Production Network Spillovers from EU-Funded R&D Grants*

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Abstract

We study an additional channel for spillovers from innovation funding: transmission through production networks. Higher expected demand from knowledge-intensive firms makes investment in producing complementary inputs more profitable and can be financed by payments from customers' orders. To assess this empirically, we link administrative records on Croatia's 2019 €225 million research and development grant program to the near-universe of domestic firm-to-firm transactions and analyze the impact of the program on suppliers of the grant recipients. Although we find no evidence of impacts on productivity, affected suppliers experienced increases in skilled worker employment and sales per worker, with larger and more persistent effects among those initially facing greater financial constraints. Despite recipients' concentration around Zagreb, indirect effects through the production network benefited distant counties. Our findings suggest that accounting for supplier effects lowers the cost per job created by the program from €106,000 to €33,000.

JEL Classification: G32, O38, L14, H25, D22, R11

Keywords: R&D grants, production networks, financial constraints, suppliers

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1 Introduction

Governments subsidize innovation partly because firms' discoveries can benefit others (Jaffe et al., 1993; Bloom et al., 2019). We study an additional channel for these spillovers: transmission through production networks. Through their purchases, grant recipients can expand suppliers' markets and ease the financial constraints on knowledge-intensive investment. Beyond positive demand shocks in general, innovation subsidies may generate demand for knowledge-intensive goods, stimulating that kind of investment the firms that supply the inputs for research and development activities.

To understand how customer funding can produce upstream spillovers, we model suppliers' investment in knowledge. Expected future demand raises the return to improvements in production in the spirit of Carvalho and Draca (2017). When external finance is costly, retained earnings from initial orders help suppliers pay for that investment (Froot et al., 1993). Knowledge investment is particularly difficult to finance externally because intangible capital provides limited collateral (Falato et al., 2022). In our model, suppliers invest in knowledge that raises skilled workers' productivity and lowers production costs.

We examine Croatia's €225 million R&D grant program, which awarded funding to 174 of 295 applicants. The most common project duration was 24 months, within a range of 12 to 42 months. We link administrative grant records to annual financial statements, matched employer-employee records, and the near-universe of domestic firm-to-firm transactions. This data allows us to identify recipients' suppliers before the award and follow their subsequent outcomes.

To estimate the effects of customer funding on suppliers, we first match recipients to non-funded Croatian firms on pre-award characteristics, including lagged outcomes and production-network measures. We then separately match suppliers of these two groups of buyers, excluding suppliers that sold to both groups before the award. We use difference-in-differences to compare subsequent outcome changes between each treated group and its matched controls, assuming that their outcomes would have followed parallel trends without the grants.

We find that grant recipients increased material purchases by about 22%, expanding demand for their suppliers. Suppliers of award recipients increased sales and material purchases in the award year, then add workers and capital. Supplier revenue rose by about 28% in the award year and 46% three years later, while employment rose by about 9–12% in years one through four. These gains persist four years later, exceeding the typical funded project's 2-year duration.

Our results suggest that the upstream effects may have been the result of easing financial frictions that prevented prior investment in knowledge-intensive activity as highlighted by our model. Suppliers experienced increases in sales per worker and raised their skilled worker share by 1.2 percentage points in the first and second post-award years and by 1.0 percentage point in year four. Using a novel measure of financial distress, we find that suppliers facing the tightest financial constraints before the grant, measured using the Omega score, expand most and have the largest increases in sales per worker and the skilled worker share. These differences suggest a role for internal funds in financing suppliers' investment. However, we find no clear increase in total factor productivity or consistent increase in intangible assets for these firms.

Because we also observe firm locations, we can assess the geographic incidence of the direct and spillover effects. Most recipients were located in the City of Zagreb and surrounding Zagreb County, yet suppliers more than 171 kilometers from their funded customers also benefited from their relationships with recipients. Measures that assign spillovers only to nearby firms would miss these distant suppliers. For place-based policy, these gains show how funding concentrated in an agglomeration can support employment in other regions through production networks.

Our back-of-the-envelope estimates suggest that including supplier effects substantially improves the program's estimated cost-effectiveness. Accounting for supplier employment cuts grant expenditure per predicted job from about €106,000 to €33,000, roughly one-third of the recipient-only estimate.

We contribute to the literature assessing the rationale and impact of public spending on firm innovation. Evaluations of R&D grants have found increases in recipients' investment, innovation, and growth (Bronzini and Iachini, 2014; Howell, 2017; Santoleri et al., 2024), while related investment subsidies raised employment and capital investment, with larger employment gains among small firms (Criscuolo et al., 2019; Decramer and Vanormelingen, 2016). Research on spillovers have primarily focused on horizontal spillovers in the technology space: Dechezleprêtre et al. (2023) found that R&D tax relief increased patenting among technologically connected firms in smaller technology classes , and (Myers and Lanahan, 2022) studied the content of patents generated by public R&D grants to pin down evidence of knowledge externalities. We document an additional channel through recipients' purchases, identifying gains from increased demand for knowledge-intensive production upstream.[1]

[1]Technology grants also increased employment in Finnish manufacturing firms (Hirvonen et al., 2025), and R&D-grant cash windfalls reached incumbent workers (Howell and Brown, 2023). Lanahan et al. (2021) argued that recipient employment can miss grant-funded activity undertaken by external research partners.

Our second contribution is to research on the interaction between supply chains and financial constraints. Previous work has focused on supplier financing driven by payment terms: shorter customer payment terms reduced default among French trucking firms (Barrot, 2016), and faster government payments increased employment among small US contractors (Barrot and Nanda, 2020). Supply-chain relationships also helped firms preserve innovation during banking shocks through trade credit and R&D cooperation (Brancati et al., 2026).[2] We examine how additional purchases by grant-funded customers support suppliers' investment, linking innovation policy to the financing role of customer relationships.

Third, we contribute to research on the transmission of demand shocks through production networks. Government procurement raised employment in recipient industries and the industries supplying them (Barattieri et al., 2023), while firms passed foreign demand increases to domestic suppliers through higher input purchases (Dhyne et al., 2025). Lerche (2025) found that local employment spillovers from investment tax credits were concentrated within five kilometers and were strongest between firms in industries connected through input-output linkages. We observe actual pre-award buyer–supplier relationships, allowing us to trace effects to connected suppliers far from funded customers. We also examine how suppliers' employment and workforce composition change as these demand effects persist.[3]

Section 2 describes the program and data. Sections 3 and 4 present the model and empirical design. Section 5 reports the results, Section 6 evaluates employment and fiscal gains, and Section 7 concludes. The appendices provide the full model, data and estimation details, and additional results.

2 Institutional Background and Data

2.1 Institutional Background

Croatia's gross domestic expenditure on R&D rose from €502 million in 2018 to €1.08 billion in 2023 (Eurostat, 2026). Businesses perform 54.7% of R&D. Foreign sources, principally EU structural and investment funds, provide 18.3% of R&D funding, compared with roughly 11% across the EU (Croatian Bureau of Statistics, 2024). HAMAG-BICRO administers national grant programs that channel these funds to firms.

[2]Related work found that credit-supply shocks affected borrowers' trading partners (Alfaro et al., 2021), public credit benefited downstream firms while displacing competitors (Ru, 2018), and low liquidity amplified adverse shocks along production links (Demir et al., 2024).

[3]Carvalho and Draca (2017) found that procurement stimulated upstream innovation by expanding suppliers' markets, and Hvide and Meling (2023) proposed learning to explain startups' continued growth after temporary demand shocks.

We study the EU-funded R&D call launched in late 2019, which accepted applications in early 2020.[4] Of 295 applicants, 174 received funding and 121 were rejected. Contracted grants totaled €225.2 million, with a median award of €1.00 million. Grants covered about 64% of eligible project costs on average; the maximum co-financing rate was 80%.

Evaluators scored applications on project design and maturity, implementation capacity, value for money, novelty and significance, sustainability, and commercialization potential, and assigned an overall score. To qualify for funding, applicants had to meet both the criterion-specific thresholds and the overall threshold. We obtain detailed scores for a subset of successful and rejected applications and compare firms around the cutoff in Appendices D and E.

The most common project duration in our sample was 24 months, within a range of 12 to 42 months. Recipients received payments after verified project milestones. They could use grants to pay research and technical staff, buy equipment, infrastructure, and materials, and commission research from universities, research institutes, and other providers. Funded projects included Rimac Automobili's software platform for autonomous driving in extreme conditions, PASTOR's autonomous firefighting device, and SAMPLE CONTROL's FoodForensics project combining analytical methods with machine learning. To carry out these projects, recipients need engineering, equipment, materials, and specialized services that domestic suppliers can provide.[5]

Other EU business-support programs operated at the same time. We account for innovation-commercialization and digital-transformation grants when constructing the comparison groups.[6] The commercialization programs funded 238 firms, with a mean grant of €271 thousand, a median of €182 thousand, and average grant intensity of 65%; 44 firms were rejected. Digital-transformation grants funded 989 firms, with a mean grant of €48 thousand, a median of €37 thousand, and average intensity of 68%; 111 firms were rejected. Section 4.1 describes how we exclude their recipients and account for their supplier links.

2.2 Descriptive Statistics

We obtain application timing, scores, thresholds, funding decisions, project duration, and grant amounts from the grant records of the Ministry of Regional Development and EU Funds

[4]The call was *"Povećanje razvoja novih proizvoda i usluga koji proizlaze iz aktivnosti istraživanja i razvoja – faza II"*, code `KK.01.2.1.02`.

[5]Project descriptions are available in the program documentation: https://efondovi.mrrfeu.hr/MISPublicApi/poziv/download/c8e242a1-e797-420e-8ace-a77187a779e4.

[6]The commercialization calls were *"Inovacije novoosnovanih MSP-ova – II faza"*, code `KK.03.2.2.04`, and *"Inovacije u S3 područjima"*, code `KK.03.2.2.06`. The digital-transformation call was *"Poboljšanje konkurentnosti i učinkovitosti MSP-a kroz informacijske i komunikacijske tehnologije (IKT) – 2"*, code `KK.03.2.1.19`.

and HAMAG-BICRO. We link these records to FINA's annual financial statements and obtain revenue, material costs, employment, tangible assets, and other financial outcomes.

We study four innovation-related outcomes: sales per worker, total factor productivity (TFP), intangible assets, and the skilled worker share. We estimate TFP using the ACF procedure developed by Ackerberg, Caves and Frazer (2015). We measure intangible assets using the accounting stock of capitalized development expenditure and other intangibles. Using pension-insurance records, we calculate the skilled worker share as the share of employees in occupations requiring higher levels of education.

We obtain domestic firm-to-firm sales within the VAT system from confidential Croatian Tax Administration records. We use pre-award relationships to define suppliers' exposure to funded customers.[7] We link transactions to firms' headquarters municipalities to measure the distance between each customer and supplier and estimate how spillovers vary across locations. National industry input-output tables identify sectoral connections; these records identify the individual suppliers exposed to each recipient.

We measure suppliers' pre-award financial constraints with the Omega score, which Altman et al. (2023) developed to predict creditor-payment default. Default occurs when unpaid obligations lead to bank-account blockage. Suppliers with more negative scores face tighter financial constraints in our sample. We assign them to least, middle, and most constrained groups, with the most constrained labeled the top tercile in the exhibits. Appendix B.1 describes the score's construction and how we assign suppliers to these groups.

Recipients are mature firms, with a mean age of 19 years. Before the award, median revenue was roughly €2.4 million, material purchases €1.3 million, tangible assets €440 thousand, and employment 40 (Table 2). Among recipients, 86% exported and 73% imported; nearly 80% reported intangible assets and 5% held a patent. They maintained about 65 supplier and 25 customer relationships on average, compared with roughly 11 and 4 in the firm population (Online Appendix Table OA.1). Most recipients were located in the City of Zagreb and surrounding Zagreb County, but their purchases extended across regions before funding.

Among the 159 recipients retained in the matched sample, nearly two-thirds operated in industries with high or medium-high digital intensity and about 60% in higher-technology sectors. IT services accounted for the largest sector share, followed by electronics, electrical equipment, and telecommunications (Table 1). Suppliers in the spillover analysis are substantially smaller than recipients, with mean employment of about 12 and median employment of 4. Section 4.1 describes the recipient and supplier samples and the matching procedure.

[7] We access the data in secure environments. Transaction records are linked and pseudoanonymized before analysis, and we report aggregate results.

Table 1: R&D grant recipients by sector and industry knowledge intensity

Category	Firms	Share (%)
Panel A. Top 10 broad sectors		
IT services	32	20.1
Electronics, electrical and telecom	17	10.7
Metals and mineral products	16	10.1
Trade, transport and vehicles	13	8.2
Engineering	12	7.5
Professional and business services	11	6.9
R&D, information and publishing	11	6.9
Construction and installation	10	6.3
Food and beverages	8	5.0
Chemicals, pharmaceuticals and fuels	6	3.8
Other sectors	23	14.5
Panel B. Knowledge-intensity classifications		
High or medium-high digital intensity	105	66.0
Higher-technology industries[a]	95	59.7
High or medium-high R&D intensity	68	42.8
Total firms	159	100.0

Notes: We group the 159 matched recipients by broad sector (Panel A) and by their industry's digital, technology, and R&D intensity (Panel B). We list the ten largest sectors separately and combine the rest as other sectors. All shares are percentages of the 159 recipients. [a] Higher-technology industries comprise higher-technology manufacturing and higher-technology services.

3 Supplier Demand, Investment, and Skills

Production networks provide an additional channel for spillovers from innovation funding. Customer grants can induce suppliers to invest in knowledge by increasing expected demand and generating receipts from initial orders. Expected later orders raise the return to production improvements, even without financial frictions (Carvalho and Draca, 2017). When external finance is costly, retained receipts help suppliers pay for that investment.

Consider a customer that receives an R&D grant and buys inputs from two incumbent suppliers. The suppliers fill the initial orders with their existing technology, pay operating costs and existing obligations, and retain the balance of the payments. They can use the cash they retain to invest in knowledge before competing for the customer's later orders. By

improving skilled workers' productivity, investment lowers unit production costs. All firms know the later demand conditions when suppliers choose investment.

We take the customer's initial purchases and later input demand as given. Initial purchases lower suppliers' financing costs if they leave suppliers with more cash to invest. Later demand can rise if the funded project improves the customer's product or lowers its production costs.

Supplier j produces output q_j using skilled workers S_j and unskilled workers U_j. We use a constant-returns, constant-elasticity-of-substitution (CES) production function with skill-augmenting technology (Acemoglu, 2002):

$$q_j = \left[(1-\alpha)U_j^{\rho} + \alpha\Big(Z_j(E_j)S_j\Big)^{\rho}\right]^{1/\rho}, \qquad \rho = \frac{\sigma-1}{\sigma}.$$

The supplier spends E_j on knowledge to raise skilled workers' productivity, $Z_j(E_j) > 0$, with $Z_j' > 0$. Each worker supplies one unit of labor. We normalize unskilled productivity to one and restrict the parameter governing skilled labor's contribution to $0 < \alpha < 1$. Suppliers take skilled and unskilled wages, $w_S, w_U > 0$, as given; the elasticity of substitution between the two types of labor is $\sigma > 1$.

