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Granting more bang for the buck: The heterogeneous effects of firm subsidies[☆]

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A R T I C L E I N F O

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A B S T R A C T

We estimate the effects of a large program of public investment subsidies targeting Italian firms of different size and age. Investment projects were ranked by numerical scores of project quality and funded until exhaustion of funds. Exploiting this allocation mechanism as an ideal regression discontinuity design, we estimate that subsidies increased investment of marginal firms near the cutoff by 39 percent, and employment by 17 percent over a 6-year period. Smaller firms exhibit higher employment growth upon receiving the subsidy, but larger firms generate more jobs at a lower cost, and younger firms do better than older firms.

1. Introduction

Public subsidies to private business are an important instrument through which governments sustain employment levels and economic development. While they are on top of the political agenda in many countries in the wake of the COVID-19 pandemic and the energy crisis, there is great uncertainty regarding their effectiveness. One relevant concern is that public subsidies might end up financing projects that would have been undertaken anyway (i.e., they have no "additional" effect). This would be the case of programs that do not effectively target firms constrained by frictions or market imperfections, a typical example in this respect being small businesses.

Small firms make a significant contribution to economic activity and employment opportunities, generating disproportionately more new jobs relative to their employment share.[1] At the same time, small firms are more likely to miss available growth opportunities, as they depend more on external finance (due to limited internal resources and higher volatility of earnings) while having at the same time less access to that (due to greater information and transaction costs, low availability of collateral etc.).[2] Against this background, however, it is unclear whether public interventions targeting small firms may address these constraints,[3] and, importantly, whether it is more cost-effective than targeting other firms.

In this paper, we quantify the effects and the cost-effectiveness of subsidies targeting firms of different size and age within a large program of public support to private business implemented in Italy for more than 10 years. The analysis leverages an ideal regression discontinuity design (RDD), as firms' applications for subsidies were ranked on quantitative indicators of project quality and funded until the exhaustion of available funds. Comparing applicants ranked just above and just below the cutoff for being funded, we estimate that obtaining the subsidy increases firm employment by 17 percent over a period of six years. When we distinguish applicants by size, smaller firms generate larger percent increases in employment than large firms - respectively, +22 and +8

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1 The idea that small firms facilitate faster job creation emerged from early studies of firm dynamics in the US (Birch, 1987; Evans, 1987; Sutton, 1997), and was confirmed when addressing important measurement and data issues (Neumark et al., 2011). Haltiwanger et al. (2013), however, pointed out that this fact is largely explained by small firms being younger and including most of the startups.

2 See, for example, Gertler and Gilchrist (1994), Petersen and Rajan (1994), Beck et al. (2005), Beck et al. (2008). Angelini and Generale (2008) focus on the case of Italy.

3 See Criscuolo et al. (2019), Denes et al. (2022), Rotemberg (2019), Banerjee and Duflo (2014).

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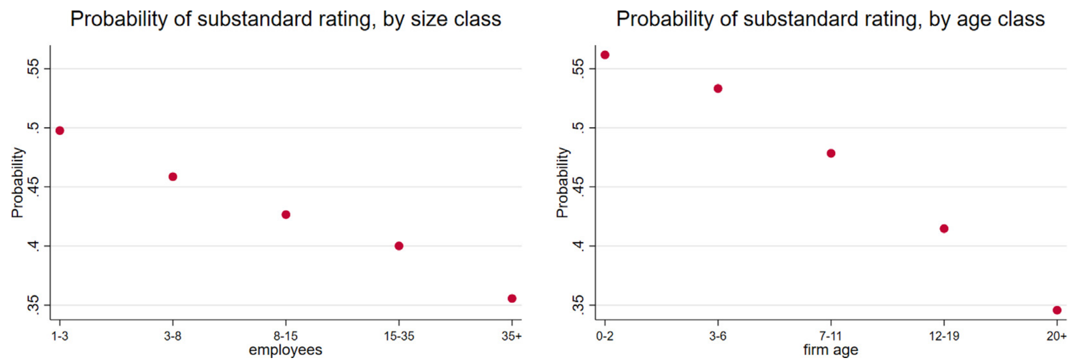

Fig. 1. Credit rationing of Italian firms, by size and age. *Source*: own calculations from the Cerved Group database.

percent. However, given the difference in the initial size, these percent increases translate into a greater increase in the number of new jobs for large firms than for small firms - respectively, +5 and +0.7 jobs per subsidized applicant. Therefore, the cost effectiveness of the subsidy - in terms of euros transferred to the firm per each newly-created job - is higher for large firms than for small firms close to the cutoff. Specifically, the cost of a new job surviving six years into the program is 866 thousand euros in the case of small firms, as opposed to 159 thousand euros in that of large firms. However, these estimates are only valid across firms close to the cutoff and, as such, they do not allow us to compute the overall cost-effectiveness of the policy.

We address this limitation following the approach of Angrist and Rokkanen (2015), who provide a method for extrapolating RDD estimates away from the cutoff. In a nutshell, their method leverages on the RDD to test (i) ignorability of treatment assignment and (ii) common support conditional on a vector of observable characteristics. The average cost of a new job estimated across all large and small (inframarginal) firms away from the cutoff (121 and 633 thousand euros, respectively) is lower than the cost estimated across marginal firms close to the cutoff. On the other hand, the average cost across all inframarginal firms is slightly higher than the cost estimated close to the cutoff due to a different composition by size. These results highlight the importance of estimating policy effects – whenever possible - over a larger population than only marginal units close to the cutoff. In any event, all estimates confirm that large firms are more cost-effective than small firms. Echoing the findings by Haltiwanger et al. (2013), we also document that, conditional on size, young firms generate larger percent increases in employment and are more cost-effective than old firms.

These findings stand in contrast with previous evidence on heterogeneity of subsidy effects by firm size. Criscuolo et al. (2019) document significant employment effect of investment subsidies in the UK and attribute them to the activity of small firms (i.e., up to 50 employees). Interestingly, such effect does not seem to be driven by (the removal of) financial constraints, as young firms also respond less to the policy. Bronzini and Iachini (2014) also find that R&D subsidies in one Italian region only induce an increase in investment by small firms, fully displacing private expenditure in the case of large firms. On a more general note, Denes et al. (2022) find that the crowding out of smallest firms (i.e., up to 20 employees) from a US subsidy program (the Small Business Act) led to lower employment growth, a higher probability of unemployment, and lower wages. Closer to our findings, several works find that the removal of preferential treatment for small firms in India led to increases in profits, employment, and output (Banerjee and Duflo, 2014; Martin et al., 2017; Rotemberg, 2019). We contribute to this literature by leveraging on an ideal research design to estimate the effect of an important subsidy program along the firm size distribution.

