The Value of Strategic Consulting

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Abstract

We study the effects of strategic consulting on firm performance using the universe of business-to-business transactions in Italy (2019–2023), linked to balance sheets and employer-employee records. A matched difference-in-differences design exploiting approximately 3,000 consulting events shows that consulting raises firm size and revenues by 8–10% but has no effect on value added per worker or profits over a three-year horizon. The increase in employment is driven by new permanent hires concentrated in white-collar and managerial positions, with a simultaneous increase in internal promotions. Incumbent workers at client firms experience positive earnings growth, but the gains accrue disproportionately to white-collar workers and managers, while blue-collar workers see earnings decline. Lastly, we apply the report card methodology of Kline, Rose, and Walters (2024) to rank consulting firms based on their estimated impact on client profitability. This approach reveals meaningful differentiation when one places sufficient weight on correctly ranking firms relative to the cost of misranking them. We interpret this as evidence that each consulting firm embodies firm-specific expertise that is difficult to standardize.

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1 Introduction

Strategy and management consulting is a large and growing industry. Global revenues amount to several hundred billion dollars per year and have expanded rapidly over the past two decades.[1] Many firms—especially large ones—routinely rely on consulting services for organizational restructuring, strategic planning, and operational improvements. Standard economic theory offers a clear rationale for this: firms outsource non-routine tasks for which they lack either the time or the required expertise. By importing specialized knowledge and aligning internal practices with industry best practices, consulting firms may raise client productivity and profitability.

Despite its economic significance, there is remarkably scarce evidence on the systematic effects of consulting on firm performance, especially in advanced economies. Even less is known about how consulting firms achieve changes in productivity—whether through knowledge transfer, organizational restructuring, or the legitimization of pre-existing plans. And we have essentially no evidence on whether consulting firms differ in their effectiveness. Do some firms consistently raise their clients' productivity while others do not? What does the distribution of these treatment effects look like, and what explains the heterogeneity? These questions remain open, in large part because consulting relationships are inherently opaque: consulting firms are typically closely held partnerships that do not disclose client lists, and client firms rarely announce their consulting engagements.

In this paper, we overcome these data constraints by exploiting the universe of business-to-business (B2B) transactions between Italian firms over the period 2019–2023. These records, obtained from the Italian Tax Authority, allow us to observe every invoice issued between a client firm and any of the strategic consulting firms operating in Italy. We define a consulting event as the first time a firm (henceforth a client firm) pays a consulting provider, conditional on no transactions with any consulting firm in the two preceding quarters. This

[1] See, e.g., Source Global Research (https://www.sourceglobalresearch.com) and Statista for market size estimates.

yields approximately 3,000 consulting events. We link the B2B data to firms' balance sheets and to matched employer-employee records from the Italian Social Security Institute (INPS). This allows us to trace out not only whether consulting affects aggregate firm performance but also *how* it reshapes the internal organization of the firm—in terms of hiring, occupational composition, contract types, and internal promotions. The richness of the data also permits us to move beyond average effects and assess treatment effect heterogeneity across consulting firms, asking which consultant firms appear particularly valuable to their clients and which do not.

Our research design is a matched difference-in-differences. For each client firm, we identify a control firm that operates in the same 2-digit sector, has similar size, revenues, and return on assets in the year before the consulting event, but never relies on consulting services during our sample period. On this matched sample, we estimate event-study regressions that trace out the differential evolution of outcomes between treated and control firms around the consulting event. The matching procedure retains approximately 80% of client firms and produces a control group that is highly comparable along observables. Importantly, client firms do not appear to be on any systematic upward or downward trajectory prior to the consulting event: pre-trends in revenues, firm size, value added per worker, and labor costs are flat. We further corroborate this finding using data from the Bank of Italy's INVIND survey, which asks managers about their expectations for employment and revenue growth. We find no significant difference in expected growth between client and control firms before the consulting event occurs.

Our main results show that consulting leads to a substantial expansion in firm size and revenues. Log firm size increases by approximately 4% in the first year and grows to 8–10% within a few years. Log revenues follow a similar pattern. Log value added also rises, but value added per worker does not: the expansion in output is fully absorbed by a proportional increase in headcount. Profits—defined as value added minus labor costs—are also unaffected. Consulting helps firms scale up, but this growth does not translate into

higher productivity per worker or improved profitability, at least within our time horizon. These findings are robust to alternative matching bandwidths, to restricting the sample to high-spending consulting events, and to controlling for mergers and acquisitions.

We then investigate where the expansion comes from. Firms appear to expand geographically, increasing the number of municipalities where they employ at least one worker, consistent with the creation of new offices or establishments. The revenue growth is driven by both the extensive margin (more customers) and the intensive margin (higher sales per customer), with the formation of new commercial relationships playing the dominant role. On the expenditure side, client firms increase purchases from new suppliers rather than deepening pre-existing relationships. Despite this expansion in the volume of trade, the sectoral composition of expenditures remains broadly unchanged: consulting does not appear to induce a reallocation of the firm's input mix.

Exploiting the matched employer-employee data, we then examine how consulting reshapes the internal organization of the firm. The increase in headcount is driven entirely by new hires—not by higher retention of incumbent workers—and there is no increase in layoffs. The new jobs are permanent and full-time: the share of temporary and part-time workers declines. The expansion is concentrated in the upper part of the occupational hierarchy, with significant increases in white-collar and managerial employment but no change in blue-collar headcount. Internal promotions to managerial positions also rise. Consulting thus triggers a structured upgrading of the workforce: firms add skilled workers at the top while promoting incumbents from within.

We then track individual incumbent workers—those employed at the client firm before the consulting event—using a worker-level matched difference-in-differences design. Incumbent workers at client firms are more likely to be employed in the years following the event and experience positive earnings growth: log yearly earnings increase by approximately 1.7% two years after the consulting event. These gains, however, are unevenly distributed across the occupational hierarchy. White-collar workers and managers see significant earnings

increases of 2–3%, while blue-collar workers experience a decline of approximately 1–1.5%. The reorganization that follows consulting thus has clear distributional consequences.

The average null effect on profits may mask substantial heterogeneity across consulting firms. Our final contribution is to move beyond the average and ask whether some consulting firms are genuinely better than others at raising their clients' profitability. We estimate the distribution of consulting-firm-specific effects on profits using empirical Bayes deconvolution techniques that separate true variation from sampling noise (Kline et al., 2020; Walters, 2024). The standard deviation of the true effects is approximately 30 log points—large relative to the near-zero mean. The distribution is well approximated by a normal, and we confirm this using the nonparametric approach of Efron (2016). We then apply the report card methodology of Kline et al. (2024) to rank consulting firms while controlling the risk of incorrect rankings. The report card reveals meaningful differentiation only when the decision maker places sufficient weight on correctly ranking firms relative to the cost of misranking: under these conditions, several firms are clearly separated at the top and bottom of the distribution. When the cost of misranking is high relative to the benefit of a correct ranking, the procedure pools most firms into the same category and only one firm stands out as unambiguously superior. This is, to our knowledge, the first evidence on the distribution of treatment effects across consulting firms and the first attempt to rank them based on their causal impact on clients' profits. It also suggests that consulting firms are far from homogeneous—each embodies a particular combination of industry expertise and consulting practices that cannot be taken as common knowledge.

Our paper contributes to several strands of the literature. A first strand has documented the importance of management quality for firm performance and productivity (Bloom and Van Reenen, 2007; Bloom et al., 2016). A related body of work has shown that managerial practices can be transferred across firms—through government-sponsored programs (Giorcelli, 2019; Bianchi and Giorcelli, 2022) or through direct consulting interventions in developing countries (Bloom et al., 2013; Bruhn et al., 2018). Whether these findings extend

to the market for strategic consulting in advanced economies has remained an open question, largely because of data limitations. The closest paper to ours is Bijnens et al. (2025), who use B2B transaction data from Belgium to study approximately 300 consulting events via synthetic difference-in-differences.

We contribute to this nascent literature along three dimensions. First, the scale of our data—approximately 3,000 consulting events—gives us substantially more statistical power to detect effects and explore heterogeneity. Second, the availability of matched employer-employee records allows us to go beyond aggregate firm outcomes and examine how consulting reshapes the internal organization of the firm, including hiring, occupational composition, and promotions. Third, we use empirical Bayes techniques (Kline et al., 2020; Efron, 2016; Walters, 2024) and the report card methodology of Kline et al. (2024) to estimate the distribution of treatment effects across consulting firms and produce the first ranking of consulting providers based on their causal impact on client profitability.

2 Data

We combine four administrative datasets covering the universe of Italian firms between 2005 and 2023. All datasets are linked via firms' tax identifiers (*codice fiscale*).

Business-to-business transactions. Our main data source is the universe of business-to-business (B2B) invoices between Italian firms, obtained from the Italian Tax Authority (*Agenzia delle Entrate*). These data cover 2019–2023 and are collapsed at the quarterly level. Each record identifies the buyer, the seller, and the transaction value. We use these data to identify consulting events and to characterize the network of trade relationships between firms.

Balance sheets. We obtain balance-sheet data from Cerved for the period 2005–2023. These data provide information on revenues, value added, labor costs, and profits for the

near-universe of Italian corporations.

Firm characteristics. We supplement the balance-sheet data with administrative records from the Italian Social Security Institute (INPS), specifically the *Anagrafica* registry, which covers the universe of Italian firms from 2005 to 2023. This dataset provides information on firm size, sector of activity, and other firm characteristics such as share of temporary or part-time workers, number of employees and earnings divided by broad category of occupations (blue, white collar and managers).

Employer-employee data. We use matched employer-employee records from the Bank of Italy's Survey of Industrial and Service Firms (INVIND), linked to INPS employment histories (INPS-INVIND) (see also Daruich et al., 2023; Di Addario et al., 2023). The INVIND survey covers approximately 3,000 firms in industry, 1,000 in non-financial services, and 500 in construction, all with more than 20 employees. To include smaller businesses, we complement this with a representative sample of firms below 20 employees, also linked to INPS employee records. The combined dataset provides us the entire worker history of any worker that at any point was employed by a firm in either sample over 2005–2023.

3 Research Design

Our research design proceeds in four steps. We first identify consulting firms and define consulting events using B2B transaction data. We then describe the dynamics of client firms before consulting. Next, we match each client firm to a control firm and estimate event-study regressions on the matched sample. We describe each step in turn.

Consulting firms. We identify strategic consulting firms in three steps. First, we use a large language model (ChatGPT o3-mini-high) to generate a list of the top 50 strategic consulting firms operating in Italy. We retrieve each firm's tax identifier (*codice fiscale*) from

public records. Second, we match these firms to the B2B transaction data and keep those whose number of clients or total transaction value (averaged over 2019–2023) exceeds the median, yielding 36 firms. Third, we manually review each firm's website and exclude those not primarily engaged in strategic consulting. This leaves a final sample of 26 consulting firms. For firms with multiple legal entities—particularly the "Big Four" (Deloitte, EY, KPMG, and PwC)—we retain only the entity corresponding to the strategic or management consulting branch.

Table 1 reports summary statistics for the 17 out of 26 consulting firms that we could match with Cerved, alongside the universe of Italian firms. Consulting firms are large: the average consulting firm employs approximately 1,110 workers, compared to 19 for the average Italian firm. They pay high wages (average monthly wage of 7,033 euros versus 1,643 euros) and have a high share of managers (27% versus 0.3%). Their workforce skews young: 55% of employees are aged 15–34, compared to 29% economy-wide. On the client side, consulting firms serve on average 164 customers with median sales per customer of approximately 190 thousand euros.

Consulting events. We define a consulting event as the first occurrence of a B2B invoice between a client firm and any of the 26 consulting firms, conditional on a clean window with no invoices in the two preceding quarters. When payments for a single consulting engagement are split across multiple quarters, we assign the start to the first observed quarter. This procedure yields approximately 3,000 consulting events over the 2019–2023 period. Figure 2 shows the distribution of annual spending on consulting services among client firms. Panel (a) plots the log of spending in 2020 euros. The distribution is centered around a mean of 10.5 log points (approximately 36,000 euros), close to the median. Panel (b) reports spending as a share of labor costs. For most firms, consulting is a small expense relative to their scale of operations: the median firm spends 0.7% of its payroll on consulting, the mean firm 1.7%.

Dynamics of client firms before consulting events. Figure 1 reports the dynamics of client firms in the years before the consulting event. We plot averages of log revenues, log value added per worker, log labor costs, and log firm size, expressed as deviations from pre-event levels, pooling all cohorts. Before hiring a consulting firm, client firms exhibit flat revenues, a relatively modest downward trend in value added per worker (approximately 3% higher one year before the event), and a slight increase in labor costs and firm size. In general, it does not appear that firms that purchase consulting services are experiencing significant upward or downward trajectories along key performance indicators.