Suppliers choose the least-cost workforce for their output. Equating relative marginal products to relative wages gives

$$\frac{S_j}{U_j} = \left(\frac{\alpha}{1-\alpha}\frac{w_U}{w_S}\right)^{\sigma} Z_j(E_j)^{\sigma-1}.$$

With $\sigma > 1$, suppliers raise the skilled worker share as investment improves skilled workers' productivity. If they instead expand output with the same technology, they increase both labor inputs proportionally and leave the skilled worker share unchanged. We derive these labor choices and the unit-cost function in Appendix A.

At the investment stage, the supplier has internal funds L_j and anticipates later operating profit $\Pi_j(E_j, E_k; D)$. Its profit depends on its rival's investment, E_k, and the customer's later input demand, whose inverse-demand intercept is D. Suppliers compete in quantities, taking one another's production choices as given. A larger D raises the return to a cost reduction because the supplier sells more units. When its rival lowers costs, the supplier sells fewer units and earns less from reducing its own costs.

Suppliers may find it difficult to finance knowledge investment because intangible capital has limited collateral value (Falato et al., 2022). Payment obligations can further restrict the cash available to expand (Barrot, 2016). In the model, the supplier uses its cash first and raises $\max\{E_j - L_j, 0\}$ externally. We normalize the risk-free interest rate to zero. The

supplier bears the cost of investment whether it uses cash or borrows: an internally financed euro could otherwise be retained, and a borrowed euro must be repaid. External funds also carry a premium C_j, whose marginal cost increases with the amount raised (Froot et al., 1993). At an interior investment choice with $E_j > L_j$, the supplier equates its marginal operating return to the marginal cost of investment:

$$\Pi_{j,E}(E_j, E_k; D) = 1 + C_j'(E_j - L_j).$$

The supplier earns an operating return of $\Pi_{j,E}$ on a marginal euro of investment and pays a marginal financing premium C_j'. We assume the marginal operating return declines with investment. Holding rival investment fixed, higher demand makes cost reductions more valuable, while additional cash lowers the marginal financing premium; either change leads the supplier to invest more. If cash strictly exceeds investment, or external finance carries no premium, additional cash has no local effect on investment.

When both suppliers respond, each has less reason to invest as its rival lowers costs. In the symmetric case, a common increase in demand or cash still raises both suppliers' investment if each supplier responds less than one for one in absolute value to its rival's investment. Each supplier then invests more, but by less than it would if its rival's investment stayed fixed.

We examine changes in the skilled worker share alongside sales per worker, capital, TFP, and intangible assets. We compare supplier responses across the baseline Omega score groups defined in Section 2.2 for suggestive evidence of a financing role.

The benefits of receipts from initial orders can persist if suppliers' investments remain productive or the additional demand continues. Learning can also sustain growth after a temporary increase in demand (Hvide and Meling, 2023).

4 Empirical Strategy

We compare recipients with matched non-funded firms and separately compare their suppliers with matched control suppliers. In each case, we match on pre-award characteristics and outcome histories to account for differences between the groups before funding (Rosenbaum and Rubin, 1983; Imbens and Rubin, 2015).

In Appendices D and E, we compare applicants near the program's evaluation thresholds, using those with available criterion-level scores. The local-randomization sample contains 92 applicants, of whom 59 are funded and 33 are not. In Appendix F, we compare suppliers with different pre-award sales shares to applicants.

4.1 Matching Procedure

Grant recipients. We draw recipient controls from non-funded firms, excluding recipients of innovation-commercialization and digital-transformation grants. Of the program's 174 recipients, 172 report pre-award revenue and 164 have complete matching covariates; we match 159 to non-funded firms. Among 124,706 non-applicants, 106,027 have complete covariates and enter the comparison pool.

Grant recipients are older, larger, and more internationally connected than firms in the comparison pool. Before matching, the 164 funded firms have a mean age of 19.03 years, compared with 10.83 among non-funded firms. In the year before the award, mean log employment is 3.85 versus 1.14, log tangible assets 13.04 versus 7.33, log revenue 15.22 versus 10.37, and log material costs 14.51 versus 9.83. Recipients are also more productive and more likely to export (0.86 versus 0.16) and import (0.73 versus 0.16). They buy from and sell to more firms (Online Appendix Table OA.1).

We match on approximately sixty pre-treatment characteristics, including demographics, scale, productivity, financial structure, industry, region, trade, and the scale and composition of purchases and sales through the production network. The matching variables include four pre-award years of revenue, material costs, tangible assets, and employment. The 159 matched recipients and their controls have similar pre-award trajectories and observed characteristics, including trade, intangible assets, and network transactions (Online Appendix Table OA.1). In years -1 through -4, the recipient-minus-control differences in mean log revenue are 0.07, 0.04, -0.37, and -0.19; the corresponding employment differences are 0.07, 0.05, -0.09, and -0.05 log points. None is statistically significant.

Suppliers. Of the 159 matched recipients, 153 have the continuous pre-award supplier relationships used in the spillover analysis and the back-of-the-envelope estimates in Section 6. We identify suppliers through their pre-award transactions with funded firms and matched non-funded firms, then exclude suppliers that sold to buyers in both groups. This removes common suppliers such as major utilities and leaves control suppliers with no pre-award sales to treated buyers in the matched comparison set.

We then match suppliers on their own pre-treatment demographics, scale, productivity, trade, customer composition, and lagged outcomes. We compare the matched suppliers' characteristics, including four pre-award observations of each main outcome, in Online Appendix Table OA.2. For this balance comparison, we exclude firms with transactions with recipients of R&D, digital-transformation, or innovation-commercialization grants from the untreated supplier pool.

We report selected baseline characteristics in Tables B.1 and B.2.

Identification requires treated and matched control firms' outcomes to have followed parallel trends in the absence of funding. We compare their pre-award trends and include firm fixed effects to account for remaining time-invariant differences.

4.2 Direct Effects

The direct effect is the difference between recipients' potential outcomes with and without a grant. For firm i, we denote these outcomes by $Y_{it}(1)$ and $Y_{it}(0)$ and use D_i to indicate grant receipt (Rubin, 1974; Holland, 1986). We estimate the average treatment effect on treated firms from their award year T_i onward:

$$\mathbb{E}[Y_{it}(1) - Y_{it}(0) \mid D_i = 1,\ t \geq T_i].$$

We estimate this effect using the treatment indicator $D_{it} = D_i \mathbf{1}\{t \geq T_i\}$, which equals one for funded firms from the award year onward:

$$Y_{it} = \alpha_i + \gamma_{s(i),r(i),t} + \beta D_{it} + \varepsilon_{it},$$

with firm fixed effects α_i and NACE 2-digit industry $s(i)$ by NUTS2 region $r(i)$ by calendar-year fixed effects $\gamma_{s(i),r(i),t}$ (Table 2). The parameter β is the average post-award effect within the matched sample. All recipients belong to one grant call and decision round, and controls are non-recipients. We therefore avoid comparisons between already-treated and later-treated firms that can bias staggered-adoption estimates (Baker et al., 2026; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021).

The direct comparison also requires that recipients' grants do not materially change the outcomes of their matched controls. The program funded 174 firms in an economy with more than 100,000 firms.

4.3 Supplier Spillovers

We classify suppliers as exposed if at least one of their pre-award buyers received funding. For supplier j, let $\mathcal{B}_j^T$ denote the set of these funded buyers. The exposure indicator is

$$E_j = \mathbf{1}\{\mathcal{B}_j^T \neq \emptyset\}.$$

We hold this classification fixed after the award. Supplier j's potential outcomes with and without exposure to a funded buyer are $Y_{jt}(1)$ and $Y_{jt}(0)$, respectively.

For domestic incumbent suppliers, we measure event time from the connected buyer's grant-decision year T_i and estimate

$$Y_{jt} = \alpha_j + \gamma_t + \sum_{k \neq -1} \theta_k \, \mathbf{1}\{t - T_i = k\} \times E_j + u_{jt},$$

with supplier fixed effects α_j and calendar-year fixed effects γ_t. We use event time $k = -1$ as the reference period. If exposed and matched control suppliers would have followed parallel trends without the grants, and suppliers did not anticipate funding in year -1, we identify the average effect of exposure among linked suppliers:

$$\theta_k = \mathbb{E}[Y_{j,T_i+k}(1) - Y_{j,T_i+k}(0) \mid E_j = 1].$$

We compare exposed and control suppliers' pre-award paths using the coefficients for $k < -1$.

5 Results

We begin with recipients' expansion and input purchases, then follow the response of their suppliers. We compare suppliers by their pre-award financial constraints and examine their productivity and skilled worker share.

5.1 Direct Effects on Grant Recipients

Relative to matched non-funded firms, grant recipients increase revenue by 0.157 log points, or about 17.0%, and material purchases by 0.195 log points, or 21.5%. They also expand tangible assets by 0.242 log points (27.4%) and employment by 0.076 log points (7.9%), on average over the post-award years (Table 2).

Table 2: Effects of R&D grants on recipient operating outcomes

	Revenue	Material Costs	Tangible Assets	Employees
	(1)	(2)	(3)	(4)
R&D Grant	0.157***	0.195***	0.242**	0.076**
	(0.058)	(0.066)	(0.097)	(0.038)
Observations	2,697	2,697	2,677	2,697
R^2	0.962	0.960	0.944	0.972
R^2 adj.	0.898	0.893	0.851	0.925
RMSE	0.38	0.44	0.64	0.26
Mean (t-1)	44.490	33.538	19.117	156.333
Median (t-1)	2.374	1.310	0.441	40.000

Notes: We compare grant recipients with matched non-funded firms. Outcomes are in logs. We include firm fixed effects and NUTS2 × NACE 2-digit × year fixed effects. Means and medians refer to year $t = -1$ and are in millions of euros for monetary outcomes and counts for employees. Standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Recipients also increase sales per worker by 0.086 log points and intangible assets by 0.974 log points (Table 3). The estimated effects on TFP (0.062) and the skilled worker share (0.013, or 1.3 percentage points) are imprecise.

Table 3: Effects of R&D grants on recipient productivity, intangible assets, and the skilled worker share

	Sales per worker	TFP	Intangible assets	Skilled worker share
	(1)	(2)	(3)	(4)
R&D Grant	0.086*	0.062	0.974**	0.013
	(0.043)	(0.055)	(0.324)	(0.007)
Observations	2,662	2,648	2,378	2,587
R2	0.911	0.963	0.849	0.957
R2 Adj.	0.758	0.900	0.521	0.879
RMSE	0.28	0.36	1.67	0.05
Mean (t-1)	0.131	8.540	2.550	0.000
Median (t-1)	0.064	8.050	0.020	0.000

Notes: We compare grant recipients with matched non-funded firms. Sales per worker, TFP, and intangible assets are in logs. The skilled worker share is in levels, so 0.01 is one percentage point. We include firm fixed effects and NUTS2 × NACE 2-digit × year fixed effects. Baseline monetary means and medians are in millions of euros; TFP is on its reported index scale. Standard errors are in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$.

5.2 Spillovers to Suppliers

Suppliers of funded and matched non-funded buyers have similar pre-award characteristics and outcome paths (Table B.2). We estimate small differences in all four operating outcomes in years −4, −3, and −2, with confidence intervals that include zero (Figure 1).

Suppliers sell and purchase more in their customers' grant-award year, then add capital and workers. Revenue rises by 0.248 log points (about 28%) in the award year and by 0.376 log points (46%) three years later. Material costs rise by 0.260 log points in the award year and reach 0.412 two years later. Suppliers initially make little change to tangible assets (0.057 log points), but expand them by 0.333 log points (about 40%) by year three. Employment is initially flat and rises by 0.088–0.112 log points, or about 9–12%, in years one through four (Table C.1).

As suppliers expand, they sell more per worker and increase their skilled worker share. Sales per worker rise by 0.129 log points in the award year, 0.270 in year three, and 0.221 in year four. The skilled worker share rises by 1.2 percentage points in years one and two and by 1.0 percentage point in year four (Figure 2; Table C.2).

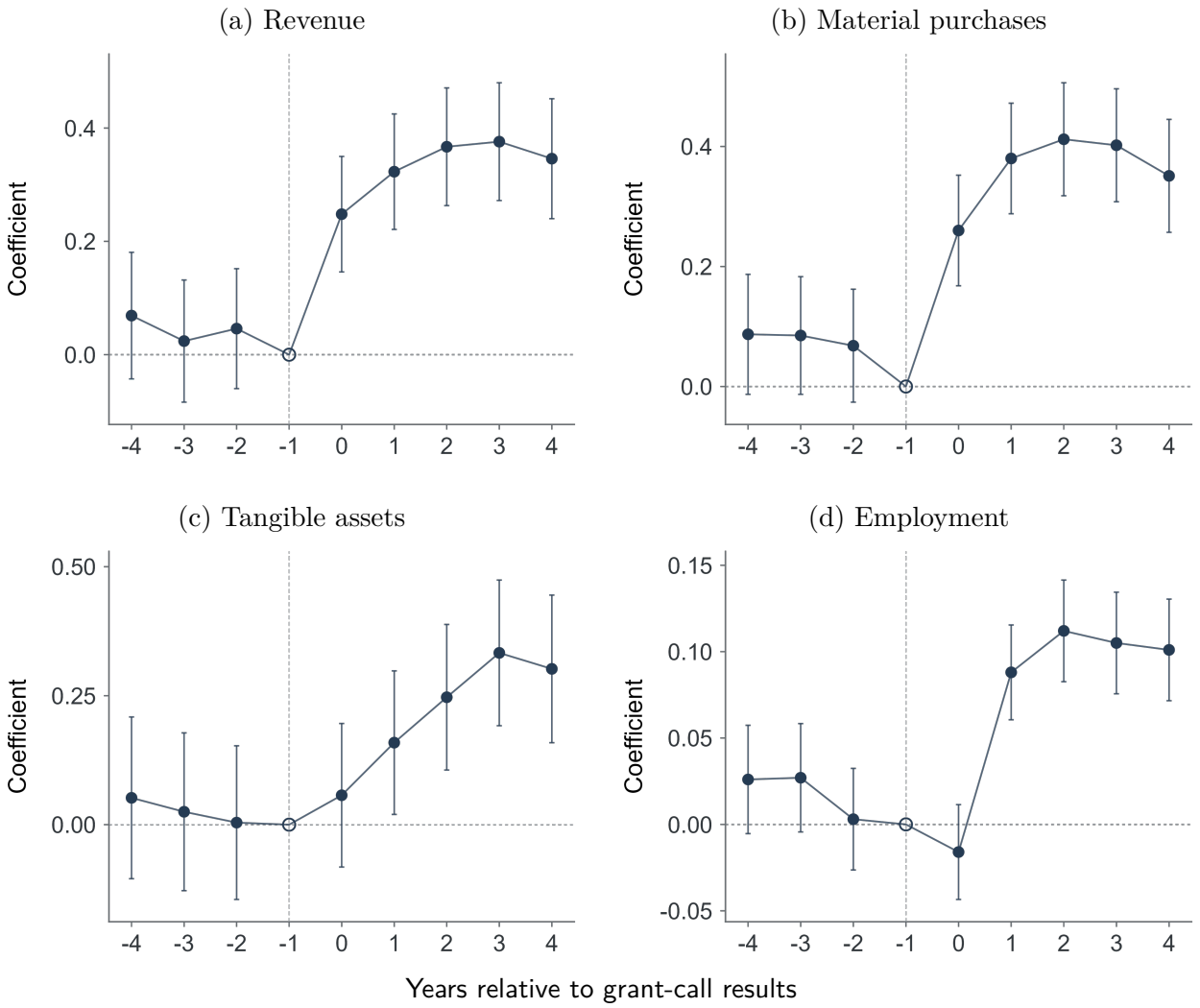

Figure 1: Supplier operating responses to customer grant awards

Note: This figure plots coefficients and 95% confidence intervals. We hold the pre-award supplier relationships fixed and estimate responses in revenue, material costs, tangible assets, and employment, all in logs. We count years from the announcement of grant-call results and compare outcomes with year −1. The dashed line marks year −1.

