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The Long-Run Effects of R&D Subsidies on High-Tech Start-Ups: Insights From Italy

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The Long-Run Effects of R&D Subsidies on High-Tech Start-Ups: Insights From Italy

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Abstract

We study the impact of a government subsidy program in Italy targeted at R&D-intensive projects presented by high-tech startups in 2009. Using the score assigned by the scientific commission to each project, we employ a Regression Discontinuity Design to study how the subsidy affected successful firms' innovation activity and performance over more than 10 years. We show that the subsidy led to substantial increases in intangible assets and had a lasting positive effect on various dimensions of firm performance. Innovation as measured by patents did not respond to the subsidy.

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1 Introduction

Public support for private innovation is a common worldwide practice (Rosário et al., 2022). As of 2022, about 0.23% of government budgets in the OECD and EU went into direct R&D funding (OECD, 2024). A large share thereof is used to support small firms and start-ups, especially in high-tech sectors, since they face higher marginal innovation costs and credit constraints (Guiso, 1998). As with larger firms, however, public support may crowd out private investment and not lead to aggregate benefits (Hall and Lerner, 2010).

In this paper, we evaluate an R&D subsidy program by the Italian government in 2009 aimed at highly technological projects by start-up firms. Exploiting the score assigned to each project by the scientific committee, we estimate the program's causal impact on firms' innovation activity and performance using a Regression Discontinuity Design (RDD) comparing firms just above and below the cut-off score. We find that the subsidy led to substantial investments in intangible fixed assets (IFA) and positive medium- and long-term firm outcomes, but had no effect on patenting.

Our study contributes to the large literature on public funding and R&D activities summarized in David et al. (2000), Zúñiga-Vicente et al. (2014), and Bloom et al. (2019). Despite their importance, high-tech startups have received somewhat less attention. For the United States, Howell (2017) and Zhao and Ziedonis (2020) find positive effects of R&D subsidies on patenting, investments and firm outcomes. For Italy, correlational evidence by Colombo et al. (2011) suggests productivity gains only from competitively allocated subsidies. Biancalani et al. (2022) further show that a nation-wide policy to improve credit access fostered higher equity, debts and employment. We provide novel evidence for Italy which reveals persistent positive effects on high-tech startups' intangible investment and performance.

We also link to the mixed evidence on the impact of national and regional R&D subsidy programs for small and medium enterprises in Italy. De Blasio et al. (2015) and Mariani and Mealli (2018) find no impact on innovation, whereas Bronzini and Iachini (2014) and Bronzini and Piselli (2016) estimate positive effects on patenting and investments. Our study documents positive effects from a competitive national R&D subsidy directed at high-tech startups.

2 Background and Data

The *Innovative Start-ups Industrial Research Program*, launched by the Italian Ministry of Economic Development (MiSE) on July 7th 2009, intended to support experimental development and industrial research projects of start-ups in high and medium-high technological sectors.[1] The Ministry allocated €35m from national funds and €20m from the European Structural Funds reserved for firms active in the Southern regions Calabria, Campania, Puglia, and Sicilia. Each project could receive jointly €2m in loans (up to 50% of costs) and direct funding (20-40%, depending on company size)[2]