Matched difference-in-differences. Let t_j^* denote the year in which firm j first pays a consulting firm. We match each client to a control firm that has similar characteristics in $t_j^* - 1$ but never relies on consulting firms during our sample period. Matching variables are: 2-digit sector, firm-size bins, log revenues (caliper of 30 log points), and return on assets (caliper of 0.05).

On the matched sample, we estimate the following event-study specification:

$$y_{jt} = \alpha_j + \lambda_t + \sum_{k=a}^{b} \beta_k \mathbf{1}\{t = t_j^* + k\} + \sum_{k=a}^{b} \theta_k (\mathbf{1}\{t = t_j^* + k\} \times T_j) + r_{jt}, \tag{1}$$

where $T_j = 1$ if firm j is a client firm, α_j are firm fixed effects, and λ_t are time fixed effects. The coefficients θ_k capture the differential change in outcome y_{jt} for client firms relative to matched controls at horizon k from the consulting event.

Summary statistics. Table 2 reports summary statistics for treated and control firms, both before and after matching. In the full sample, treated firms are substantially larger than the average control firm (314 versus 18 employees), more productive (log value added per worker of 4.50 versus 3.74), and pay higher wages (3,283 versus 1,779 euros per month). This confirms that firms that purchase consulting services are not representative of the Italian firm population: they are disproportionately large and productive.

The matching procedure retains 3,312 out of 4,117 treated firms (approximately 80%), indicating that most treated observations find suitable counterparts in the control group. Importantly, the matched treated sample remains similar to the full treated sample across key dimensions—firm size (219 versus 314), productivity (4.44 versus 4.50), and wages (3,157 versus 3,283)—suggesting that matching does not substantially alter the composition of the treated group.

After matching, treated and control firms are highly comparable. Firm size is nearly identical (219 versus 221 employees), profitability is fully aligned (ROA of 0.05 in both groups), and productivity differences narrow considerably (4.44 versus 4.27 in log value added per worker). Differences in workforce composition are also small: the share of temporary workers is 6% versus 7%, part-time workers 10% versus 12%, and managers 3% versus 2%. Wage differences are attenuated but remain moderate (3,157 versus 2,782 euros), and treated firms still serve somewhat more customers (615 versus 491). The sectoral distribution of firms is also well balanced across the five largest sectors reported in Table 2.

First stage. Figure 3 confirms that the consulting event corresponds to a sharp increase in spending on consulting services. Panel (a) shows the change in euros spent on consulting by treated firms relative to controls. Average spending increases by approximately 40,000 euros in the first year and remains around 30,000 euros in subsequent years. Panel (b) expresses this change as a share of baseline intermediate expenditures. There is an increase of about 3% on impact. Spending remains above pre-event levels for at least three subsequent years, averaging approximately 1.8% of pre-event intermediate input expenditures. The increase in consulting spending is sharp and persistent.

4 Results on Client Firms

We estimate equation (1) for five firm-level outcomes: log firm size, log revenues, log value added, log value added per worker, and profits (value added minus labor costs). Figure 4

reports the event-study coefficients θ_k. In all panels, the pre-treatment coefficients are close to zero and statistically insignificant, confirming that the matching procedure successfully eliminates differential pre-trends between client and control firms. The effects we document below therefore emerge sharply at the time of the consulting event.

Client firms grow. Log firm size increases by about 4% in the first year after the consulting event and the effect is persistent: 3-4 years after treatment, client firms are roughly 8–10% larger than matched controls (Panel a). Log revenues follow a similar pattern, rising by approximately 4% on impact and continuing to grow over subsequent years (Panel b). Log value added also increases at the time of treatment, with effects that grow monotonically over time, though with increasing variance (Panel c). The magnitude of these effects is economically meaningful and represents a substantial acceleration in firm growth relative to observationally similar firms that did not rely on consulting.

This expansion, however, does not improve efficiency or profitability. We find no significant effect on log value added per worker (Panel d), nor on log revenues per worker (not shown). Profits—defined as value added minus labor costs—are also unaffected (Panel e). The gains in value added are fully absorbed by the proportional increase in labor costs that accompanies the growth in headcount. In other words, consulting appears to help firms scale up, but the additional workers that come with the expansion are not, on average, more productive than the existing workforce. The result is growth without efficiency gains—at least within the time horizon we observe.

Robustness. We subject these findings to several robustness checks; all figures are reported in Appendix A. First, we plot raw average outcomes for treated and matched control firms in levels (Figure A.1).[2] The two groups track each other closely in the pre-period, confirming the quality of the match, and diverge after the consulting event only for firm size and revenues—not for profits. Second, we vary the matching bandwidth. Our baseline

[2]Note that control firms also display change of trajectories post-event, this is primarily due to the COVID shock overlapping with several of our cohorts of treated client firms.

uses calipers of 30 log points for revenues and 0.05 for ROA. Widening the bandwidth to 0.4 (Figure A.2) or narrowing it to 0.2 (Figure A.3) leaves the results qualitatively unchanged. Third, we restrict attention to consulting events where total spending exceeds 50,000 euros, following Bijnens et al. (2025). The results are robust to this restriction; if anything, the effects on firm size and revenues are somewhat larger among high-spending events (Figure A.4) while the effects on value added per worker tends to be more negative. Finally, we investigate whether the expansion is driven by mergers and acquisitions rather than organic growth. We find no significant increase in M&A activity around the consulting event (Figure A.5), and results on main outcomes show that the effect on size is not driven by firms involved in an M&A at time 0 while the effects on productivity and profits appear larger for firms involved in M&A (Figure A.6).

4.1 Was the Expansion Planned?

A natural concern with these results is that the expansion we document was already planned before the firm hired a consulting firm. Under this interpretation, the increase in size and revenues is not caused by consulting but rather reflects a pre-existing growth plan that would have materialized regardless. The consulting firm, in this scenario, is hired to help manage an expansion that was already underway—not to generate it.

Two pieces of evidence push against this interpretation. First, recall that Figure 1 shows no strong upward pre-trends in either revenues or firm size prior to the consulting event. If client firms had been on a clear growth trajectory before hiring consultants, we would expect to see rising revenues and employment already in the years leading up to t_j^*. We do not. This suggests that, if there is a confounding shock that simultaneously drives both the decision to hire a consultant and the subsequent expansion, it must be a contemporaneous shock—one that hits around the time of the consulting event—rather than the continuation of a pre-existing trend.

Second, we directly test whether client firms were expecting to expand before the con-

sulting event. To do so, we augment our main dataset with information from the Survey of Industrial and Service Firms (INVIND), conducted annually by the Bank of Italy. The INVIND survey asks firm managers about their expectations for employment and revenue growth in the coming year. The survey covers approximately 3,000 firms in industry, and across the various treatment cohorts we are able to match expectations data for 539 client firms in our sample, most of which are observed over multiple years given the longitudinal nature of the survey.

We estimate equation (1) with expected employment growth and expected revenue growth as outcomes. Figure 5 reports the results. We find no significant difference between treated and control firms in either expected employment growth (Panel a) or expected revenue growth (Panel b) in the years leading up to the consulting event. Client firms were not expecting to grow faster than their matched controls before hiring a consultant. This is reassuring: it suggests that the expansion we document in Figure 4 is not simply the realization of a growth plan that was already in place before the consulting engagement began. Note that expectations on growth tend to rise in the post-period, in line with our baseline findings of the previous section.

4.2 Understanding the Expansion

The previous subsection established that consulting leads to a significant expansion in firm size, revenues, and value added. We now investigate where this expansion comes from. We examine three dimensions: the geographic presence of the firm, the structure of its customer and supplier relationships, and the sectoral composition of its expenditures.

4.2.1 Geographic and Organizational Scope

We begin by asking whether client firms expand geographically after hiring a consultant. Figure 6 plots the effect of consulting on the log number of municipalities in which the firm employs workers—a proxy for establishment presence. We find a positive but statistically

insignificant effect. There is some suggestive evidence that treated firms open operations in new locations, but the estimates are too imprecise to draw strong conclusions. We also find that client firms expand the geographic and sectoral scope of their trade relationships: the number of provinces and 3-digit sectors spanned by their customers and suppliers increases after the consulting event. The expansion documented in Figure 4 is therefore not confined to the firm's existing geographic footprint—it involves reaching into new markets and new supply chains.

4.2.2 Customer Relationships

We next decompose the revenue expansion into extensive and intensive margins. Figure 7 shows that the number of customers increases significantly immediately after the consulting event (Panel a). Sales per customer also rise (Panel b). The revenue growth we document above is therefore driven by both margins: client firms acquire new customers *and* sell more to each existing customer.

We next decompose total B2B sales into trade with incumbent partners (those already present at baseline) and trade with new partners (those formed after the consulting event). Figure 8 reports the results, normalized by baseline sales. Trade with incumbent partners increases modestly, but the effect is not statistically significant. The larger increase comes from trade with new partners, though these estimates are also imprecise. Note that by construction, the 2019 cohort is excluded from this decomposition, so the results are not fully comparable to the baseline specifications. Nonetheless, the pattern is suggestive: the expansion in revenues appears primarily driven by the formation of new commercial relationships rather than the deepening of existing ones.

4.2.3 Expenditures and the Input Mix

The expansion in revenues is accompanied by a corresponding increase in expenditures. Total B2B expenditures (excluding consulting fees) increase by approximately 0.9 million

euros on impact and 1.5 million euros in subsequent years. Relative to pre-event levels, this represents an increase of about 5%. As with revenues, the bulk of this increase is driven by purchases from new suppliers rather than increased spending with pre-existing ones. Only in the quarter of the consulting event itself does the increase in expenditures appear to come from larger orders placed with incumbent suppliers (Figure 9).

Finally, we ask whether consulting induces a change in the composition of the firm's input mix. We estimate separate diff-in-diff regressions for expenditures in each supplier sector, normalizing by total baseline expenditures. Figure 10 reports the results. Apart from the mechanical increase in spending on consulting itself (+1.6% of baseline expenditures), we observe increases of approximately 1% in wholesale trade, warehousing and transport, and the manufacture of metal products, as well as smaller increases (about 0.5%) in construction and architectural/engineering activities. These increases likely reflect the operational costs associated with the firm's expansion in size. When we instead normalize by current total expenditures—so that the coefficients represent changes in expenditure shares—we find little evidence of reallocation across sectors (Figure 11). Apart from the shift toward consulting, the input mix remains broadly unchanged. Strategic consulting, and the subsequent expansion in scale, does not appear to foster a change in the composition of intermediate inputs.

5 Firm Reorganization

The results in Section 4 show that consulting leads to a significant expansion in firm size. A natural follow-up question is how this expansion is organized within the firm. Does the growth come from retaining more incumbent workers, or from hiring new ones? Are the new jobs stable or precarious? And where in the firm hierarchy does the expansion take place? We use the detailed information available in the INPS administrative records to answer these questions.

5.1 New Hires versus Incumbent Retention

We begin by decomposing the increase in headcount into contributions from incumbent workers (those already employed at the firm before the consulting event) and new hires. To allow for comparisons across firms of different sizes, we rescale all headcounts by baseline employment. Figure 12 reports the results. The number of incumbent workers does not change significantly after the consulting event: the retention of pre-existing employees is unaffected. The entire increase in firm size is therefore driven by the addition of new workers who were not at the firm before the start of consulting.

We also examine whether the firm increases the rate of layoffs. Figure 13 shows no significant change in the firing rate after the consulting event. There is no evidence that consulting triggers a wave of involuntary separations among incumbent workers. The expansion is additive: the firm grows by bringing in new employees without displacing the existing workforce.

5.2 What Types of Jobs Are Created?

We next ask whether the new jobs created after the consulting event are stable or precarious. Figure 14 shows the effect on the number and share of temporary and part-time workers. While total employment increases, the number of temporary workers and part-timers remains broadly unchanged (Panel a). As a consequence, the share of temporary and part-time workers declines (Panel b). The expansion creates permanent, full-time positions rather than relying on temporary or part-time contracts.

5.3 Occupational Composition

We then examine where in the firm hierarchy the expansion takes place. Figure 15 reports headcounts by broad occupational category—blue collar, white collar, and managers—rescaled by baseline employment. The expansion is concentrated in the upper part of the

hierarchy. Employment of white-collar workers and managers increases significantly. Blue-collar employment, by contrast, does not expand. The pattern among incumbents is informative: incumbent white-collar workers and managers show a slight decrease in numbers, while incumbent blue-collar workers are slightly better retained. This suggests that the reorganization involves some churning at the top of the hierarchy—firms bring in new white-collar workers and managers while some incumbents in these positions leave.

Part of this churning reflects internal promotions. Figure 16 shows a significant increase in the rate of promotions to managerial positions after the consulting event. Some incumbent workers move up the hierarchy toward white-collar and managerial roles. The reorganization that follows consulting is therefore not just about adding headcount at the top—it also involves reshuffling the existing workforce by promoting workers into higher positions.

