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ABSTRACT

This paper estimates the causal effect of financial constraints on the short-term performance of Finnish SMEs using survey data from 2016-2024 and propensity score matching (PSM). We examine six outcomes: turnover, employment, investment, profitability, solvency, and innovation, and report effects on both odds and probability scales. Financial constraints significantly increase the likelihood of adverse outcomes: constrained firms face 10-30% higher odds of reporting deterioration in core indicators, with the largest effects on solvency (29% higher odds) and profitability, followed by investment and turnover; employment effects are smaller, and innovation effects modest. Marginal effects indicate up to a 4 percentage point reduction in the probability of improvement for key outcomes. Results are robust to multiple-testing adjustments, and alternative specifications. Heterogeneity analysis reveals that the effects vary by firm size, pointing to a dual mechanism: turnover and profitability effects are strongest for micro and small firms, reflecting immediate liquidity stress, while employment and investment effects intensify with firm size, suggesting real adjustments (growth obstacles) are more pronounced in mid-sized SMEs. Policy implications and directions for future research are discussed.

JEL Classification: G32, D22, L25, C21, O16

Keywords: credit constraints, financing, impact analysis, propensity score matching

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1 Introduction

Understanding how financial constraints shape firms' real decisions is central to both corporate finance and macroeconomics. Yet credible measurement remains challenging because financial constraints are latent: they cannot be directly observed in administrative or accounting records and must instead be inferred from behavior or perceptions. Conceptually, they resemble other latent constructs in economics, such as the structural unemployment rate or the natural rate of interest. Against the Modigliani–Miller benchmark (Miller and Modigliani, 1958), any systematic wedge between internal and external finance has first-order implications for investment, growth, and the transmission of monetary and credit policies to the real economy. Despite its clear importance for firm dynamics and policy, the phenomenon of financial constraints remains surprisingly underexplored in the empirical literature.

The question is particularly salient in the current environment of tighter credit conditions and higher-than-before interest rates, which amplify financing frictions for small and medium-sized enterprises (SMEs). SMEs account for the majority of employment and value added in most economies, yet they are disproportionately dependent on bank credit and lack access to capital markets. Understanding how credit constraints affect their real outcomes is therefore critical for both policy design and macroeconomic stability.

The empirical literature has approached this question along several lines. A classic contribution is Fazzari et al. (1988), who argue that low-dividend firms, interpreted as more constrained, exhibit greater sensitivity of investment to internal cash flow than high-dividend firms. This line of work spurred a large literature linking internal and external finance, with investment–cash flow sensitivities often used as diagnostic tests of financing frictions (see, e.g., Almeida and Campello (2007)). Much of this early evidence, however, relies on parametric specifications and strong functional-form assumptions that can conflate genuine constraints with unobserved investment opportunities or measurement error.

A second strand constructs accounting-based indices to classify firms as constrained or unconstrained. The Kaplan–Zingales, Whited–Wu and Hadlock-Pierce indices (Kaplan and Zingales (1997), Lamont et al. (2001), Whited and Wu (2006), Hadlock and Pierce (2010)) use financial statement information to proxy for financing frictions and have been influential, especially for publicly listed firms. Recent re-evaluations question how well these proxies identify truly constrained firms. Farre-Mensa and Ljungqvist (2016) show that firms labeled as "constrained" by popular indices respond similarly to exogenous financing shocks as firms labeled "unconstrained," casting doubt on the validity of accounting-based classifications and reigniting debate over measurement at the firm level.

A third, increasingly prominent strand, also followed in this paper, leverages firm-level surveys to measure financing frictions more directly. Surveys can elicit perceptions of credit availability, loan rejections, and the importance of financing obstacles, thereby capturing aspects of the latent constraint that balance-sheet variables may miss. While survey data raise concerns about strategic responding and subjective bias, they are widely used in high-level policy work precisely because key variables are absent from administrative sources.

A notable example in research of financial constraints with survey data is Gomez (2019), who use the Survey on the Access to Finance of Enterprises (SAFE) to identify constrained firms and apply instrumental variables to estimate causal effects, finding that constraints depress fixed asset investment, with limited effects on employment or inventories. More broadly, the SAFE survey is a geographically comprehensive, recurring data source used by policymakers—including the European Central Bank—to inform credit conditions and policy design, underscoring the practical relevance of survey-based measures in environments where administrative proxies are incomplete.

This paper contributes to this literature in five ways. First, it introduces propensity score matching (PSM) to estimate the causal effects of financial constraints on firm outcomes. Matching mitigates reliance on parametric functional forms by balancing observed covariates between constrained and unconstrained firms, thereby clarifying identification under the Conditional Independence Assumption (CIA) and overlap. To the best of our knowledge, there is no prior research employing PSM to examine financial constraints in a developed-country context.[1] Second, in contrast to studies that rely on indirect accounting-based proxies (e.g., Kaplan and Zingales (1997), Whited and Wu (2006), Hadlock and Pierce (2010)), this paper exploits survey-based measures that are arguably closer to the latent construct of credit frictions and address concerns raised by Farre-Mensa and Ljungqvist (2016). Third, by examining multiple real outcomes—including investment, turnover, employment, profitability, solvency and innovation activity (including product development)—the analysis goes beyond the investment-centric focus and offers a more comprehensive assessment of the economic consequences of financing constraints. Fourth, the paper provides novel evidence for SMEs, a population often underrepresented in empirical work despite their heightened sensitivity to financing conditions and large macroeconomic relevance. Fifth, the paper explores treatment-effect heterogeneity (e.g., by firm age, size and growth orientation), yielding policy-relevant insights into which firms bear the largest real effects of credit frictions.

Methodologically, the matching framework is implemented with careful attention to identification. I document common support, report balance diagnostics (standardized differences and Love plots), and assess robustness to alternative matching algorithms and weighting estimators. Taken together, the strategy delivers transparent and reproducible estimates of the average treatment effect on the treated (ATT) for constrained firms, while clarifying the

[1] Propensity score matching (PSM) and financial frictions have been examined in other contexts; see, for example, Griffin et al. (2020) and Cintina and Love (2019).

assumptions under which the causal interpretation holds.

A brief preview of the results highlights their economic relevance. Compared with observably similar firms, credit-constrained firms exhibit markedly lower solvency, turnover, profitability, investment and employment. These adverse impacts are particularly pronounced among micro and mid-sized enterprises, consistent with theoretical models in which external finance alleviates binding investment constraints and with policy priorities emphasizing SME credit access. Overall, the evidence confirms that credit constraints hinder the economic activity of SMEs in multiple dimensions. Consistently the smallest, albeit statistically still significant, effects are found on innovation and product development activities. TThe smallest—though still statistically significant—effects are observed in innovation and product development. This modest estimate may reflect the inherently dynamic and nonlinear nature of R&D activities relative to more conventional outcome variables.

The remainder of the paper is organized as follows. Section 2 describes the data and the matching methodology. Section 3 presents the main results and the heterogeneity analysis by firm size and growth orientation. Section 4 reports robustness checks and sensitivity analyses. Section 5 concludes.

2 Data and Methods

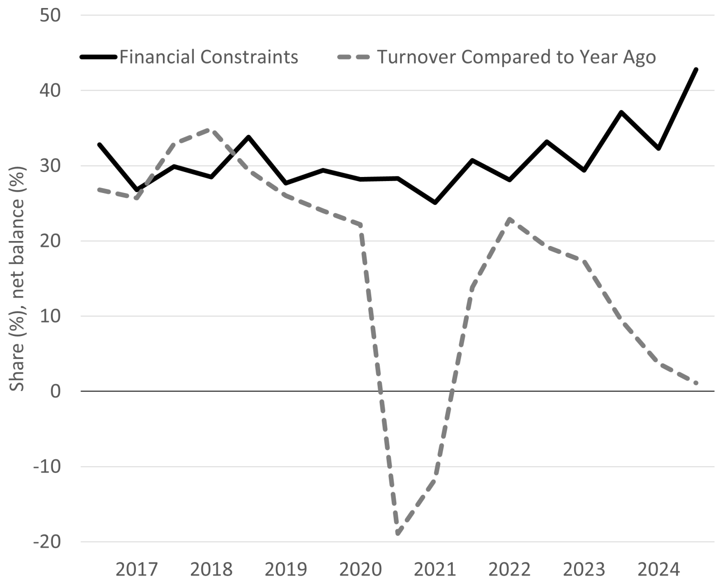
2.1 Data and Sampling Frame

The analysis uses the *SME Barometer*, a repeated cross-sectional survey of Finnish small and medium-sized enterprises (Federation of Finnish Enterprises, Finnvera, and Ministry of Economic Affairs and Employment (2024)). The survey is conducted twice a year (H1 and H2), with each wave including approximately 4,000–6,000 firms, making comparatively large SME survey by international standards. We use data from 2016H2–2024H2, the period during which the question on financial constraints has been consistently asked.