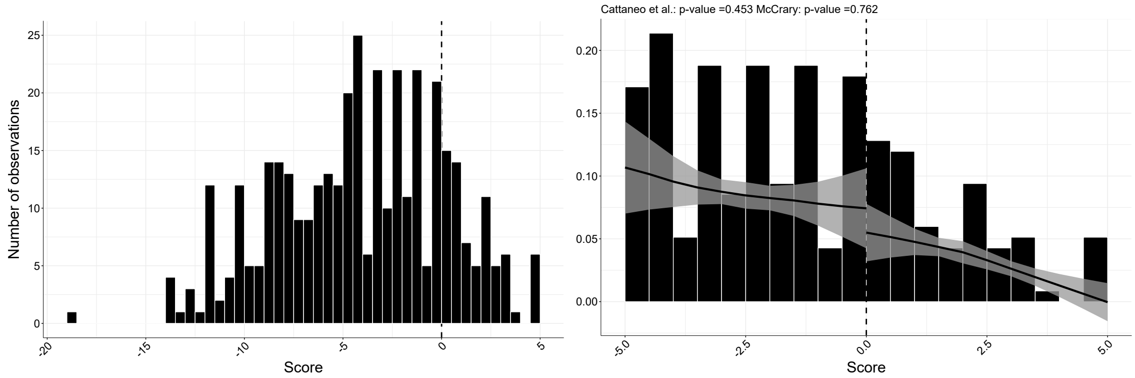
Eligible projects had to come from firms active less than 5 years and include a detailed budget plan meeting three criteria: 1) relate to product development or process innovations in high-tech sectors; 2) link to specific R&D costs like researchers' salary, equipment, consulting, patent filing, or raw materials; and 3) start after the application. Furthermore, firms could not apply to or receive other public funding and had to start within six months of the ranking publication.

Companies could apply from September 23rd 2009, to January 21st 2010, and requested on average €620k in loans and €430k in subsidies. A 5-member committee selected by the Ministry from a pre-existing register of experts scored projects on three criteria: 1) innovation (15 points); 2) firm's past R&D activity (5 points); and 3) 5% bonuses for product innovation, research partnerships, or female ownership.

The ranking was announced on April 19th 2011, funding 65 of 411 projects with joint total costs of €80m.[3] All firms up to rank 138 received the maximum score for criterion 2), suggesting the score mainly represented the committee's preferences over projects rather than companies. Projects with equal score were ranked by economic efficiency and subsidies were allocated until funds ran out. This implied that reaching the cut-off score did not guarantee funding and that firms active in Southern regions faced a lower threshold since they were eligible for both funding sources. Out of nine non-Southern and three Southern firms with scores of 18.9 and 17.25, respectively, only two were funded in each case. This complex system likely prevented the committee knowing exactly how scores would impact the funding decision of particular projects.

We obtained administrative data from MiSE on projects' applicant firms, scores, and ranking, and located 397 of 411 firms, including all winners, in the AIDA, ORBIS and ORBIS-PA databases. From these, we obtained information on compa-

[1] Decree 7 July 2009 published on 25 July 2009 in *Gazzetta Ufficiale*.
[2] See European Commission Recommendation L 124/36, 2003.
[3] Figure B.1 provides a detailed timeline.



A. Histogram B. Density around the cut-off

Figure 1: Histogram of normalized score and density around the cut-off

Notes: Both graphs use bins of 0.5 of the normalized score $NScore$. Subgraph 1a shows the entire support of $NScore$ whereas 1b zooms in on a window of 5 below and above the normalized cut-off. Shaded areas in 1b show 95% confidence bands centered around the estimated density using the method by Cattaneo et al. (2020). P-values displayed at the top refer to the tests by McCrary (2008) and Cattaneo et al. (2020).

nies' balance sheets, history and linked patents (including filing date and forward citations) for the years 2007–2021.[4] Financial values were converted to 2009 € using Istat (2024). The panel is unbalanced since 44% of firms started after 2007 and 41% were inactive by 2021, and balance sheets reporting was oftentimes inconsistent.

We measure innovation in two ways: with actual R&D expenditures not being available for many firms, we focus on its super-category IFA as a measure of R&D inputs. By law, this balance sheet entry includes R&D expenditures (incl. personnel costs), advertising costs, startup expenses, patenting costs, alternative intellectual property rights, software licenses, and other intangibles. Our analysis focuses on IFA growth rate as a proxy for R&D investment. We measure R&D output using the yearly number of patents and their forward citations. Indicators of performance include sales (turnover), employment, wages, and labor productivity. Following Biancalani et al. (2022), we use total debts to proxy for credit access.