The TFP estimates are small and nonpositive throughout the post-award period, and their confidence intervals include zero. Suppliers increase intangible assets most clearly in year three, the only year with a statistically significant effect; the year-four estimate is smaller and imprecise.

Suppliers can retain receipts from higher sales to finance later expansion (Section 3). Learning and sunk investment offer other explanations for lasting gains; Hvide and Meling (2023) found long-lived effects of temporary procurement shocks on startups. We examine the liquidity channel by comparing suppliers that faced tighter or looser financial constraints before the award.

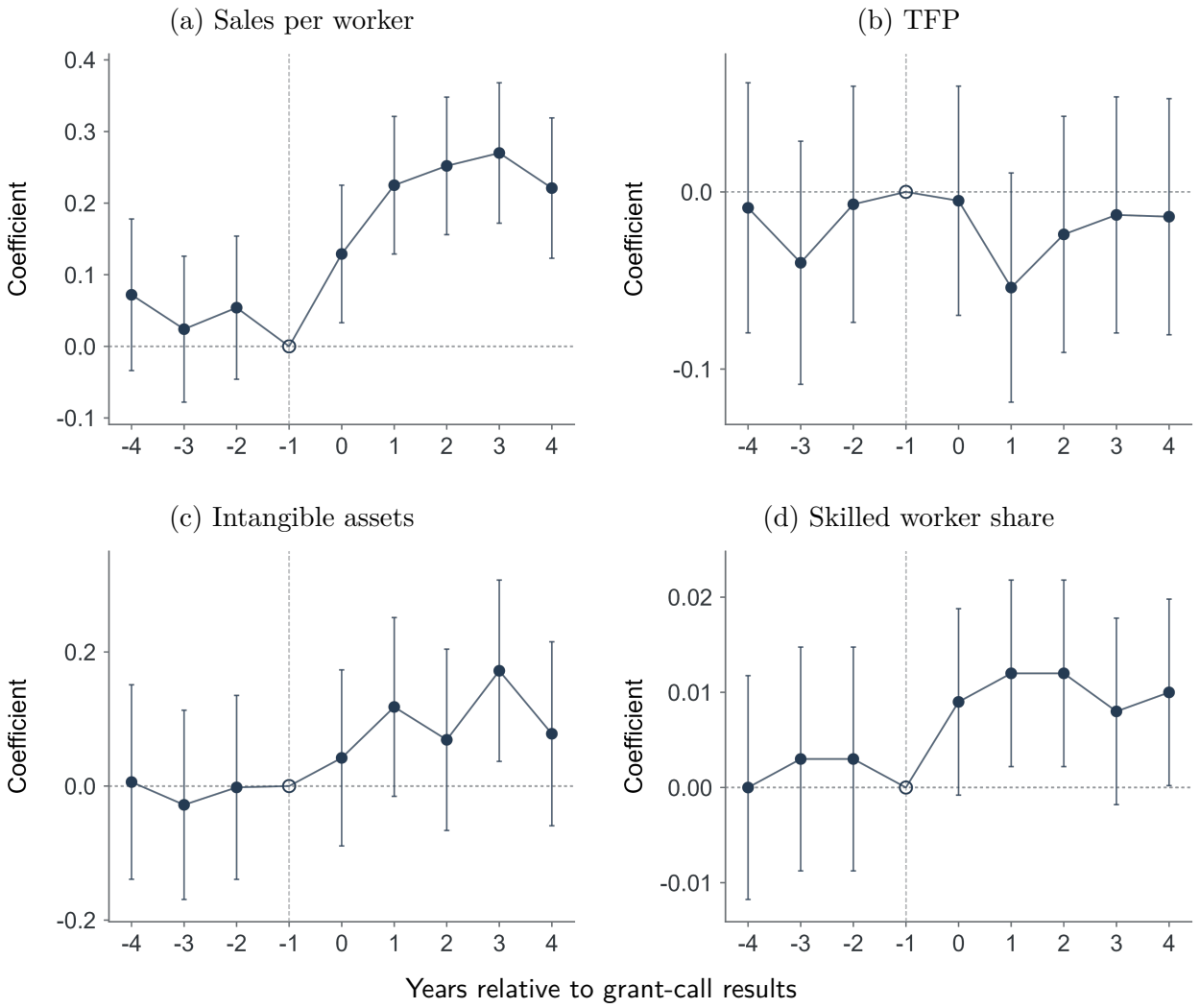

Figure 2: Supplier productivity, intangible assets, and the skilled worker share after customer grants

Note: This figure plots coefficients and 95% confidence intervals. We estimate responses relative to year −1 for the fixed set of pre-award supplier links. We measure labour productivity as sales per worker and use logs for this outcome, TFP, and intangible assets. The skilled worker share is in levels: 0.01 corresponds to one percentage point. The dashed line marks year −1.

Tables C.1 and C.2 report the baseline supplier estimates.

5.3 Supplier Liquidity and Knowledge-Intensive Expansion

Suppliers in the most constrained group expand most (Section 2; Appendix B.1). Their revenue rises by 0.489 log points in the award year and by 0.677–0.761 in subsequent years, alongside a similar expansion in material purchases. The least constrained suppliers increase revenue by at most 0.135 log points, in year two; by year four, their gain falls to 0.047. Revenue gains in the middle group lie between those of the other two groups (Figure 3).

We find no significant pre-award differences in trends. By year four, the most constrained suppliers expand tangible assets by 0.451 log points and employment by 0.168, compared with 0.154 and 0.036 among the least constrained (Online Appendix Tables OB.1 and OB.2).

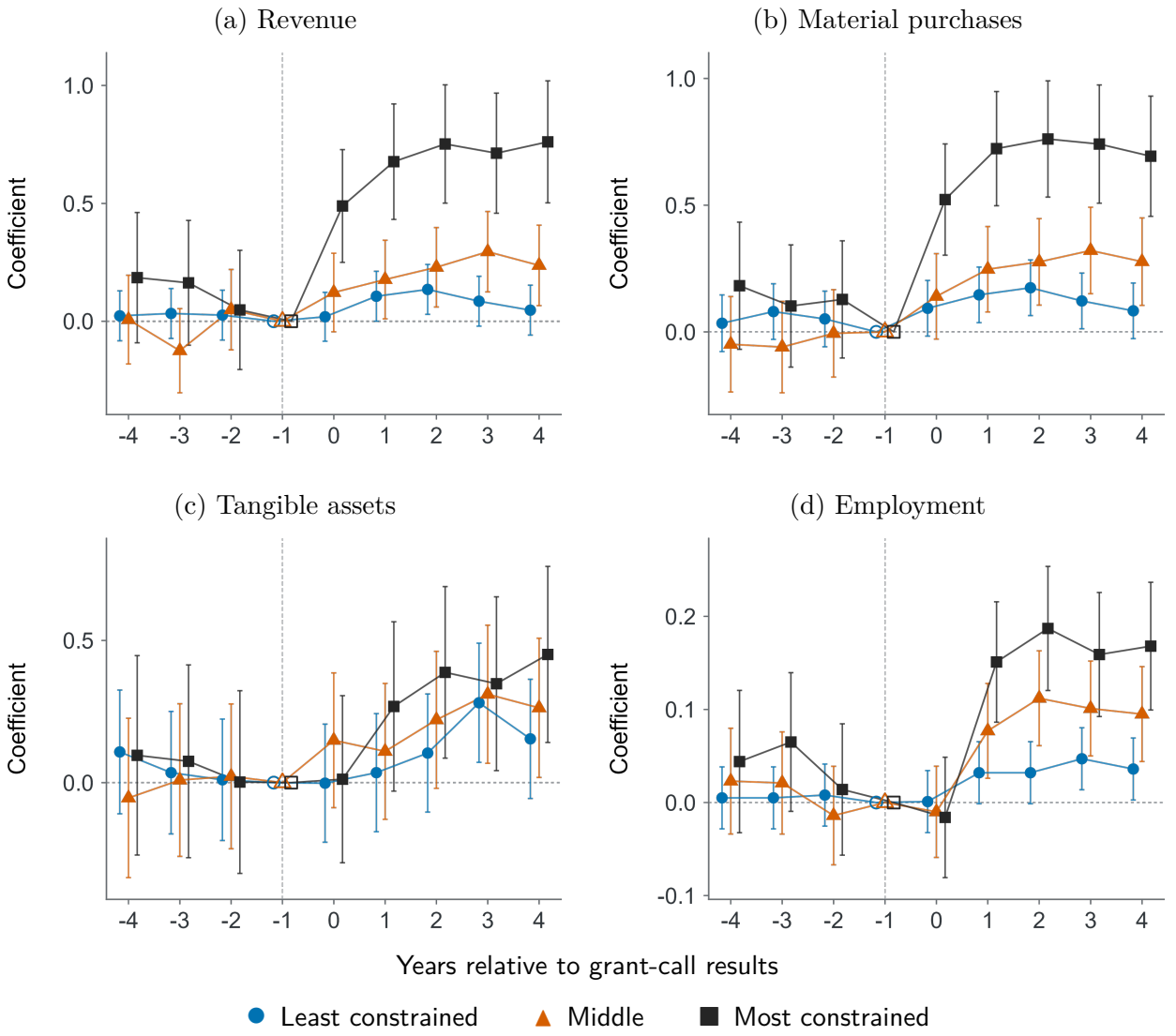

Figure 3: Supplier operating responses by financial constraints

Note: This figure plots coefficients and 95% confidence intervals. We divide suppliers into three groups by their pre-award financial constraints: the least constrained ($\Omega \geq -24.37$); middle ($-76.01 \leq \Omega < -24.37$); and the most constrained ($\Omega < -76.01$). We estimate revenue, material costs, tangible assets, and employment in logs relative to year -1. The dashed line marks year -1. We describe the Omega score in Appendix B.1 and report the operating estimates in Online Appendix Tables OB.1 and OB.2.

The most constrained suppliers also increase sales per worker and their skilled worker share more than the other groups (Figure 4). Their sales per worker rise after the award and remain elevated through year four, while their skilled worker share increases more gradually

and most clearly four years after the award. The least constrained suppliers show little change in either outcome.

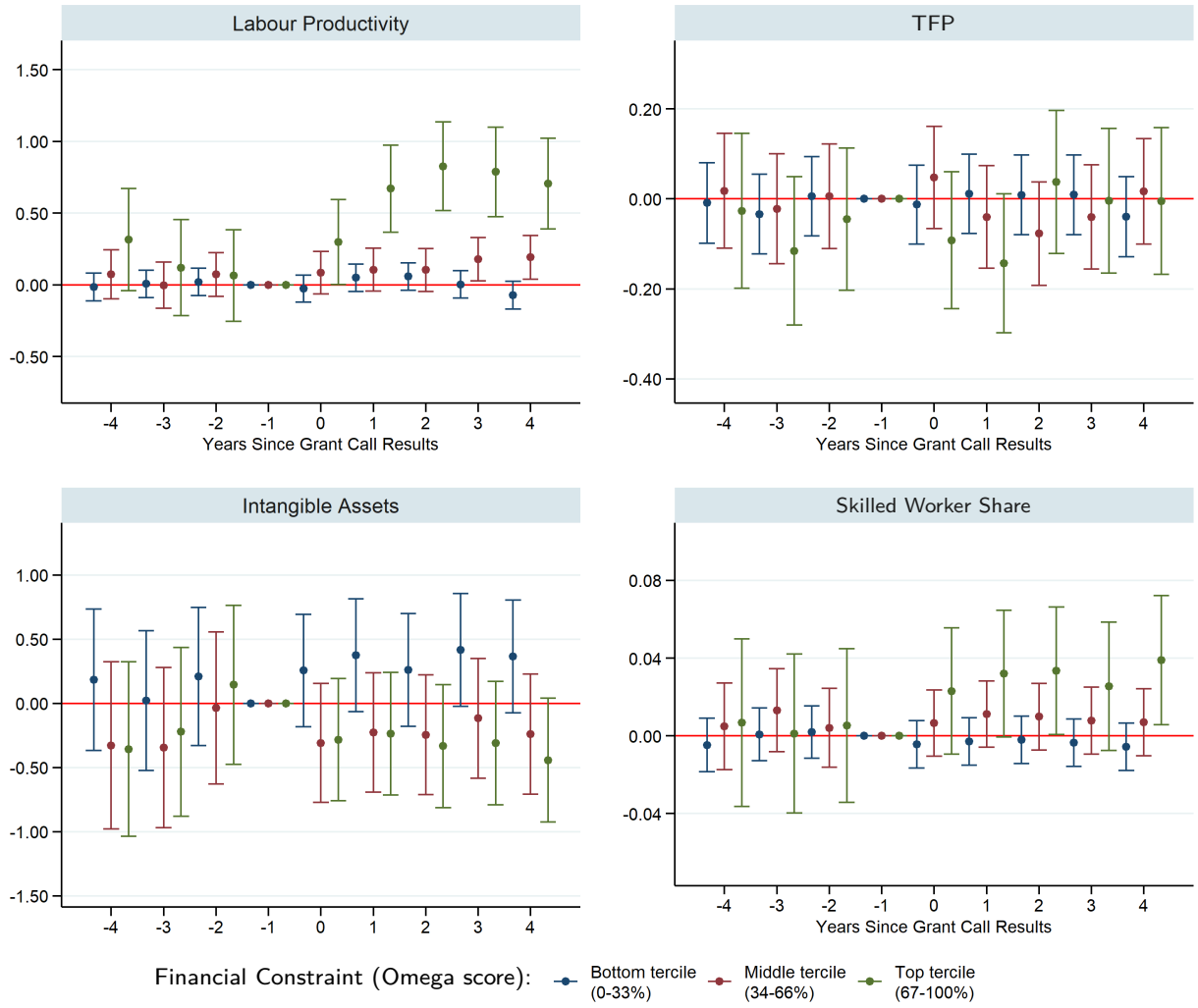

Figure 4: Supplier productivity, intangible assets, and the skilled worker share by financial constraints

Note: This figure plots coefficients and 95% confidence intervals. We estimate supplier responses for the constraint groups in Figure 3: bottom is least constrained, middle is intermediate, and top is most constrained. We use the outcomes and units defined in Figure 2; 0.01 in the skilled worker share panel is one percentage point. Year −1 is the reference.