The survey is designed to be representative of the Finnish SME population through stratification by industry, region, and firm size. Firms are not tracked over time; each wave is an independent sample. To ensure comparability across waves, we harmonize variable codings and retain only waves with consistent question wording. Observations with missing values on the treatment indicator or core covariates are excluded from the baseline sample.

Figure 1 shows the share of firms classified as financially constrained in each wave (2016H2–2024H2), illustrating substantial time variation and highlighting episodes of tighter credit conditions. Table A.1 in the Appendix reports descriptive statistics of all relevant covariates and outcome variables. The sample comprises approximately 62,500 firms, and all variable categories contain a sufficient number of observations to support the econometric analysis.

Figure 1: Credit constraints of firms, 2016H2–2024H2. Source: SME Barometer.



Notes: Share of financially constrained firms are those reporting either (i) a need for external financing but not applying, or (ii) a need and an unsuccessful application divided by all firms that reported a need for external finance.

2.2 Treatment, Outcomes and Matching Covariates

The treatment variable is based on the key survey question, which asks: *"Has your firm had a need to obtain external financing during the past 12 months?"* with four response options:

1. No;
2. Yes, and we obtained financing;
3. Yes, but we did not apply;
4. Yes, but we applied and were rejected.

The core challenge in financial constraints research is the latent nature of the constraint. Following the established literature, we employ a survey-based measure, combining firms with rejected loan applications and those who refrained from applying due to anticipation of rejection (the so-called discouraged borrowers). This approach is crucial for two reasons. First, it directly captures credit rationing as defined by Stiglitz and Weiss (1981), where firms are unable to receive financing despite being willing to pay the offered price. Second, the inclusion of discouraged borrowers addresses a fundamental selection bias; these firms represent a group where the information asymmetry between the lender and the borrower is severe enough to discourage the financing search altogether. Therefore, our measure aligns robustly with modern financial theory, specifically focusing on supply-side constraints arising from incomplete information, rather than merely reflecting low demand for investment funds.

In terms of outcomes, we focus on turnover, employment, investment, profitability, solvency and innovation activity (including product development). In all the outcome variables, the survey records whether key firm outcomes have 1=*increased*, 2=*remained unchanged*, or 3=*decreased* relative to the same period one year earlier. Outcomes are ordinal, so we report effects on the probability of an *increase* or *decrease* (binary recodes) and effects on an ordinal score $(1, 2, 3)$ as a robustness summary.

Matching covariates include industry, region, and survey wave (macro and structural controls), firm size (employment and turnover classes), market orientation (local, national, international), growth orientation (expansion plans), and payment difficulties (liquidity stress). These variables capture factors affecting both financing constraints and outcomes, supporting the selection-on-observables assumption.

2.3 Econometric Framework: Propensity Score Matching

We estimate the causal effect of financial constraints on firm outcomes using Propensity Score Matching (PSM). The matching process is as follows: (1) estimate the propensity score (probability of being constrained) using a logit model with the covariates above, (2) match each constrained firm to one or more unconstrained firms with similar scores using 1:1 nearest-neighbor matching without replacement, (3) restrict to common support to avoid extrapolation, (4) assess covariate balance using standardized differences and Love plots, and finally (5) compute the Average Treatment Effect on the Treated (ATT) as the mean outcome difference between matched pairs.

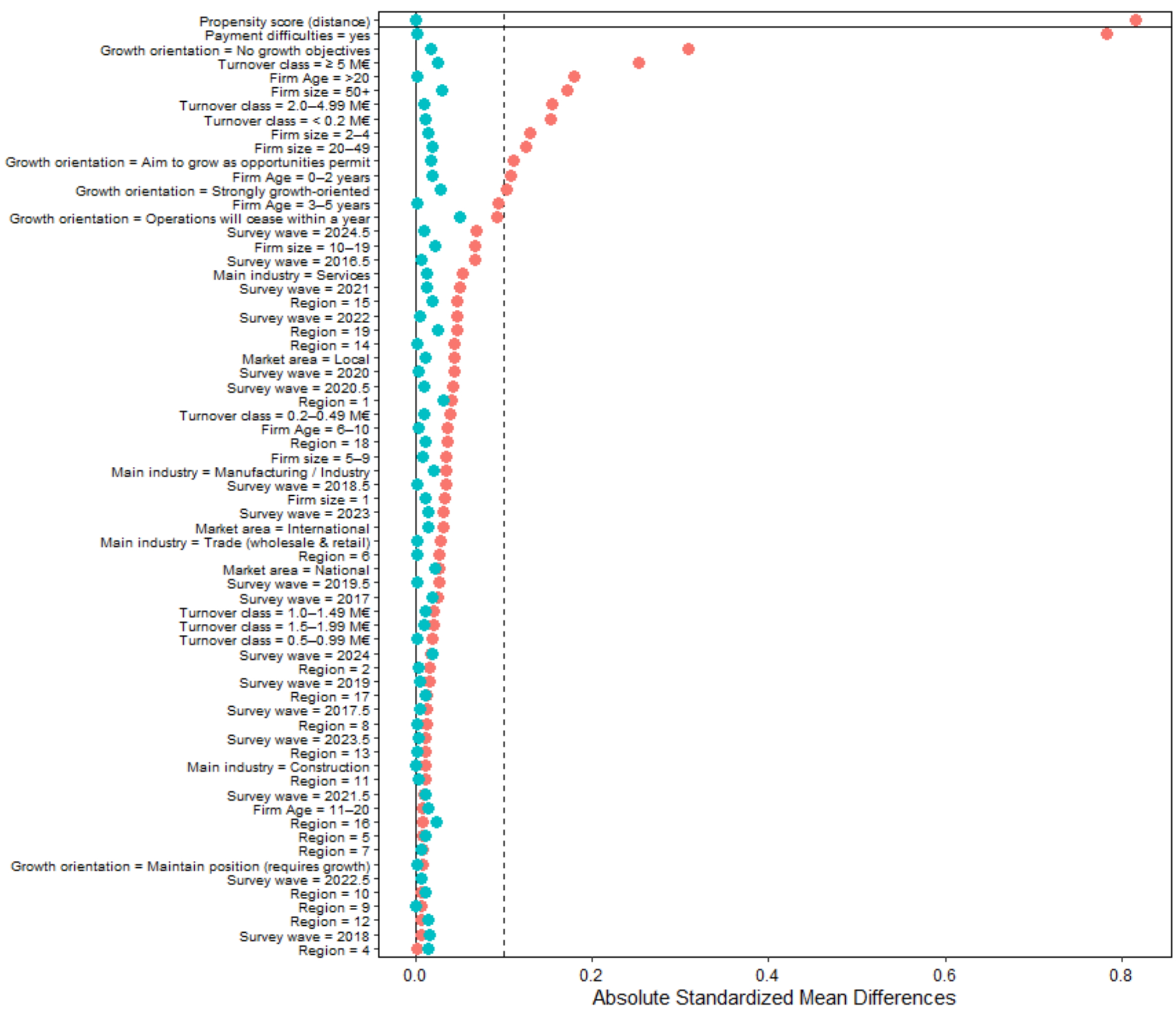
To evaluate the quality of matching, we report SMDs for all covariates before and after matching. Table 1 summarizes these results, and Figure 2 provides a Love plot for visual inspection. All post-matching SMDs fall below the conventional 0.10 threshold, indicating good covariate balance. Figure 3 shows the distribution of propensity scores for treated and control firms before and after matching. The unmatched sample exhibits clear differences in score distributions, whereas the matched sample displays substantial overlap, confirming common support and the absence of extrapolation.