3 Methodology

The ranking process naturally suggests a Fuzzy RDD with multiple cut-offs since treatment is a non-deterministic function of the final score with assignment probability increasing discontinuously at 17.25 and 18.9 for Southern and non-Southern firms, respectively. To jointly analyze both groups, we calculate $NScore$ normalizing the actual score with the particular cut-off value. The small sample, however, raises

[4] For joint applications, we used the main applicant. Eight companies presented two projects but only one project was subsidized. For simplicity, we refer to "firms" as our unit of analysis rather than "projects".

questions about the first-stage relationship between passing the normalized threshold and treatment assignment. According to Cattaneo et al. (2024), the minimum F-statistic for Fuzzy RDDs is 20. As shown below, our setup does not meet this standard and we therefore estimate a Sharp RDD, instead:

$$Y_i = \alpha + \beta T_i + f(NScore_i) + \epsilon_i \tag{1}$$

This setup estimates the effect of T_i, an indicator for receiving at least the cut-off score, on outcomes Y_i, controlling for polynomials of the running variable *NScore*. If scores are distributed continuously around the cut-off and pre-treatment firm characteristics are balanced on both sides, this specification identifies the subsidy's intention-to-treat effect (ITT). We use the robust bias-corrected RD estimate by Calonico et al. (2014) and follow Gelman and Imbens (2019) in using a local linear RD estimator. For inference, we use a nearest neighbor heteroskedasticity-robust variance estimator as in Calonico et al. (2019) with three minimum neighbors.

Figure 1a shows a frequency histogram of *NScore* and does not indicate discontinuities around the normalized cut-off. Figure 1b checks for manipulation more thoroughly by zooming into the cut-off's vicinity and providing estimates of the density function. The 95% confidence bounds on either side clearly overlap which speaks against manipulation. Finally, we perform the formal tests by McCrary (2008) and Cattaneo et al. (2020) and in both cases fail to reject the null hypothesis of no discontinuity.

Next, we estimate Equation 1 on pre-treatment characteristics to check for ex-ante differences in covariates. Since eligible firms could not be active for more than the 5 years, the availability of pre-treatment balance sheet information varies considerably. We thus use the average of firm characteristics during the last three financial years before the application deadline. Columns 1–8 of Table 1 show no indication that firms were significantly different ex-ante on assets, performance, wages, debt, and innovation experience, which further corroborates our research design's validity. Finally, column 9 shows a positive and significant relationship between reaching the cut-off score and receiving the subsidy. The implied F-statistic below 20 justifies our choice of presenting ITT estimates.

Table 1: Balance on covariates and impact on subsidy

X =	Avg(Log X 2007–2009)								
	Tangible assets	Intangible assets	Sales	Sales/ Employees	Employees	Wage	Total debts	Ever patented = 1	Subsidy = 1
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated	1.085	−1.062	1.053	0.899	−0.200	0.697	−0.063	0.074	0.363***
	(0.866)	(0.919)	(0.802)	(1.583)	(1.187)	(1.286)	(0.697)	(0.183)	(0.136)
Observations	78	117	71	53	36	32	119	133	84
Bandwidth	1.792	2.132	1.654	2.103	1.346	1.402	2.368	2.476	1.529

Notes: Coefficients show the point estimate using the conventional RD estimate with a first-order polynomial, a triangular kernel, and a single common MSE-optimal bandwidth. Standard errors (in parentheses) and p-values refer to the robust bias-corrected RD estimate using a nearest neighbor (minimum: 3) heteroskedasticity-robust variance estimator: *p<0.1; **p<0.05; ***p<0.01.

4 Results

Table 2 shows the impact of achieving the cut-off score on measures of R&D activity and innovation.[5] We analyze short-, medium-, and long-run effects by looking at the time periods 2010–2013, 2014–2017, and 2018–2021. Column 1 shows that IFA grew by about 240% between the pre-treatment years 2007–2009 and the first four treatment years.[6] The effect is highly significant and, considering the low pre-treatment IFA levels in the chosen bandwidth implies a €45k increase. For the medium- and long-run, the coefficients are even slightly higher, suggesting that the initial growth in IFA continued at a slightly slower pace and lasted for at least 10 years.