5.4 Summary

The picture that emerges from this section is coherent. Consulting leads to firm expansion, and this expansion is organized in a specific way. The growth comes entirely from new hires, not from retaining more incumbents. The new jobs are stable—permanent, full-time contracts rather than temporary or part-time positions. The expansion is concentrated in the upper part of the occupational hierarchy: more managers and white-collar workers, not more blue-collar workers. And within the firm, incumbents are promoted into managerial roles at higher rates. Taken together, these results suggest that consulting facilitates a structured upgrading of the firm's workforce—one that adds skilled workers at the top while promoting incumbents from within.

6 Results on Incumbent Workers

The firm-level analysis in Section 5 showed that consulting triggers a reorganization of the workforce: new hires at the top of the occupational hierarchy, more promotions, and no

change in the retention of incumbents. A natural question is whether these organizational changes have distributional consequences for the workers who were already employed at the client firm before the consulting engagement began. Do incumbent workers benefit from the expansion—for instance, through higher earnings or more stable employment—or does the restructuring leave some of them worse off?

To answer these questions, we move from firm-level to worker-level data. Our research design mirrors the matched difference-in-differences used for the firm-level analysis. Let t_i^* denote the year in which the employer of worker i first pays a consulting firm. We define treated workers as those employed in year $t_i^* - 1$ by a firm that starts a consulting engagement in year t_i^*. For each treated worker, we identify a control worker whose employer never relied on consulting firms during our sample period, matched on 2-digit sector, firm-size bins, log real earnings (caliper of 0.1), log revenues (caliper of 0.2), and ROA (caliper of 0.05) of the employer in year $t_i^* - 1$. We then estimate the event-study specification:

$$y_{it} = \alpha_i + \lambda_t + \sum_{k=a}^{b} \beta_k \mathbf{1}\{t = t_i^* + k\} + \sum_{k=a}^{b} \theta_k (\mathbf{1}\{t = t_i^* + k\} \times T_i) + r_{it}, \tag{2}$$

where $T_i = 1$ if worker i is a treated worker. An important feature of this specification is that it tracks workers regardless of whether they remain at the original employer. Equation (2) therefore captures the total effect of the consulting event on incumbent workers—including any consequences that operate through job separations and subsequent reallocation to other firms.

6.1 Main Results

Figure 17 reports the results for four outcomes: separation from the employer at $t_i^* - 1$, employment, log real earnings, and log weekly wages. The probability of separating from the baseline employer increases modestly at $t + 1$ (approximately 0.7 percentage points) but reverses at $t + 3$, where treated workers are actually less likely to have separated than

controls (Panel a). This pattern is consistent with the firm-level finding in Section 5 that shows little effect on overall turnover of incumbent workers. Incumbent workers at client firms are significantly more likely to be employed in the years following the consulting event, with the effect growing from approximately 0.8 percentage points at $t = 0$ to 2.4 percentage points at $t+3$ (Panel b). Turning to earnings, we find positive and significant effects on both log real earnings and log weekly wages. Log yearly earnings increase by approximately 0.7% at $t + 1$ and 1.7% at $t + 2$ (Panel c). Log weekly wages follow a similar pattern, rising by approximately 0.5% at $t + 1$ and 1.6% at $t + 2$ (Panel d). The restructuring documented in Section 5—the inflow of new white-collar and managerial hires, the increase in promotions—translates into measurable earnings gains for the average incumbent worker.

6.2 Results by Occupation

The positive average effect on earnings masks substantial heterogeneity across the occupational hierarchy. Figure 18 reports the effect on log real earnings separately by occupation. The gains are concentrated among white-collar workers and managers. White-collar incumbents experience earnings increases of approximately 1–2% at $t + 1$ and 2–3% by $t + 2$. Managers display even larger effects—around 3–4%—though their estimates exhibit a significant dip at $t - 1$. Blue-collar workers, by contrast, experience a modest decline in earnings of approximately 1–1.5% in the post-period. The reorganization that follows consulting thus has clear distributional consequences: workers higher in the occupational hierarchy benefit from the expansion, while blue-collar incumbents see their earnings fall. This pattern is consistent with the firm-level finding that the expansion is concentrated in managerial and white-collar positions. The gains from consulting accrue disproportionately to skilled workers.

7 A Report Card of Consulting Firms

The previous sections established that, on average, consulting leads to firm expansion without gains in profitability. But this average null effect on profits may mask substantial heterogeneity across consulting firms. Some consultants may genuinely improve their clients' performance while others do not—or even harm it. This section asks two questions. First, how much variation is there in the effects of different consulting firms on client profits? Second, can we rank consulting firms based on their effectiveness? To answer the first question, we use empirical Bayes deconvolution techniques to estimate the distribution of consulting firm effects, netting out sampling error. To answer the second, we apply the report card methodology of Kline et al. (2024), which provides a principled framework for ranking noisy estimates while controlling the risk of incorrect rankings.

7.1 Methodology

Let θ_c denote the average causal effect of consulting firm c on client profits, defined as

$$\theta_c = \frac{1}{b+1} \sum_{k=0}^{b} \theta_{k,c}, \tag{3}$$

where $\theta_{k,c}$ are the event-study coefficients defined in equation (1), estimated on the subsample of clients of firm c. Estimates of $\theta_{k,c}$ are rescaled by average profits observed in $t_j^* - 1$ to ease comparability. We assume that these effects across consulting firms are distributed according to G. We have two goals: (i) estimate G; (ii) rank consulting firms based on their θ_c, using the recent methodology of Kline et al. (2024).

Estimation. To estimate θ_c we run equation (1) separately for each firm, using only clients with $c(j) = c$, where $c(j)$ denotes the consulting firm hired by client j. We restrict to firms with at least 10 clients, yielding $C = 22$ firms. Figure 19 shows the distribution of clients per firm. This produces consulting firm-specific estimates on profits $\hat{\theta}_c$ along with their squared

standard errors s_c^2. Henceforth, we will therefore assume that each $\hat{\theta}_c$ is approximately normally distributed with mean θ_c and variance s_c^2.

Standard errors are computed via the leave-out procedure of Kline et al. (2020) (KSS). KSS standard errors correct for the downward bias in conventional standard errors estimators based on the White (1980) sandwich estimator, a bias that is particularly pronounced when the number of clients per firm is small. We find no evidence of correlation between $\hat{\theta}_c$ and $\log s_c^2$, so we assume that effect sizes and sampling variances are independent when deconvolving and shrinking the effects of consulting on profits (Walters, 2024).

Deconvolution. The first key object of interest is the cross-sectional variance of effects:

$$\sigma_\theta^2 = \frac{1}{C}\sum_{c=1}^{C}(\theta_c - \bar{\theta})^2, \tag{4}$$

which we estimate by the bias-corrected moment:

$$\hat{\sigma}_\theta^2 = \frac{1}{C}\sum_{c=1}^{C}(\hat{\theta}_c - \hat{\bar{\theta}})^2 - s_c^2. \tag{5}$$

We also estimate the covariability between effects on profits and effects on other outcomes γ_c:

$$\hat{\sigma}_{\theta,\gamma} = \frac{1}{C}\sum_{c=1}^{C}(\hat{\theta}_c - \hat{\bar{\theta}})\hat{\gamma}_c - s_{c,\gamma}, \tag{6}$$

where $s_{c,\gamma}$ is the sampling covariance between $\hat{\theta}_c$ and $\hat{\gamma}_c$.

We are also interested in estimating the full distribution of θ_c, denoted as G. We model G both parametrically (i.e. by assuming that G is normal) and nonparametrically following Efron (2016) spline approach calibrating the number of splines so that the resulting distribution of effects has a variance close to the unbiased estimate provided in (4)—see Walters (2024) for more details.

7.2 Results

Figure 20 re-prints our key finding: the null average effect of consulting on profits documented in Section 4.

Figure 21 plots firm-specific estimates $\hat{\theta}_c$ with 95% confidence intervals. This graph shows considerable heterogeneity in the effects of consulting on profits. However, part of this heterogeneity could simply be due to sampling error. Notably, the KSS standard errors are substantially larger than White standard errors for firms with few clients, confirming that conventional ("robust") standard errors are downward biased in small samples.

Figure 22 shows the estimated distribution G. The Normal-Normal and nonparametric estimates are nearly identical. The standard deviation of effects, once netting out the sampling error, is approximately 30 log points. This is fairly large compared to the near-zero mean effect. Figure 23 shows the unbiased estimates of θ_c, along with a linear shrunk estimate (the posterior mean of θ_c in the normal-normal model) along with firm names.

Figure 24 shows the cross-firm relationship between effects on profits and effects on other outcomes. Effects on profits are positively correlated with effects on log revenues, log size, log value added per worker (VA/L), and log labor costs. The correlation with VA/L is particularly high, and dispersion in VA/L effects across firms is low, suggesting that improvements in profitability are driven primarily by productivity gains rather than cost-cutting or revenue expansion alone.

Figure 25 plots estimated effects on profits against total consulting spending. Higher spending is not associated with larger effects.

7.3 Report Card

Our goal is to produce a report card on which consulting firms appear better at increasing clients profits. To rank firms we follow Kline et al. (2024) (KRW). Consider a decision maker comparing firms c and ℓ. Correctly ranking them yields payoff λ; reversing the true rank

yields -1; a tie yields 0. Let $\pi_{c\ell} \equiv \Pr(\theta_c > \theta_\ell)$. Expected utility is:

$$\bar{U} = (\lambda\pi_{c\ell} - \pi_{\ell c})\mathbf{1}\{d_c > d_\ell\} + (\lambda\pi_{\ell c} - \pi_{c\ell})\mathbf{1}\{d_\ell > d_c\}. \tag{7}$$

Expected utility is maximized by a threshold rule: rank c above ℓ iff $\pi_{c\ell} > \frac{1}{1+\lambda}$; declare a tie otherwise. The parameter λ governs discordance aversion. KRW show that $\lambda = \frac{1-q}{1+q}$ where q is the share of the audience that already knows the true ranking: the more informed the audience, the more conservative the report card should be. We compute posterior probabilities $\pi_{c\ell}$ from the empirical Bayes estimates of G and generalize the pairwise rule to rank all $C = 22$ firms simultaneously.

Figures 26 and 27 show the report cards for $\lambda = 0.5$ and $\lambda = 0.25$, corresponding respectively to one-third and one-half of the audience being informed.

With $\lambda = 0.5$—meaning the decision maker places substantial weight on correctly ranking firms relative to the cost of misranking—several firms receive distinct grades, with a small number clearly separated at the top and bottom of the distribution. We are able to classify firms into four separate categories. The firms ranked highest combine a large shrinkage estimate of θ_c with a sufficiently small standard error to achieve high posterior probabilities of outperforming competitors. Moving to $\lambda = 0.25$ raises the cost of misranking relative to the benefit of a correct ranking: more firms are pooled into the same category and the report card becomes more conservative. When the decision maker is sufficiently averse to incorrect rankings, the procedure identifies only *one* firm as being clearly above the rest in raising profits. The remaining 21 firms are all viewed as equivalent, given their posterior probabilities. This conservatism reflects, in part, the noise inherent in estimating firm-specific effects with a limited number of clients per consulting firm. We hope to obtain a new wave of data soon in order to update this report card and provide a more precise ranking.

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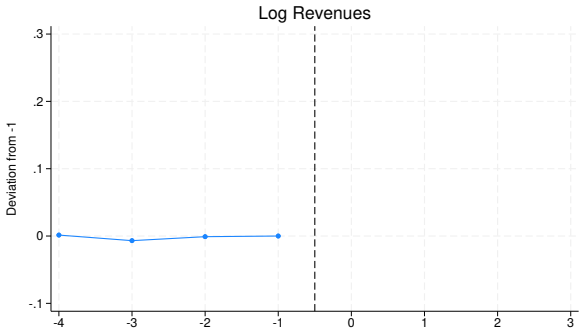
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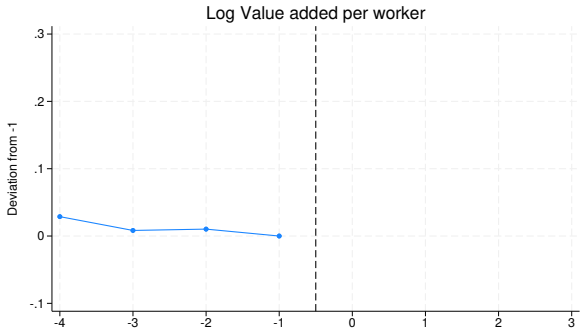
Christopher R. Walters. Empirical Bayes methods in labor economics. NBER Working Paper 33091, National Bureau of Economic Research, 2024. Prepared for the Handbook of Labor Economics, Volume 5.

Figure 1: Pre-event dynamics of client firms.