Although all covariates are categorical and lack a natural numerical interpretation, the reported means and maxima of SMDs remain meaningful. This is because SMDs for categorical variables are computed at the level of individual factor categories (e.g., each industry or region) and then aggregated across levels. The "Mean" column in Table 1 represents the average absolute SMD across all levels of a variable, while "Max" indicates the largest imbalance observed for any single level. These metrics provide a concise summary of how well the matching procedure balanced the distribution of categories between treated and control groups.

Table 1: Variable-level covariate balance. Standardized mean differences (SMD) aggregated across factor levels. Threshold = 0.1.

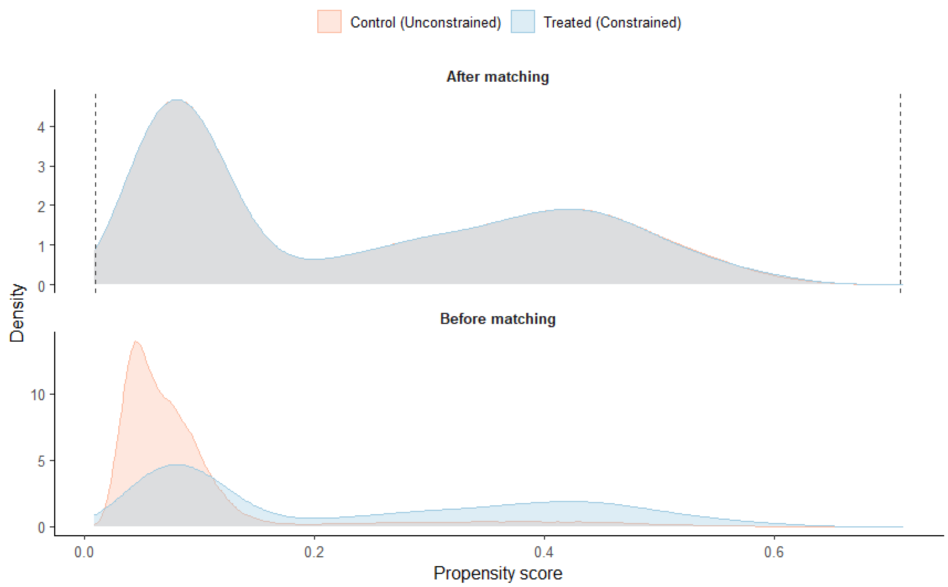
		Before		After		
Variable	Lvl	Mean (B)	Max (B)	Mean (A)	Max (A)	Share $\leq$ 0.10
Propensity score (distance)	1	0.815	0.815	0.001	0.001	yes
Growth orientation	5	0.125	0.310	0.023	0.050	yes
Main industry	4	0.033	0.054	0.009	0.021	yes
Region	18	0.020	0.048	0.011	0.031	yes
Firm size (employees)	6	0.094	0.172	0.018	0.030	yes
Turnover class	7	0.095	0.253	0.011	0.026	yes
Firm age	5	0.086	0.180	0.008	0.020	yes
Market orientation	3	0.035	0.045	0.016	0.022	yes
Payment difficulties	1	0.783	0.783	0.002	0.002	yes
Survey wave	17	0.031	0.069	0.009	0.020	yes

Figure 2: Covariate Balance Before and After Matching (Love plot).



Notes: The plot displays absolute standardized mean differences (SMD) for all covariates before (red) and after (green) matching. The vertical dashed line at 0.10 marks the conventional threshold for acceptable balance.

Figure 3: Propensity score distributions by treatment status before and after matching.



Notes: The upper panel shows the matched sample with density weighted by matching weights; the lower panel shows the unmatched sample without weights. Dashed vertical lines in the upper panel indicate the **common support interval**, i.e., the range of propensity scores where treated and control units overlap after matching. Observations outside this range are excluded to avoid extrapolation.

2.4 Multiple Testing and Effect Interpretation

To account for multiple hypothesis testing across six outcome variables, we control the *False Discovery Rate* (FDR) using the *Benjamini–Hochberg* (BH) procedure. Unlike Bonferroni correction, which controls the family-wise error rate and can be overly conservative, the BH method adjusts p-values to limit the expected proportion of false positives among rejected hypotheses. We report both raw confidence intervals and BH-adjusted q-values, considering results significant at $q < 0.05$.

For interpretability, we complement odds ratios from ordered logit models with *average marginal effects* (AMEs). AMEs quantify the change in predicted probabilities (expressed in percentage points) associated with financial constraints, holding other covariates constant and averaging over the matched sample. This approach illustrates how constraints shift probability mass across outcome categories (e.g., from "improved" to "deteriorated"), providing a more intuitive measure of economic significance than odds ratios alone.

2.5 Robustness and Sensitivity Analyses

We assess the robustness of our main findings through several complementary checks. First, we vary the matching algorithm to ensure results are not driven by the choice of estimator.

Specifically, we compare nearest-neighbor matching to Mahalanobis distance matching, propensity score subclassification, and weighting-based estimators (IPW and IPW combined with an outcome model). Second, we examine sensitivity to the propensity score specification by estimating models with alternative link functions (logit vs. probit) and by trimming observations in the tails of the score distribution to enforce common support. Third, we test alternative outcome models, including linear probability models and logit specifications for binary deterioration indicators, alongside ordered response models for ordinal outcomes. Finally, we explore alternative matching ratios and caliper restrictions to verify that overlap assumptions do not drive the results. Finally, we conduct hidden-bias sensitivity analysis using Rosenbaum bounds for matched pairs, which evaluates how large an unobserved confounder would need to be to overturn the conclusion that credit constraints increase the likelihood of adverse outcomes.

2.6 Limitations and Interpretation

Three limitations merit emphasis. First, the treatment relies on self-reported financing experiences and intentions, which may contain subjective components (e.g., discouraged borrowing). This is, however, a necessary feature for measuring latent constraints that balance-sheet proxies often cannot capture. Second, outcomes are ordinal and qualitative; while they do not yield exact euro magnitudes, distributional effects on *increase* and *decrease* are highly informative for economic significance. To aid interpretation, we translate percentage-point effects into approximate impacts under plausible baselines in the results section and verify that conclusions do not hinge on a particular coding of the ordinal scale.

Finally, as with any propensity score approach, identification relies on the critical Conditional Independence Assumption (CIA): conditional on the included covariates, treatment assignment is as good as random. While we include a rich set of firm characteristics, regional, sectoral, and time controls, residual bias may remain if important determinants of both credit constraints and outcomes are omitted. Specifically, because our data is a **repeated cross-section** and not a firm-level panel, the PSM approach cannot control for unobserved, time-invariant firm-specific heterogeneity (e.g., managerial ability, intrinsic firm efficiency, or reliance on informal financing channels). These factors could simultaneously influence the probability of becoming financially constrained and the firm's subsequent performance. Consequently, the estimated Average Treatment Effect on the Treated (ATT) should be interpreted as causal only to the extent that the bias from such unobserved variables is not significantly greater than the bias addressed by controlling for the observed covariates. We evaluate this key limitation using Rosenbaum bounds sensitivity analysis (Section 4) to determine how strong an unobserved confounder would need to be to overturn our main conclusions.

3 Results

This section reports the estimated effects of financial constraints on firm outcomes in three steps: (i) odds ratios from ordered logit models, (ii) probability changes for interpretability, (iii) heterogeneous effects, and (iv) discussion of economic significance. All estimates are based on the matched sample and correspond to the Average Treatment Effect on the Treated (ATT).

3.1 Model Estimates on the Odds Scale

Figure 4 reports the estimated treatment effects of financial constraints across six firm outcomes as odds ratios (OR) with 95% cluster-robust confidence intervals from ordered logit models. An OR greater than 1 indicates higher odds of reporting a worse category for constrained firms relative to otherwise similar unconstrained firms. All effects are statistically significant, but their magnitudes vary.

