes	No
Sector FE	No	Yes	No	Yes	No	Yes	No
Cohort FE	No	Yes	No	Yes	No	Yes	No
Competition FE	Yes	Yes	No	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	Yes	No	Yes	No
Firm-application FE	No	No	Yes	No	Yes	No	Yes
N	16704	16320	16704	2676	2716	1562	1584
# competitions	176	176	176	176	176	176	176
R-squared	0.03	0.11	0.84	0.23	0.82	0.36	0.79

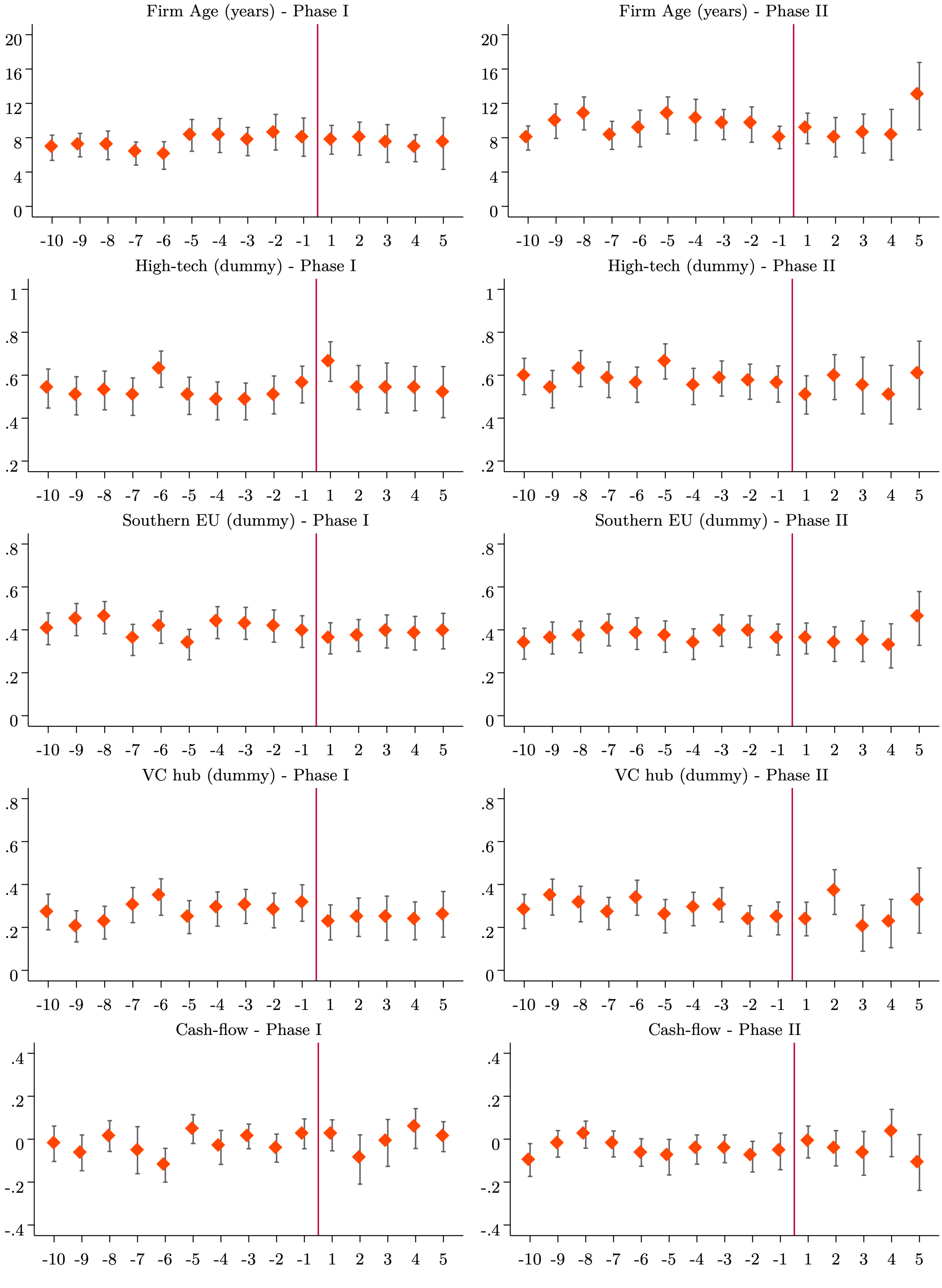
Notes: two-period DID estimations using different specifications of equation (2) by means of OLS. The dependent variables are the average (log) of patents (or private equity amount) for the 10 years preceding the treatment and the average (log) of patents (or private equity amount) for the 5 years after treatment. All specifications include the standalone Grant and Post variables as well as linear controls for centered ranks on both sides of the threshold and year fixed effects. Columns 1 to 4 use infinite bandwidths whereas columns 4-5 and 6-7 employ bandwidths of 10 and 5, respectively. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Fig. A4: Point estimates by bandwidth (Phase II)