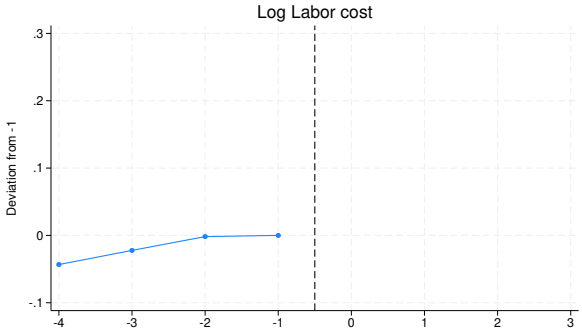
(a) Log revenues



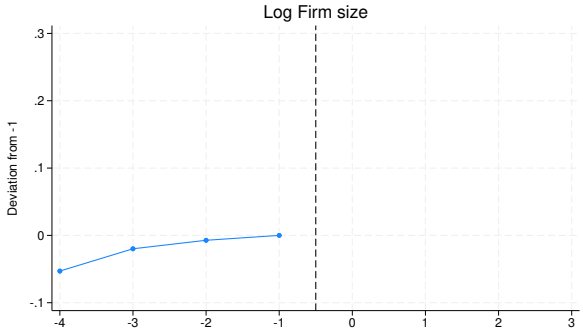
(b) Log value added per worker



(c) Log labor costs



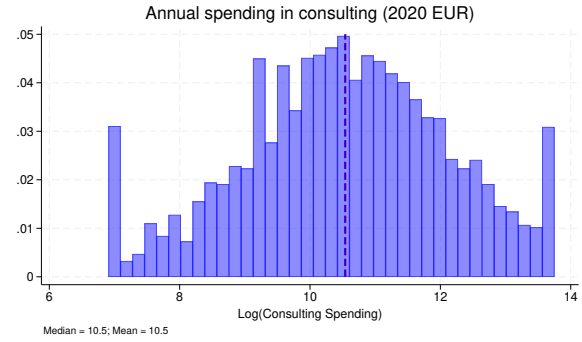
(d) Log firm size



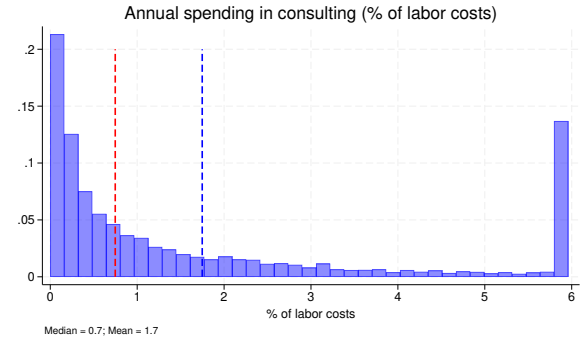
Notes: Each panel plots the average of the outcome variable for client firms, expressed as deviations from the pre-event level. All cohorts pooled.

Figure 2: Distribution of annual spending on consulting services.

(a) Log spending (euros)



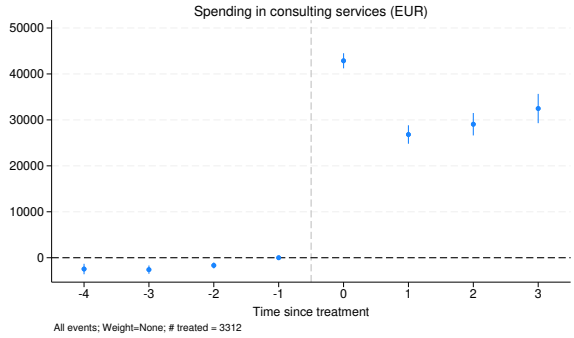
(b) Spending as % of labor costs



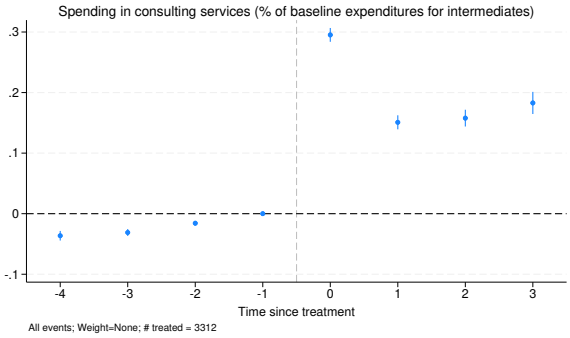
Notes: Panel (a) plots the distribution of log annual spending on consulting in 2020 euros. Panel (b) reports spending as a percentage of annual labor costs.

Figure 3: First stage: spending on consulting around the event.

(a) Euros



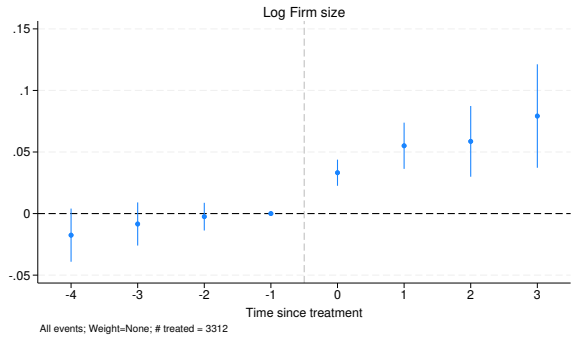
(b) % of baseline intermediate expenditures



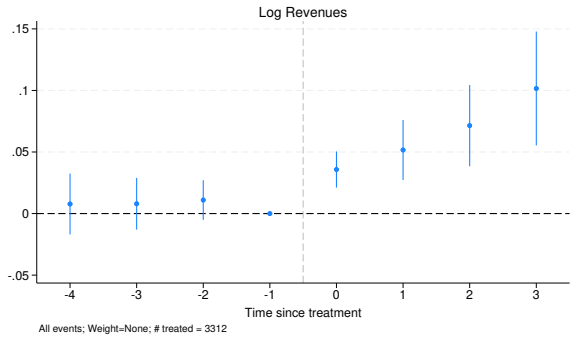
Notes: Panel (a) shows the change in euros spent on consulting by treated firms relative to matched controls. Panel (b) expresses the change as a share of baseline intermediate expenditures in $t_j^* - 1$. 95% confidence intervals based on standard errors clustered at the firm level. The coefficients in the year before the event are normalized to zero.

Figure 4: Effects of consulting on client firms.

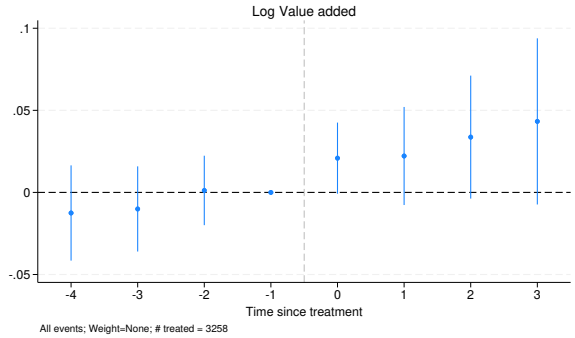
(a) Log firm size



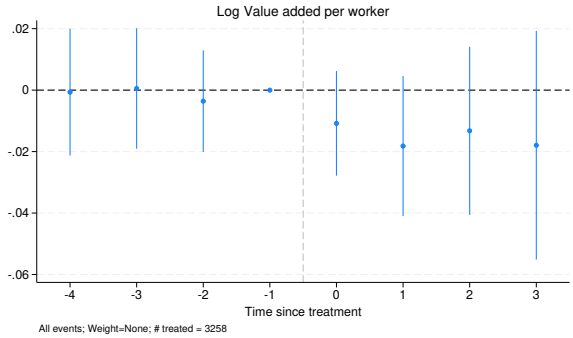
(b) Log revenues



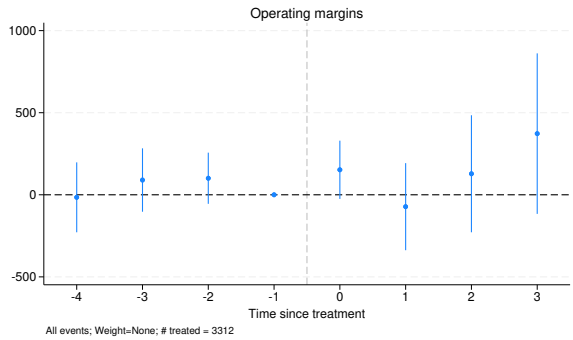
(c) Log value added



(d) Log value added per worker



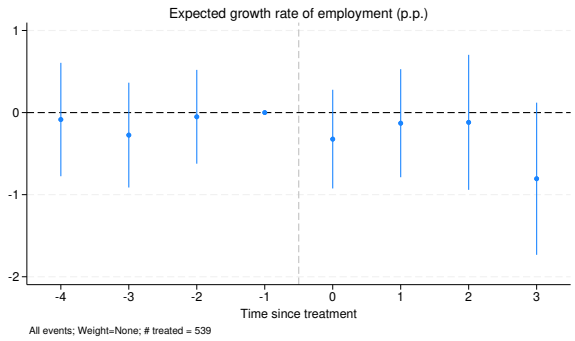
(e) Profits



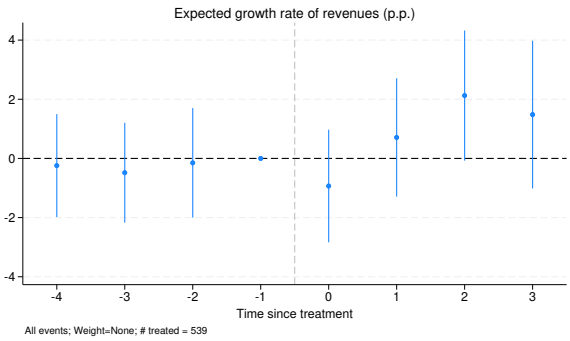
Notes: Each panel plots event-study coefficients θ_k from equation (1). Firm size is measured as the average number of employees. Profits are defined as value added minus labor costs. 95% confidence intervals based on standard errors clustered at the firm level.

Figure 5: Expected growth: client firms versus matched controls.

(a) Expected employment growth

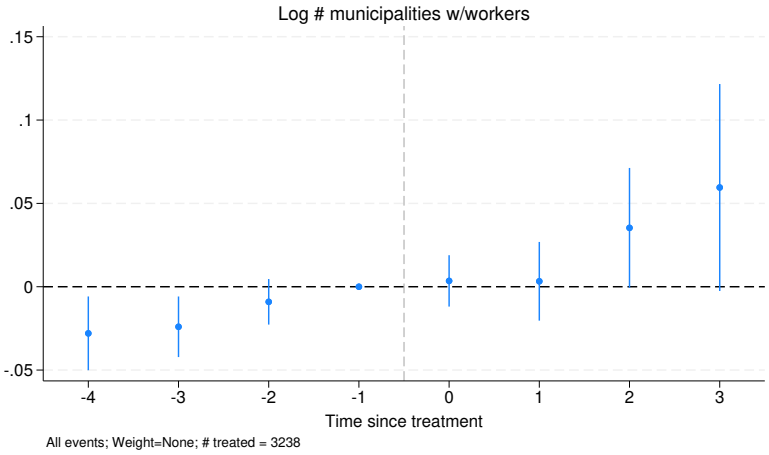


(b) Expected revenue growth



Notes: Each panel plots event-study coefficients θ_k from equation (1), where the outcome is the firm's self-reported expected growth from the INVIND survey. Sample restricted to firms matched to the INVIND survey ($N = 539$ client firms).

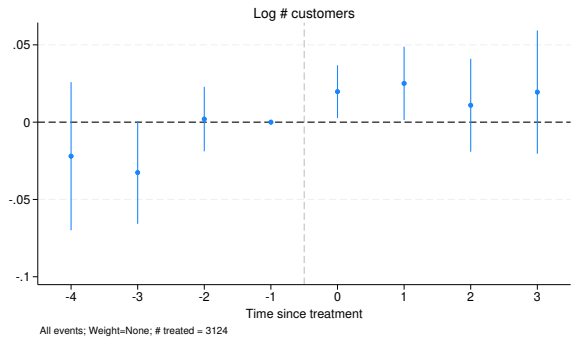
Figure 6: Geographic scope: number of municipalities with employees.



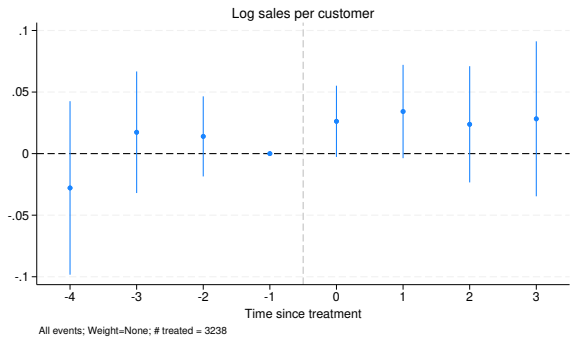
Notes: Event-study coefficients θ_k from equation (1). Outcome is log number of distinct municipalities in which the firm employs workers.

Figure 7: Customer relationships: extensive and intensive margins.