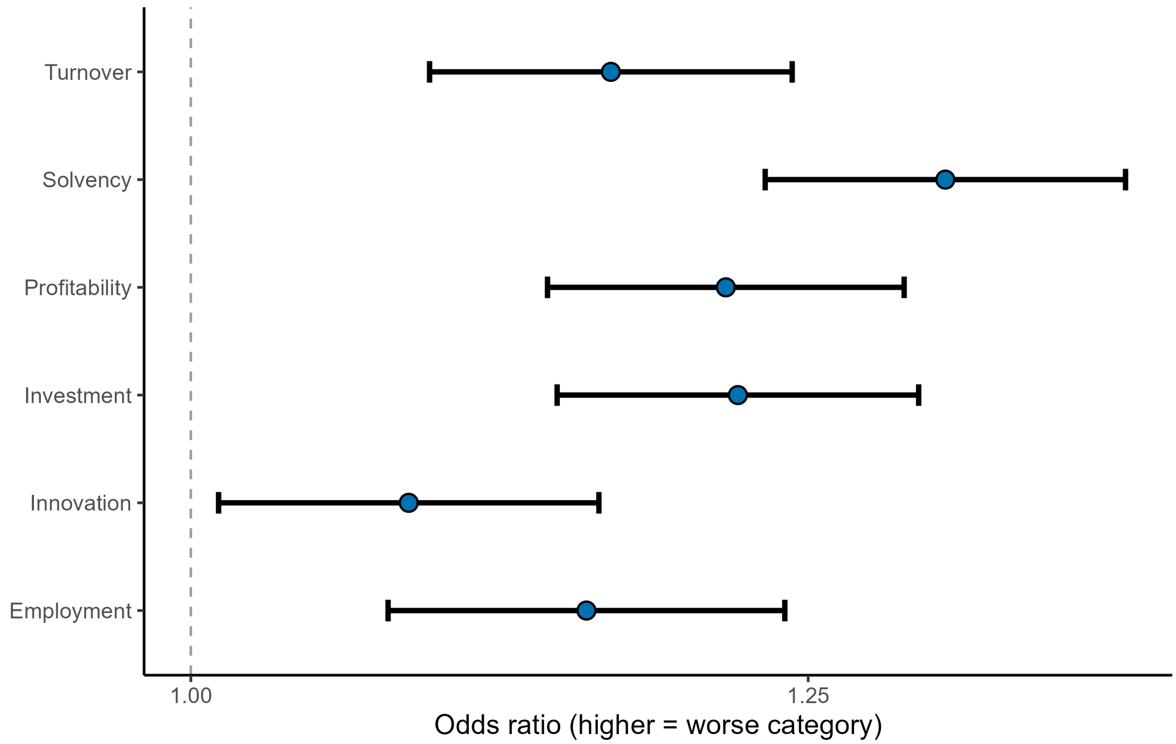
The largest effect is observed for **solvency** (OR = 1.29), meaning that financially constrained firms face about 29% higher odds of deteriorating solvency compared to their matched peers. This is intuitive: liquidity and solvency are the most immediate dimensions affected when external finance is scarce. **Profitability** (OR = 1.21) and **investment** (OR = 1.19) follow closely, reflecting that constrained firms cut back on capital expenditures and experience margin pressure. **Employment** (OR = 1.19) and **turnover** (OR = 1.17,) show smaller but still meaningful effects, suggesting that demand-side adjustments and labor shedding occur but less dramatically than balance sheet stress. Finally, **innovation** and product development exhibits the smallest effect (OR = 1.10): while constraints do hinder innovation, firms may postpone or scale down projects rather than abandon them entirely, making the short-term impact less pronounced.

Overall, the ranking of effects—*solvency* > *profitability* ≈ *investment* ≈ *employment* > *turnover* > *innovation*—is consistent with the idea that financial frictions first hit liquidity and capital-intensive activities, while strategic activities like innovation adjust more gradually.

3.2 Effects on the Probability Scale (ATT)

To enhance interpretability, Table 2 reports absolute changes in category probabilities—expressed in percentage points—under the *Average Treatment Effect on the Treated* (ATT). For each outcome, we focus on two policy-relevant margins: the probability of *Improved* and the probability of *Worsened*; the residual *Unchanged* category follows by construction. Estimates are obtained by standardization from ordered logit models with cluster-robust inference at the firm level. Importantly, these effects are estimated *on impact*, i.e., they capture very short-run adjustments immediately following the onset of financial constraints rather than long-term dynamics.

Figure 4: Treatment effect (financial constraint) on ordered outcomes: odds ratios (ordered logit). Points show OR; bars show 95% cluster-robust confidence intervals. The vertical line marks OR = 1 (no effect).



The results reveal a consistent pattern: financial constraints significantly reduce the likelihood of improvement and increase the likelihood of deterioration across all six dimensions. The largest reallocations occur for *Solvency* and *Profitability*, where the probability of *Improved* falls by 4.1 pp and 3.3 pp, respectively, while the probability of *Worsened* rises by 4.5 pp and 3.6 pp. *Investment* and *Turnover* also exhibit meaningful shifts (around 3 pp), whereas *Employment* effects are smaller (2.1 pp). Even *Innovation*, where odds ratios suggested only modest effects, shows statistically significant changes: a 1.4 pp decline in *Improved* and a 1.3 pp increase in *Worsened*. All BH-adjusted q-values remain below 0.01, indicating strong control for multiple testing.

To contextualize these magnitudes, consider that the baseline probability of reporting a worsening in *Solvency* among unconstrained firms is 24.7%; an increase of 4.5 pp represents a relative rise of approximately 18%. Similar proportional increases are observed for *Profitability* (from 23.9% to 27.5%) and *Investment* (from 13.7% to 16.8%). These short-run effects underscore how quickly financial frictions propagate to core financial indicators, even before firms adjust employment or innovation strategies.

Findings reported in this subsection align with credit-rationing theory (Stiglitz and Weiss, 1981), where liquidity constraints restrict growth-oriented activities and weaken financial resilience. From a policy perspective, easing credit frictions could yield first-order gains in solvency and profitability, with spillovers to investment and employment. Overall, the evidence points to real and economically meaningful effects of financial constraints on firms' near-term business conditions.

Table 2: Average Treatment Effect on the Treated (ATT) of financial constraints on the probability of reporting an *Improved* or *Worsened* outcome (percentage points).

Outcome	ΔP(Improved, pp)	ΔP(Worsened, pp)
Turnover	-3.1 [-4.5; -1.8], q=0.000	2.8 [1.6; 3.9], q=0.000
Employment	-2.1 [-3.0; -1.3], q=0.000	2.1 [1.2; 2.9], q=0.000
Investment	-2.6 [-3.5; -1.6], q=0.000	3.1 [1.9; 4.2], q=0.000
Profitability	-3.3 [-4.5; -2.2], q=0.000	3.6 [2.4; 4.9], q=0.000
Solvency	-4.1 [-5.1; -3.1], q=0.000	4.5 [3.4; 5.7], q=0.000
Innovation	-1.4 [-2.4; -0.4], q=0.005	1.3 [0.4; 2.2], q=0.005

Notes: ΔP denotes the absolute change in probability (percentage points) for treated firms relative to their counterfactual. Confidence intervals are based on parametric simulation with cluster-robust covariance (firm level). q-values control the false discovery rate using the Benjamini–Hochberg procedure across 12 tests.

3.3 Heterogeneous Effects

We examine whether the impact of financial constraints varies by (i) firm age, (ii) firm size, and (iii) growth orientation. Heterogeneity is assessed both via global interaction tests on the ordered logit scale and through an inspection of the group-specific average treatment effects on the treated (ATT) on the probability scale. The ATT estimates capture the percentage point change in the probability of reporting a 'Worsened' outcome, ΔP(Worsened). Standard errors are clustered at the firm level, and q-values for global interaction blocks are adjusted for multiple testing across the six outcomes using the Benjamini–Hochberg procedure.

Table 3: Global tests of heterogeneity (treatment $\times$ moderator interaction). Entries: BH-adjusted q-values within moderator across six outcomes.

Outcome	Firm age	Firm size	Growth orientation
Turnover	0.893	0.916	0.972
Employment	0.189	**0.000**	0.352
Investment	**0.024**	0.061	0.364
Profitability	0.893	0.916	0.431
Solvency	0.823	0.640	0.238
Innovation	0.379	0.061	0.238

Table 3 reports BH-adjusted q-values for global interaction tests, evaluating whether the treatment effect differs across groups on the ordered logit scale. Overall, the evidence for heterogeneity is limited at the 5% threshold, with the notable exception of *firm size* on employment ($q = 0.000$) and a suggestive difference in investment and innovation ($q \approx 0.06$). Age differences are generally weak, except for investment ($q = 0.024$). This limited rejection of the null hypothesis of equal effects is consistent with the non-linearity of the ordered logit model, where baseline risk differences can generate variation in probability-scale effects even without true interaction on the logit scale. We therefore focus on the more policy-relevant ATT estimates.