In the next section we describe the institutional context; Section 3 and 4 introduce the data and empirical strategy, respectively; Section 5 presents the results, and Section 6 concludes.

2. Institutional background

2.1. Small firms in the Italian economy

In Italy micro and small firms account for a larger fraction of businesses and employment than in comparable European countries or the US, see e.g. OECD (2020). As in virtually all other economies, small firms face greater difficulties in tapping external sources of finance. During the period 2005–2019 the average interest rate charged on bank loans to micro firms (1–9 employees) was nearly 4 percentage points higher than that paid by large firms (250+ employees); similarly, small firms (10–49 employees) paid an interest rate premium close to 3 percentage points; see Bank of Italy (2022). One reason is that micro and small firms are perceived as riskier. The left panel of Fig. 1 shows that probability of being rated as substandard by the credit system decreases in firm size (here, the quintiles of the size distribution of firms applying to the program we study).[4] A similar pattern emerges when looking at credit risk against firm age, another commonly used proxy for firms exposure to credit frictions; see the right panel.

Small firms are also perceived as significantly contributing to job creation. To assess their role in Italy, we follow Davis and Haltiwanger (1992) and compute measures of gross job creation and gross job destruction for the same size classes used in Fig. 1.[5] The analysis confirms that smaller firms generate disproportionately more new jobs relative to their employment share (see Fig. 2). However, they are also responsible for a large amount of job destruction, which tends to be larger or very close to the amount of job creation. This implies in turn that the largest contribution to net employment growth is traceable to the largest size class (35+) in our data.

2.2. Law 488/92

To ease the constraints faced by small-medium firms, in 1992 the Italian government approved Law 488 (L488 henceforth). The program ran between 1996 and 2007 and promoted fixed investment by firms in less developed areas, targeting in particular small-medium enterprises. Subsidies were allocated through public invitations to bid ("calls") that

[4] The risk index is an indicator of the likelihood of default within two years that is computed on the basis of multiple discriminant analyses of financial ratios, as in Altman (1968) (see Rodano et al., 2018). It is computed by an external agency (*Centrale dei Bilanci*) and used for risk assessment purposes by all major Italian financial intermediaries.

[5] The analysis is based on National Social Security Institute (INPS) archives covering the universe of Italian firms with at least one dependent worker. For each firm, the INPS data reports the firm identifier; yearly information on the number employees; date of birth and cessation of activity; detailed geographical (municipality) and industry (3-digit) data; and an identifier for firms belonging to business groups. Gross job creation if obtained adding employment gains at expanding and new firms, and gross job destruction adding employment losses at shrinking and dying firms.

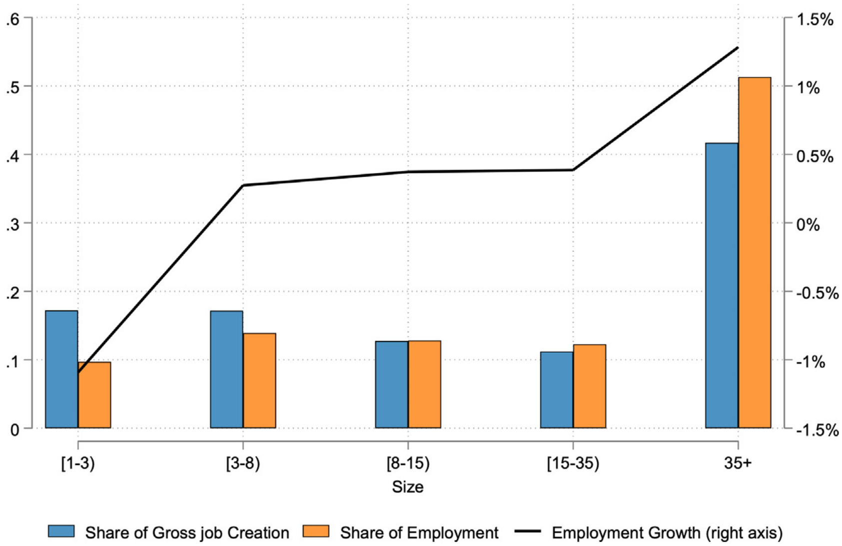

Fig. 2. Job creation, employment share, and employment growth by firm size. *Source*: own calculations from the Italian Social Security Institute (INPS) firm archive.

targeted specific industries such as manufacturing, tourism, and commerce. At each call, available funds were distributed among the 20 Italian regions and projects submitted by applicant firms in each call-region were ranked and funded based on quantitative indicators of project quality, subject to minimum quotas reserved to specific categories of applicants such as small-medium firms.

The indicators used to rank investment projects at the regional level included: 1) the quota of own capital invested in the project, 2) the number of new jobs to be generated, and 3) the ratio between the subsidy requested by the firm and the highest subsidy applicable under rules determined by the EU Commission. Criteria 1 and 3 measured and favoured firms involvement in the project. Criterion 2 was closely tied to the main goal of L488, i.e. increasing employment. Two additional criteria were added starting from the 3rd call in 1998: one rewarding projects that align with regional priorities in terms of location, project type, and sector;[6] and another based on the environmental impact of the project.

The values of each of the five indicators are standardized and combined with equal weight to produce a single score s that measured the overall quality of the project. Funds were allocated combining the ranking of applicants based on s within each call-region with additional rules prioritizing certain categories of applicants and projects, including small-medium firms and projects eligible for co-financing with EU funds. Within each cell c identified by the triplet call-region-additional rule, funds were assigned to firms following the ranking until the exhaustion of financial resources. Winning firms received subsidies in three annual tranches, conditional on complying with the project's execution plan.

3. Empirical strategy

The allocation mechanism described above generates an ideal setting for RDD estimation. Only firms scoring above the cutoff defined by the marginal firm funded in each cell are eligible for funding; in turn, the cutoff for each cell is unknown ex-ante, being defined by the last "marginal" applicant being funded. As a result, firms scoring just above and just below the cut-off are as good as randomly assigned into eligibility.