The most constrained suppliers do not show a clear positive TFP response, and their intangible-asset estimates are negative after the award and imprecise.

The larger expansion and rise in the skilled worker share among more financially constrained suppliers suggest a role for internal funds in financing investment. Receipts from customer purchases can help pay for knowledge-intensive activities that provide limited col-

lateral (Falato et al., 2022), as in Appendix A. Differences in demand exposure across the Omega score groups can also contribute to their responses.

5.4 Supplier Size, Distance, and Network Position

We also compare suppliers by size, distance to the recipient, and network position, defining each group before the award.

Supplier size. Smaller suppliers increase revenue and material purchases by more in proportional terms (Figure 5; Online Appendix Tables OB.3 and OB.4). A given increase in customer demand is larger relative to a small supplier's initial sales. We divide suppliers at €89,440 and €381,046 in pre-award revenue, compared with median recipient revenue of about €2.4 million. Suppliers in all three groups expand, adding capital and workers more gradually than revenue and materials. We report their skilled worker share and productivity responses in Online Appendix Figure OB.1.

Distance to the buyer. We use observed firm-to-firm transactions to identify each funded customer's suppliers and compare their responses by distance. We group links by straight-line distance between the municipalities of the applicant's and supplier's headquarters: below 23.55 km, 23.55–171.39 km, and at least 171.39 km, with roughly 1,850–1,930 unique suppliers in each group. Suppliers in the first two groups expand revenue and tangible assets more than the most distant suppliers, whose revenue gains are also less precisely estimated. Material purchases and employment rise in all three groups. Two years after the award, employment rises by 0.135, 0.112, and 0.099 log points, respectively (Figure 6; Online Appendix Tables OB.5 and OB.6).

Supplier gains extend beyond the City of Zagreb and surrounding Zagreb County, where recipients are concentrated. Investment tax credits in East Germany generated highly local employment spillovers (Lerche, 2025); in Croatia, we trace gains to suppliers far from funded customers. Firms trade across Croatian regions (Srhoj and Mikulić, 2025), so grants concentrated in an agglomeration can support employment elsewhere. Restricting exposure to firms near recipients would miss these distant supplier gains. We report productivity and skilled worker share outcomes by distance in Online Appendix Figure OB.2.

Network position. Firms transmit shocks through their trading relationships, with effects that depend on their partners' network positions (Acemoglu et al., 2012; Carvalho, 2014; Golub, 2025). To account for whom a firm trades with, we use eigenvector centrality, weighting each link by the trading partner's centrality. We compare suppliers by their own pre-award centrality and, separately, by that of their funded customer.

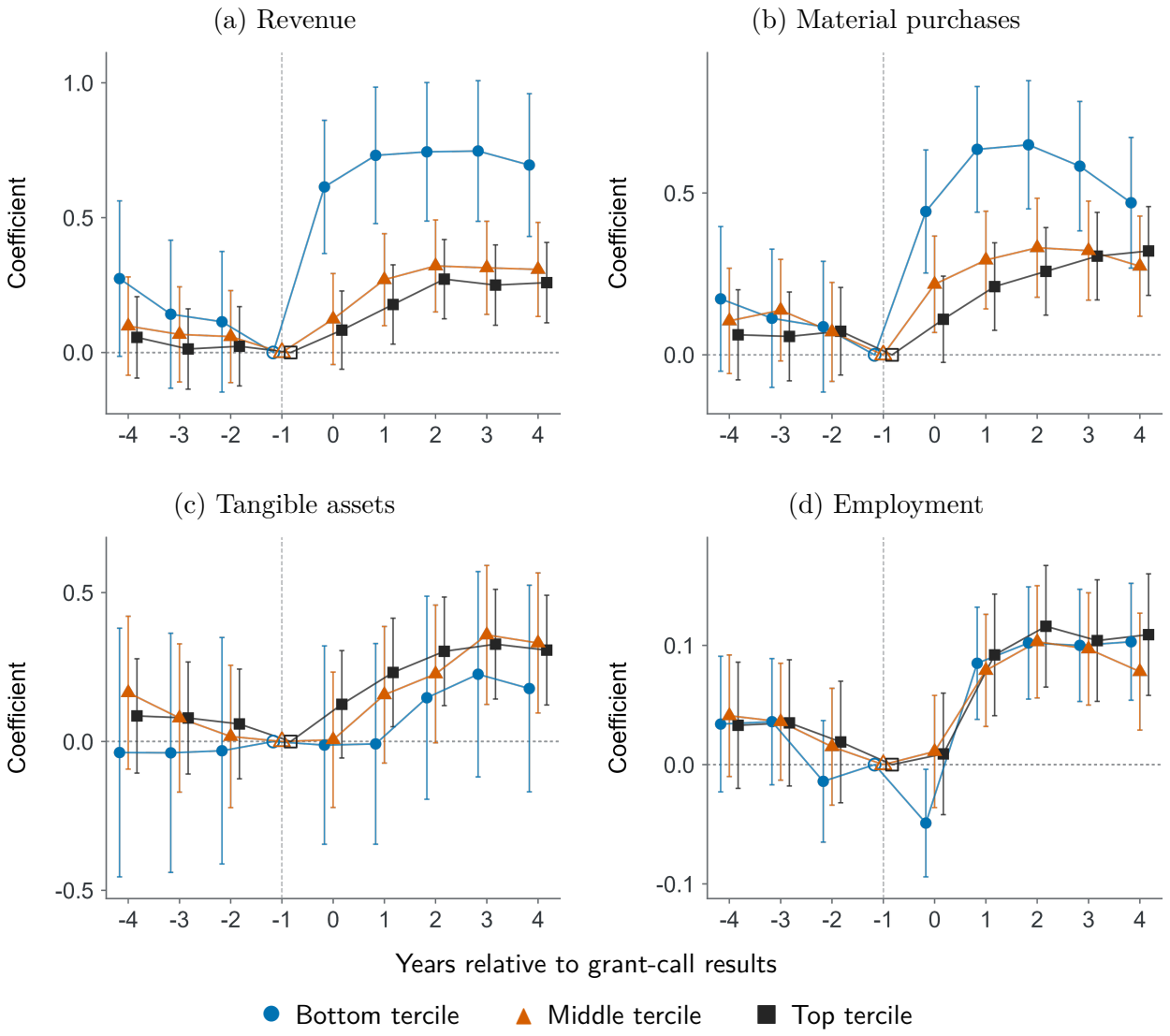

Figure 5: Supplier operating responses by pre-award revenue

Note: This figure plots coefficients and 95% confidence intervals. We assign suppliers to revenue groups using their pre-award sales: below €89,440 (bottom), €89,440 to below €381,046 (middle), and at least €381,046 (top). We estimate responses in revenue, material costs, tangible assets, and employment relative to year −1, using logs for all four outcomes. The dashed line marks year −1.

Less central suppliers expand revenue, material purchases, and employment by more in proportional terms. Four years after the award, revenue rises by 0.475 log points in the lowest supplier-centrality tercile and 0.170 in the highest (Online Appendix Figure OB.4; Online Appendix Tables OB.9 and OB.10). The most central suppliers expand tangible assets later, by 0.273 log points in year four. Suppliers in the lowest tercile are also smaller: their mean pre-award revenue is €0.309 million, compared with €1.789 million in the highest.

Suppliers of more central recipients have larger revenue gains in later years (Figure 7). By year four, supplier revenue rises by 0.277, 0.413, and 0.584 log points from the lowest to

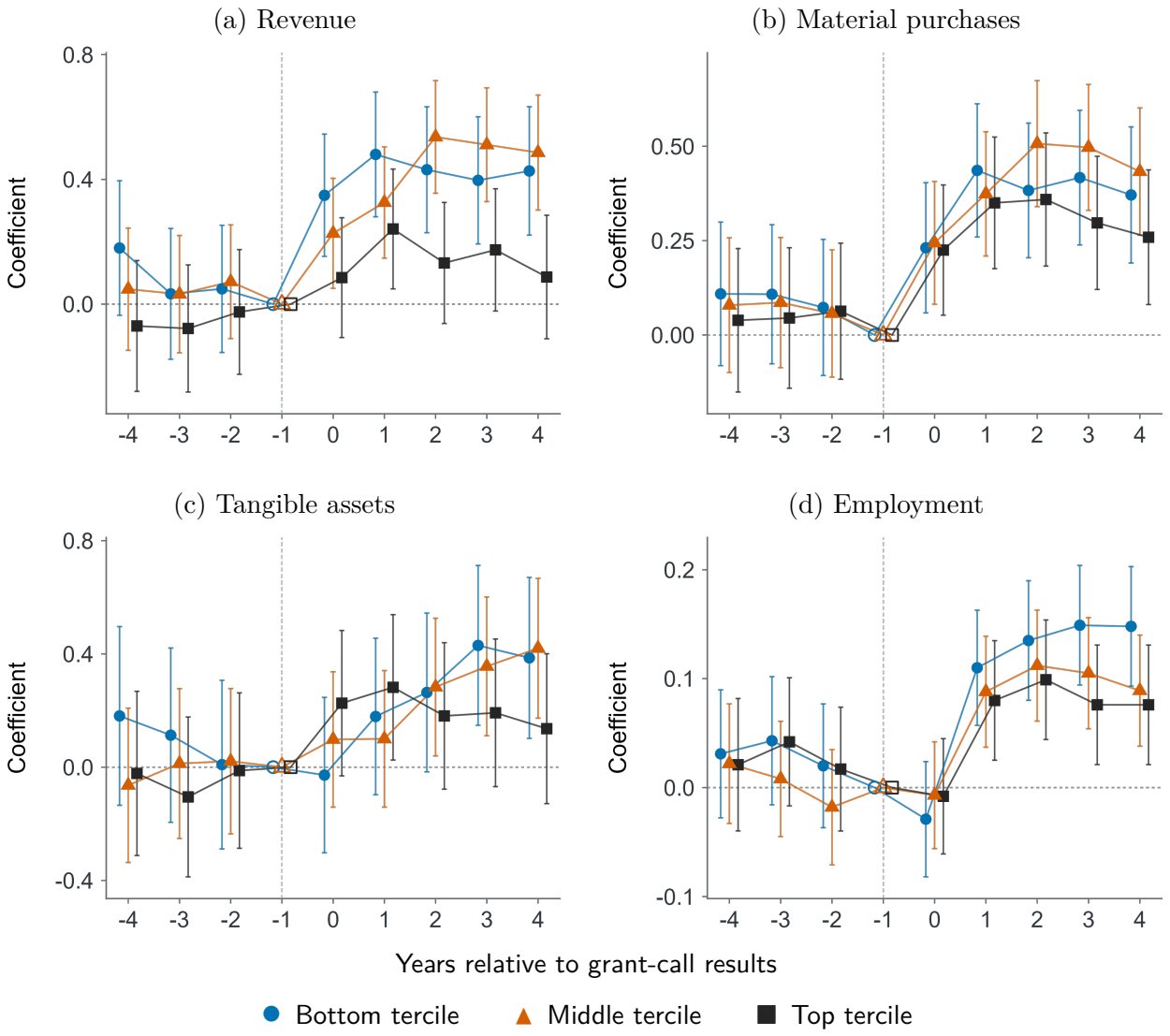

Figure 6: Supplier operating responses by distance to the recipient

Note: This figure plots coefficients and 95% confidence intervals. We calculate straight-line distance between the supplier's and recipient's headquarters municipalities and form three groups: below 23.55 km (bottom), 23.55 km to below 171.39 km (middle), and at least 171.39 km (top). Revenue, material costs, tangible assets, and employment are in logs, and we estimate their changes relative to year −1. The dashed line marks year −1.

the highest recipient-centrality tercile. Suppliers of the most central recipients also increase material purchases and tangible assets most at that point. Their employment gains are closer to those of suppliers in the other groups (Online Appendix Tables OB.7 and OB.8). We report productivity and skilled worker share outcomes by recipient centrality in Online Appendix Figure OB.3.

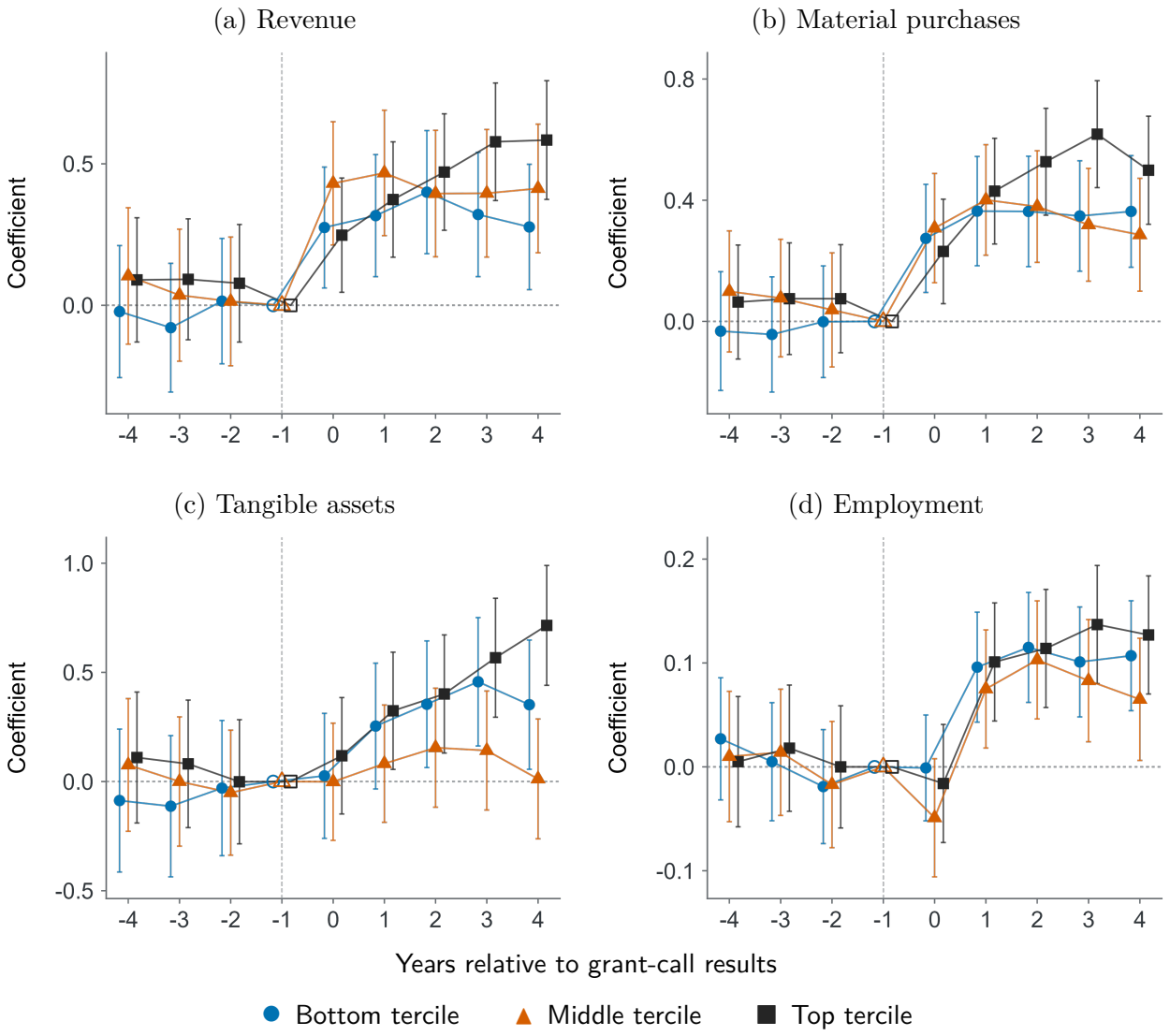

Figure 7: Supplier operating responses by recipient eigenvector centrality

Note: This figure plots coefficients and 95% confidence intervals. We group suppliers by their funded customer's pre-award eigenvector centrality, from the bottom to the top tercile. We measure revenue, material costs, tangible assets, and employment for suppliers and express all four outcomes in logs. Year −1 is the reference. The dashed line marks year −1.