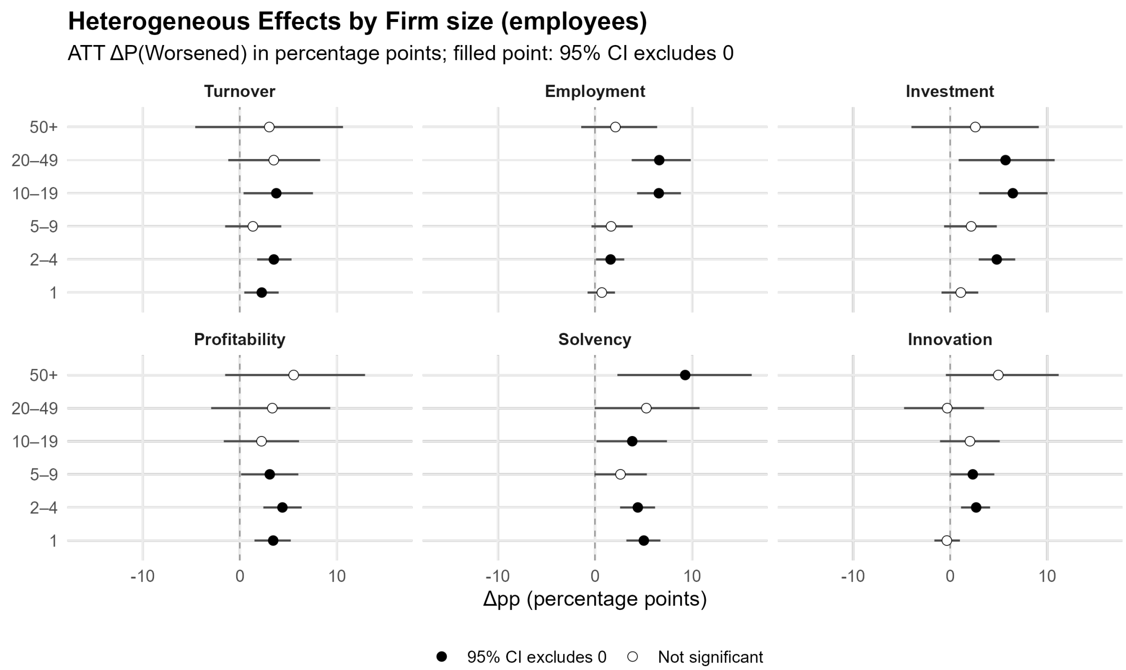
While the global tests are mixed, the subgroup ATT estimates (Figure 5 and Appendix figures for age/growth orientation) reveal a pattern of selective impact, where constraints affect different outcomes based on the firm's life stage and size class. We identify two primary mechanisms:

1. **Growth Obstacle (Mid-Sized SMEs, 10–49 employees):** The adverse effects are amplified in firms actively engaged in scaling their operations. Firms in the 10–49 employee range show the largest and most significant negative effects on employment and investment (Figure 5). Employment effects peak at ΔP(Worsened) $\approx +6$ percentage points (pp) for the 20–49 employee segment, suggesting that credit frictions act as a severe bottleneck to the real economic growth of established SMEs.

2. **Liquidity Shock (Micro/Young Firms):** Contrary to a simple linear size gradient, the smallest (1–4 employees) and youngest firms do not suffer the most in terms of employment or investment, but are instead disproportionately harmed in terms of solvency, profitability, and turnover. Smallest micro firms (1 employee) show one of the largest solvency effects ($\Delta P \approx +9$ pp for the 50+ group is larger but with very wide CI), underscoring their extreme sensitivity to immediate cash flow and liquidity pressures. This

outcome is consistent with the theory that young, growth-oriented firms face high information asymmetry and rely on agile financing, making them acutely vulnerable to sudden liquidity shocks, rather than long-term capital rationing.

Figure 5: Heterogeneous effects of financial constraints by firm size. Effects are ATT ΔP(Worsened) (percentage points) with 95% CIs.



Global interaction tests and individual subgroup estimates answer different questions. The global test evaluates whether treatment effects differ *across groups* on the model scale, accounting for sampling variability and multiple testing. In contrast, subgroup ATT estimates indicate whether the effect is nonzero *within a group*. These can diverge for two reasons. First, if effects are similar in magnitude across groups, the global test may fail to reject even when all groups show significant effects relative to zero. Second, nonlinearity in the ordered logit means that baseline risk differences can generate variation in probability-scale effects even without true interaction on the logit scale. Thus, the failing of global equality test doesn't necessarily rule out lack of heterogeneity in the ATT plots.

Overall, these findings demonstrate that financial constraints are not a monolithic problem impacting all SMEs equally. The common policy assumption that credit frictions are exclusively a micro-firm survival issue is too simplistic. Our results strongly suggest that the largest real effects (employment, investment) are transmitted through established, middle-sized SMEs and middle-aged (10–49 employees, 6-19 years old) who are actively seeking external capital for expansion. For these firms, financing problems act as an immediate growth inhibitor.

Conversely, for the smallest firms, the effect is primarily concentrated in financial stability margins (solvency and profits). From a policy perspective, this advocates for targeted credit mechanisms that distinguish between capital needed for expansion (mid-sized growth SMEs) and immediate liquidity support (micro-firms).

3.4 Discussion

Our findings confirm that financial constraints substantially worsen firms' short-term performance perceptions across multiple dimensions. After matching on observable characteristics and controlling for residual covariate imbalance, constrained firms exhibit lower odds of reporting improvements in turnover, employment, investment, profitability, and solvency. The estimated odds ratios range from approximately 1.1 to 1.3, and the effects remain statistically significant after controlling the false discovery rate using the Benjamini–Hochberg procedure.

Marginal effects on the probability scale provide a clearer sense of magnitude. Financial constraints shift probability mass away from *Improved* and toward *Worsened* categories. For example, the likelihood of reporting a deterioration in *Solvency* rises by about 4.8 percentage points (pp), while the probability of improvement falls by 4.5 pp. Similar reallocations occur for *Profitability* (-3.4 pp vs. +3.7 pp) and *Investment* (-2.9 pp vs. +3.4 pp). Turnover effects are slightly smaller (-3.1 pp vs. +2.7 pp), and employment effects are modest but significant (1.8 pp). Even innovation, often considered less sensitive to short-term liquidity, shows a measurable impact: a 1.2 pp decline in improvement and a 1.0 pp increase in worsening. These shifts are economically meaningful given the short horizon and the fact that they occur across diverse firm types.

Interestingly, innovation outcomes appear less sensitive to financial constraints, with smaller and statistically weaker effects. This may reflect the longer time horizon of innovation projects or reliance on internal resources rather than external finance. However, the muted effect could also indicate measurement limitations in self-reported innovation indicators.

Heterogeneity analysis highlights that firm size matters: employment and investment effects intensify with firm size, while turnover and profitability effects are somewhat stronger among micro firms. Age-related differences are modest, and growth orientation does not significantly moderate the effect. Interestingly, strongly growth-oriented companies don't seem to suffer more from financial constraints. These patterns suggest that both very small and mid-sized firms face distinct vulnerabilities.

From a policy perspective, these findings underscore the importance of maintaining credit access for viable, growth-oriented firms while recognizing that micro firms and those without strong growth ambitions are particularly vulnerable. Financial constraints not only impair operational performance but also dampen expectations, potentially accelerating exit and reducing aggregate productivity. The relatively muted effect on innovation suggests that constrained firms may deprioritize long-term strategic investments, which could undermine future competitiveness if constraints persist.

Finally, although these results are based on survey data, they likely reflect real economic conditions rather than mere sentiment. The reported changes combine observed outcomes, making the evidence particularly relevant for understanding near-term risks and policy priorities—even if numerical interpretation in practice remains challenging.

4 Robustness: Alternative Designs and Specifications

Table A.2 summarizes ATT estimates on $\Delta P(\text{Worsened})$ (pp) across a range of alternative research designs and outcome models. All checks target the ATT and use the same covariate set as the baseline specification. Three main findings emerge.