Let $Y_{ic}(1)$ and $Y_{ic}(0)$ be the potential outcomes of firm i in cell c when scoring above ($Z_{ic} = 1$) and below ($Z_{ic} = 0$) the cutoff. The observed outcome is $Y_{ic} = Z_{ic}Y_{ic}(1) + (1 - Z_{ic})Y_{ic}(0)$. Since the score $\widetilde{S}_{ic}$ completely determines treatment assignment, the difference in observed outcomes between firms with score just above and just below the cutoff $\bar{s}_c$,

$$\lim_{\theta\to\bar{s}_c^+} \mathrm{E}\,[Y_{ic} \mid \widetilde{S}_{ic} = \theta] - \lim_{\theta\to\bar{s}_c^-} \mathrm{E}\,[Y_{ic} \mid \widetilde{S}_{ic} = \theta] = \mathrm{E}\,[Y_{ic}(1) - Y_{ic}(0) \mid \widetilde{S}_{ic} = \bar{s}_c],$$

quantifies the effect of obtaining the subsidy on the marginal firm (Hahn et al., 2001). To estimate such effect, we pool data for all calls, regions, and additional rules and regress firm outcomes on the dummy for receiving the subsidy Z_{ic} controlling for the standardized score $S_{ic} := (\widetilde{S}_{ic} - \bar{s}_c)$,

$$Y_{ic} = \alpha_c + \beta_1 Z_{ic} + \beta_2 S_{ic} + \beta_3 (S_{ic} \times Z_{ic}) + \epsilon_{ic}, \tag{1}$$

where α_c is a cell-specific fixed effect that accounts for the fact that the cutoffs are endogenously determined within each cell (see Fort et al., 2022).[7] The coefficient β_1 identifies the average effect of the subsidy across firms in a neighbourhood of $\bar{s}_c$, provided that other determinants of Y_{ic} vary smoothly at the cutoff (Lee and Lemieux, 2010). In our sample, the results of the McCrary (2008) test and other balance tests are consistent with this assumption for the entire sample (see Cingano et al., 2022).

To explore the heterogeneity of treatment effects between large and small firms, we will estimate Eq. (1) separately on the sub-samples of firms with above- and below-median size (in terms of employment). Figure 3 shows that the density of the running variable S is smooth around the cutoff within each of the two sub-samples, as confirmed by the McCrary test implemented as in Cattaneo et al. (2020).

In presence of treatment heterogeneity, neither the average nor the group specific treatment effects estimated at the cutoff need to be the same for inframarginal firms away from the cutoff. This issue has been addressed in recent developments of the literature Angrist and Rokkanen (see 2015); Cattaneo et al. (see 2021).

The approach proposed by Angrist and Rokkanen (2015) leverages the fact that, in RD designs, the running variable fully determines treatment assignment, and is therefore the only source of selection bias. Hence, a set of observable covariates that makes the running variable ignorable in the prediction of potential outcomes could serve as the basis for a matching estimator.

[6] In Cingano et al. (2022) we estimate the implications of this discretionary criterion for the allocation and effectiveness of subsidies.

[7] While the baseline specification (1) is linear in the assignment variable $\bar{s}$, we extensively explore the sensitivity of results to second order polynomials (Gelman and Imbens, 2019) and triangular kernels attaching greater weight to observations closer to the cutoff.

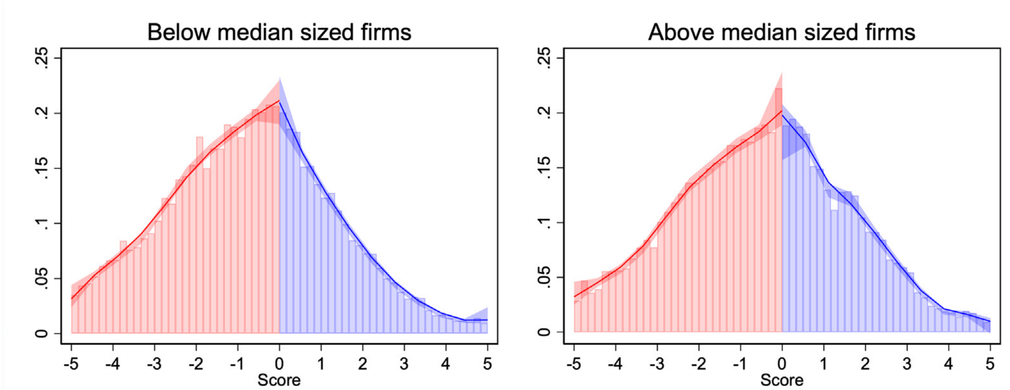

Fig. 3. Density of applications around the cutoff, by firm size. *Notes*: The histograms show the distribution of applicant scores is) separately for below-median size firms (left graphs) and above-median size firms. Local polynomial density estimates (solid lines) and robust bias-corrected 95% confidence intervals (shaded areas) computed according to Cattaneo et al. (2020) are also reported.

Specifically, if there exists a set of covariates X such that (i) potential outcomes are mean independent of the running variable S conditional on X (Conditional Independence Assumption, CIA),

$$\mathrm{E}\,[Y(j) \mid S, X] = \mathrm{E}\,[Y(j) \mid X]\,,\ j \in \{0,1\}$$

and (ii) treatment status varies conditional on X (Common Support),

$$0 < \Pr(Z=1 \mid X) < 1, \quad \text{a.s.,}$$

then one can estimate the average treatment effect in any interval $\mathcal{I}$ contained in the support of the running variable S. Specifically, this can be accomplished by, first, comparing treated and controls conditional on X and then averaging with respect to the distribution of X conditional on $S \in \mathcal{I}$. For example, the average treatment effect on the treated is identified in the data by

$$\mathrm{E}\,[Y(1)-Y(0) \mid S \in \mathcal{I}] = \mathrm{E}\,[\mathrm{E}\,[Y \mid X, Z=1] - \mathrm{E}\,[Y \mid X, Z=0], S \in \mathcal{I}],$$
$$\mathcal{I} = [0, \infty), \tag{2}$$

where we assumed, for simplicity, that the support of the running variable is unbounded to the right.

Importantly, both conditions described above are -at least partially-testable. In particular, regressing outcomes on X and S on either side of the cutoff provides a simple test for the CIA. As shown in Cingano et al. (2022), applying the approach of Angrist and Rokkanen (2015) in our context amounts to:

1. estimate the linear regression
$$\mathrm{E}\,[Y \mid X, S, Z=j] = \sum_{k=1}^{p} S^k \alpha_k^j + X^{'} \delta_j, \quad j \in \{0,1\};$$
2. test the restrictions
$$\alpha_k^1 = \alpha_k^0 = 0, \qquad \forall\, k = 1, \ldots, K,$$
where failure to reject such restrictions provides evidence consistent with the vector X satisfying the CIA;
3. check that the overlap condition $\Pr(Z=1 \mid X) \in (0,1)$ is satisfied;
4. if a certain vector of covariates X satisfies the restrictions in steps 2 and 3, it is then sufficient to use it in Eq. (2) to compute
$$\mathrm{E}\,[Y(1)-Y(0) \mid S \in \mathcal{I}] = (\delta_1 - \delta_0)' \mathrm{E}[X \mid S \in \mathcal{I}],$$
where δ_0 and δ_1 are defined in step 2.

