The Causal Effects of R&D Grants: Evidence from a Regression Discontinuity

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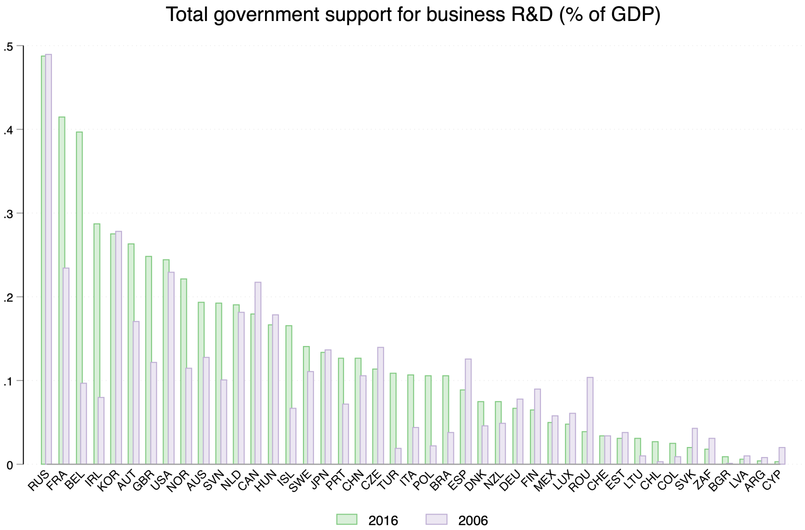
Motivation



- Increased public spending to support business R&D in most OECD countries
- Direct and indirect measures amount to ≈ $110 billion annually

Motivation

- R&D grants represent the most direct form of support to private innovation efforts
- In principle better equipped to prioritize areas plagued by heavier market failures or to address specific societal challenges (Van Reenen, 2020)

Introduction

- Market failures lead to underinvestment in private R&D (Hall and Lerner, 2010)
- Governments try to offset it by stimulating investments in innovation through a variety of policy measures (e.g. R&D grants, R&D tax credits) (Bloom et al, 2019)
- Recent years saw a stronger preference towards R&D tax credits (Appelt et al, 2019)
- Do R&D grants work? Abundant literature, conflicting results (Zúñiga-Vicente et al., 2014)
- Two recent studies proposed the use of regression discontinuity designs (RDD) to properly assess the causal effects of R&D grants:
  - Bronzini and Iachini (2014) for a limited geographical context $\rightarrow \beta = 0$
  - Howell (2017) for a single sectoral domain of the US SBIR $\rightarrow \beta > 0$
- Mixed results persist even with better identification strategy
- Yet, their limited scope poses a challenge in terms of the external validity, i.e. response to treatment may be influenced by idiosyncratic factors being therefore different from the potential response of firms in different sectors or regions

This paper

- **What do we do?**
  - Examine the *first* large-scale direct R&D grant scheme for SMEs in Europe (**SME Instrument**)
  - Policy-transfer case → SME Instrument is modelled after the US SBIR
  - Leverage discontinuity in assignment mechanism of the policy and adopt a sharp RDD
  - Provide the broadest quasi-experimental evidence (in terms of both sectoral and geographical scope) and for a more comprehensive range of performance outcomes than prior studies
- **Do R&D grants work?**
  - R&D grants cause sizable effects on firm innovation, investment, assets, employment, revenues (albeit noisy), survival, and the likelihood of receiving subsequent private equity financing.
- **Who benefits the most from R&D grants?**
  - Younger and smaller firms, and firms in financially vulnerable sectors
  - Firms in countries and regions with lower economic development
- **How R&D grants work?**
  - Central mechanism behind the results is funding as opposed to certification

Institutional setting: the SME Instrument

- Established in 2014 and implemented by the Executive Agency for Small and Medium-sized Enterprises (EASME)
- Unprecedented innovation policy: first scheme providing direct support to SMEs in Europe
- Endowed with €3bln budget over 2014-2020
- Eligible firms: SMEs from any sector in EU/Horizon2020 associated country (42 countries)
- As the US SBIR, the SME Instrument is organized in phases
- SMEs can apply to Phase I or directly to Phase II:
  - **Phase I** awards a lump-sum grant of €50,000 to transform a business idea into a business concept by evaluating its commercial and technological viability (duration: up to 6 months);
  - **Phase II** accounts for 90% of the total budget of the scheme and awards between €0.5 and 2.5mln in R&D activities such as prototyping, demonstration, testing, piloting, scaling up and market replication (duration: up to 2 years).