(a) Log number of customers

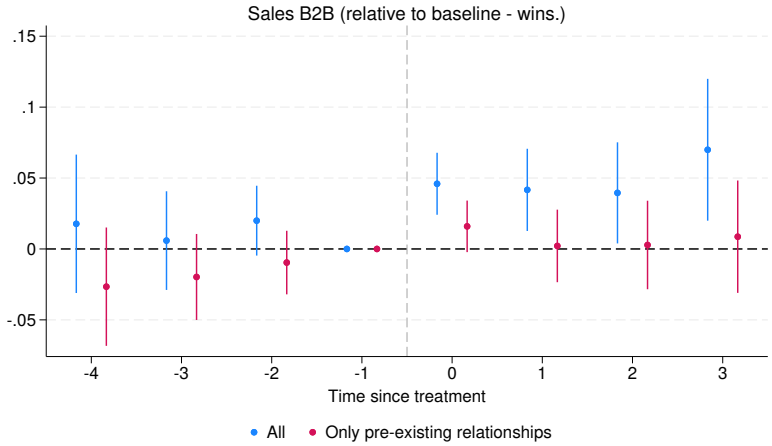


(b) Log sales per customer



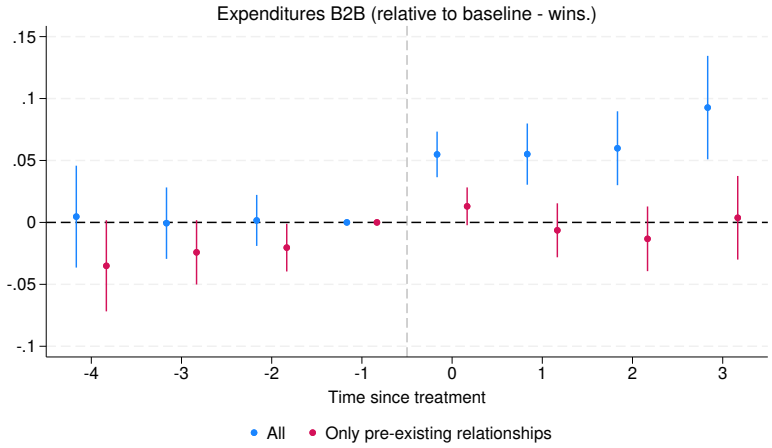
Notes: Event-study coefficients θ_k from equation (1). Panel (a): log number of distinct B2B customers. Panel (b): log average sales per customer.

Figure 8: Decomposition of B2B sales: incumbent versus new partners.



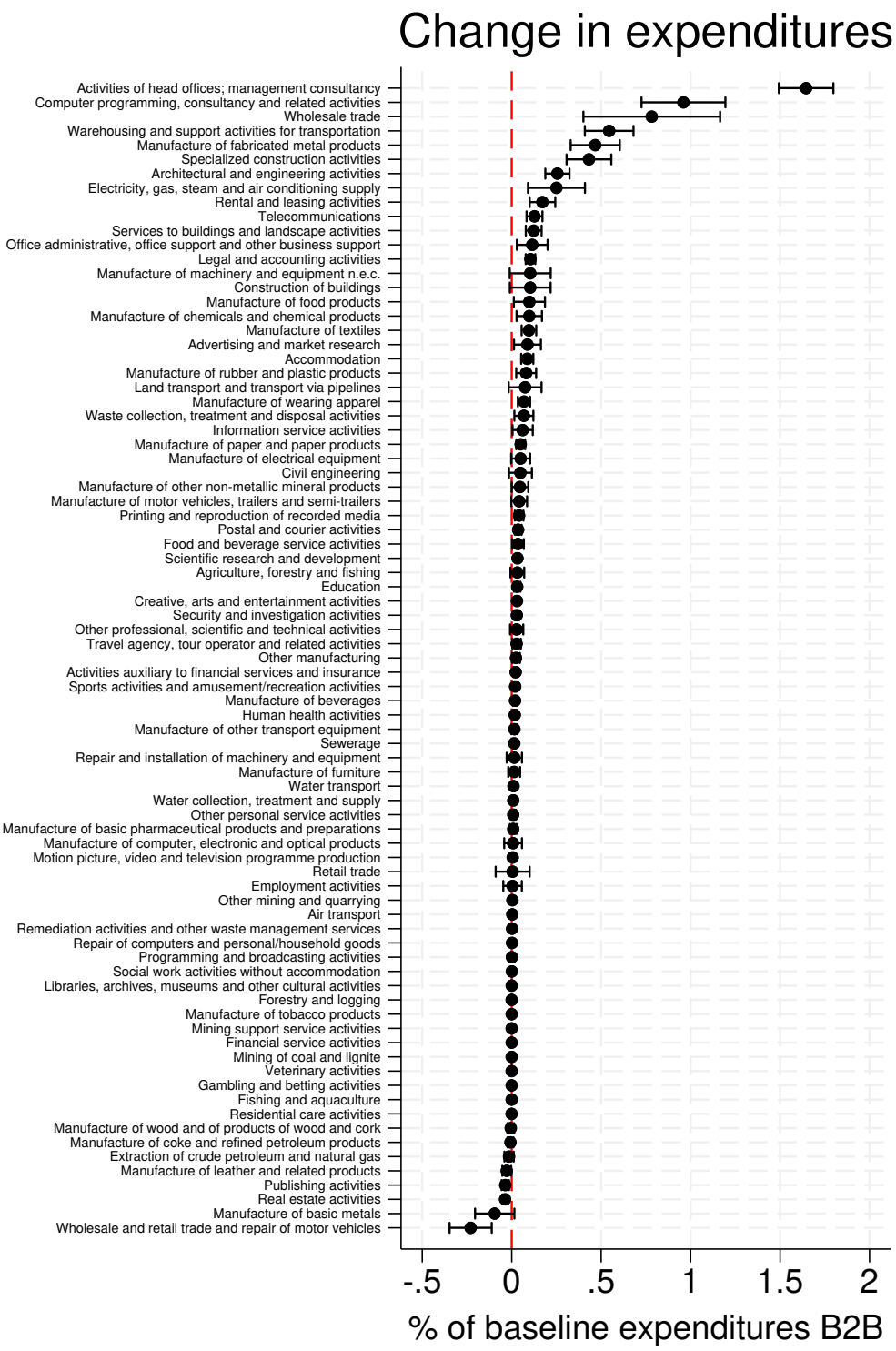
Notes: Sales decomposed into trade with incumbent partners (present at baseline) and new partners (formed after the consulting event), normalized by baseline sales. Outcomes winsorized at the 95th percentile. The 2019 cohort is excluded by construction.

Figure 9: Decomposition of B2B expenditures: incumbent versus new suppliers.



Notes: Expenditures (excluding consulting fees) decomposed into purchases from incumbent suppliers (present at baseline) and new suppliers, normalized by baseline expenditures. Outcomes winsorized at the 95th percentile. The 2019 cohort is excluded by construction.

Figure 10: Impact on expenditures by supplier sector (normalized by baseline).



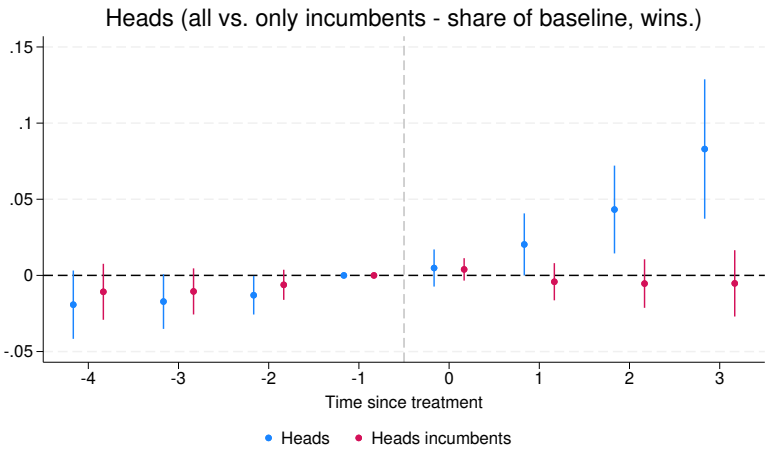
Notes: Each point reports a diff-in-diff coefficient for sector-specific expenditure normalized by total baseline B2B expenditures. Sectors ordered by estimated effect. Horizontal axis in percentage points of baseline expenditures.

Figure 11: Impact on expenditure shares by supplier sector.



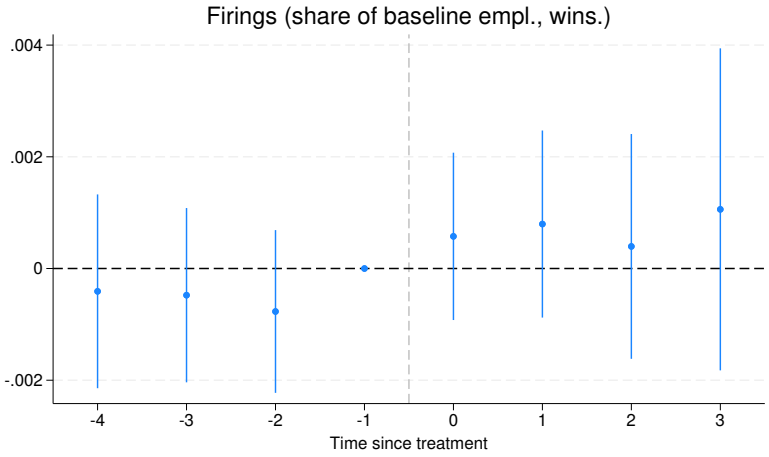
Notes: Each point reports a diff-in-diff coefficient for sector-specific expenditure normalized by current total expenditures. Coefficients represent changes in expenditure shares and sum to zero across sectors by construction. Sectors ordered by estimated effect.

Figure 12: Headcounts: all workers versus incumbents.



Notes: Event-study coefficients θ_k from equation (1). Headcounts rescaled by baseline employment. "All workers" includes both incumbents and new hires. "Incumbents" are workers employed at the firm before the consulting event. Outcomes winsorized.

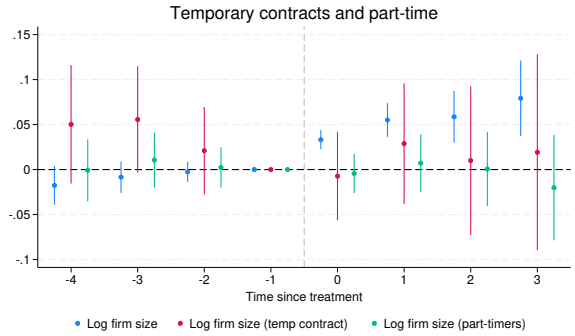
Figure 13: Firing rate around the consulting event.



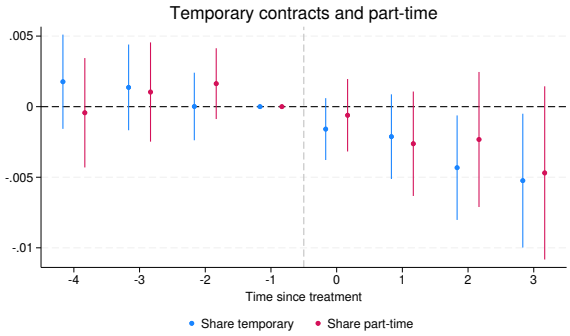
Notes: Event-study coefficients θ_k from equation (1). Firing rate rescaled by baseline employment. Outcomes winsorized.

Figure 14: Contract composition: temporary and part-time workers.

(a) Log number of temp/PT workers



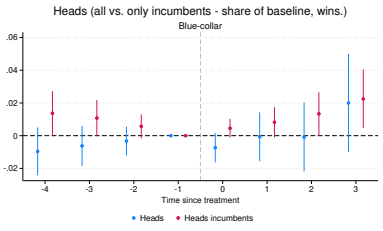
(b) Share of temp/PT workers



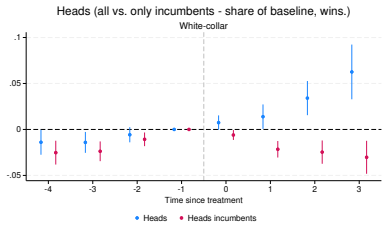
Notes: Event-study coefficients θ_k from equation (1). Panel (a): log number of temporary and part-time workers. Panel (b): share of temporary and part-time workers over total employment.

Figure 15: Occupational composition: headcounts by occupation.