The subsidy, however, did not have any impact on innovation as we fail to detect significant effects in either period on patenting and citation-weighted patents. One potential explanation could be that eligible projects had to be strictly linked to product development or process innovation which likely increases productivity and revenue but may not always result in patents. Furthermore, firms often strategically choose not to patent to avoid disclosing valuable information (Arora et al., 2008).

Table 3 looks at general firm performance. During the short-run period, we do not find positive responses along any dimension. In the medium- and long-run, however, companies reaching the cut-off fare significantly better. Turnover is about 11 times higher in the medium-run, implying an average increase of €4m. The effect is even higher in the long-run, indicating a sustained boost in performance. Labor productivity, in turn, rises by 330% in the medium-run. The effect is similar, yet

[5] For completeness, Tables A.1 and A.2 also show Fuzzy RDD estimates, which are larger but qualitatively similar to the Sharp RDD.

[6] While the ranking was published on April 19th 2011, many companies had presumably not yet submitted their 2010 balance sheets. Since they were potentially able to still declare the subsidy for 2010, we regard it as the year of treatment onset.

Table 2: The subsidy's impact on IFA and innovation

	Growth rate Intangibles in X vs 2007–2009			Any patents in X = 1			Log(1+Citations in X)		
X = 20..	10-13	14-17	18-21	10-13	14-17	18-21	10-13	14-17	18-21
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated	2.404***	3.276***	4.243**	0.014	0.026	0.077	−0.119	0.738	−0.057
	(0.899)	(1.261)	(2.104)	(0.200)	(0.215)	(0.202)	(0.288)	(0.477)	(0.035)
Observations	123	70	24	104	71	65	121	81	55
Bandwidth	2.426	1.887	0.974	2.007	1.849	1.868	2.35	1.999	1.605

Notes: See Table 1.

insignificant, in the short- and long-run so we cannot say with certainty whether productivity immediately responded and whether the response was persistent.

For employment, we see a persistent positive effect of 300% and 930% in the medium- and long-run, respectively. Considering average pre-treatment employment in the chosen bandwidth, this implies hiring 17 and 47 employees per firm, respectively. For wages, we only find a negative significant effect in the short-run which, however, seems to be transitory. An positive effect on credit access, proxied by total debt, shows up only in the long-run, but is not precisely estimated.

While our data cannot fully pin down whether R&D expenditures drove the increases in productivity and firm performance, several points speak in favour of such interpretation. First, both Crass and Peters (2014) and Niebel et al. (2017) demonstrate that the positive association between IFA and productivity is predominantly driven by R&D. Second, while the subsidy's impact on IFA growth is immediate, the increases in firm performance are more pronounced and precisely estimated only few years later.

One may worry our findings being confounded by differences in firm survival. To address this, columns 16–18 examine how many years companies operated for during the three post-periods. We find no systematic differences, which further strengthens our results. To address concerns about selective reporting, Tables A.3 and A.4 show that our findings are qualitatively similar when using only firms reporting basic information like total assets throughout the 2007–2021 sample period.

Table 3: The subsidy's impact on firm performance

	Avg. Log (Sales) in X			Avg. Log (Sales/Employees) in X			Avg. Log (Employees) in X		
X = 20..	10-13	14-17	18-21	10-13	14-17	18-21	10-13	14-17	18-21
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated	0.905	2.957**	3.606**	1.259	1.189**	1.414	0.173	1.106*	2.231*
	(0.697)	(1.211)	(1.513)	(0.918)	(0.546)	(0.881)	(0.447)	(0.652)	(1.334)
Observations	120	44	30	48	50	32	101	54	30
Bandwidth	2.441	1.162	1.029	1.221	1.452	1.106	2.557	1.498	0.956
	Avg. Log (Wage) in X			Avg. Log (Total debts) in X			Years active in X		
X = 20..	10-13	14-17	18-21	10-13	14-17	18-21	10-13	14-17	18-21
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Treated	−1.961*	−0.256	0.262	0.508	0.027	1.622	−0.198	−0.364	0.450
	(1.100)	(1.054)	(1.292)	(0.706)	(1.199)	(1.379)	(0.196)	(0.396)	(0.466)
Observations	40	25	30	97	50	38	89	67	53
Bandwidth	1.207	1.041	1.104	1.883	1.055	1.136	1.773	1.585	1.5

Notes: See Table 1.