An increase in orders can be large relative to a peripheral supplier's sales, while a central recipient can pass demand to more firms. Firms' trade-credit provision and profitability also vary with network position (Gofman and Wu, 2022).

5.5 Robustness and Sensitivity

We estimate larger recipient gains when we omit firm fixed effects or match on fewer characteristics (Online Appendix Figures OC.1 and OC.4). Funded firms also expand all four operating outcomes relative to rejected applicants (Online Appendix Table OC.1), although we estimate their productivity and skilled worker share responses less precisely (Online Appendix Table OC.2). Suppliers' gains change little when we vary fixed effects, matching characteristics, or project-score samples (Online Appendix Figures OC.2, OC.5, and OC.7). We report productivity and skilled worker share estimates for these comparisons in Online Appendix OC. Excluding transport and storage and accommodation and food service, to assess differences in pandemic exposure, also leaves supplier operating gains broadly unchanged (Online Appendix Table OC.3).

Applicants just above the funding cutoff also expand relative to those just below it. In the full scored sample, we estimate positive difference-in-discontinuities effects on all four operating outcomes, with an imprecise tangible-asset effect (Appendix D). Under local randomization, we estimate employment gains of about 14% in year one and 34% in year four, significant at the 10% level. Revenue and tangible-asset gains are positive but imprecise in this 92-applicant sample (Appendix E). In the network-exposure design, suppliers with greater direct exposure have larger post-award outcome increases at the funding cutoff. We estimate second-order effects imprecisely (Appendix F).

Using degree, closeness, or betweenness to group firms yields the same ordering: less central suppliers expand more in proportional terms, as do suppliers of more central recipients. Responses in the middle groups vary more across measures (Online Appendix OB.3).

6 Cost-Benefit Analysis and Policy Implications

Our back-of-the-envelope estimates suggest that including suppliers cuts grant expenditure per predicted job to roughly one-third, from about €106,000 to €33,000, and lowers expenditure per euro of illustrative VAT from €20.50 to €2.10 (Table 4). We calculate these amounts for 153 recipients and 3,370 unique suppliers, using the €199.82 million in grants contracted to these recipients.

We predict each firm's gain by applying the average post-award recipient effects in Table 2 or the fourth-year supplier effects in Table C.1 to its pre-treatment outcomes. For employment, we multiply baseline employment by $\exp(\hat{\beta}) - 1$ and sum across firms. This gives 1,882 jobs at recipients and 4,184 at suppliers, or 6,066 in total: 3.2 times the gain at recipients alone. Dividing contracted grants by these predicted jobs gives expenditure per

job. We also use median baseline employment to reduce the influence of the largest firms. Multiplying this median by the log-point coefficient and firm count gives 1,823 jobs at about €110,000 per job, with a combined gain 3.9 times that at recipients alone.

We predict €2,240.2 million in additional revenue: €923.1 million at recipients and €1,317.1 million at suppliers. To calculate the fiscal base, we subtract each firm's predicted increase in material purchases from its predicted increase in revenue and sum across firms. This reduces the double counting of sales along the supply chain and gives €554.6 million: €67.5 million at recipients and €487.1 million at suppliers. Including suppliers raises the gain to 2.4 times the recipient-only amount for gross revenue and 8.2 times for revenue less material purchases.

We multiply each firm's predicted increase in revenue less material purchases by its domestic sales share. This gives €39.0 million at recipients and €341.8 million at suppliers, or €380.8 million in total, 9.8 times the recipient-only amount. Applying a 25% VAT rate gives illustrative receipts of €9.7 million at recipients and €85.5 million at suppliers, or €95.2 million in total. We divide grant expenditure by these receipts to obtain the cost per euro of VAT, which falls from €20.50 to €2.10 when we include suppliers.

Suppliers linked to the most central recipients account for 2,076 predicted jobs and €212.4 million in domestic revenue less materials (Part II of Table 4). A supplier can serve recipients in several centrality terciles. Counting it in each tercile gives 5,736 supplier–tercile observations from 3,370 unique suppliers. For each group, we divide the recipients' contracted grants by their suppliers' predicted gains to calculate expenditure per job and per euro of domestic revenue less materials.

We assume a 25% VAT rate on domestic revenue less material purchases. Effective rates, exemptions, deductions, and timing determine actual receipts, and domestic sales need not equal taxable value added. Domestic transactions can also include imported inputs (Dhyne et al., 2021; Srhoj and Mikulić, 2025). We count recipients and their direct suppliers; estimates for second-tier suppliers remain imprecise (Appendix F).

Table 4: Back-of-the-envelope estimates of employment and fiscal gains

Part I. Program outcomes

	Direct	Upstream	Total	Total/ Direct
Grant value, analysis sample (mil. €)			199.82	
Number of firms (N)	153	3,370		
Panel A: Jobs				
Jobs, median-based (MB)	463	1,359	1,823	×3.9
Cost per job (€)	431,000	147,000	110,000	
Jobs, firm-level predicted (FLP)	1,882	4,184	6,066	×3.2
Cost per job (€)	106,000	48,000	33,000	
Panel B: Value added and VAT (mil. €)				
Induced revenue, FLP	923.1	1,317.1	2,240.2	×2.4
− Induced material purchases, FLP	855.6	830.0	1,685.6	×2.0
= Revenue less material purchases, FLP	67.5	487.1	554.6	×8.2
× domestic share (1−export), FLP	39.0	341.8	380.8	×9.8
× 25% VAT rate	9.7	85.5	95.2	
Cost per euro of VAT	20.50	2.34	2.10	

Part II. Upstream incidence by recipient network centrality

	Bottom	Middle	Top	Top/ Bottom
Supplier–tercile observations	1,950	1,892	1,894	
Mean applicant eigenvector centrality	0.0151	0.0308	0.3741	×24.7
Upstream jobs, FLP	1,018	612	2,076	×2.0
Cost per job (€)	110,239	79,670	6,013	
Upstream domestic revenue less materials (mil.), FLP	46.6	89.6	212.4	×4.6
Cost per euro of domestic value added	2.4	0.54	0.06	
Upstream jobs, MB	330	255	514	×1.6
Cost per job (€)	340,177	190,943	24,280	
Upstream domestic revenue less materials (mil.), MB	11.4	23.9	43.6	×3.8
Cost per euro of domestic value added	9.8	2.0	0.3	

Note: We construct back-of-the-envelope estimates by applying average post-award recipient effects (Table 2) and year-four supplier effects (Table C.1) to pre-award outcomes. For firm-level predictions (FLP), we sum baseline$_i \times [\exp(\hat{\beta}) - 1]$ across firms. For median-based predictions (MB), we multiply the median baseline by the log-point coefficient and firm count. We calculate illustrative VAT by multiplying each firm's predicted increase in revenue less material purchases by its domestic sales share and the 25% rate. In Part II, a supplier can serve funded customers in several pre-award eigenvector-centrality terciles; we count it in each, so the group totals overlap. For each cost ratio, we divide contracted grants by the corresponding predicted gain. Monetary activity is in millions of euros; cost per job is euros per predicted job. Top/Bottom compares the highest and lowest recipient-centrality terciles.

7 Conclusion

Purchases by grant recipients provide an additional channel for spillovers from innovation funding through the production network. In Croatia's €225 million R&D grant program, recipients and their pre-existing suppliers expanded revenue, material purchases, employment, and capital. Suppliers facing the tightest financial constraints before the grant expanded most and increased both sales per worker and their skilled worker share.

In the model, higher customer demand raises the return to knowledge investment, while receipts retained from initial orders help suppliers finance it. This investment lowers production costs and raises the skilled worker share. The greater expansion among more financially constrained suppliers suggests that internal funds help finance their response. We find no clear positive TFP response or consistent increase in intangible assets.

Our back-of-the-envelope estimates suggest that accounting for supplier effects improves the program's estimated cost-effectiveness. Including these effects cuts grant expenditure per predicted job to roughly one-third, from about €106,000 to €33,000. Combining average post-award recipient effects with year-four supplier effects gives 6,066 predicted jobs, compared with 1,882 at recipients alone. Including suppliers also increases the domestic revenue-less-materials base almost tenfold and lowers grant expenditure per euro of illustrative VAT from €20.50 to €2.10.

Most recipients were located in the City of Zagreb and surrounding Zagreb County, yet suppliers more than 171 kilometers from their funded customers also benefited. By following firms' trading links, we observe gains that spillover measures based only on proximity would omit. This channel allows place-based funding to draw on the advantages of an agglomeration while also benefiting suppliers in other regions.

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Appendix Contents

The separate Online Appendix contains the full balance tables, additional supplier comparisons, and specification and sample sensitivity results. Its section and exhibit numbers begin with O.

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A Supplier Investment, Demand, and Internal Funds

We model one customer and two incumbent suppliers to examine how innovation funding induces supplier investment through a production-network channel. Higher expected demand raises the return to knowledge investment, while retained receipts from initial orders help finance it when external funds are costly. Suppliers invest to raise skilled workers' productivity before choosing their workforce and competing in quantities. We use the constant-elasticity-of-substitution (CES) treatment of factor-biased technical change in Acemoglu (2002), the customer–supplier market structure in Carvalho and Draca (2017), and the financing cost in Froot et al. (1993).

A.1 Environment and timing

The customer uses one unit of a homogeneous intermediate input for each unit of final output and buys it from a fixed set of suppliers indexed by $j \in \{1, 2\}$. For either supplier, $k \neq j$ denotes its rival. All firms maximize profits. Technologies and financing costs are common knowledge, and all firms know demand and cash conditions when suppliers choose investment. We normalize the risk-free interest rate to zero and distinguish three dates.

At date 0, the customer receives a grant of size G and places initial orders, which suppliers fill with their existing production technology. Supplier j retains net cash $r_j(G)$ after receiving payment, covering operating costs, and paying existing obligations. At date 1, it has internal funds

$$L_j(G) = L_{j0} + r_j(G) \geq 0, \tag{A.1}$$

where L_{j0} is its available cash apart from the net receipts r_j.

At date 1, suppliers simultaneously choose knowledge investment $E_j \in [0, \overline{E}_j]$, where $\overline{E}_j$ is a finite bound on feasible expenditure, and arrange external finance. They pay for investment at date 1 and use it in production at date 2. At date 2, suppliers observe both investments and simultaneously choose quantities $q_j \geq 0$, employing the least-cost workforce for their output. The input market clears, the customer produces, and firms receive operating profits. We assume suppliers can fill initial orders with existing resources and finance date-2 production from contemporaneous sales. They face financing costs on the earlier investment expenditure.

The customer faces inverse demand $a(G) - x$ for final output x, with demand intercept $a(G)$. It pays $c_d(G) \geq 0$ per unit in other production costs. Taking the input price P as

given, it chooses $x \geq 0$ to maximize

$$\Big[a(G) - x - c_d(G) - P\Big]x.$$

Net of the customer's other production costs, the demand intercept is $D(G) = a(G) - c_d(G) > 0$. Differentiating the customer's profit gives input demand $x = \max\{[D(G) - P]/2, 0\}$. Since one unit of input produces one unit of output, market clearing requires $x = q_j + q_k$. Suppliers therefore face the inverse input demand

$$P = D(G) - 2(q_j + q_k) \tag{A.2}$$

at positive purchases.

We take $r_j(G)$ and $D(G)$ as continuously differentiable functions of the grant, determined before suppliers invest. The customer's project can increase later input demand, D, by improving its product and raising a, or by lowering production costs, c_d. A grant that generates only initial orders can raise L_j while leaving D unchanged. For the positive investment responses derived below, we assume $D'(G) \geq 0$ and $L_j'(G) = r_j'(G) \geq 0$.

A.2 Production, skills, and financing

Supplier j hires skilled workers S_j and unskilled workers U_j at fixed wages $w_S, w_U > 0$. Each worker supplies one unit of labor. Spending on knowledge raises skilled workers' productivity to $Z_j(E_j) > 0$; we assume Z_j is twice continuously differentiable and $Z_j' > 0$. We normalize unskilled productivity to one. Output is

$$q_j = \Big[(1-\alpha)U_j^{\rho} + \alpha\Big(Z_j(E_j)S_j\Big)^{\rho}\Big]^{1/\rho}, \qquad \rho = \frac{\sigma - 1}{\sigma}, \tag{A.3}$$

with $0 < \alpha < 1$ and $\sigma > 1$. The parameter α governs the contribution of skilled labor, and σ is the elasticity of substitution between the two types of labor. We apply the standard CES specification with skill-augmenting technology (Acemoglu, 2002, pp. 785–786) to a supplier taking wages as given. With $\sigma > 1$, the supplier employs relatively more skilled workers as their productivity improves.

For a given output level, the supplier minimizes $w_S S_j + w_U U_j$ subject to equation (A.3). Equating the ratio of marginal products to relative wages gives

$$\frac{w_S}{w_U} = \frac{\alpha}{1-\alpha} Z_j(E_j)^{\rho} \left(\frac{S_j}{U_j}\right)^{\rho-1}.$$

Solving for the employment ratio yields

$$\frac{S_j}{U_j} = \left(\frac{\alpha}{1-\alpha}\frac{w_U}{w_S}\right)^{\sigma} Z_j(E_j)^{\sigma-1}. \tag{A.4}$$

The supplier thus increases skilled employment relative to unskilled employment when it invests in knowledge. To expand output with the same technology, it increases both labor inputs proportionally.