Design Stability Results are highly robust to alternative matching algorithms. Across nearest-neighbor (1:1) with caliper and common support, nearest-neighbor (1:2), propensity-score subclassification (10 strata), and Mahalanobis distance, estimated effects remain positive, economically meaningful, and statistically significant for all core outcomes. For example, the ATT for *Solvency* ranges from about 4.6 to 5.6 pp, and for *Profitability* from 3.5 to 4.3 pp. Trimming on overlap ($PS \in [0.05, 0.95]$ or 1% tails) leaves conclusions unchanged, with *Innovation* showing the smallest effects ($\approx$1 pp) under trimming, yet remaining positive and significant. These patterns indicate limited sensitivity to matching design or common-support enforcement.

Outcome-Model Variation Switching the link from ordered logit to ordered probit reduces point estimates by roughly 20–30%, but signs and significance remain unchanged. For example, Solvency declines from about 4.8 pp to 3.5 pp, and Investment from 3.3 pp to 2.5 pp. Dichotomizing outcomes and estimating ATT for *Worsened* with logit or LPM yields larger magnitudes (e.g., *Solvency* $\approx$ 6.7 pp), as expected because the estimand focuses on the tail event rather than pooling across categories. The ranking of outcomes is preserved in all cases.

Weighting and Augmentation Inverse probability weighting (ATT) produces estimates very close to the matched baseline or slightly larger (e.g., *Profitability*: 4.08 pp vs. 3.70 pp; *Solvency*: 4.90 vs. 4.80 pp). Augmenting IPW with an ordered probit outcome model yields smaller, yet still significant estimates, mirroring the ordered-probit behavior on the matched sample. These checks confirm that results are not driven by the choice of matching versus weighting.

Auxiliary Outcome Analysis To probe whether estimated effects reflect genuine causal relationships rather than residual confounding or model artifacts, we examine an outcome that is only indirectly related to financing frictions: *material input prices*. This is not a strict placebo, as financial constraints could plausibly affect procurement strategies—e.g., by reducing order sizes (raising unit costs), delaying purchases, or shifting suppliers—so some effect cannot be ruled out.

Table 4 reports ATT estimates for this outcome under two specifications: IPW (ATT) and baseline matching with ordered logit. Both estimates are small (≈0.7–0.8 pp) compared to core outcomes (≈ 4–6 pp) but statistically significant. Because the outcome is coded as 1 = prices increase, 2 = same, 3 = prices decrease, a negative ATT indicates that constrained firms are *less likely* to report price decreases—consistent with relatively higher input price pressure. This pattern suggests a secondary channel rather than invalidating the main results.

The auxiliary outcome provides partial reassurance: while the magnitude is small, the effect is statistically precise and directionally consistent with procurement adjustments under financial stress. Robustness checks with industry-by-period fixed effects and alternative matching specifications attenuate but do not eliminate the signal, implying that sectoral composition explains part, but not all, of the difference.

Table 4: Placebo checks: ATT on material prices (pp), 95% simulation intervals

Spec	Outcome	Estimate	LCI	UCI
Placebo: IPW (ATT)	Material prices	-0.7035931	-1.080084	-0.3199474
Placebo: baseline matched, ordered logit	Material prices	-0.8467741	-1.259583	-0.4904610

Notes: The outcome variable is coded as: 1=material prices increase, 2=prices stay the same, 3=prices decrease. In other words, negative ATT refers to higher pressure to price-increases.

Rosenbaum Sensitivity Analysis We assess hidden-bias robustness using Rosenbaum's bounds on binary deterioration indicators (1 = worsened) for matched pairs, treating constrained firms as treated. The one-sided sign test at $\Gamma = 1$ yields $p < 10^{-16}$ for all outcomes, indicating that constrained firms are significantly more likely to deteriorate than matched controls. Among discordant pairs, treated firms worsen in 55–60% of cases (odds ratios ≈ 1.22–1.49), corresponding to risk differences of roughly 4–7 pp—consistent with ATT magnitudes.

The Rosenbaum upper-bound p-value remains below 0.05 up to at least $\Gamma = 4$ across all outcomes ($\Gamma^* \geq 4$), implying that an unobserved covariate would need to increase the odds of treatment by a factor of four to overturn significance—a level considered strong in applied settings. Full details appear in Table A.4.

Summary Across alternative matching and weighting designs, link functions, dichotomizations, overlap restrictions, and placebo checks, the evidence is consistent: financial constraints significantly increase the likelihood of adverse realizations across all core outcomes. Effects are largest for *Solvency* and *Profitability*, followed by *Investment* and *Turnover*, then *Employment*, with smaller but positive effects for *Innovation*. The robustness suite indicates limited design dependence and stable inference.

5 Conclusions

This paper examined the causal impact of financial constraints on the short-term performance of Finnish SMEs using survey-based measures and propensity score matching. The analysis focused on six outcome dimensions—turnover, employment, investment, profitability, solvency, and innovation—and complemented odds ratio estimates with marginal effects for interpretability.

The results provide clear evidence that financial constraints significantly increase the likelihood of adverse outcomes across all dimensions. On the odds scale, constrained firms face 29% higher odds of deteriorating solvency and 17–19% higher odds for turnover, employment, and investment, with the smallest effect observed for innovation (10%). These findings remain robust after controlling for multiple testing and across alternative matching and weighting specifications.

Marginal effects underscore the economic significance of these results. The largest shifts occur in core financial indicators: constraints reduce the probability of reporting an improvement in solvency and profitability by approximately 3.3 to 4.1 percentage points (pp), while the probability of reporting a deterioration rises by 3.6 to 4.5 pp. The effects on turnover and investment are also meaningful (around ± 3 pp). However, the short-term impact on employment and innovation is more modest, resulting in probability shifts of 2.1 pp or less. These differences indicate that financial distress first hits a firm's balance sheet and easily adjustable capital expenditures, with labor and strategic activities adjusting more slowly.

Heterogeneity analysis indicates that the adverse effects of financial constraints are not uniform. Firm size matters: employment and investment effects intensify with firm size, reaching their largest magnitude in mid-sized SMEs (10–49 employees), while turnover and profitability effects are somewhat stronger among micro firms. Age-related differences are modest, and growth orientation does not significantly moderate the effect. These patterns highlight that both very small (liquidity-sensitive) and mid-sized (growth-constrained) firms face distinct vulnerabilities.

It is important to note that the matching approach balances firms on observed characteristics, and the model performs well according to placebo tests and robustness checks. Nevertheless, as with any observational design, the possibility of bias from unobserved factors cannot be fully ruled out. To quantify the robustness of the findings to potential unobserved heterogeneity, we conducted Rosenbaum bounds sensitivity analysis. The results indicate that the treatment effects are highly robust, requiring substantial unobserved confounding (e.g., an unobserved covariate that triples or quadruples the odds of being constrained) to render the main findings statistically insignificant. While the potential for unobserved bias remains a caveat, the strong performance in the bounds test increases confidence in the estimated causal effects.

From a policy perspective, the results underscore the importance of maintaining credit access for viable SMEs, especially micro firms and those with ambitious growth plans. Financial constraints not only impair operational performance by forcing adjustments in employment and investment but also increase the probability of financial distress, potentially accelerating exit and reducing aggregate productivity. While targeted credit support can mitigate these risks, the social desirability of supporting firms with persistently low growth orientation remains an open question. More broadly, this study does not address what might constitute an "optimal" level of financial constraints. Not all firms should receive external finance, yet excessively tight credit conditions can stifle productive investment and growth. Our findings speak to the negative consequences of constraints as currently measured, but they do not imply that the first-best outcome is universal credit access.

A key next step in future research is to merge survey data with administrative registers to link subjective assessments with objective financial accounts. This would allow researchers to validate self-reported outcomes, explore mechanisms behind observed patterns, and quantify the short-term and long-term consequences of financial constraints on firm business indicators, productivity, and innovation. Further work should also evaluate the effectiveness of policy interventions aimed at alleviating financing frictions and examine dynamic effects beyond the short horizon considered here.

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Appendix

A Descriptive Statistics

Table A.1: Descriptive statistics: category counts and percentages (over non-missing).