Note that for any sub-vector W of X, $\mathrm{E}[Y(1)-Y(0) \mid X, W] = \mathrm{E}[Y(1)-Y(0) \mid X]$. This simple result can be used to compute the average treatment effect along the values of the variable W,

$$\begin{aligned}\mathrm{E}[Y(1)-Y(0) \mid W] &= \mathrm{E}[\mathrm{E}[Y(1)-Y(0) \mid X, W] \mid W] \\ &= \mathrm{E}[\mathrm{E}[Y(1)-Y(0) \mid X] \mid W].\end{aligned}$$

We will use this result in Section 5 to explore the heterogeneity of the effect along the firm size distribution.

4. Data description

The analysis leverages a unique dataset combining administrative and balance sheet data. Information on projects submitted and funded under Law 488 was obtained from the Italian Ministry of Economic Development and complemented with data scraped from several issues of the Official Journal of the Italian Republic (*Gazzetta Ufficiale*). The resulting dataset covers over 70 thousand projects submitted to 26 calls for funds issued in the period 1996 – 2007, accounting for nearly 85% of the 26 billion funded under the program. Each record provides information on the applicant (fiscal code, location, and industry), the details of the application (the subsidy requested and amount awarded along with the project's application score), and the cell of applicants competing for funds. The cell identifies a group based on the following criteria: company size (large, medium-small), industry sector (manufacturing, energy, tourism, trade, services), availability of co-financing (yes or no), and location (region). This information enables accurate placement of projects into the various sub-rankings populating the same grant call, region, and possibly characteristics of the applicant.

Fiscal identifiers made possible the merge of L488 data with National Social Security Institute (INPS) archives covering the universe of Italian companies with at least one employee (around 1.6 million companies per year between 1985 and 2014). These administrative registers record the employment figures of each enterprise at monthly frequencies, as well as the dates of birth and death of each enterprise. Hence, we could precisely determine the job numbers of applicant companies on a monthly basis, as well as their survival rates over long time horizons. In merging the data, we lost around 20 thousand applications from sole proprietorships, whose fiscal identification is anonymized in INPS data. Moreover, we excluded around 10 thousand applications submitted by new-born firms (i.e. first appearing in the INPS data in the year of the call).[8] Our main analysis of employment effects will therefore be based on a sample of 40 thousand projects submitted by 27 thousand different firms.

Finally, we recovered in-depth balance sheet information from the Firm Register managed by the Cerved group. This database contains information on all Italian limited liability companies, including 80% of the firms in the matched L488-INPS data, for a total of 21,459 compa-

[8] We also removed the top 1% of firms in terms of size. Such firms typically employ around 5000 workers and are 100 times the size of the median firm in our sample. These firms are dominant in high-returns-to-scale industries such as utilities, automotive or chemicals, and it would be difficult to reliably match them to comparable units. We have verified that none of these sample restrictions significantly affects our results.

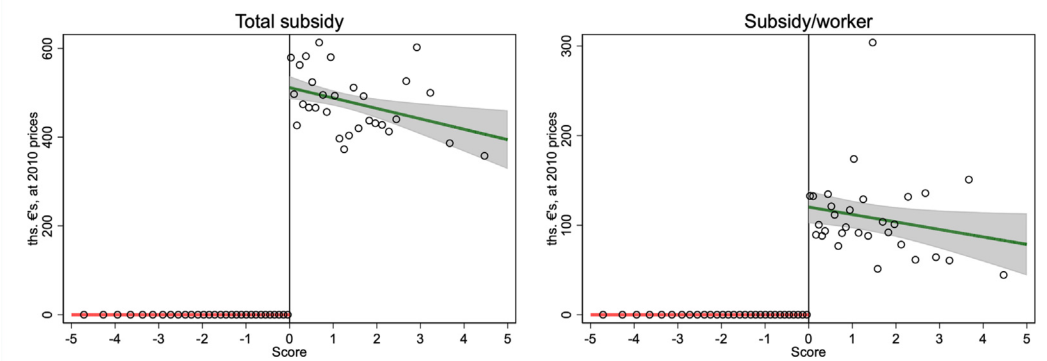

Fig. 4. Funds paid to winning firms. *Notes*: This figure shows the relationship between the total amount of funds obtained by firms applying for L488/92 subsidies (left graph) and the ratio of funds over workers employed in the firm one year before the application (right graph) against the standardized application score (on the horizontal axis). Both graphs plot averages within equally-sized bins and the predicted relationship based on a linear regression together with 90% confidence intervals based on heteroskedasticity-robust standard errors clustered by cell.

nies and 33,511 distinct projects. Importantly, the final sample is fully representative of the population of applicants (Cingano et al., 2022).

5. Results

5.1. Treatment effects near the cutoff

Sourcing on L488 data, the left panel in Fig. 4 shows the average subsidy paid to firms conditional on the application score. The graph plots the average values within 30 equally-sized subsamples on either size of the cutoff along with fitted regressions and confidence intervals. The average subsidy obtained by applicants just above the cutoff amounts approximately to 500 thousand euros, while applicants just below the cutoff receive no subsidy - as it should be expected.[9] The right panel of Fig. 4 plots the same graph for the ratio between the value of the subsidy and the number of workers employed by the firm during the previous year. The average subsidy-per-worker is above 100 thousand euros for applicants above the cutoff.

However, these averages mask extreme heterogeneity by firm size, as visible from the merged L488-INPS dataset. Figure 5 replicates the graphical analysis in Fig. 4 distinguishing between firms below and above the median number of employees in the year before application (10.8 employees). Not surprisingly, above-median size firms receive larger subsidies than below-median size firms - 600 and 400 thousand euros, respectively (top graphs in Fig. 5). However, their average size equals 66.4 and 4.0 employees, respectively, so smaller firms receive much higher subsidies relative to the number of workers employed before the application. Indeed, the subsidy per employed worker requested by below-median size firms (200 thousand euros) is ten times larger than that requested by above-median size firms scoring just above the cutoff (bottom graphs of Fig. 5). When comparing the cost effectiveness of subsidies paid to different types of firms, it will thus be important to keep these differences into account.