Substituting the cost-minimizing labor inputs into the wage bill gives unit cost

$$c_j(E_j) = \left[(1-\alpha)^{\sigma} w_U^{1-\sigma} + \alpha^{\sigma}\left(\frac{w_S}{Z_j(E_j)}\right)^{1-\sigma}\right]^{1/(1-\sigma)}. \tag{A.5}$$

The supplier's total operating cost is $c_j(E_j)q_j$ because production has constant returns to labor. Since $Z_j' > 0$, investment lowers the cost of an effective unit of skilled labor; the supplier adjusts its workforce and produces at a lower unit cost, c_j. We assume diminishing cost reductions, $c_j'' > 0$, and impose a further curvature condition on operating profit below.

Given investments, supplier j chooses its quantity to maximize $[D - 2(q_j + q_k) - c_j]q_j$. If both suppliers produce, their first-order conditions are $D - c_j - 4q_j - 2q_k = 0$ and $D - c_k - 4q_k - 2q_j = 0$. Solving these two equations gives

$$q_j = \frac{D - 2c_j(E_j) + c_k(E_k)}{6}, \qquad \Pi_j(E_j, E_k; D) = 2q_j^2. \tag{A.6}$$

We obtain operating profit by substituting the quantity first-order condition, $P - c_j = 2q_j$, into the supplier's profit expression. The supplier anticipates this operating profit, Π_j, when choosing investment; we deduct investment and financing costs below.

Let $A_j = D - 2c_j(E_j) + c_k(E_k)$, so $\Pi_j = A_j^2/18$. We restrict the investment intervals and the neighborhood of G so that $A_j > 0$ for both firms at every investment profile. Both suppliers then produce positive quantities. Subscripts on Π_j denote partial derivatives with respect to own investment E, rival investment E_k, and the demand intercept D. Differentiating gives

$$\begin{aligned} \Pi_{j,E} &= -\frac{2}{9}A_j c_j' > 0, & \Pi_{j,ED} &= -\frac{2}{9}c_j' > 0, \\ \Pi_{j,EE} &= \frac{4}{9}(c_j')^2 - \frac{2}{9}A_j c_j'', & \Pi_{j,EE_k} &= -\frac{2}{9}c_j' c_k' < 0. \end{aligned} \tag{A.7}$$

A larger market raises the return to a cost reduction because the supplier sells more units. When the rival invests and lowers its costs, the supplier loses sales and earns less from reducing its own costs.

As a supplier invests, it sells more units and has more to gain from further cost reductions. Each additional euro of investment, however, reduces costs by less. We assume this diminishing cost reduction dominates by imposing $A_j c_j'' > 2(c_j')^2$ throughout the investment intervals. This condition gives $\Pi_{j,EE} < 0$: the marginal operating return declines with investment expenditure.

Supplier j first uses its own cash, then raises external funds $e_j = \max\{E_j - L_j, 0\}$ to cover the remaining investment cost. In addition to repaying principal, it pays a financing premium $C_j(e_j)$. We assume $C_j(0) = C_j'(0) = 0$, $C_j' \geq 0$, and $C_j'' > 0$, with C_j twice continuously differentiable for $e_j \geq 0$. The marginal premium rises with borrowing. Suppliers can raise any amount at this premium and repay it in full. The condition $C_j'(0) = 0$ avoids a jump in marginal investment cost when the firm exhausts its internal funds.

The cost of investment is E_j regardless of how it is financed. An internally financed euro could otherwise be retained, and an externally financed euro must be repaid. The supplier retains unused internal cash $\ell_j = \max\{L_j - E_j, 0\}$, so terminal wealth is $\ell_j + \Pi_j - e_j - C_j(e_j) = L_j + \Pi_j - E_j - C_j(e_j)$. Since L_j is fixed when investment is chosen, the supplier solves

$$\max_{0 \leq E_j \leq \overline{E}_j} \left\{ \Pi_j(E_j, E_k; D(G)) - E_j - C_j(\max\{E_j - L_j(G), 0\}) \right\}. \tag{A.8}$$

Each supplier has a unique investment best response because operating profit is strictly concave and financing costs are convex. The objective is continuous and the investment intervals are compact, so the unique best responses are continuous. They map the compact investment rectangle into itself, ensuring that an investment equilibrium exists. In this equilibrium, suppliers anticipate the quantity choices in equation (A.6). We study local changes around interior investment choices, where neither zero nor $\overline{E}_j$ binds. A supplier using external funds, $E_j > L_j$, chooses investment to satisfy

$$\Pi_{j,E} = 1 + C_j'(E_j - L_j). \tag{A.9}$$

The marginal operating return equals one euro of investment expenditure plus the marginal financing premium. If $E_j < L_j$, internal cash suffices and the condition is $\Pi_{j,E} = 1$.

A.3 Investment responses

We first hold rival investment fixed to distinguish the effects of demand and cash from the supplier's response to competition.

Proposition (demand and internal funds). *Under the active-supplier and concavity conditions above, consider an interior investment choice with $E_j > L_j$. Holding rival invest-*

ment fixed, an increase in later customer demand or in internal funds raises investment. A marginal grant increase therefore raises investment if $D' \geq 0$ and $L'_j \geq 0$, with at least one strict inequality. Internal funds have no local effect on investment when finance is frictionless or when the supplier has strictly more cash than its investment requires, $E_j < L_j$.

Proof. Differentiate equation (A.9), allowing demand, internal funds, and rival investment to vary:

$$\Pi_{j,EE}\, dE_j + \Pi_{j,ED}\, dD + \Pi_{j,EE_k}\, dE_k = C''_j(dE_j - dL_j).$$

The difference between the slopes of marginal financing cost and marginal operating return is $H_j = C''_j - \Pi_{j,EE} > 0$. Holding $dE_k = 0$ and collecting terms gives $H_j\, dE_j = \Pi_{j,ED}\, dD + C''_j\, dL_j$. Consequently,

$$\begin{aligned} \frac{\partial E_j}{\partial D} &= \frac{\Pi_{j,ED}}{H_j} > 0, \qquad \frac{\partial E_j}{\partial L_j} = \frac{C''_j}{H_j} \in (0,1), \\ \left.\frac{dE_j}{dG}\right|_{E_k} &= \frac{\Pi_{j,ED} D' + C''_j L'_j}{H_j}. \end{aligned} \tag{A.10}$$

The signs use $\Pi_{j,ED} > 0$, $\Pi_{j,EE} < 0$, and $C''_j > 0$. Under frictionless finance, $C_j \equiv 0$, the first-order condition becomes $\Pi_{j,E} = 1$. The same condition applies when $E_j < L_j$ remains strict. Internal funds do not enter either condition, so their local effect is zero. At $E_j = L_j$, the response is one-sided and depends on which financing regime the firm enters. □

Higher demand makes unit-cost reductions more valuable, while additional cash lowers the marginal financing premium. The supplier uses some of the extra cash to replace external funds and the rest to invest, so investment rises by less than one for one with cash.

We next allow both suppliers to respond. The cross derivative $T = \Pi_{j,EE_k} = -(2/9)c'_j c'_k < 0$ describes how rival investment changes the supplier's marginal operating return. For a given investment pair, a marginal grant increase changes the supplier's marginal return net of financing cost by $b_j = \Pi_{j,ED} D' + C''_j L'_j$. The cross derivative T is the same in the two suppliers' first-order conditions at a given investment profile. If both firms remain interior and externally financed, their equilibrium responses satisfy

$$H_j E'_j - T E'_k = b_j, \qquad H_k E'_k - T E'_j = b_k, \tag{A.11}$$

where $E'_j = dE_j/dG$. A firm invests less when its rival invests more: its best-response slope is $T/H_j < 0$. To obtain a locally unique equilibrium with stable best-response adjustment, assume $H_j H_k > T^2$. This requires the product of the two best-response slopes to be less

than one in absolute value. Solving equation (A.11) then gives

$$E_j' = \frac{H_k b_j + T b_k}{H_j H_k - T^2}. \tag{A.12}$$

Additional demand and cash raise the supplier's investment through $H_k b_j$, while its rival's response lowers it through $T b_k$. Because $T < 0$, the reduction induced by the rival can outweigh the direct increase.

For a common shock, suppose technologies, financing costs, internal funds, and their changes with G are identical, and consider a symmetric interior equilibrium with $E > L$. Let $H_j = H_k = H$ and $b_j = b_k = b$. The stability condition becomes $H > |T|$. Since $E_j' = E_k'$, equation (A.11) yields

$$\frac{dE}{dG} = \frac{\Pi_{ED} D' + C''' L'}{H - T} \geq 0, \tag{A.13}$$

strictly so if demand increases or internal funds increase. The denominator exceeds H because $T < 0$: competition reduces the common investment response relative to holding the rival fixed. Each supplier's physical output is $q = (D - c(E))/6$, so $dq/dG = [D' - c'(E)E']/6 \geq 0$. A fall in the input price can offset these output gains, leaving the revenue response ambiguous.

Knowledge investment also changes workforce composition. Skilled workers account for a share $s_j = S_j/(S_j + U_j)$ of employment. Differentiating equation (A.4) gives

$$\frac{ds_j}{dE_j} = (\sigma - 1)\frac{Z_j'(E_j)}{Z_j(E_j)} s_j(1 - s_j) > 0, \qquad \frac{ds_j}{dG} = \frac{ds_j}{dE_j}\frac{dE_j}{dG}. \tag{A.14}$$

Grant-induced investment raises the skilled worker share under the conditions for the fixed-rival response in equation (A.10) or the symmetric equilibrium response in equation (A.13). Holding investment fixed, a demand increase expands output without changing the skilled worker share.

A.4 Empirical interpretation

Customer funding can induce supplier investment by raising expected demand and generating receipts from initial orders. Expected demand increases the return to investment; retained receipts help finance it when external funds are costly. We compare supplier responses across the baseline Omega score groups defined in Section 2.2 for suggestive evidence of a financing role.

Suppliers that invest in knowledge raise their skilled worker share; those expanding with the same technology leave the share unchanged. This distinction motivates our analysis of workforce composition. We also estimate effects on sales per worker, TFP, and intangible assets.

For suppliers to benefit persistently from receipts on initial orders, the improvements they finance must remain productive or demand must stay elevated. Suppliers can also retain cash to finance future opportunities (Bolton et al., 2011).

B Data, Sample Construction, and Measurement

B.1 Financial Constraints and Supplier Groups

Altman et al. (2023) developed the Omega score to predict creditor-payment default among Croatian SMEs. Default occurs when unpaid obligations to suppliers, financial institutions, or the government lead to bank-account blockage, which the authors measured at 30- and 60-day durations. This event precedes formal bankruptcy.

The authors used LASSO to select variables from financial ratios, payment history, and management and employee information, then constructed the score with discriminant analysis. They predicted default more accurately with payment and personnel information than with financial ratios alone.

Using pre-award Omega scores, we assign suppliers to terciles and keep each supplier in the same group after the award. More negative scores indicate tighter financial constraints, so the least constrained suppliers have the highest scores:

Least constrained	$\Omega \geq -24.37$	bottom in figure legends,
Middle	$-76.01 \leq \Omega < -24.37$	middle in figure legends,
Most constrained	$\Omega < -76.01$	top in figure legends.

B.2 Recipient Balance

Table B.1: Recipient balance on selected pre-award characteristics

	Before matching			After matching		
	Funded	Not funded	Difference	Funded	Not funded	Difference
Age (years)	19.03	10.83	8.2	18.81	19.03	-0.22
Employment	3.85	1.14	2.7	3.8	3.73	0.07
Tangible assets	13.04	7.33	5.71	12.95	13.11	-0.16
Revenue	15.22	10.37	4.84	15.16	15.09	0.07
Material costs	14.51	9.83	4.68	14.45	14.37	0.08
Value added (IHS)	16.93	11.3	5.64	16.86	16.6	0.26
Profit (IHS)	14.36	7.78	6.58	14.37	14.3	0.08
TFP	8.12	6.62	1.5	8.12	8.01	0.12
Exports	11.79	1.67	10.12	11.65	11.57	0.08
Imports	9.82	1.6	8.22	9.74	9.56	0.18
Exporter (indicator)	0.86	0.16	0.7	0.86	0.87	-0.01
Importer (indicator)	0.73	0.16	0.57	0.72	0.72	0
Intangible assets	8.93	0.99	7.94	8.78	8.35	0.43
Intangible assets (indicator)	0.8	0.13	0.67	0.79	0.79	0
N	164	106027		159	159	

Note: We compare grant recipients with non-funded firms before and after matching. All characteristics are measured in year $t = -1$. Employment and monetary values are in logs; we use the inverse hyperbolic sine (IHS) for value added and profit. The indicator rows report shares of firms. Differences are funded minus non-funded means, and N is the number of firms. We exclude recipients of R&D, digital-transformation, and innovation-commercialization grants from the non-funded pool. Full balance results appear in Online Appendix Table OA.1.

B.3 Supplier Balance

Table B.2: Supplier balance on selected pre-award characteristics

	Before matching			After matching		
	Treated	Control	Difference	Treated	Control	Difference
Age (years)	11.54	8.96	2.59	11.48	11.43	0.05
Employment	1.56	0.83	0.73	1.54	1.56	-0.02
Tangible assets	8.1	5.8	2.3	8.06	8.05	0.01
Revenue	11.11	8.49	2.62	11.08	11.11	-0.04
Material costs	10.47	8.02	2.45	10.44	10.45	-0.01
Value added (IHS)	12.26	9.25	3.01	12.23	12.22	0.01
Profit (IHS)	8.89	6.18	2.7	8.87	8.91	-0.04
TFP	6.73	5.63	1.1	6.73	6.72	0
Exports	2.14	1.18	0.96	2.09	2.19	-0.1
Imports	2.17	0.99	1.18	2.14	2.14	0.01
Exporter (indicator)	0.2	0.11	0.08	0.19	0.2	-0.01
Importer (indicator)	0.21	0.11	0.11	0.21	0.21	0
Intangible assets	1.44	0.66	0.77	1.41	1.4	0.01
Intangible assets (indicator)	0.17	0.09	0.09	0.17	0.17	0
N	3392	114313		3370	3370	

Note: We compare suppliers of funded customers with control suppliers before and after matching. Treated suppliers sold to R&D grant recipients before the award. All characteristics are measured in year $t = -1$. Employment and monetary values are in logs; we use the inverse hyperbolic sine (IHS) for value added and profit. The indicator rows report shares of firms. Differences are treated minus control means, and N is the number of firms. We exclude suppliers with transactions with recipients of R&D, digital-transformation, or innovation-commercialization grants from the control pool. Full balance results appear in Online Appendix Table OA.2.

C Baseline Supplier Estimates

We report the baseline supplier estimates discussed in Section 5.2.