The SME Instrument: evaluation process

- Grants are assigned after a committee of independent experts appointed by EASME assesses the projects.
  - They score the proposal based on i) impact, ii) excellence, and iii) quality & efficiency of implementation (scale: 0 to 5).
  - Final scores are computed by adding up the median scores of all three criteria (scale: 0 to 15). These final scores are used to compile rankings (our "running" variable in the RDD).
  - The effective number of R&D grants is decided based on EASME budgetary constraints.
  - Projects above the minimum quality threshold (usually 13 points) but do not receive the grant because of budget availability receive the 'Seal of Excellence' to certify their high-quality.
- The evaluation process is conducted remotely and individual experts do not know the scores given by the other experts.
- Experts do not know *ex-ante* the effective number of grants that will be assigned in any specific competition (manipulation in this context is highly unlikely).

Data

- We use data on all SME Instrument competitions organized by EASME during 2014-2017:
    - Phase I: 28,198 firm-applications (173 competitions)
    - Phase II: 14,904 firm-applications (176 competitions)
- We employ Bureau van Dijk's (BvD) ORBIS database to link applicants with firm-level data based on probabilistic matching on firm name and exact matching on country.
- Around 68% of all applications are successfully matched with a valid BvD identification number (64% Phase I; 74% Phase II).
- We link the following data:
    - Patent applications and citations: ORBIS Intellectual Property (up to March 2019)
    - Balance-sheet variables: ORBIS (up to and including 2018)
    - Equity financing: Zephyr (up to March 2019)
    - Exit (failure and IPO): ORBIS (up to March 2019)

Stats I Stats II

Empirical strategy

- Baseline RDD equation:

$$Y_{ic}^{Post} = \alpha + \beta Grant_{ic} + f\left(Rank_{ic}\right) + \gamma Y_{ic}^{Pre} + \delta_c + \varepsilon_{ic} \quad \text{with} \; -r \leq Rank_{ic} \leq r \tag{1}$$

where

- Y_{ic}^{Post} = outcome of firm i after competition c
- $Grant_{ic}$ = firms above or below the threshold (i.e. treated or untreated)
- $f\left(Rank_{ic}\right)$ = polynomial control for centered ranks on both sides of the threshold
- Y_{ic}^{Pre} = outcome of firm i before competition c
- δ_c = competition fixed effect (which are time-specific and sector-specific)
- ε_{ic} = error term

- β identifies the causal impact (LATE)
- 1^{st} or 2^{nd} order polynomial of the running variable (Gelman and Imbens, 2019)
- Estimated via OLS using different bandwidths (Lee and Lemieux, 2010)
- Standard errors are robust and clustered at the competition-level

RDD validity

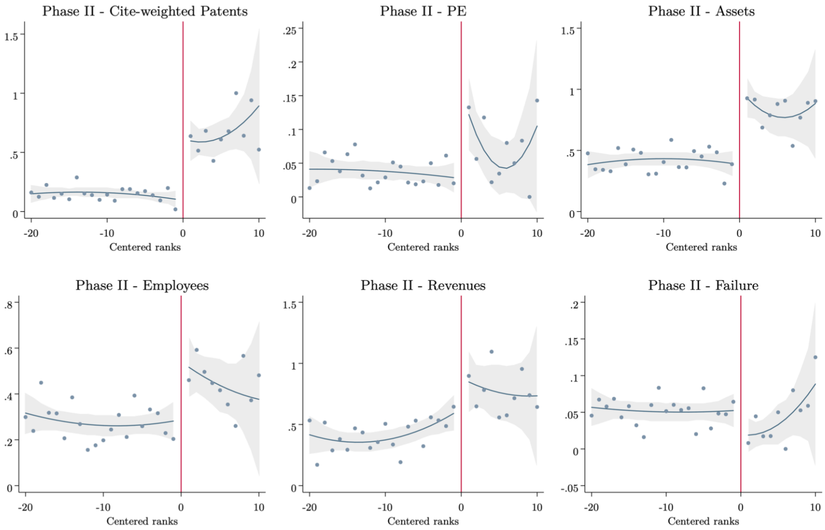
Table 1: Balancing tests of pre-grant covariates - Phase II