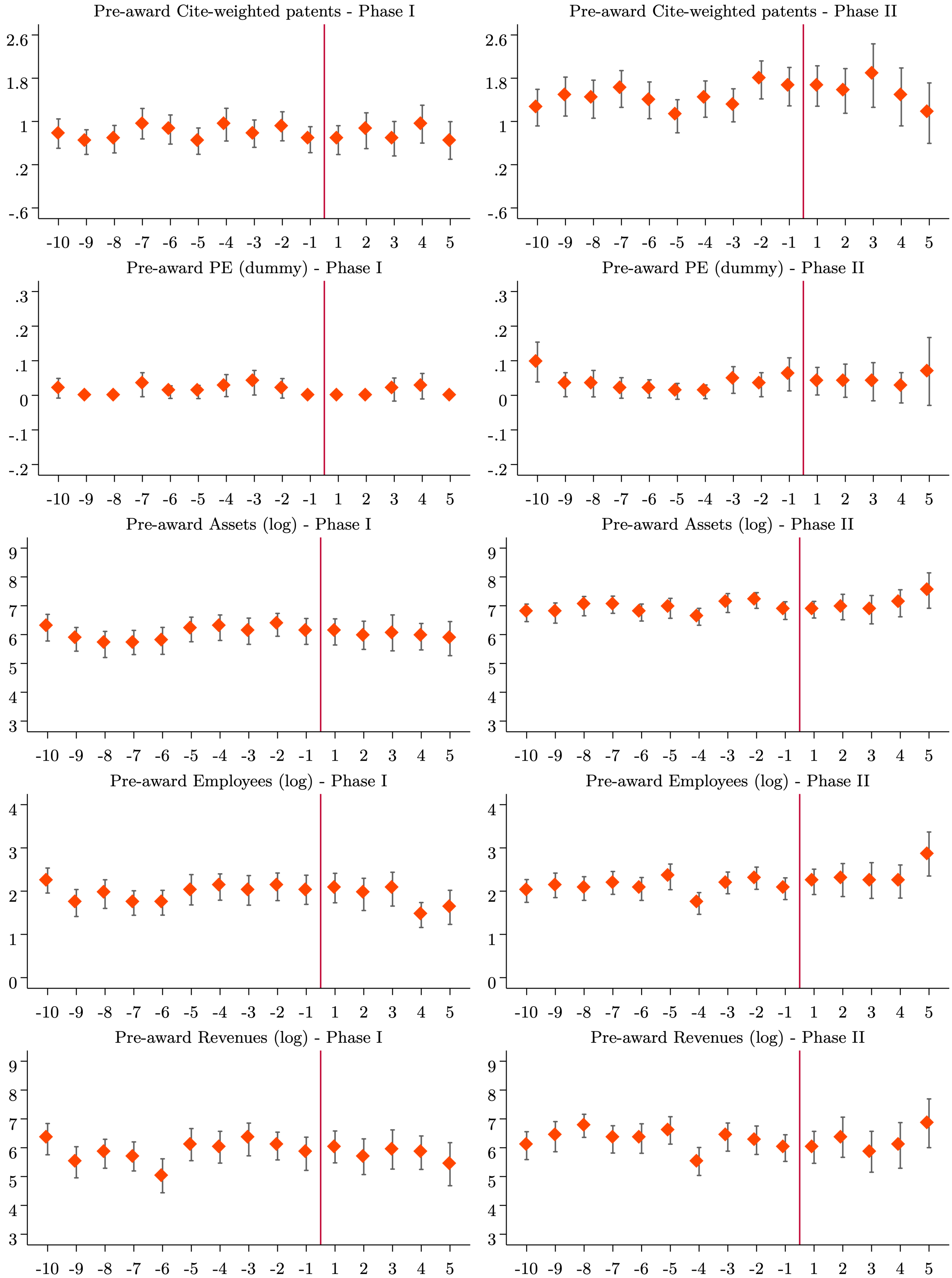
Notes: results obtained by estimating equation (1). All regressions include linear ranks on both sides, pre-grant dependent variable, competition fixed effects and based on the whole sample of firms. Standard errors clustered at the competition-level. 95% confidence intervals reported.

Fig. A5: Graphical evidence of continuity in pre-assignment observables



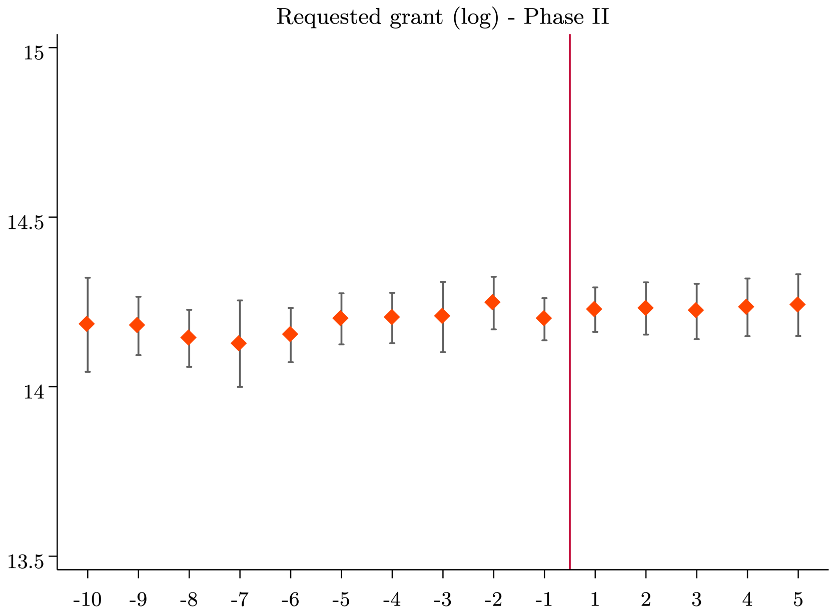
Notes: the figure reports average pre-assignment observables by centered rankings across the threshold. 95% confidence intervals reported.

Fig. A6: Graphical evidence of continuity in pre-assignment outcomes



Notes: the figure reports average pre-assignment outcomes by centered rankings across the threshold. 95% confidence intervals reported.

Fig. A7: Graphical evidence of continuity in requested funding



Notes: the figure reports average requested funding by centered rankings across the threshold for Phase II competitions. 95% confidence intervals reported.