Figure 6 plots the log of firm investment during the three years since having applied for the subsidy across all applicant firms (left graph), smaller firms (middle graph), and larger firms (right graph). For all types of firms, applicants scoring just above the cutoff (receiving the subsidy) invest more than applicants scoring just below the cutoff (not receiving the subsidy). Panel A of Table 1 reports the size of the discontinuity, as estimated from regression (1) when using either a linear specification in the application score S (odd columns) or a quadratic specification (even columns). In the linear specification, receiving the subsidy increases investment by 0.33 log points (+39 percent) across all firms (column 1), and the effect is only slightly smaller when employing a quadratic specification (column 2). Columns (3)–(6) show that small firms generate a greater (percent) increase than large firms 0.58 and 0.18 log points, respectively, when using a linear specification.

In Panels B and C of Table 1, we move to the main outcome of interest of the policy, namely employment, measured at three and six years since applying for the subsidy. During the first three years, which corresponds to the period over which winning applicants receive the subsidy, the difference in employments between applicants scoring just above and just below the cutoff amounts to 0.10 log points (+11 percent), statistically significant at the 1% confidence level. The effect increases to 0.15 log points (+16 percent) six years after receiving the subsidy, i.e. three years after the end of the subsidy period; we obtain a similar estimate when replicating the analysis over longer time horizons. Therefore, the policy seems to generate a permanent change in the employment of subsidized firms, as opposed to a mere intertemporal substitution of hiring and firing decisions. These results are robust to including a quadratic polynomial in S instead of the linear specification.[10]

In columns (3)-(6) we explore the heterogeneity of the effects on investment and employment between small and large firms. In line with the evidence on investment (Panel A), the subsidy produces greater employment growth for smaller firms compared to larger firms (+20 and +8 percent, respectively, over a six-year period). These findings are confirmed in Fig. 8, which plots the cumulated log-change in employment between 2 years before and 6 years after applying for the subsidy, separately for small and large firms.

At the same time, larger firms employ (by construction) a much larger number of workers, as shown in Fig. 7, so even small percent effects of subsidies on such firms could generate large increases in the total number of employed workers. A similar argument holds for investment, as larger firms generate of course higher levels of total investment than small firms - as it is also clear from the second and third graph in Fig. 6. In addition, smaller firms receive relatively larger subsidies compared to large firms.

Therefore, it is ultimately unclear whether it is more cost-effective to fund small or large firms. To answer this question, in Table 2 we compute the cost-per-newly-created job, defined as the ratio between the subsidy and the (estimated) number of new jobs generated by firms obtaining the subsidy, for different categories of firms. We proceed in steps:

[9] Within the subset of winning applicants, the average subsidy declines slightly with the value of the score. This is due to the fact that the third subcomponent of the overall score is inversely related to the amount requested by the firm so, other things equal, applicants requesting lower amounts score higher on average.

[10] Results are also robust to varying the RD bandwidth and to using a triangular kernel; see Cingano et al. (2022) for extensive robustness checks.

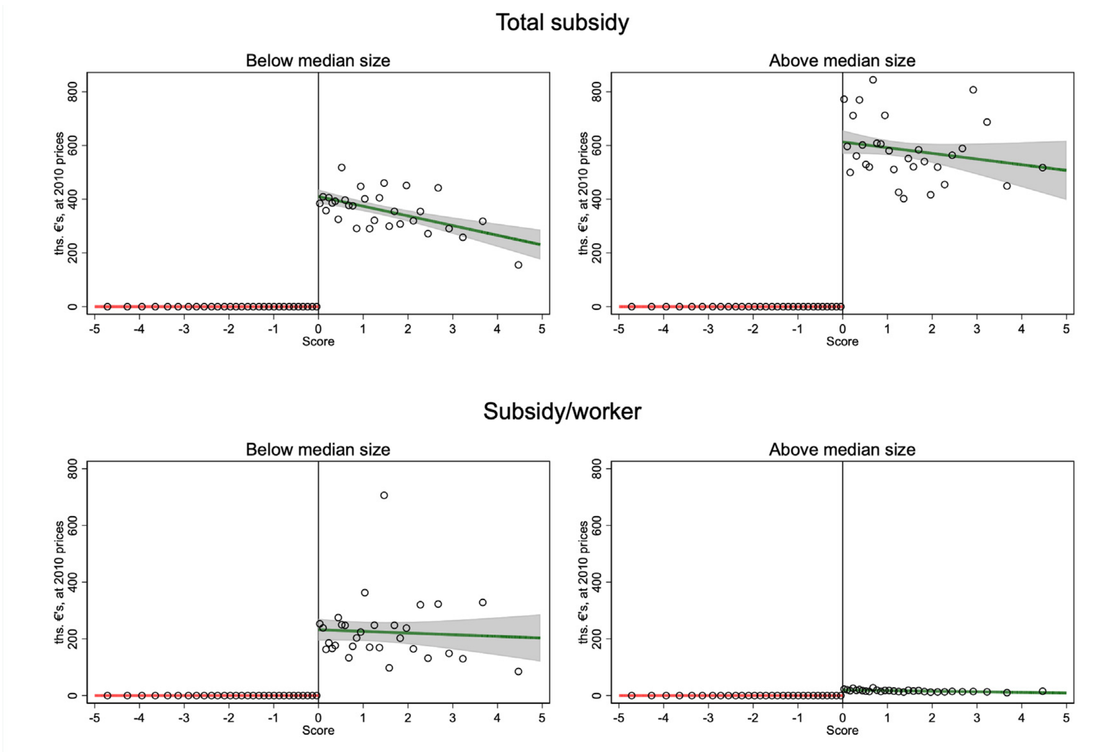

Fig. 5. Funds paid to winning firms, by size. *Notes*: This figure shows the relationship between the total amount of funds obtained by firms applying for L488/92 subsidies (top graphs) and the ratio of funds over workers employed in the firm one year before the application (bottom graphs) against the standardized application score (on the horizontal axis), separately for below-median size firms (left graphs) and above-median size firms (right graphs). All graphs plot averages within equally-sized bins and the predicted relationship based on a linear regression together with 90% confidence intervals based on heteroskedasticity-robust standard errors clustered by cell.