5 Conclusion

We study the impact of an R&D subsidy to high-tech start-ups introduced by the Italian Government in 2009. Using the score assigned to each project in an RDD framework, we document a substantial increase in firms' IFA investment and performance for at least 10 years. Patents did not respond to the subsidy.

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Appendix

This Web Appendix (not for publication) provides additional material discussed in the unpublished manuscript *The Long-Run Effects of R&D Subsidies on High-Tech Start-Ups: Insights From Italy* by Letizia Borgomeo, Christoph Koenig, and Martina Miotto.

Table of Contents

A Tables

Table A.1: The subsidy's impact on IFA and innovation (Fuzzy RDD)

	Growth rate Intangibles in X vs 2007–2009			Any patents in X = 1			Log(1+Citations in X)		
X = 20..	10-13	14-17	18-21	10-13	14-17	18-21	10-13	14-17	18-21
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Subsidy = 1	5.947***	6.642***	6.844**	0.035	0.050	0.125	−0.274	1.477	−0.093
	(2.002)	(2.301)	(3.184)	(0.483)	(0.414)	(0.328)	(0.618)	(1.106)	(0.057)
Observations	123	70	24	104	71	65	121	81	55
Bandwidth	2.426	1.887	0.974	2.007	1.849	1.868	2.35	1.999	1.605

Notes: Coefficients show the point estimate using the conventional RD estimate with a first-order polynomial, a triangular kernel, and a single common MSE-optimal bandwidth. Standard errors (in parentheses) and p-values refer to the robust bias-corrected RD estimate using a nearest neighbor (minimum: 3) heteroskedasticity-robust variance estimator: *p<0.1; **p<0.05; ***p<0.01.

Table A.2: The subsidy's impact on firm performance (Fuzzy RDD)

	Avg. Log (Sales) in X			Avg. Log (Sales/Employees) in X			Avg. Log (Employees) in X		
X = 20..	10-13	14-17	18-21	10-13	14-17	18-21	10-13	14-17	18-21
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Subsidy = 1	2.364	7.324**	5.868*	3.462	2.551*	2.293	0.429	2.364	3.628
	(1.625)	(3.669)	(3.281)	(2.698)	(1.396)	(1.505)	(0.927)	(1.492)	(2.639)
Observations	120	44	30	48	50	32	101	54	30
Bandwidth	2.441	1.162	1.029	1.221	1.452	1.106	2.557	1.498	0.956
	Avg. Log (Wage) in X			Avg. Log (Total debts) in X			Years active in X		
X = 20..	10-13	14-17	18-21	10-13	14-17	18-21	10-13	14-17	18-21
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Subsidy = 1	−4.838	−0.625	0.504	1.534	0.082	2.589	−0.514	−0.757	0.749
	(3.077)	(2.564)	(2.504)	(2.000)	(2.840)	(2.420)	(0.528)	(0.877)	(0.799)
Observations	40	25	30	97	50	38	89	67	53
Bandwidth	1.207	1.041	1.104	1.883	1.055	1.136	1.773	1.585	1.5

Notes: Coefficients show the point estimate using the conventional RD estimate with a first-order polynomial, a triangular kernel, and a single common MSE-optimal bandwidth. Standard errors (in parentheses) and p-values refer to the robust bias-corrected RD estimate using a nearest neighbor (minimum: 3) heteroskedasticity-robust variance estimator: *p<0.1; **p<0.05; ***p<0.01.