	1^{st} order polynomial			2^{nd} order polynomial		
	All	±10	±5	All	±10	±5
Citw patents^{Pre}	0.13 (0.15)	-0.12 (0.20)	-0.12 (0.28)	0.27 (0.22)	-0.18 (0.33)	-0.12 (0.60)
PE^{Pre}	-0.028 (0.023)	0.0047 (0.024)	-0.028 (0.030)	0.017 (0.031)	-0.070 (0.037)	-0.0054 (0.076)
Revenues^{Pre}	-0.44 (0.25)	-0.077 (0.30)	-0.45 (0.43)	-0.65 (0.38)	-0.10 (0.50)	0.40 (0.90)
Assets^{Pre}	-0.047 (0.16)	-0.19 (0.18)	-0.52** (0.25)	-0.096 (0.20)	-0.31 (0.28)	0.11 (0.56)
Employees^{Pre}	0.0068 (0.13)	0.014 (0.17)	-0.11 (0.22)	-0.00026 (0.19)	-0.031 (0.25)	0.17 (0.47)
Age^{Pre}	-0.067 (0.074)	-0.078 (0.097)	-0.16 (0.14)	-0.088 (0.11)	-0.11 (0.16)	0.29 (0.26)
Cash-flow^{Pre}	0.017 (0.030)	0.069 (0.040)	0.037 (0.069)	0.00083 (0.043)	0.044 (0.077)	0.11 (0.14)
Profit margin^{Pre}	5.29 (3.46)	5.54 (4.65)	6.28 (7.93)	-1.47 (5.91)	1.40 (8.72)	10.2 (16.0)
High-Tech	-0.056 (0.039)	-0.055 (0.050)	-0.025 (0.067)	-0.058 (0.057)	-0.031 (0.081)	-0.16 (0.15)
VC Hub	-0.027 (0.038)	-0.015 (0.048)	0.036 (0.065)	-0.0082 (0.054)	0.043 (0.076)	0.13 (0.14)

Notes: results obtained estimating our baseline RDD equation by means of OLS with pre-determined 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. $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Graphical evidence of discontinuity in post-grant outcomes (Phase II)

Figure 1: Discontinuity close to the threshold



Notes: the figure reports RD plots for Phase II. 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.

Do R&D grants cause an increase in innovation output?

Table 2: The effects on cite-weighted patents

Bandwidth	All		±10		±5	
	(1)	(2)	(3)	(4)	(5)	(6)
Grant	0.203***	0.282**	0.147*	0.236*	0.314***	0.390*
	(0.068)	(0.117)	(0.085)	(0.138)	(0.113)	(0.230)
Rank × Grant	✓	✓	✓	✓	✓	✓
$\text{Rank}^2 \times$ Grant	-	✓	-	✓	-	✓
N	11095	11095	1822	1822	1050	1050
R-squared	0.36	0.36	0.45	0.45	0.51	0.51
AIC	23473.47	23472.94	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 2 report estimates using infinite bandwidths (i.e. all firms). Columns 3-4 and 5-6 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. $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

- Estimated increase in quality-adjusted patents within the range of 15 to 31%
- Results hold when e.g. using a simple patent dummy variable, negative binomial models

Do R&D grants increase follow-on private investments?

Table 3: The effects on private equity financing

Bandwidth	All		±10		±5	
	(1)	(2)	(3)	(4)	(5)	(6)
Grant	0.070**	0.126***	0.080***	0.123***	0.117***	0.157*
	(0.028)	(0.045)	(0.027)	(0.047)	(0.039)	(0.085)
Rank × Grant	✓	✓	✓	✓	✓	✓
$\text{Rank}^2 \times$ Grant	-	✓	-	✓	-	✓
N	8352	8352	1358	1358	784	784
R-squared	0.07	0.07	0.17	0.17	0.27	0.27
AIC	-5105.58	-5113.51	-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 2 report estimates using infinite bandwidths (i.e. all firms). Columns 3-4 and 5-6 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. $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

- Estimated effect of 11.7-12.6 pp (sample mean = 4% $\rightarrow$ 3x increase)
- Positive effects confirmed when using the amount as well as the number of deals of private equity financing

Go

Do R&D grants cause higher growth?