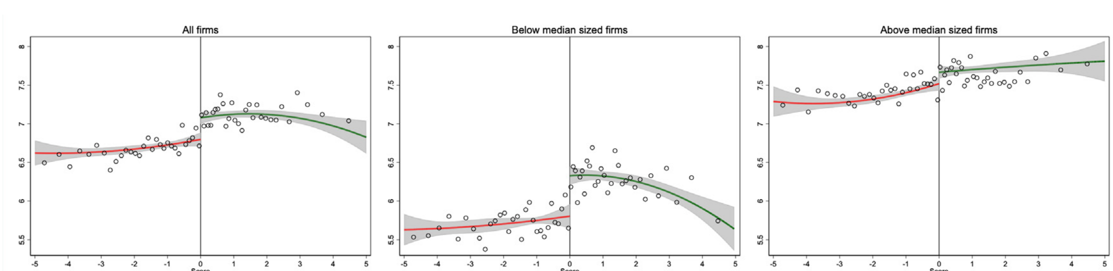

Fig. 6. Firm investment in the three years after having applied for the subsidy. *Notes*: This figure shows the relationship between the log of cumulated investment during the three years after having applied for L488/92 subsidies against the standardized application score (on the horizontal axis) across all firms (left graph), below-median size firms (middle graphs), and above-median size firms (right graph). All graphs plot averages within equally-sized bins and the predicted relationship based on a linear regression together with 90% confidence intervals based on heteroskedasticity-robust standard errors clustered by cell.

- columns (1) and (2) report, respectively, the RD coefficient and the average number of workers employed in the year before application by firms close to the cutoff, defined as firms within a bandwidth of size 10 around the cutoff (i.e., $S \in [-5, 5]$);[11]
- in column (3), we compute the number of newly created jobs as the product between columns (1) and (2);
- column (4) shows the average subsidy requested by the same set of firms close to the cutoff;
- finally, column (5) computes the cost of creating an additional job as the ratio between requested funds and number of jobs.

According to this calculation, the cost of creating one new job in below-median size firms is more than five times larger than the cost required to create a job in above-median size firms. This is due to fact that the average initial number of employees of large firms is 15 times that of small firms, so even a smaller employment growth generated by the subsidy translates into a higher number of new jobs – 4.9 and 0.7, respectively. In addition, larger firms request subsidies that are only slightly larger, on average, than those requested by small firms – 774 and 571 thousand, respectively.

Therefore, Table 2 conveys a very different message than Table 1, which only considers the effect of subsidies on the percent change in firm employment. Once we translate such effect into the number of newly created jobs and we account, in addition, for the amount of subsidies paid to each type of firm, subsidies to large firms are more cost-effective than subsidies to small firms.

At the same time, the validity of estimates and the cost-calculations in Table 2 remains limited to a narrow subset of "marginal" applicants close to the cutoff. We next address this limitation using the procedure illustrated in Section 4.

[11] Results are robust to using different bandwidths and different (non-uniform) kernels. See Cingano et al. (2022) for extensive robustness checks.

Table 1
Firm investment and employment after having applied for the subsidy.

Sample	all firms		small (below-median)		large (above-median)	
Specification	Linear (1)	Quadratic (2)	Linear (3)	Quadratic (4)	Linear (5)	Quadratic (6)
Panel A. Log cumulated investment over 3 years						
Subsidy	0.360***	0.278***	0.612***	0.523***	0.203***	0.148*
	(0.055)	(0.073)	(0.071)	(0.113)	(0.054)	(0.076)
Observations	17,425	17,425	7164	7164	10,261	10,261
R^2	0.229	0.229	0.128	0.128	0.267	0.267
Panel B. Log change of employment over 3 years						
Subsidy	0.103***	0.106***	0.163***	0.184***	0.035*	0.034
	(0.020)	(0.025)	(0.030)	(0.039)	(0.018)	(0.025)
Observations	31,681	31,681	15,612	15,612	16,069	16,069
R^2	0.059	0.059	0.094	0.094	0.068	0.068
Panel C. Log change of employment over 6 years						
Subsidy	0.152***	0.123***	0.202***	0.158***	0.082***	0.077**
	(0.024)	(0.029)	(0.035)	(0.048)	(0.026)	(0.035)
Observations	28,759	28,759	13,976	13,976	14,783	14,783
R^2	0.066	0.066	0.105	0.105	0.067	0.067

Notes: This table shows the effect of L488/92 subsidies on firm investment and employment growth, as estimated from linear and quadratic specifications of Eq. (1), as indicated on top of each column, across all applicant firms (columns 1–2), below-median size applicants (columns 3–4), and above-median size applicants (columns 5–6). The dependent variable in each regression is indicated on top of each panel: log of cumulated investment in the 3 (calendar) years after the award of subsidies (Panel A); and log change of firm employment in the 36 months and 72 months after the award of subsidies (Panels B and C). Heteroskedasticity-robust standard errors clustered by cell are reported in parenthesis($^{*} p < 0.1$;$^{**} p < 0.05$;$^{***} p < 0.01$).

Table 2
Treatment effect, number of newly-created jobs, and cost per new job, by firm size.

	Treatment effect (% change) (1)	initial employment (2)	number of new jobs (3)	Funds (ths. €) (4)	Cost/job (ths. €) (5)
all firms	12.3	33.9	4.2	673.6	161.4
small firms	15.8	4.2	0.7	571.4	866.3
large firms	7.7	63.1	4.9	773.9	158.8

Notes: The table computes the estimated cost of generating additional employment by small (below median size) and large (above median size) firms *around the cutoff*. Treatment effects are the estimated effects of L488/92 subsidies on 6-year employment growth reported in even columns of Table 1, Panel C.

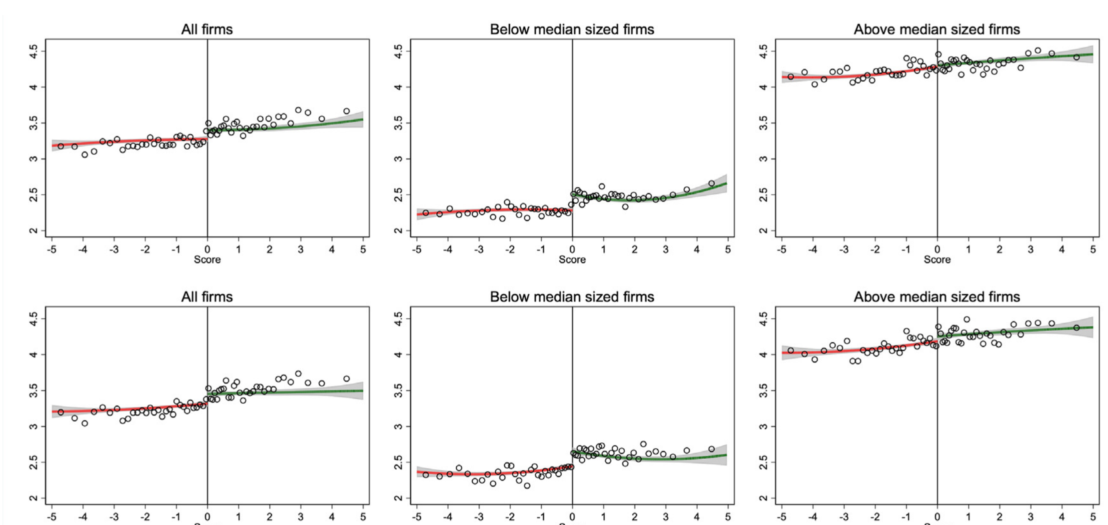

Fig. 7. Firm employment three and six years after having applied for the subsidy. *Notes*: This figure shows the relationship between the log of firm employment three and six years after having applied for L488/92 subsidies (top and bottom graphs, respectively) against the standardized application score (on the horizontal axis) across all firms (left graph), below-median size firms (middle graphs), and above-median size firms (right graph). All graphs plot averages within equally-sized bins and the predicted relationship based on a linear regression together with 90% confidence intervals based on heteroskedasticity-robust standard errors clustered by cell.