Section	Variable	Category	N (non-missing)	Count	Percent (%)
Treatment	Access to finance (treatment)	No	62494	39318	62.9
		Yes, received full funding	62494	15892	25.4
		Yes, but did not apply	62494	5007	8.0
		Yes, applied but rejected	62494	2277	3.6
Covariates	Main industry	Manufacturing / Industry	62494	8056	12.9
		Construction	62494	6484	10.4
		Trade (wholesale & retail)	62494	9452	15.1
		Services	62494	38502	61.6
	Region	Uusimaa	62494	17212	27.5
		Varsinais-Suomi	62494	5092	8.1
		Satakunta	62494	2507	4.0
		Kanta-Häme	62494	2309	3.7
		Pirkanmaa	62494	6608	10.6
		Päijät-Häme	62494	2069	3.3
		Kymenlaakso	62494	1827	2.9
		Etelä-Karjala	62494	1189	1.9
		Etelä-Savo	62494	1539	2.5
		Pohjois-Savo	62494	2878	4.6
		Pohjois-Karjala	62494	1887	3.0
		Keski-Suomi	62494	3241	5.2
		Etelä-Pohjanmaa	62494	3431	5.5
		Pohjanmaa	62494	2718	4.3
		Keski-Pohjanmaa	62494	1321	2.1
		Pohjois-Pohjanmaa	62494	3470	5.6
		Kainuu	62494	855	1.4
		Lappi	62494	2341	3.7
	Firm size (employees)	1 person (sole proprietor)	62494	23636	37.8
		2–4 persons	62494	17348	27.8
		5–9 persons	62494	9426	15.1
		10–19 persons	62494	6052	9.7
		20–49 persons	62494	3795	6.1
		$\geq$ 50 persons	62494	2237	3.6
	Turnover class	$<$ 0.2 M€	62494	28898	46.2
		0.2–0.49 M€	62494	11041	17.7
		0.5–0.99 M€	62494	7423	11.9
		1.0–1.49 M€	62494	3606	5.8
		1.5–1.99 M€	62494	2208	3.5
		2.0–4.99 M€	62494	4876	7.8
		$\geq$ 5 M€	62494	4442	7.1
	Market area	Local	62494	37067	59.3
		National	62494	19835	31.7
		International	62494	5592	8.9
	Firm age	0–2 years	62494	4764	7.6
		3–5 years	62494	7849	12.6
		6–10	62494	8829	14.1
		11–20	62494	15930	25.5
		$>$ 20	62494	25122	40.2
	Growth orientation	Strongly growth-oriented	62494	5334	8.5
		Aim to grow as opportunities permit	62494	22073	35.3
		Maintain position (which requires growth)	62494	18876	30.2
		No growth objectives	62494	14066	22.5
		Operations will cease within the next year	62494	2145	3.4
	Payment difficulties dur. the past 3m	no	62494	52735	84.4
		yes	62494	9759	15.6
Outcomes	Turnover (change)	Increased	62494	26707	42.7
		No change	62494	19787	31.7
		Decreased	62494	16000	25.6
	Employment (change)	Increased	62494	11082	17.7
		No change	62494	43864	70.2
		Decreased	62494	7548	12.1
	Investment (change)	Increased	62494	12736	20.4
		No change	62494	37269	59.6
		Decreased	62494	12489	20.0
	Profitability (change)	Increased	62494	17532	28.1
		No change	62494	28847	46.2
		Decreased	62494	16115	25.8
	Solvency (change)	Increased	62494	16436	26.3
		No change	62494	35236	56.4
		Decreased	62494	10822	17.3

B Additional Heterogeneity Results

Figure 6: Heterogeneous effects of financial constraints by firm age. Effects are ATT ΔP(Worsened) (percentage points).

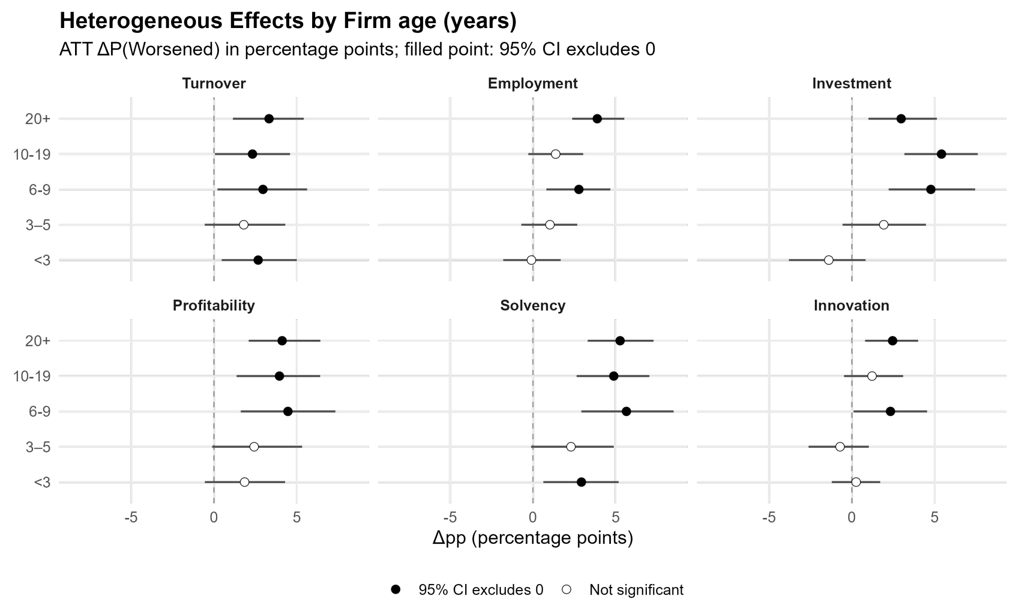
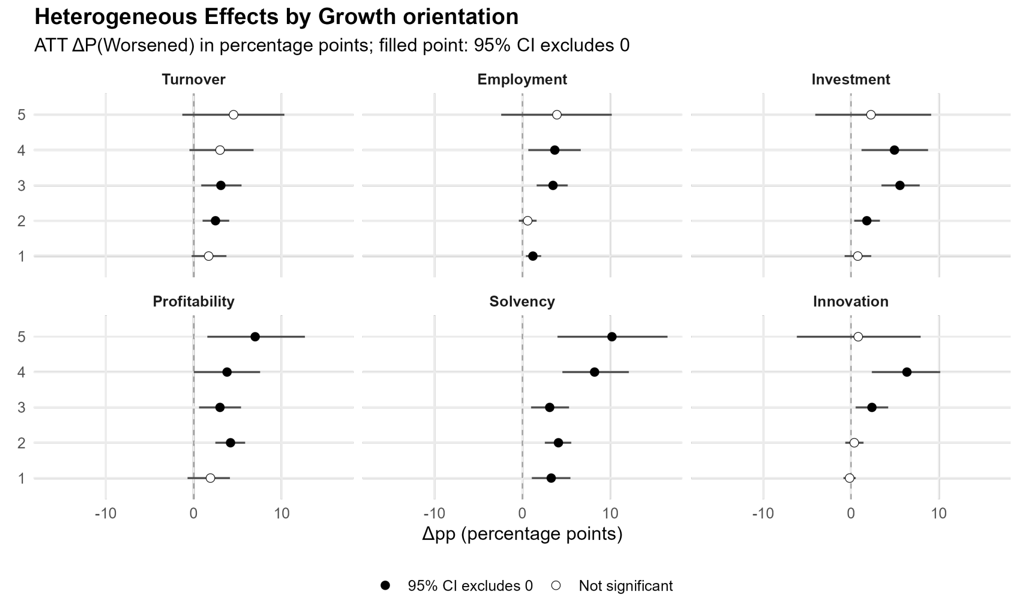


Figure 7: Heterogeneous effects of financial constraints by growth orientation. Effects are ATT ΔP(Worsened) (percentage points).



Notes: 1=Strongly growth-oriented, 2=Aim to grow if possible, 3=Aim to maintain market position (and this requires growth), 4=No growth objectives, 5=Operations will cease within the next year.

C Robustness of the Results

Table A.2: Robustness checks (main outcomes): ATT ΔP(Worsened) in percentage points (pp), with 95% simulation intervals.