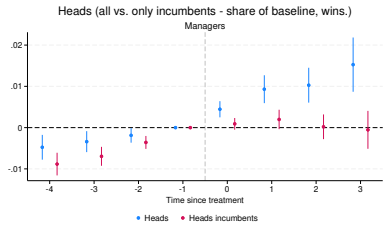
(a) Blue collar



(b) White collar

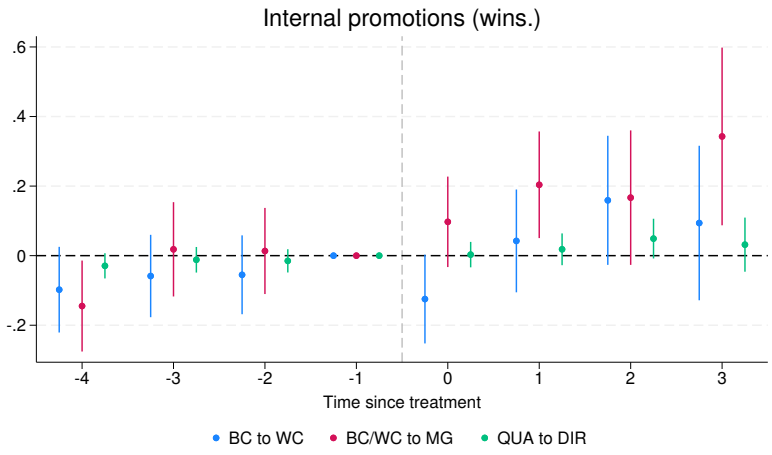


(c) Managers



Notes: Event-study coefficients θ_k from equation (1). Headcounts by occupation rescaled by baseline employment. Each panel shows total and incumbent workers separately. Outcomes winsorized.

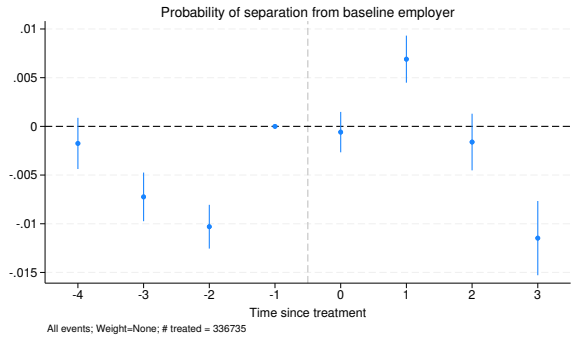
Figure 16: Internal promotions to managerial positions.



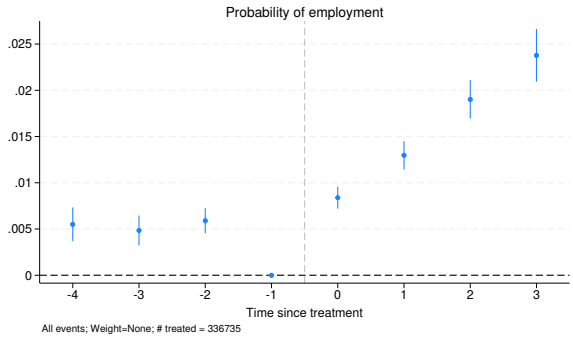
Notes: Event-study coefficients θ_k from equation (1). Outcome is an indicator for promotion to a managerial position.

Figure 17: Effects of consulting on incumbent workers.

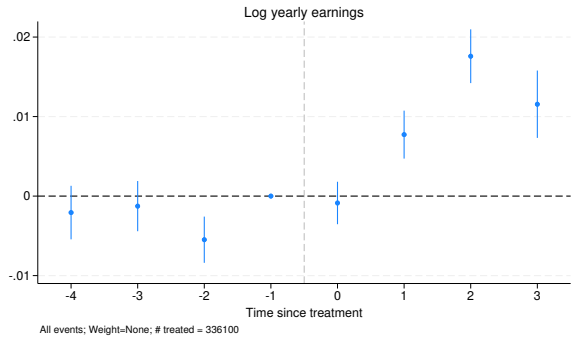
(a) Separation from employer at $t_i^* - 1$



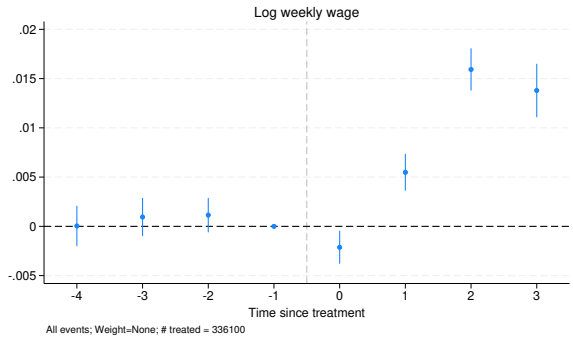
(b) Employment



(c) Log real earnings

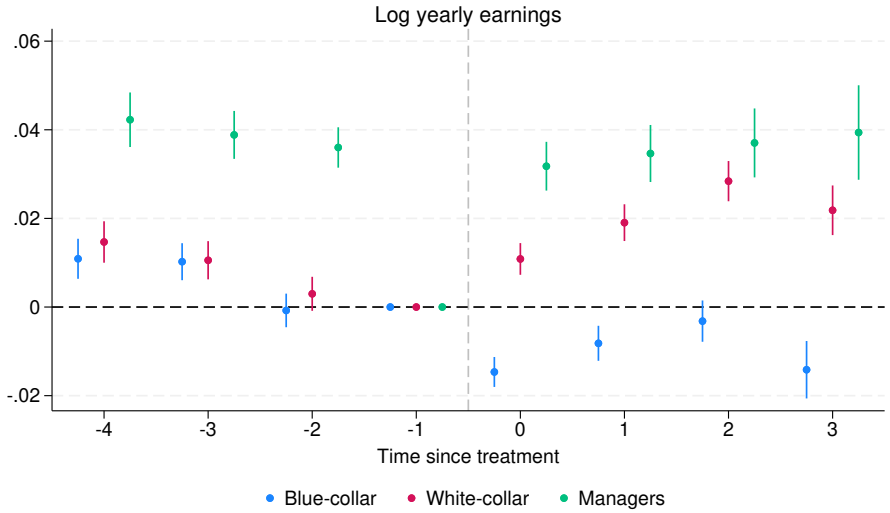


(d) Log weekly wages



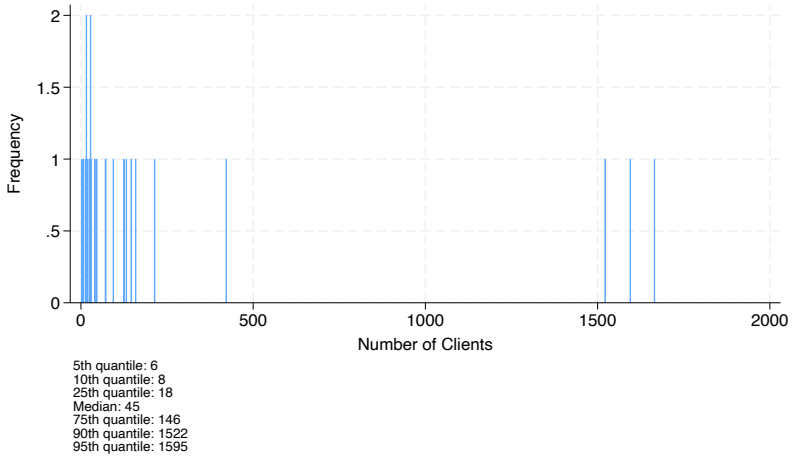
Notes: Event-study coefficients θ_k from equation (2). Sample: workers employed at the client firm in $t_i^* - 1$, matched to control workers at firms that never use consulting. Workers are tracked regardless of whether they remain at the original employer.

Figure 18: Effect on log real earnings by occupation.



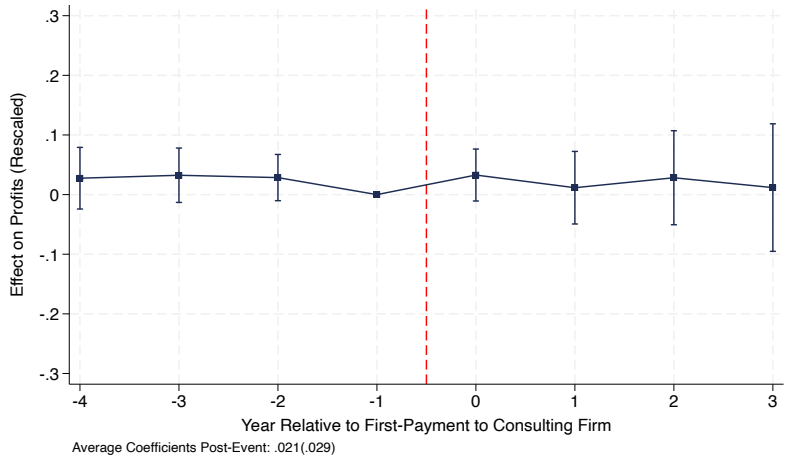
Notes: Event-study coefficients θ_k from equation (2), estimated separately by broad occupational category (blue collar, white collar, managers). Workers are tracked regardless of whether they remain at the original employer.

Figure 19: Clients per consulting firm.



Notes: Sample restricted to firms with at least 10 clients ($C = 22$).

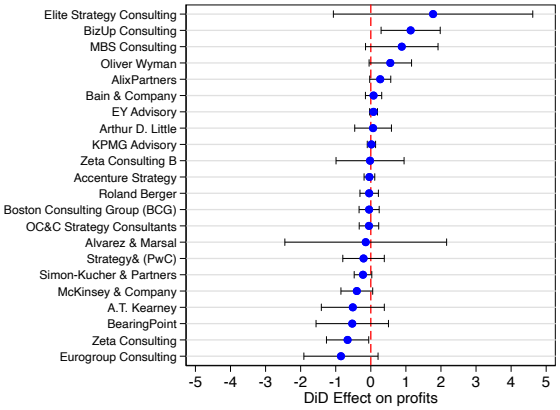
Figure 20: Average event study for profits.



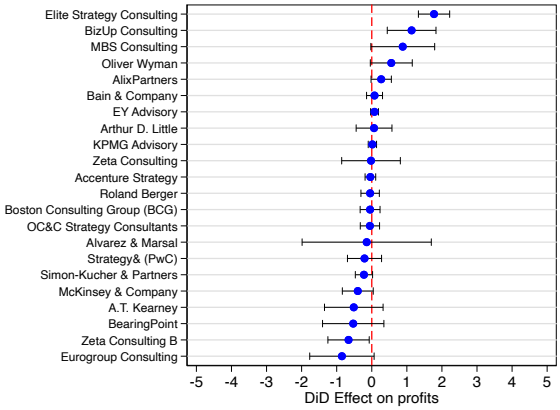
Notes: Each coefficient scaled by average profits at $t_j^* - 1$. 95% confidence intervals based on standard errors clustered at the client level.

Figure 21: Firm-specific estimates $\hat{\theta}_c$.

(a) KSS standard errors



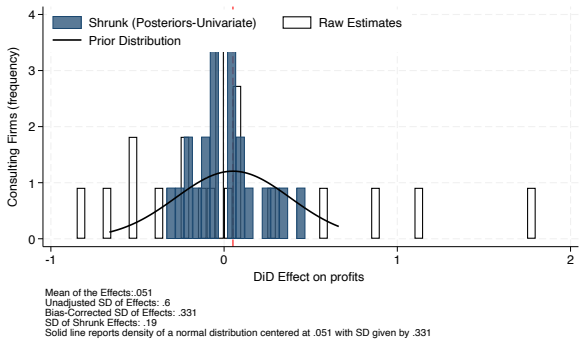
(b) White standard errors



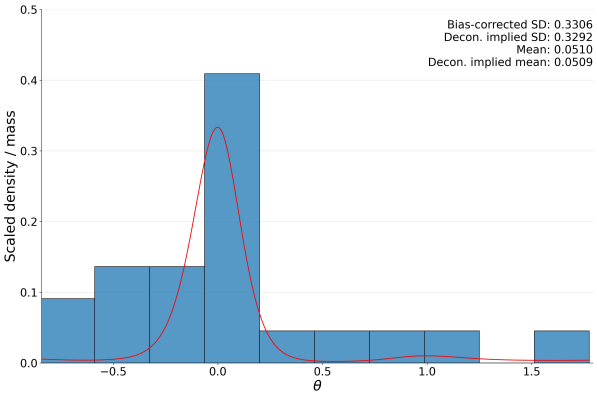
Notes: 95% confidence intervals. Firms ordered by point estimate. Left panel uses KSS leave-out standard errors (Kline et al., 2020). Right panel uses heteroscedasticity-robust (White) clustered standard errors.

Figure 22: Distribution of consulting firm effects on profits.