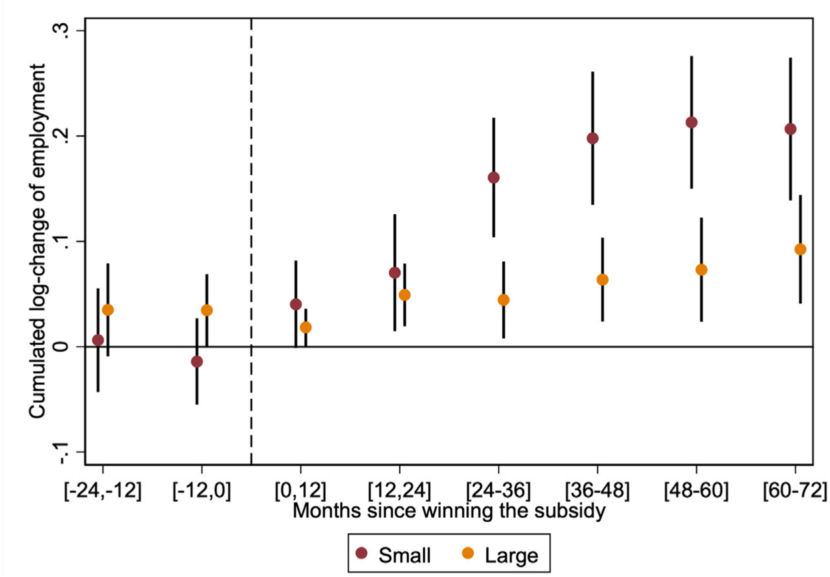

Fig. 8. Effect of the subsidy on firm employment at different horizons, by size. *Notes*: This figure shows the estimated effect of the subsidy (and associated 90% confidence intervals) on the log of firm employment up to 6 years after obtaining the subsidy as well as the (placebo) estimated effects for up to 2 years before obtaining the subsidy, separately for small and large firms. Point estimates and confidence intervals refer to the linear regression in (1) and heteroskedasticity-robust standard errors are clustered by cell.

Table 3
Cost per new job across all applicant firms, by size.

	cost per job
all firms	185.2
small firms	632.8
large firms	121.4

Notes: The table reports the estimated cost (in thousands of euros) of generating additional employment by marginal and inframarginal firms of small (below median) and large (above median) size in the sample.

5.2. Treatment effects and cost effectiveness across all firms

Following Angrist and Rokkanen (2015), we characterize the distribution of treatment effects along the size distribution in two steps. In the first step, we extrapolate the distribution of treatment effects along the running variable by invoking (i) mean independence of the outcome on the running variable, and (ii) common support between treated and control conditional on a vector X of covariates. In Cingano et al. (2022), we show that both conditions hold for a vector that includes the following covariates: firm age, lagged firm growth, 3-year forward growth of firms in the same market (as defined by the local-labor-market and 3-digit sector), average wage of white-collar workers, binary indicators for having managers or apprentices, size of the investment project over initial employment, and cell fixed-effects.[12] In the second step, we compute average treatment effects for small and large firms, respectively, as well as the corresponding cost-per-job.

Table 3 shows the estimated cost-per-job, defined as total subsidies over the estimated number of newly created jobs, across all applicant firms (including also inframarginal firms) and distinguishing between below- and above-median firms. Interestingly, there are some important differences with the results obtained for marginal firms close to the cutoff, reported in Table 2. When including inframarginal firms away for the cutoff, the estimated cost per new job is considerably lower (by about 20%) for both small and large firms; at the same time, the estimated cost across all firms turns out to be higher (by 15%), due to a different composition by size. These findings highlight the importance of extending the analysis to applicants away from the cutoff in order to correctly assess the cost-effectiveness of the policy. Turning to the comparison between small and large firms, the evidence is qualitatively similar to the results in Table 2: large firms exhibit a lower cost per new job than small firms.

The top panel of Fig. 9 confirms that the cost per new job declines monotonically with size – from about 100 thousand euros in the top quintile of firm size distribution (35 + employees) to 1.5 million in the bottom quintile (0–2 employees). The bottom panel of 9 investigates heterogeneity along a different dimension, namely firm age. In this respect, the evidence is less clear-cut. The cost per new job is highest for the youngest firms – 323 thousand euros per job for firms between 0 and 2 years old, and 181 thousand euros for firms between 3 and 6 years old; it (slightly) declines to 153 thousand euros for firms between 7 and 19 years old only to increase to 181 thousand for the oldest firms. However, the pattern of heterogeneity by age may reflect also heterogeneity by size, as younger firms are typically smaller than older firms, which may partly explain their higher cost per new job.

To disentangle heterogeneity along these two dimensions, in Fig. 10 we plot heterogeneity of treatment effects for (percent) employment changes (left graph) and cost per newly-created job (right graph) by quintiles of firm size (vertical axis) and firm age (horizontal axis). The cost per new job varies mostly along the size dimension – as opposed to along the age dimension – and it is lowest for younger and larger firms.

An alternative criterion to classify firms follows the institutional features of the policy, which reserved part of the funds to small-medium enterprises, defined as firms with 50 + employees. This implies splitting the sample in two groups of around 2.5 thousand "large" firms with a median size of 135 (mean 240) employees on one hand, and nearly 31 thousand "small-medium enterprises" (SME) with a median size of 9.6 (mean 20) employees on the other.

Figure 11 plots the estimated cost per new job (left graph) and the subsidy to investment ratio (right graph) and associated confidence intervals for large and small-medium enterprises, respectively. The average cost per new job in the first group of large firms is even lower than in the case of above median firms (€ 78 thousand per job). The estimated average cost in case of SMEs is also lower than in below-median firms (because SMEs also include larger firms) but it is still three times (€ 253 thousand) higher than the cost of larger firms, a difference that is statistically significant. As for investment, the same methodology reveals that public subsidies induce much higher investment multipliers in large firms than in small firms: the former invest on average € 2.5 per euro of subsidy, whereas small firms only invest the amount of the subsidy.