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	Spec	Outcome	EST	LCI	UCI	Set
1	Baseline: matched, ordered logit	Turnover	2.6929132	1.5406780	3.764733	Main
2	IPW (ATT)	Turnover	3.2011444	2.1010616	4.295345	Main
3	IPW + outcome model (ordered probit)	Turnover	2.3295055	1.5181916	3.155764	Main
4	Mahalanobis (1:1)	Turnover	2.7166552	1.5660394	3.873037	Main
5	Matched + Trim PS 1% tails	Turnover	2.6684884	1.4778660	3.759953	Main
6	Matched + Trim PS in [0.05,0.95]	Turnover	2.5824583	1.4063109	3.684213	Main
7	Matched, LPM (Worsened=1)	Turnover	3.7424385	2.3987414	5.081107	Main
8	Matched, logit (Worsened=1)	Turnover	3.5735101	2.1274010	4.989372	Main
9	Matched, ordered probit	Turnover	1.9558082	1.1662644	2.756682	Main
10	Nearest (1:1) + caliper 0.05 (overlap)	Turnover	2.7515585	1.6790775	3.847733	Main
11	Nearest (1:2) (overlap)	Turnover	3.1764154	2.1814279	4.149668	Main
12	PS subclassification (10 strata)	Turnover	3.0421588	2.2187608	3.886756	Main
13	Baseline: matched, ordered logit	Employment	1.7658503	0.9425791	2.584982	Main
14	IPW (ATT)	Employment	2.5325380	1.7463882	3.419563	Main
15	IPW + outcome model (ordered probit)	Employment	2.1076944	1.3735131	2.862421	Main
16	Mahalanobis (1:1)	Employment	1.5690271	0.6626364	2.430469	Main
17	Matched + Trim PS 1% tails	Employment	1.7536559	0.9223748	2.558143	Main
18	Matched + Trim PS in [0.05,0.95]	Employment	1.6370938	0.7843270	2.472089	Main
19	Matched, LPM (Worsened=1)	Employment	3.2050752	2.0725375	4.362805	Main
20	Matched, logit (Worsened=1)	Employment	3.0980669	1.9436143	4.170494	Main
21	Matched, ordered probit	Employment	1.4896182	0.7619848	2.229002	Main
22	Nearest (1:1) + caliper 0.05 (overlap)	Employment	1.7415490	0.8804679	2.620802	Main
23	Nearest (1:2) (overlap)	Employment	2.0327668	1.2847227	2.812244	Main
24	PS subclassification (10 strata)	Employment	2.3888600	1.7554685	3.042105	Main
25	Baseline: matched, ordered logit	Investment	3.4149258	2.3646838	4.533184	Main
26	IPW (ATT)	Investment	3.9058640	2.8337481	5.003704	Main
27	IPW + outcome model (ordered probit)	Investment	2.8491472	2.0599346	3.599844	Main
28	Mahalanobis (1:1)	Investment	3.3104611	2.1827555	4.435568	Main
29	Matched + Trim PS 1% tails	Investment	3.3789898	2.2535986	4.532196	Main
30	Matched + Trim PS in [0.05,0.95]	Investment	3.3662322	2.1869877	4.515683	Main
31	Matched, LPM (Worsened=1)	Investment	5.2326819	3.7898162	6.598288	Main
32	Matched, logit (Worsened=1)	Investment	5.1387752	3.7610407	6.557348	Main
33	Matched, ordered probit	Investment	2.5240482	1.7231959	3.310858	Main
34	Nearest (1:1) + caliper 0.05 (overlap)	Investment	3.3803286	2.2736206	4.525705	Main
35	Nearest (1:2) (overlap)	Investment	3.4680446	2.4545973	4.517567	Main
36	PS subclassification (10 strata)	Investment	3.8051462	2.9231786	4.733453	Main

Table A.3: Robustness checks (main outcomes): ATT ΔP(Worsened) in percentage points (pp), with 95% simulation intervals. (cont.)

	Spec	Outcome	EST	LCI	UCI	Set
37	Baseline: matched, ordered logit	Profitability	3.7045057	2.6067040	4.910414	Main
38	IPW (ATT)	Profitability	4.0805765	2.8835012	5.213210	Main
39	IPW + outcome model (ordered probit)	Profitability	2.8353103	2.0134119	3.678378	Main
40	Mahalanobis (1:1)	Profitability	4.3390721	3.1337178	5.503997	Main
41	Matched + Trim PS 1% tails	Profitability	3.6105523	2.4414014	4.788629	Main
42	Matched + Trim PS in [0.05,0.95]	Profitability	3.4730759	2.2999833	4.658045	Main
43	Matched, LPM (Worsened=1)	Profitability	5.4006826	4.0203185	6.877655	Main
44	Matched, logit (Worsened=1)	Profitability	5.3477544	3.9732026	6.722069	Main
45	Matched, ordered probit	Profitability	2.6360628	1.8344408	3.459010	Main
46	Nearest (1:1) + caliper 0.05 (overlap)	Profitability	3.7299118	2.5805471	4.958063	Main
47	Nearest (1:2) (overlap)	Profitability	3.8819130	2.8067518	4.961439	Main
48	PS subclassification (10 strata)	Profitability	4.0626864	3.1735457	4.926781	Main
49	Baseline: matched, ordered logit	Solvency	4.8044019	3.7076128	5.937052	Main
50	IPW (ATT)	Solvency	4.8985038	3.8106727	6.008605	Main
51	IPW + outcome model (ordered probit)	Solvency	3.5592918	2.7608227	4.344006	Main
52	Mahalanobis (1:1)	Solvency	5.5973606	4.4682591	6.732802	Main
53	Matched + Trim PS 1% tails	Solvency	4.8176763	3.7598290	5.951211	Main
54	Matched + Trim PS in [0.05,0.95]	Solvency	4.5737445	3.4037687	5.675058	Main
55	Matched, LPM (Worsened=1)	Solvency	6.7336468	5.4636423	8.035882	Main
56	Matched, logit (Worsened=1)	Solvency	6.5517850	5.2460944	7.926767	Main
57	Matched, ordered probit	Solvency	3.5288560	2.7208798	4.370108	Main
58	Nearest (1:1) + caliper 0.05 (overlap)	Solvency	4.7931650	3.8174672	5.914537	Main
59	Nearest (1:2) (overlap)	Solvency	4.9045320	3.9304345	5.832368	Main
60	PS subclassification (10 strata)	Solvency	4.9309544	4.0520385	5.794813	Main
61	Baseline: matched, ordered logit	Innovation	1.0637114	0.1752578	1.981235	Main
62	IPW (ATT)	Innovation	1.4530302	0.5666861	2.309602	Main
63	IPW + outcome model (ordered probit)	Innovation	1.2729505	0.5628274	1.985047	Main
64	Mahalanobis (1:1)	Innovation	0.9559392	-0.0349237	1.843427	Main
65	Matched + Trim PS 1% tails	Innovation	1.0027351	0.0711010	1.901671	Main
66	Matched + Trim PS in [0.05,0.95]	Innovation	0.9349683	0.0084942	1.875245	Main
67	Matched, LPM (Worsened=1)	Innovation	4.7587917	3.5957449	5.847690	Main
68	Matched, logit (Worsened=1)	Innovation	4.6260925	3.4330469	5.819199	Main
69	Matched, ordered probit	Innovation	0.9361821	0.2526186	1.650168	Main
70	Nearest (1:1) + caliper 0.05 (overlap)	Innovation	1.0493452	0.2022415	1.916362	Main
71	Nearest (1:2) (overlap)	Innovation	1.0747915	0.3959595	1.831590	Main
72	PS subclassification (10 strata)	Innovation	1.4170984	0.7557951	2.077382	Main

Table A.4: Rosenbaum sensitivity (matched pairs)

Outcome	N_{pairs}	Discordant	b	c	Ties	Prop. (T worse | disc.)	$p(\Gamma{=}1)$	Γ^*
Turnover worsened (=1)	7867	3220	1767	1453	4647	0.549	$< 10^{-16}$	≥ 4
Employment worsened (=1)	7867	1983	1144	839	5884	0.577	$< 10^{-16}$	≥ 4
Investment worsened (=1)	7867	3008	1723	1285	4859	0.573	$< 10^{-16}$	≥ 4
Profitability worsened (=1)	7867	3288	1873	1415	4579	0.570	$< 10^{-16}$	≥ 4
Solvency worsened (=1)	7867	2990	1777	1213	4877	0.594	$< 10^{-16}$	≥ 4
Innovation worsened (=1)	7867	2280	1364	916	5587	0.598	$< 10^{-16}$	≥ 4

Notes: Treated = constrained; outcome coded as worsened = 1. One-sided Wilcoxon/sign test reports $p(Gamma{=}1)$ under no hidden bias. $Gamma^*$ denotes the smallest $Gamma$ at which the Rosenbaum upper-bound p-value exceeds 0.05. Ties are excluded by the sign test; Discordant = b + c.

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