Table A.3: The subsidy's impact on IFA and innovation (consistent reporters only)

	Growth rate Intangibles in X vs 2007–2009			Any patents in X = 1			Log(1+Citations in X)		
X = 20..	10-13	14-17	18-21	10-13	14-17	18-21	10-13	14-17	18-21
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated	3.552**	5.698***	5.267**	−0.020	−0.082	0.226	−0.432	0.436	−0.010
	(1.401)	(1.904)	(2.100)	(0.220)	(0.254)	(0.334)	(0.409)	(0.398)	(0.043)
Observations	45	38	20	88	61	43	64	61	47
Bandwidth	1.147	1.15	0.909	2.477	2.055	1.666	1.709	2.033	2.042

Notes: Coefficients show the point estimate using the conventional RD estimate with a first-order polynomial, a triangular kernel, and a single common MSE-optimal bandwidth. Standard errors (in parentheses) and p-values refer to the robust bias-corrected RD estimate using a nearest neighbor (minimum: 3) heteroskedasticity-robust variance estimator: *p<0.1; **p<0.05; ***p<0.01.

Table A.4: The subsidy's impact on firm performance (consistent reporters only)

	Avg. Log (Sales) in X			Avg. Log (Sales/Employees) in X			Avg. Log (Employees) in X		
X = 20..	10-13	14-17	18-21	10-13	14-17	18-21	10-13	14-17	18-21
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated	0.990	2.703*	3.542**	0.988	1.219**	1.595*	−0.272	0.544	1.931
	(0.933)	(1.609)	(1.724)	(0.795)	(0.614)	(0.934)	(0.514)	(1.068)	(1.408)
Observations	58	36	25	48	41	27	53	28	25
Bandwidth	1.62	1.053	1.048	1.724	1.416	1.123	1.87	0.98	1.046
	Avg. Log (Wage) in X			Avg. Log (Total debts) in X			Years active in X		
X = 20..	10-13	14-17	18-21	10-13	14-17	18-21	10-13	14-17	18-21
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Treated	−1.247	0.794	0.011	−0.511	−1.091	0.648	−0.375	−0.610	0.627
	(0.985)	(1.513)	(1.337)	(0.759)	(1.341)	(1.467)	(0.250)	(0.617)	(0.469)
Observations	57	14	26	64	34	32	81	70	45
Bandwidth	2.24	0.85	1.292	1.651	0.917	1.086	2.307	2.145	1.875

Notes: Coefficients show the point estimate using the conventional RD estimate with a first-order polynomial, a triangular kernel, and a single common MSE-optimal bandwidth. Standard errors (in parentheses) and p-values refer to the robust bias-corrected RD estimate using a nearest neighbor (minimum: 3) heteroskedasticity-robust variance estimator: *p<0.1; **p<0.05; ***p<0.01.

B Figures

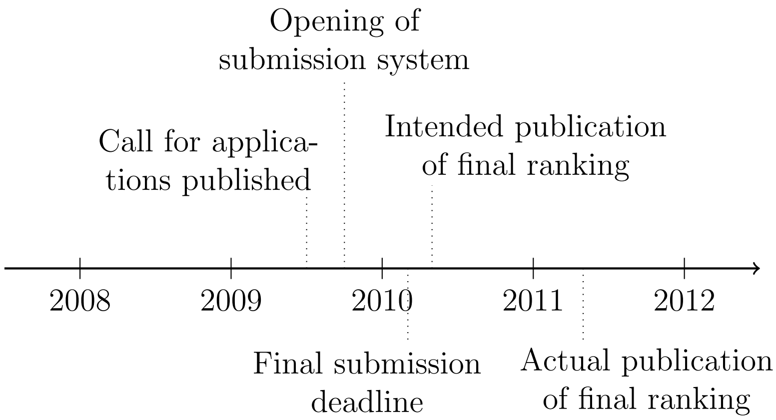

Figure B.1: Timeline of events

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