[12] All results are robust to conditioning on an alternative set of covariates selected according to data-driven algorithm in the spirit of Imbens and Rubin (2015). This algorithm implements a greedy approach that selects, at each step, the variable making the ignorability condition most likely to hold (see Palomba, 2023, for further details on the algorithm).

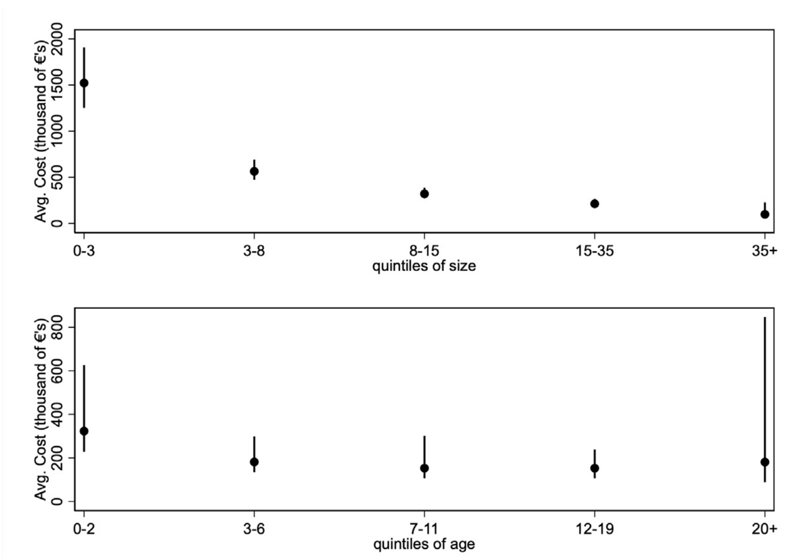

Fig. 9. Cost per new job, by quintiles of firm size and age. *Notes*: This figure shows the estimated cost of generating additional employment, as measured by the subsidy per new job, by quintiles of firm size (top graph) and age (bottom graph). Vertical bars represent 90% confidence intervals computed using 1.000 draws of a non-parametric cluster Efron bootstrap, where clusters are defined at the cell-level.

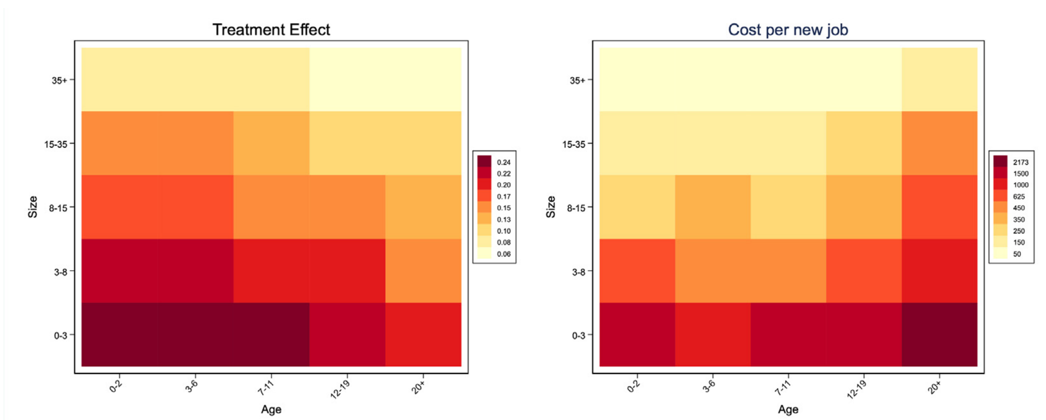

Fig. 10. Treatment effects and cost per new job, by firm size and age. *Notes*: This figure shows the estimated treatment effect on employment (left graph) and the cost of generating additional employment, as measured by the subsidy per new job, (right graph) by quintiles of firm size (vertical axis) and age (horizontal axis).

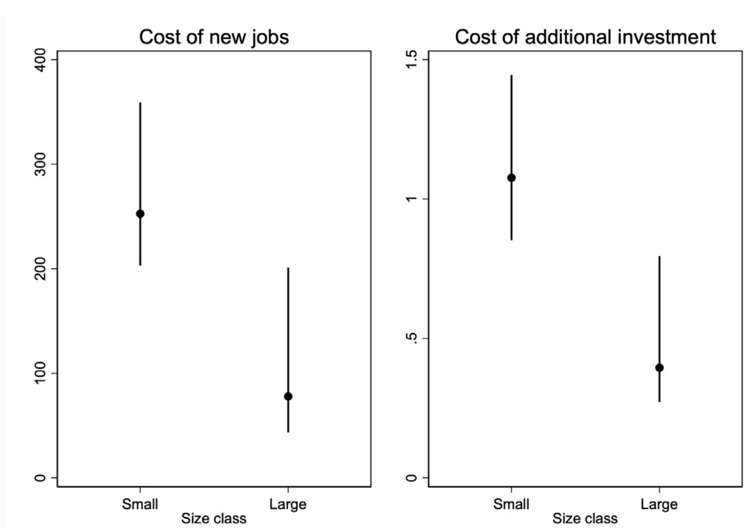

Fig. 11. Cost per new job and subsidy to investment ratio, by firm size. *Notes*: This figure shows estimated cost of generating additional employment, as measured by the subsidy per new job, (left graph) and the cost of generating additional investment, as measured by the subsidy per euro of investment, (right graph) separately for small and large firms. Vertical bars represent 90% confidence intervals computed using 1.000 draws of a non-parametric cluster Efron bootstrap, where clusters are defined at the cell-level.

6. Conclusion

Public subsidies to private business are justified only to the extent that they generate additional employment over and above the level that would be observed under a pure market allocation. We characterize the effects and (cost-)effectiveness of subsidies to different types of firms in Italy, focusing in particular on heterogeneity by size and age. We find that -conditionally on age- small firms generate greater percent increases in employment than large firms when receiving the subsidy, but the latter generate a higher number of new jobs per euro of subsidy. Younger firms generate both higher employment growth and a higher number of new jobs per euro of subsidy compared to older firms, ceteris paribus.

These results suggest that tuning the allocation of subsidies on a few observable characteristics – namely, firm size and age – may improve the cost-effectiveness of similar government policies. From a methodological perspective, we highlight the importance of moving beyond local effects for a (potentially small) subset of compliers in order to correctly assess the costs and benefits of policy interventions.

Data availability

The data that has been used is confidential.

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