Table C.1: Supplier outcomes around R&D grant awards

	Revenue	Material Costs	Tangible Assets	Employees
-4	0.069	0.087	0.052	0.026
	(0.057)	(0.051)	(0.080)	(0.016)
-3	0.024	0.085	0.025	0.027
	(0.055)	(0.050)	(0.078)	(0.016)
-2	0.046	0.068	0.004	0.003
	(0.054)	(0.048)	(0.076)	(0.015)
0	0.248**	0.260**	0.057	−0.016
	(0.052)	(0.047)	(0.071)	(0.014)
1	0.323**	0.380**	0.159*	0.088**
	(0.052)	(0.047)	(0.071)	(0.014)
2	0.367**	0.412**	0.247**	0.112**
	(0.053)	(0.048)	(0.072)	(0.015)
3	0.376**	0.402**	0.333**	0.105**
	(0.053)	(0.048)	(0.072)	(0.015)
4	0.346**	0.351**	0.302**	0.101**
	(0.054)	(0.048)	(0.073)	(0.015)
Num.Obs.	53 393	53 324	49 995	51 328
R2	0.736	0.785	0.799	0.895
R2 Adj.	0.679	0.739	0.752	0.871
AIC	200 535.6	189 015.1	214 120.8	58 103.6
BIC	284 049.8	272 517.2	297 016.9	141 247.1
RMSE	1.33	1.19	1.71	0.35
Mean dep. var.	0.842	0.511	0.626	11.939
Median dep. var.	0.137	0.064	0.013	4.000
Unique firms	6740	6740	6740	6740

Note: We compare suppliers that sold to funded firms before the award with suppliers of matched non-funded firms that had no pre-award sales to treated firms. We keep these links fixed, count event time from the buyer's grant-decision year, and use $t = -1$ as the reference. Outcomes are in logs. We include supplier and calendar-year fixed effects. Standard errors are in parentheses. *$p < 0.05$; **$p < 0.01$.

Table C.2: Supplier productivity, intangible assets, and the skilled worker share after customer grants

	Sales per worker	TFP	Intangible assets	Skilled worker share
-4	0.072	−0.009	0.006	0.000
	(0.054)	(0.036)	(0.074)	(0.006)
-3	0.024	−0.040	−0.028	0.003
	(0.052)	(0.035)	(0.072)	(0.006)
-2	0.054	−0.007	−0.002	0.003
	(0.051)	(0.034)	(0.070)	(0.006)
0	0.129**	−0.005	0.042	0.009
	(0.049)	(0.033)	(0.067)	(0.005)
1	0.225**	−0.054	0.118	0.012*
	(0.049)	(0.033)	(0.068)	(0.005)
2	0.252**	−0.024	0.069	0.012*
	(0.049)	(0.034)	(0.069)	(0.005)
3	0.270**	−0.013	0.172*	0.008
	(0.050)	(0.034)	(0.069)	(0.005)
4	0.221**	−0.014	0.078	0.010*
	(0.050)	(0.034)	(0.070)	(0.005)
Num.Obs.	46 785	49 316	53 668	36 760
R2	0.597	0.791	0.721	0.867
R2 Adj.	0.507	0.743	0.662	0.828
AIC	163 807.0	137 055.0	230 363.9	−55 577.0
BIC	238 149.0	218 783.6	313 926.4	16 716.8
RMSE	1.16	0.80	1.74	0.09
Mean dep. var.	0.082	7.912	0.019	0.000
Median dep. var.	0.033	7.620	0.000	0.000
Unique firms	6740	6740	6740	6740

Note: We compare suppliers linked to funded applicants before the award with control suppliers that had no pre-award sales to treated firms. We hold these links fixed and estimate responses relative to year −1, including supplier and calendar-year fixed effects. We use logs for sales per worker, TFP, and intangible assets, and levels for the skilled worker share; 0.01 in the share corresponds to one percentage point. Standard errors are in parentheses. *$p < 0.05$; **$p < 0.01$.

D Difference-in-Discontinuities Design

D.1 Eligibility and the Running Variable

Applicants must meet every criterion-specific threshold and the total-score requirement to receive funding. We compare their outcome changes before and after the award near this eligibility frontier. By comparing outcome changes, we remove time-invariant firm differences; identification requires untreated outcome changes to be continuous at the frontier (Lee and Lemieux, 2010).

For applicant i, we normalize the margin above the minimum on each criterion k and denote it by M_{ik}. We use the smallest of these margins as the running variable:

$$R_i = \min_k M_{ik}. \tag{D.1}$$

An applicant passes every threshold when $R_i \geq 0$ and fails at least one when $R_i < 0$.

Every funded applicant is closest to the total-score requirement (Table D.1). Among rejected applications, the total score is the binding constraint for only 0.8%; most fall furthest below the project-design and maturity threshold (42.9%) or the implementation capacity threshold (38.3%). Value for money accounts for 9.0%. Applicants on opposite sides of the frontier therefore often approach different criterion-specific thresholds. We report binding constraints for all scored applications before filtering, then estimate effects for those linked to firm outcomes.

Table D.1: Binding eligibility constraints among scored applications before filtering

Funded	Binding Constraint	N	Percentage Within funded or non-funded
Yes	Total Score	178	100.0
No	Project Design and Maturity	57	42.9
No	Implementation Capacity	51	38.3
No	Sustainability	4	3.0
No	Novelty Significance	6	4.5
No	Value for Money	12	9.0
No	Total Score	1	0.8
No	Potential for Commercialization	2	1.5

We estimate

$$Y_{it} = \eta_i + \lambda_t + \tau(D_i \times \text{Post}_t) + \varepsilon_{it}, \tag{D.2}$$

where we use D_i to identify grant recipients and Post_t for the post-award period. We account for fixed firm and year differences through η_i and λ_t.

We estimate this specification in the full scored sample and in narrower samples defined by

$$R_i \in [-h_L, h_R], \tag{D.3}$$

where $h_L, h_R > 0$ are the distances included below and above the cutoff. We use symmetric intervals $[-3, 3]$ and $[-1, 1]$ and the asymmetric interval $[-3, 1]$. Because the score is discrete, the narrowest DiDisc sample compares applicants at $R_i = -1$ with those at $R_i \in \{0, 0.5, 1\}$.

D.2 Difference-in-Discontinuities Design: Results

More applicants score above the funding threshold than below it, and few lie immediately below the frontier (Figure D.1). Some have scores well below zero because they miss one criterion by a large margin, even if they score highly on the others.

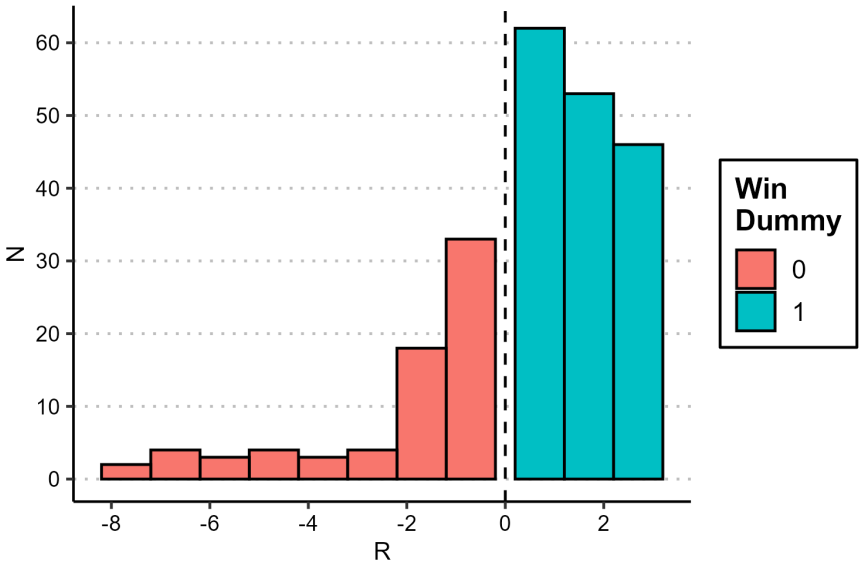

Figure D.1: Distribution of the normalized running variable around the grant-award cutoff

Note: We plot the normalized running variable R separately for funded and non-funded applicants. The dashed line at $R = 0$ marks the eligibility threshold. In the legend, Win Dummy = 1 denotes funded applicants and Win Dummy = 0 non-funded applicants.

Before the award, funded applicants in the scored sample have higher log revenue (14.864 versus 13.820), material costs (14.130 versus 12.814), tangible assets (12.657 versus 11.424), and employment (3.807 versus 3.116); each difference is significant at the 1% level (Table D.2).

Labor productivity is also higher (11.140 versus 10.834), while average wages and TFP do not differ significantly.

Applicants have more similar pre-award characteristics near the frontier. Close sample 1, $R \in [-3, 3]$, contains 144 funded and 50 non-funded firms. The remaining statistically significant difference is in material costs (14.130 versus 13.430), at the 10% level. Close sample 2, $R \in [-3, 1]$, contains 56 funded and 50 non-funded firms; Close sample 3, $R \in [-1, 1]$, contains 56 funded and 26 non-funded firms. None of the baseline differences is statistically significant in these two samples, although the small samples limit the power of the tests.

Table D.2: Pre-award characteristics of scored applicants

Variable	Full Sample		Close Sample 1		Close Sample 2		Close sample 3	
	T	C	T	C	T	C	T	C
Revenue	14.864	13.820***	14.864	13.820	14.850	14.376	14.850	14.214
Material costs	14.130	12.814***	14.130	13.430*	14.181	13.430	14.181	13.170
Tangible assets	12.657	11.424***	12.657	12.153	12.606	12.153	12.606	12.058
Employees	3.807	3.116***	3.807	3.399	3.754	3.399	3.754	3.306
Average wage	9.429	9.333	9.428	9.480	9.410	9.480	9.410	9.497
Labor productivity	11.140	10.834**	11.140	11.053	11.162	11.053	11.162	10.947
TFP	8.866	8.920	8.866	8.633	8.743	8.633	8.743	8.281
N	144	65	144	50	56	50	56	26

Note: We compare pre-award characteristics of funded (T) and non-funded (C) applicants with evaluation scores. Monetary values and employment are in logs. The full sample includes scored applicants with linked outcomes. Close samples 1, 2, and 3 restrict the running variable to $R \in [-3, 3]$, $R \in [-3, 1]$, and $R \in [-1, 1]$, respectively. Stars indicate the significance of differences in means: $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

After the award, funded applicants have higher revenue, material costs, tangible assets, and employment than applicants below the cutoff (Figure D.2).

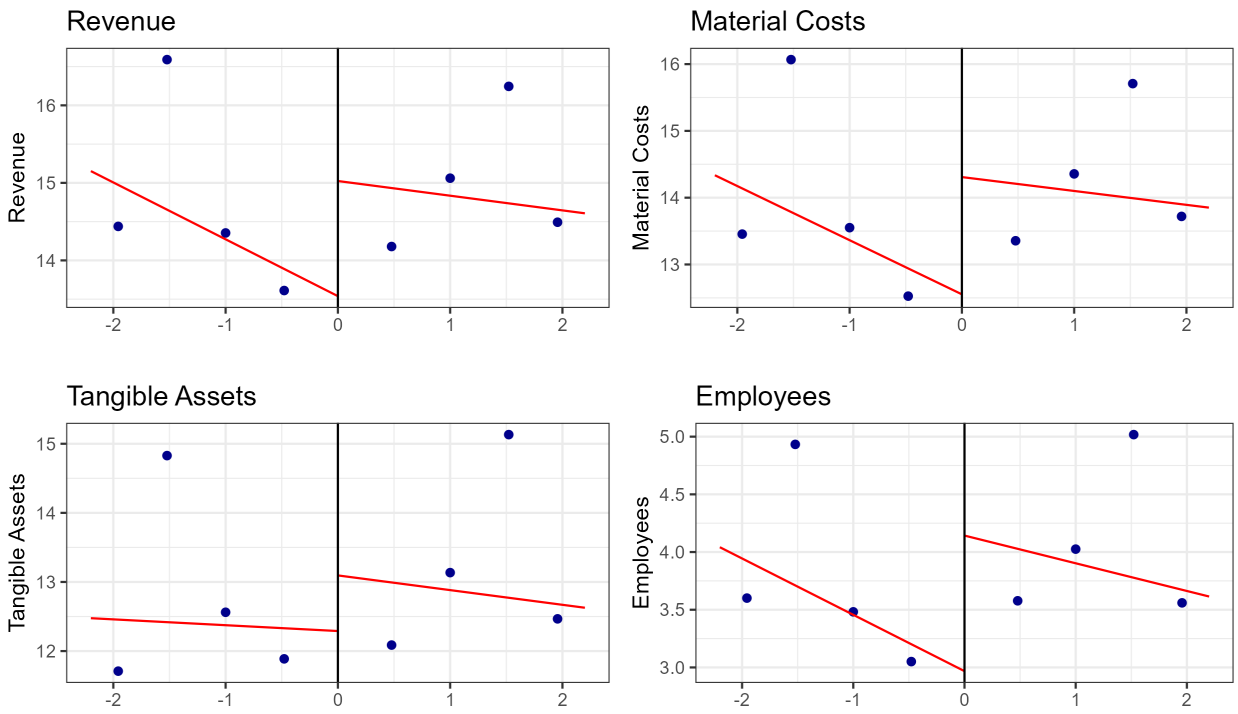

Figure D.2: Applicant outcomes around the grant-award cutoff

Note: We plot mean post-award log revenue, material costs, tangible assets, and employment within bins of the normalized running variable R. The vertical line marks the cutoff at $R = 0$; solid lines are separate local linear fits on each side.

Grant recipients expand sales, purchases, and employment in the DiDisc comparisons (Table D.3). In the full sample of 1,853 observations, recipients increase revenue by 0.193 log points, material costs by 0.147, and employment by 0.136, equivalent to about 21%, 16%, and 15%. The tangible-asset estimate is 0.135 log points (about 15%) but imprecise.

In Close sample 1, with 1,721 observations, recipients increase revenue by 0.212 log points, material costs by 0.196, tangible assets by 0.285, and employment by 0.111, equivalent to about 24%, 22%, 33%, and 12%, respectively. In Close sample 2, with 936 observations, the corresponding gains are 0.252, 0.219, 0.429, and 0.099 log points, or about 29%, 25%, 54%, and 10%.

In the narrowest comparison, Close sample 3, with 750 observations, recipients increase revenue by 0.185 log points (about 20%), although the estimate is not statistically distinguishable from zero. Material costs rise by 0.216 (about 24%), tangible assets by 0.339 (about 40%), and employment by 0.146 (about 16%). The material-cost and tangible-asset estimates are significant at the 10% level and employment at the 1% level.