(a) Normal-Normal model

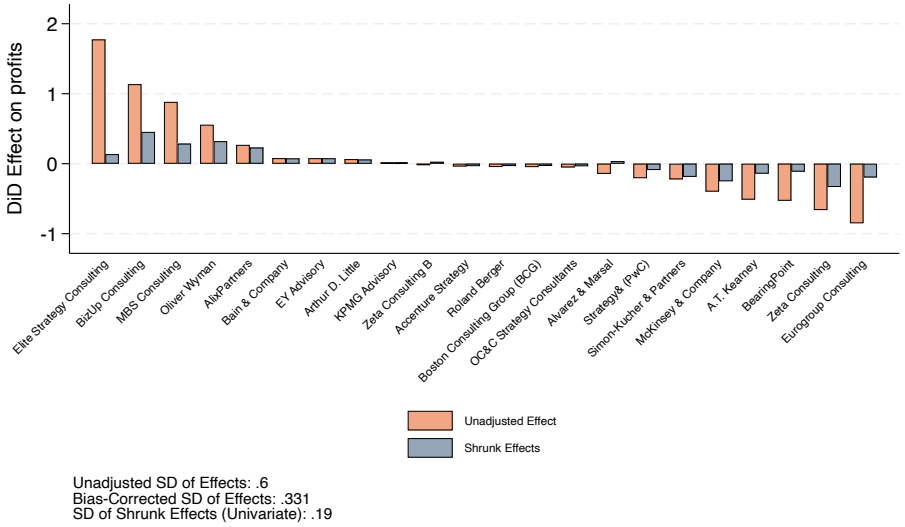


(b) Non-parametric



Notes: Left panel assumes a Normal-Normal model. Right panel uses the nonparametric deconvolution of Efron (2016); number of splines chosen to match the bias-corrected variance estimate in equation (4).

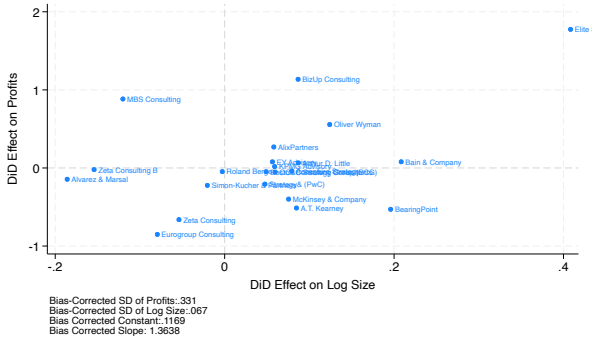
Figure 23: Consulting firm effects on profits



Notes: This figure shows unbiased estimates of θ_c alongside linear posterior shrunk means (posterior means from the Normal-Normal model).

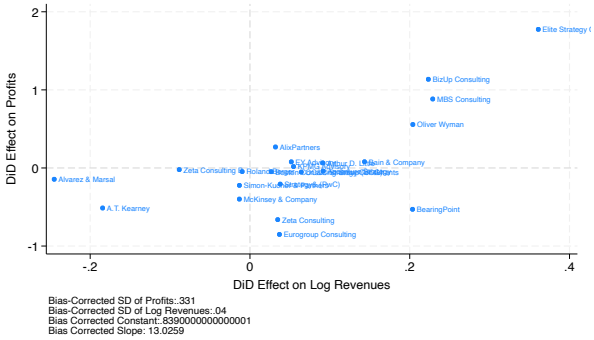
Figure 24: Covariability of effects on profits and other outcomes.

(a) Profits vs. log labor costs



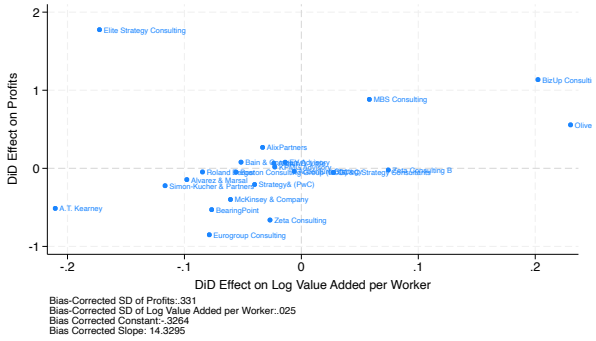
Bias-Corrected SD of Profits:.331
Bias-Corrected SD of Log Size:.067
Bias Corrected Constant:.1169
Bias Corrected Slope: 1.3638

(b) Profits vs. log revenues



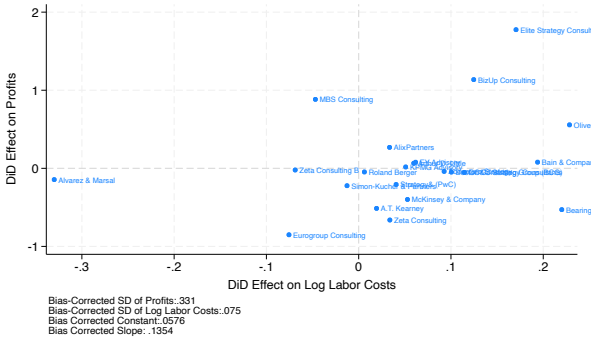
Bias-Corrected SD of Profits:.331
Bias-Corrected SD of Log Revenues:.04
Bias Corrected Constant:.8390000000000001
Bias Corrected Slope: 13.0259

(c) Profits vs. log size



Bias-Corrected SD of Profits:.331
Bias-Corrected SD of Log Value Added per Worker:.025
Bias Corrected Constant:-.3264
Bias Corrected Slope: 14.3295

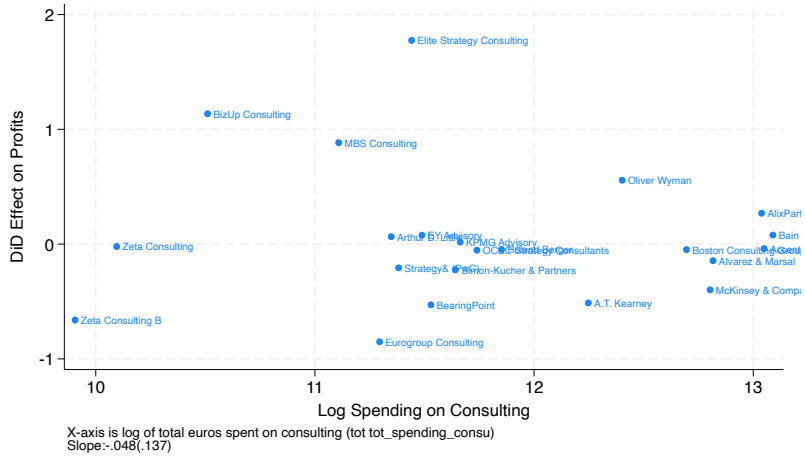
(d) Profits vs. log VA/L



Bias-Corrected SD of Profits:.331
Bias-Corrected SD of Log Labor Costs:.075
Bias Corrected Constant:.0576
Bias Corrected Slope: .1354

Notes: Each point is a consulting firm. Axes show effect of consulting firm on the outcome listed in each axes. Below each graph we report the bias-corrected standard deviation of the effect for each outcome along with the constant and the slope of the resulting relantionship, after accounting for sampling error.

Figure 25: Effects on profits versus total consulting spending.



Notes: Each point is a consulting firm. Vertical axis shows $\hat{\theta}_c$ for each consulting firm and horizontal axis measures average fees paid to a given consulting firm.

Figure 26: Report card of 22 consulting firms.



Notes: $\lambda = 0.5$, corresponding to one-third of the audience being informed ($q = 1/3$). Grades based on posterior probabilities $\pi_{c\ell}$ using the non-parametric estimate of G.

Figure 27: Report card of 22 consulting firms, conservative specification.



Notes: $\lambda = 0.25$, corresponding to one-third of the audience being informed ($q = 1/3$). Grades based on posterior probabilities $\pi_{c\ell}$ using the non-parametric estimate of G.

Table 1: Summary statistics: consulting firms versus all firms.

	All firms	Consulting firms	Top-3 consulting
Firm size	18.74	1109.91	4976.98
Value added per worker	56.38	177.99	74.03
Profits per worker	15.42	49.12	6.66
Avg. monthly wage	1643.21	7033.29	4486.76
Share of young (15-34) workers	0.29	0.55	0.59
Share of female workers	0.39	0.35	0.37
Share of managers	0.00	0.27	0.12
Number of customers	73.59	163.87	574.67
Median sales per customer	6.94	189.82	224.91
Number of firms	730,092	17	3

Notes: Consulting firms are defined as the subset of the initial 26 firms that could be successfully matched to Cerved records. Averages computed over 2019–2023. Firm size is the average number of employees. Value added per worker and profits per worker are in thousands of euros. Average monthly wage is in euros. Number of firms reports the total count in each column.

Table 2: Summary statistics: treated and control firms.

	Whole sample		Matched	
Variable	Treated	Controls	Treated	Controls
Firm size	314.06	17.71	218.89	220.63
Log Value added per worker	4.50	3.74	4.44	4.27
Profits/Assets (ROA)	0.04	0.06	0.05	0.05
Avg. monthly wage	3282.50	1779.49	3156.68	2782.01
Spending in consulting (EUR)	95273.55	0.00	86146.78	0.00
Spending in consulting (% of baseline tot. int.)	1.65	0.00	1.82	0.00
Share of managers	0.03	0.00	0.03	0.02
Share of temp workers	0.06	0.11	0.06	0.07
Share of part-time workers	0.10	0.32	0.10	0.12
Share of female workers	0.36	0.38	0.35	0.33
Number of customers	898.52	74.13	615.28	491.26
Economic sectors				
Wholesale trade	0.08	0.15	0.09	0.09
Computer programming, IT	0.07	0.04	0.07	0.07
Repair and installation of machinery	0.05	0.04	0.06	0.06
Office admin support	0.05	0.04	0.05	0.05
Manufacture of food products	0.04	0.02	0.04	0.04
Number of firms	4,117	563,036	3,312	3,082
Number of cons. firms	25	0	25	0

Notes: "Whole sample" reports means for all treated and control firms. "Matched" reports means for the matched sample. Firm size is the average number of employees. Log value added per worker is in logs. Average monthly wage is in euros. Spending in consulting is in euros (row 5) and as a percentage of baseline total intermediate expenditures (row 6). Number of firms reports the total count in each column.

Appendices

A Additional Results

A.1 Trends in firms using consulting services

Figure A.1 complements the event-study estimates by presenting the underlying levels of outcomes for treated and matched control firms corresponding to Figure 4. Pre-treatment trajectories are closely aligned across all outcomes, and levels prior to treatment are comparable between treated and control groups.

The post-treatment dynamics in firm size and revenues (panels a and b) are driven by sustained increases among treated firms relative to controls. Figure A.1 also helps interpret the absence of positive productivity effects. In panel (c), value added per worker declines for treated firms relative to controls after treatment, consistent with the negative or imprecise estimates in Figure 4. In levels, this pattern suggests that the expansion in inputs outpaces gains in efficiency, pointing to scale-driven growth rather than improvements in productivity.

Finally, panel (d) shows that the increase in operating margins for treated firms is modest and gradual, becoming more pronounced only in later periods. The levels representation indicates that profits track the expansion in revenues with a lag.

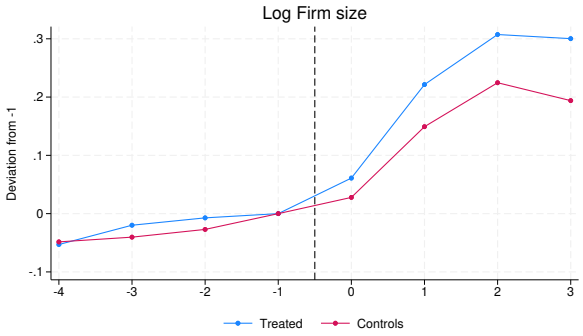
A.2 Robustness with alternative cleaning and matching strategy

We have tested variations of our baseline estimates. First, we checked how alternative matching strategies affect our results by imposing a wider and a narrower bandwidth than the one used in the baseline (0.4 and 0.2 respectively, wider in Figure A.2, narrower in Figure A.3). The estimated effects remain similar to baseline estimates.

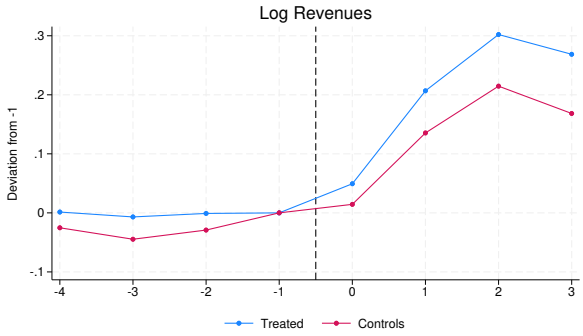
Next, Figure A.4 presents the main specification restricting the sample to client firms spending at least 50,000 euro on consulting services, following the data cleaning choice used

Figure A.1: Levels of outcomes for treated and matched control firms.