Table 4: The effects on firm growth

Assets	All		±10		±5	
Grant	0.518***	0.569***	0.456***	0.569***	0.556***	0.966***
	(0.062)	(0.096)	(0.088)	(0.136)	(0.125)	(0.269)
N	7306	7306	1311	1311	743	743
R-squared	0.16	0.16	0.37	0.37	0.45	0.45
AIC	16122.35	16122.65	2677.11	2679.75	1462.10	1461.56
Employees	All		±10		±5	
Grant	0.299***	0.222***	0.251***	0.271**	0.211*	0.204
	(0.053)	(0.081)	(0.071)	(0.123)	(0.112)	(0.206)
N	5493	5493	962	962	548	548
R-squared	0.14	0.14	0.33	0.33	0.46	0.46
AIC	7890.43	7892.21	1286.54	1289.41	625.87	629.86
Revenues	All		±10		±5	
Grant	0.451***	0.587***	0.248**	0.141	0.154	0.172
	(0.117)	(0.165)	(0.121)	(0.205)	(0.177)	(0.376)
N	5119	5119	867	867	480	480
R-squared	0.19	0.19	0.42	0.42	0.55	0.55
AIC	12887.24	12886.09	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 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 2 report estimates using infinite bandwidths (i.e. all firms). Columns 3-4 and 5-6 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. $^{*}\ p<0.1$, $^{**}\ p<0.05$, $^{***}\ p<0.01$.

- Increase in assets (46-96%), employees (21-30%), revenues (15-25%)

Additional performance measures

We examine further firm-level outcomes:

- Investment in fixed assets Go
- Firm failure Go
- IPO and M&A Go

Heterogeneous effects of R&D grants

- Absent market failures, R&D grants should not induce an effect on firm-level outcomes.
- R&D grants have positive causal effects. Hence, some kind of friction is deterring the investment in innovative projects without the grant $\rightarrow$ financial constraints
  - heterogeneous effects across firm age and size Go
- The large scope of the program in terms of sectoral and geographical dimensions allows us to test heterogeneous effects over several observables:
  - sector-level proxies of financial vulnerability Go
  - country-level economic and financial development Go
  - regional-level economic development Go

Potential mechanism: Funding vs certification

- Two mechanisms could drive the positive results of the grant (Lerner, 1999; Howell, 2017):
  - **Funding**: R&D grants allow to successfully develop a technology which mitigates information asymmetry and reduces investment risks.;
  - **Certification**: R&D grants serve as a signal that conveys market-relevant information about firm quality; this mitigates information asymmetries and reduces investment risks.
- We exploit data on Seal of Excellence (SOE) $\rightarrow$ quality label to firms not funded due to budget limits.
- Certification would imply that:
  - SOE firms should perform as well as grant-winning firms Go
  - SOE firms should outperform the rest of unsuccessful applicants Go
  - the effects are not sensitive to grant size Go
  - certification might explain the positive effect on equity. The effect on patents should be driven by those firms getting external equity. It's the other way around.
  - the effects on private equity should be immediate
  - increase in ability to secure credit $\rightarrow$ higher debt and shift towards long-term debt Go
- Overall, certification effects not attached to funding do not appear to explain the effects

Falsification and robustness tests

- Placebo tests with fictitious thresholds; Go
- Estimates stability and external validity (TED) (Cerulli et al, 2017); Go
- Alternative and automated bandwidth selection (Cattaneo et al, 2018); Go
- Alternative standard error clustering (Kolesár and Rothe, 2018);
- Richer fixed effects structure (e.g. cohort, country, sector);
- Difference-in-differences; Go
- Local randomization approach (Cattaneo et al, 2015); Go
- Different estimation sample, for instance:
  - only first-time applicants;
  - without competitions with largest number of applicants;
  - without health-related topic competitions (grants are up to €5mln)

Conclusions

- The paper provides the broadest quasi-experimental evidence on R&D grants available to date
- R&D grants have a significant, large and positive effect on firm-level innovation output, investment, firm growth, access to equity finance, and survival chances
- Evidence is consistent with R&D grants alleviating financial constraints that hamper innovation and growth; stronger effects for firms in less advanced countries/regions
- They appear to mitigate technology and market uncertainty through funding effects
- First quasi-experimental evidence documenting positive effects of SBIR-type policies in contexts other then US.
- Our findings join a recent stream of literature leveraging clearer casual identification strategies on the effects of R&D grants (Howell, 2017), R&D procurement (Dechezleprêtre, et al, 2019), and R&D tax credits (Moretti et al, 2019) which together constitute a robust empirical base in favor of government intervention in innovation.

Thank You!