Table D.3: Recipient effects around the eligibility threshold: difference in discontinuities

	Revenue	Material costs	Tangible assets	Employees	N
Full sample					
	0.193**	0.147*	0.135	0.136***	1853
	(0.089)	(0.081)	(0.143)	(0.039)	
Close sample 1					
	0.212**	0.196**	0.285*	0.111**	1721
	(0.095)	(0.087)	(0.146)	(0.040)	
Close sample 2					
	0.252**	0.219*	0.429***	0.099**	936
	(0.115)	(0.112)	(0.160)	(0.049)	
Close sample 3					
	0.185	0.216*	0.339*	0.146***	750
	(0.126)	(0.124)	(0.177)	(0.056)	

Note: We estimate difference-in-discontinuities effects on applicants' log outcomes around the eligibility threshold, including firm and year fixed effects. Sample intervals are defined in Table D.2. Standard errors are in parentheses; N is the number of observations. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

E Local Randomization Inference

We compare outcome changes for 92 applicants near the eligibility cutoff using local randomization inference, following Cattaneo et al. (2015). Within the selected score interval, we assume treatment assignments are exchangeable with respect to potential outcome changes, conditional on the numbers of funded and non-funded firms. We implement the tests with the `rdlocrand` package (Cattaneo et al., 2016) and 5,000 randomization draws.

E.1 Score Interval Selection

We select a score interval using `rdwinselect`. Starting near the cutoff, we increase the half-width in increments of 0.25 and record the smallest balance-test p-value across eleven pre-treatment characteristics: employment, revenue, material costs, capital, TFP, labor productivity, average wage, contracts in non-financial transactions, contracts in the high- and low-value categories, and the skilled worker share.[8]

We cannot test balance in the first three candidate intervals, with half-widths from 0.5 to 1.0, because none contains applicants below the cutoff in the selection sample. From a half-width of 1.25 onward, we obtain the smallest balance-test p-value for material costs (Table E.1). We select $[-1.75, 1.75]$, the narrowest interval where this value exceeds 0.15. We retain 33 control and 59 treated firms, with a minimum p-value of 0.184. Minimum p-values remain above 0.15 in the wider candidate intervals.

We reject equal assignment probabilities in every reported interval using a binomial test. In the randomization tests, we condition on the observed numbers of treated and control firms.

[8] We exclude pre-treatment intangible assets from the balance tests because the evaluation rewards innovation capacity and intangible assets differ across the cutoff at every candidate interval.

Table E.1: Covariate balance and selection of the local-randomization interval

Interval	Min. p-value	Variable	Binom. test	Obs $< c$	Obs $\geq c$
$[-1.25, 1.25]$	0.100	Material costs (t-1)	0.005	29	56
$[-1.50, 1.50]$	0.108	Material costs (t-1)	0.005	29	56
$[-1.75, 1.75]$	**0.184**	**Material costs (t-1)**	0.009	**33**	**59**
$[-2.00, 2.00]$	0.209	Material costs (t-1)	0.009	33	59
$[-2.25, 2.25]$	0.224	Material costs (t-1)	0.000	43	101
$[-2.50, 2.50]$	0.235	Material costs (t-1)	0.000	43	101
$[-2.75, 2.75]$	0.331	Material costs (t-1)	0.000	46	103
$[-3.00, 3.00]$	0.320	Material costs (t-1)	0.000	46	103

Notes: We test balance on eleven pre-treatment covariates among 209 applicants and report the smallest p-value for each interval. We select $[-1.75, 1.75]$, the narrowest interval with a minimum above 0.15. Intervals with half-widths from 0.5 to 1.0 contain no observations below the cutoff. The binomial test assesses equal assignment probabilities; the subsequent randomization tests condition on the observed numbers of treated and control firms.

E.2 Main Results: First-Differenced Outcomes

We compare changes from the year before the award to the first year after it, $\Delta y_i = y_{i,t=+1} - y_{i,t=-1}$, removing time-invariant level differences between applicants on either side of the cutoff. We test for differences in these changes using difference-in-means, Wilcoxon rank-sum, and Kolmogorov–Smirnov statistics (Table E.2).

Table E.2: Recipient effects one year after the award: local randomization

Outcome	Effect (log pts)	Diff. in means p-value	Rank-sum p-value	Kolmogorov-Smirnov p-value
Δ Employment	0.132	**0.072**	**0.089**	0.151
Δ Revenue	0.126	0.309	0.437	0.453
Δ Material costs	0.093	0.643	0.308	0.658
Δ Capital	0.218	0.463	0.172	0.155

Notes: We compare changes in log outcomes from $t = -1$ to $t = +1$, relative to the grant-decision year, for 33 control and 59 treated firms within $[-1.75, 1.75]$. We use the interval selected in Table E.1 and calculate randomization p-values from 5,000 draws. Bold values indicate significance at the 10% level.

Recipients increase employment by 0.132 log points, or about 14%, at $t = +1$. The difference-in-means and rank-sum tests reject at the 10% level, while the Kolmogorov–

Smirnov test does not. We estimate increases of 0.126 log points in revenue, 0.218 in capital, and 0.093 in material costs, but these estimates are imprecise.

E.3 Dynamic Effects Across Post-Treatment Horizons

We compare outcomes in each post-award year, $t = +1$ through $t = +4$, with outcomes at $t = -1$ (Table E.3).

Table E.3: Recipient effects across post-award years: local randomization

	$t = +1$		$t = +2$		$t = +3$		$t = +4$	
Outcome	Eff.	p	Eff.	p	Eff.	p	Eff.	p
Δ Employment	0.132	**0.072**	0.181	**0.049**	0.241	**0.030**	0.294	**0.039**
Δ Revenue	0.126	0.309	0.090	0.593	0.217	0.282	0.336	0.317
Δ Material costs	0.093	0.643	−0.102	0.753	0.036	0.910	−0.022	0.946
Δ Capital	0.218	0.463	0.090	0.807	0.254	0.532	0.219	0.602

Notes: We compare changes in log outcomes from $t = -1$ to each post-award year within $[-1.75, 1.75]$. The sample contains 33 control and 59 treated firms at $t = +1, +3, +4$, and 33 control and 58 treated firms at $t = +2$. We report difference-in-means estimates and randomization p-values from 5,000 draws. Bold p-values indicate significance at the 10% level. Rank-sum and Kolmogorov-Smirnov p-values for employment range from 0.077 to 0.224 across horizons.

Recipients' employment gains rise from 0.132 log points at $t = +1$ to 0.181, 0.241, and 0.294 in successive years, or roughly 14%, 20%, 27%, and 34%.

Recipients' estimated revenue and capital gains are positive in all four years, reaching 0.336 and 0.219 log points at $t = +4$. Material costs rise in some years and fall in others. We estimate these revenue, capital, and material-cost responses imprecisely.

E.4 Falsification Tests

Pre-treatment levels. Funded applicants are larger before the award by 0.32 to 0.78 log points across the four outcomes, although none of these differences is statistically significant (Table E.4).

Table E.4: Pre-award outcome differences around the eligibility cutoff

Pre-treatment outcome	Mean (left)	Mean (right)	Difference	p-value
Employment ($t = -1$)	3.485	3.806	0.321	0.347
Revenue ($t = -1$)	14.474	14.918	0.444	0.319
Material costs ($t = -1$)	13.486	14.268	0.782	0.181
Capital ($t = -1$)	12.395	12.721	0.326	0.628

Notes: We compare pre-treatment log outcomes for 33 control and 59 treated firms within $[-1.75, 1.75]$. We report applicants below the eligibility cutoff on the left and those at or above it on the right. We calculate difference-in-means p-values from 5,000 randomization draws.

Pre-treatment trends. We compare changes from $t = -2$ to $t = -1$ on either side of the cutoff to test for growth differences before grant receipt (Table E.5).

Table E.5: Pre-award growth differences around the eligibility cutoff

Pre-treatment trend	Mean (left)	Mean (right)	Difference	p-value
Δ Employment ($t = -2 \to t = -1$)	0.154	0.166	0.012	0.912
Δ Revenue ($t = -2 \to t = -1$)	0.387	0.166	−0.221	0.420
Δ Material costs ($t = -2 \to t = -1$)	0.131	0.216	0.085	0.546
Δ Capital ($t = -2 \to t = -1$)	0.115	0.263	0.148	0.702

Notes: We compare changes in log outcomes from $t = -2$ to $t = -1$ for 33 control and 57 treated firms within $[-1.75, 1.75]$. Two treated firms have missing outcomes at $t = -2$. We report applicants below the eligibility cutoff on the left and those at or above it on the right. We calculate difference-in-means p-values from 5,000 randomization draws.

We find no significant pre-treatment growth differences in the four outcomes. The employment difference is 0.012 log points, compared with 0.132 after the award at $t = +1$. Revenue growth is lower on the funded side before treatment (−0.221), whereas all post-award revenue estimates are positive.

Artificial cutoffs. We repeat the comparison at $c = -2$ and $c = +2$, restricting each sample to one side of the true funding cutoff so that eligibility does not change at the artificial cutoff (Table E.6).

Table E.6: Placebo: artificial cutoffs

Fake cutoff	Outcome	Effect	p-value	n_L	n_R
$c = -2$	Δ Employment	-0.110	0.240	18	33
	Δ Revenue	0.147	0.376	18	33
	Δ Material costs	0.085	0.792	18	33
	Δ Capital	0.589	0.173	18	33
$c = +2$	Δ Employment	-0.088	0.101	55	85
	Δ Revenue	-0.071	0.547	55	85
	Δ Material costs	0.057	0.650	55	85
	Δ Capital	0.110	0.693	55	85

Notes: Outcomes are changes in logs. We calculate difference-in-means p-values from 5,000 randomization draws within intervals of half-width 1.75 around each artificial cutoff. We restrict each sample to one side of the true cutoff, so eligibility does not change at the artificial threshold. We count firms below and above the artificial cutoff as n_L and n_R, respectively.

None of the eight artificial-cutoff estimates is significant at the 10% level. We estimate employment differences of -0.110 and -0.088 log points at the two cutoffs, compared with the positive estimate at the funding threshold. At $c = -2$, we estimate a capital increase of 0.589 log points, but the estimate is imprecise in the sample of 51 firms.

E.5 Discussion

We compare average post-award effects in the matched panel and the winner–loser panel of 267 applicant firms with effects at $t = +4$ for applicants near the cutoff (Table E.7). We estimate larger employment gains in the local comparison. Recipients' estimated revenue and capital gains are positive across designs but imprecise under local randomization.

Table E.7: Recipient effects across identification strategies

	Matched sample (panel ATT)	Winner–loser (applicants only)	Local randomization (marginal applicants, $t = +4$)
Revenue	0.157***	0.228*	0.336
Material costs	0.195***	0.242*	—
Tangible assets / capital	0.242**	0.363*	0.219
Employment	0.076**	0.127*	0.294**
Population	matched recipients	applicant sample	marginal applicants
Sample	matched panel	267 firms	92 firms
Inference	clustered SEs	clustered SEs	randomization, 5,000 draws

Notes: We compare average post-award estimates in log points from the matched panel (Table 2) and funded versus rejected applicants (Online Appendix Table OC.1) with local-randomization estimates at $t = +4$ within $[-1.75, 1.75]$ (Table E.3). The local material-cost estimates appear in Table E.3. */**/*** indicate 10/5/1% significance in columns 1 and 3; */** indicate 5/1% in column 2.

F Network Exposure

F.1 Empirical Approach

We relate suppliers' outcome changes to their pre-award sales to scored applicants. For supplier i, we divide pre-award sales to applicants in the cutoff sample by total pre-award sales to obtain the share W_i. We denote its pre-award exposure to other suppliers that sell to those applicants by $W2_i$.

We interact exposure with the post-award indicator D_{it} and include interactions with the associated applicant's running variable R_j:

$$\begin{aligned} Y_{it} = {} & \beta_1 (W_i \times D_{it}) + \beta_2 (W_i \times R_j) + \\ & + \beta_3 (W_i \times R_j \times D_{it}) + \beta_4 (W2_i \times D_{it}) + \\ & + \rho Y_{i,t-1} + \lambda_t + \varepsilon_{it} \end{aligned} \tag{F.1}$$

At $R_j = 0$, β_1 is the post-award association between first-order exposure and supplier outcomes. We allow this association to vary with the applicant's score through $W_i \times R_j$ and $W_i \times R_j \times D_{it}$. We use $W2_i \times D_{it}$ to compare changes among suppliers one additional step upstream. We control for the pre-treatment outcome and calendar-year fixed effects. A causal interpretation requires suppliers with different exposure to have followed parallel paths absent the grants, conditional on these controls.

F.2 Results

Suppliers with a 10 percentage point higher pre-award sales share to scored applicants have post-award increases that are about 0.033 log points larger in revenue, 0.035 in material costs, 0.037 in tangible assets, and 0.012 in employment, conditional on $R = 0$ and the other regressors (Table F.1). These correspond to approximately 3–4% differences in revenue, material costs, and assets, and 1% in employment.

Before the award, the association between suppliers' exposure and their revenue, material costs, and employment is more negative at higher applicant scores. We estimate exposure–score interactions of -0.147 for revenue and material costs and -0.050 for employment. After the award, these interactions change by 0.061 for revenue and 0.037 for material costs; we estimate the changes imprecisely for all four outcomes.

For suppliers one additional step upstream, we estimate $W2 \times D$ coefficients of 0.047 for revenue, -0.009 for material costs, 0.088 for tangible assets, and -0.019 for employment. These estimates are imprecise.

Table F.1: Supplier outcomes and pre-award network exposure

	Revenue	Material Costs	Tangible Assets	Employees
WD	0.331***	0.349***	0.371**	0.116***
	(0.094)	(0.088)	(0.152)	(0.031)
WR	−0.147**	−0.147*	−0.148	−0.050**
	(0.070)	(0.065)	(0.113)	(0.023)
WRD	0.061	0.037	0.072	0.019
	(0.080)	(0.075)	(0.130)	(0.027)
W2D	0.047	−0.009	0.088	−0.019
	(0.043)	(0.040)	(0.069)	(0.014)
Revenue (t-1)	0.796***			
	(0.004)			
Material Costs (t-1)		0.843***		
		(0.003)		
Tangible Assets (t-1)			0.743***	
			(0.003)	
Employees (t-1)				0.877***
				(0.002)
Num.Obs.	32 205	32 205	32 205	32 205
R2	0.613	0.685	0.588	0.861
R2 Adj.	0.613	0.684	0.588	0.861
R2 Within	0.612	0.684	0.587	0.861
R2 Within Adj.	0.612	0.684	0.587	0.861
AIC	119 972.7	115 879.1	150 970.9	48 734.6
BIC	120 048.1	115 954.5	151 046.3	48 810.0
RMSE	1.56	1.46	2.52	0.52
Year FE	Yes	Yes	Yes	Yes
Mean dep. var.	1.532	1.062	1.124	15.409
Median dep. var.	0.124	0.057	0.014	3.000

Note: We estimate the regression with log outcomes. We use W for suppliers' pre-award sales share to applicants in the cutoff sample and $W2$ for their pre-award exposure to suppliers selling to those applicants. The post-award indicator is D, and the applicant's running variable is R, with eligibility at $R \geq 0$. We compare post-award outcome changes by exposure at $R = 0$, conditional on the other regressors. We include the pre-treatment outcome and year fixed effects. Standard errors are in parentheses. We report outcome means and medians in millions of euros for monetary outcomes and counts for employment. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.