(a) Log firm size



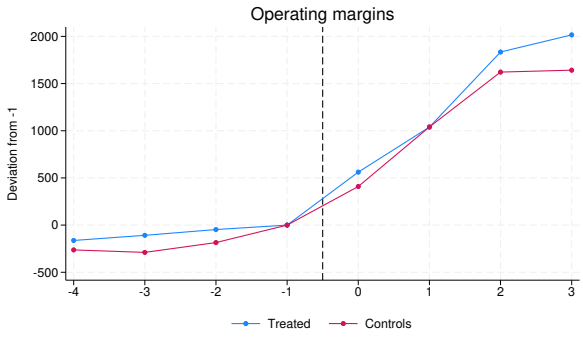
(b) Log revenues



(c) Log value added per worker



(d) Profits



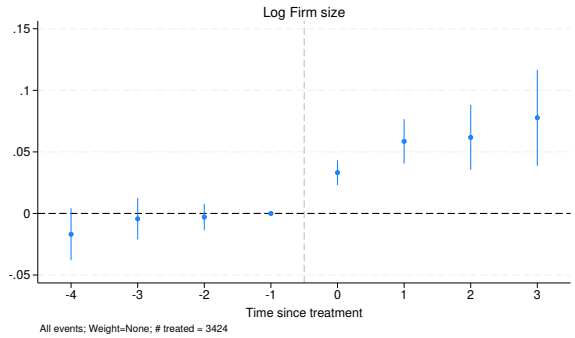
Notes: Raw average outcomes for treated (solid) and matched control (dashed) client firms in levels.

in Bijnens et al. (2025). The number of treated firms shrinks by around one third, resulting in 1,150 treated firms. Results for this subsample of events are qualitatively similar to the baseline events, and in some cases stronger in magnitude.

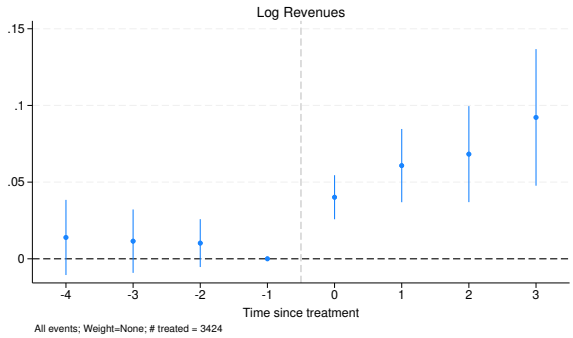
Finally, we examine whether the expansion is driven by mergers and acquisitions by estimating the likelihood that a firm is involved in an M& A around the consulting event. We find no significant increase in M& A activity following the event (Figure A.5). We further repeat the analysis separately for client firms involved and not involved in M& A events, and find that the main results are robust across both subsamples (Figure A.6).

Figure A.2: Alternative matching: wider bandwidth (0.4).

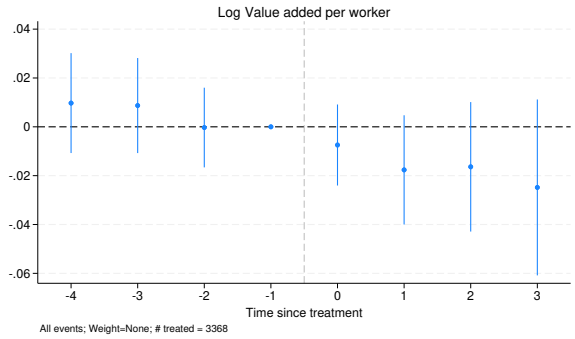
(a) Log firm size



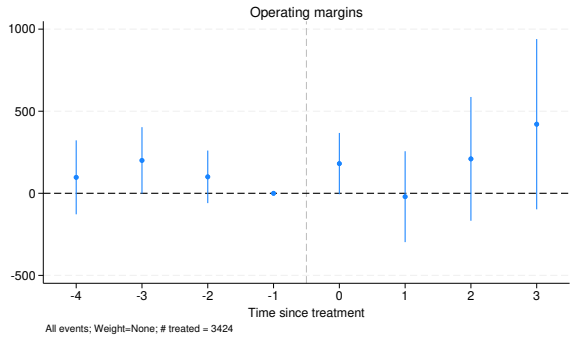
(b) Log revenues



(c) Log value added per worker



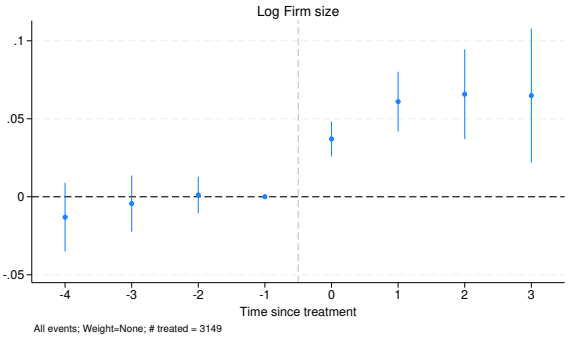
(d) Profits



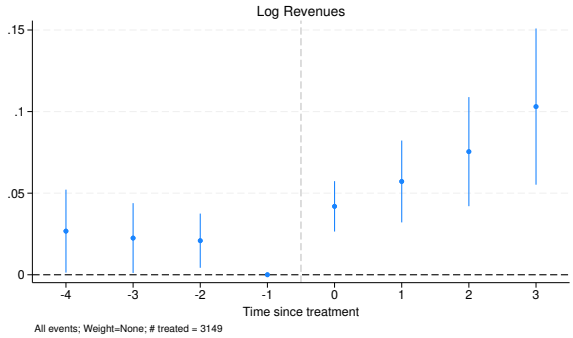
Notes: Event-study coefficients θ_k from equation (1). Matching bandwidth set to 0.4 (wider than baseline).

Figure A.3: Alternative matching: narrower bandwidth.

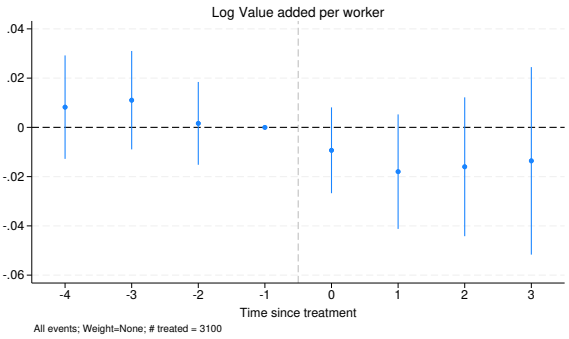
(a) Log firm size



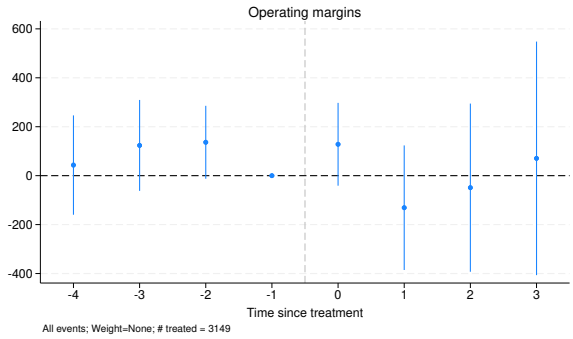
(b) Log revenues



(c) Log value added per worker



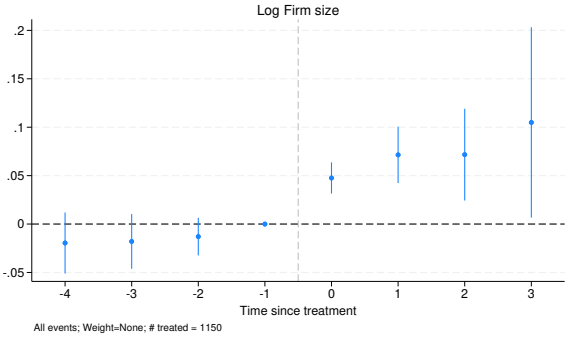
(d) Profits



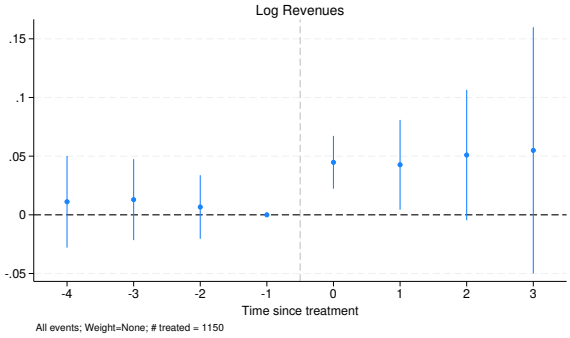
Notes: Event-study coefficients θ_k from equation (1). Matching bandwidth set to 0.2 (narrower than baseline).

Figure A.4: Effect of consulting events with total spending > 50,000 euros.

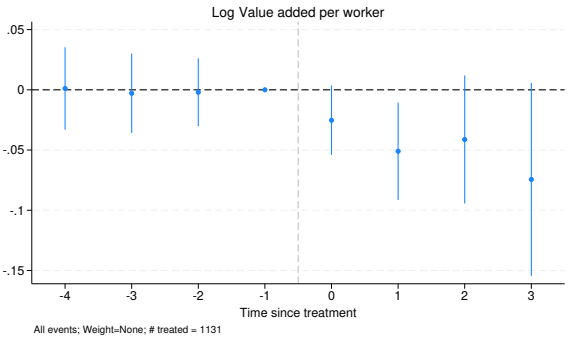
(a) Log firm size



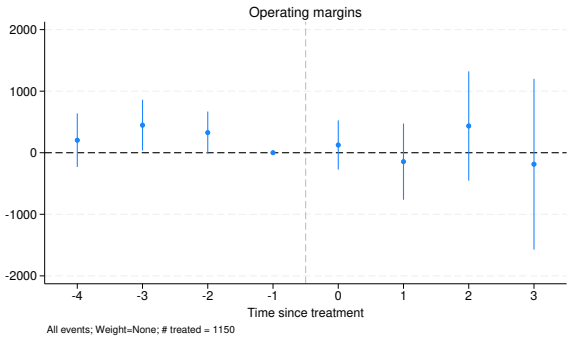
(b) Log revenues



(c) Log value added per worker

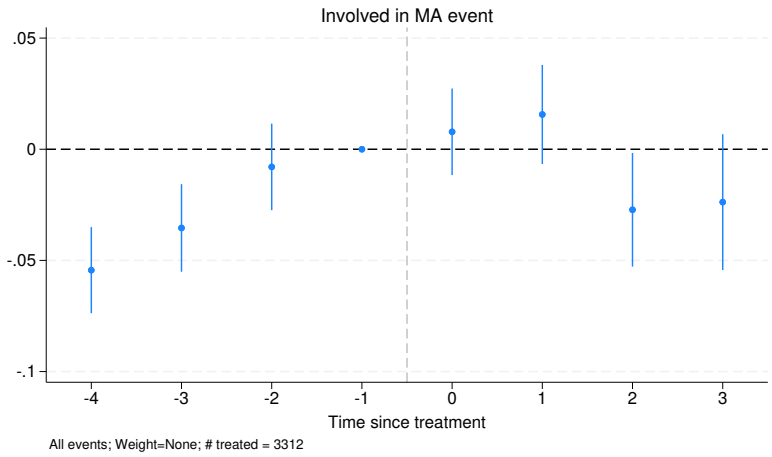


(d) Profits



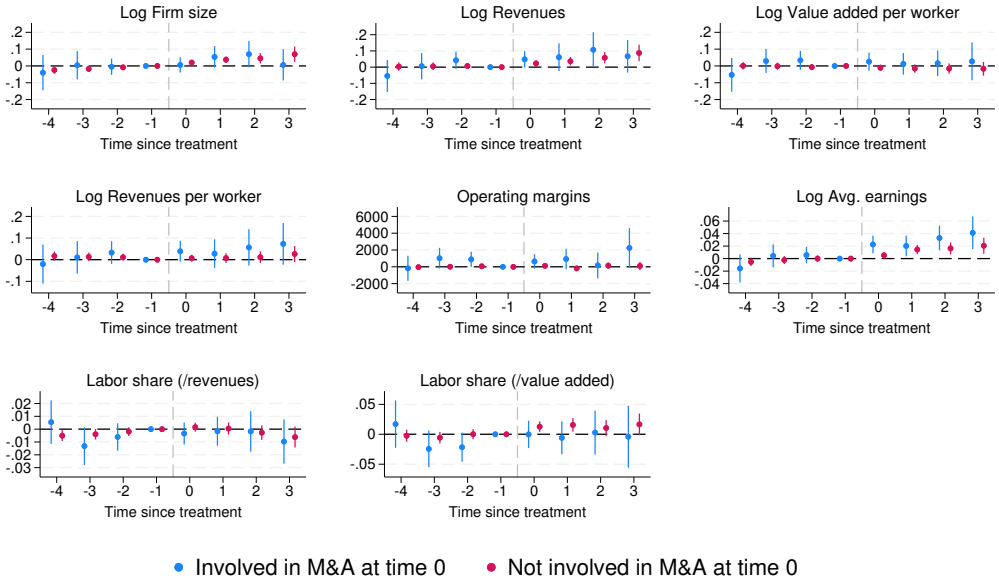
Notes: Event-study coefficients θ_k from equation (1). Sample restricted to consulting events where total spending exceeds 50,000 euros.

Figure A.5: Mergers and acquisitions around the consulting event.



Notes: Event-study coefficients θ_k from equation (1). Outcome is an indicator for whether the firm is involved in a merger or acquisition event.

Figure A.6: Main outcomes by M&A status.



Notes: Event-study coefficients θ_k from equation (1), estimated separately for firms involved and not involved in M&A events.