Precautionary Debt Capacity*

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Abstract

Firms with ample financial slack are unconstrained... or are they? In a field experiment that randomly expands debt capacity on business credit lines, treated small-and-medium enterprises (SMEs) draw down 35 cents on the dollar of expanded debt capacity in the short-run and 55 cents in the long-run despite having debt levels far below their borrowing limit before the intervention. SMEs direct new borrowing to financing investment gradually over time and do not exhibit a measurable impact on delinquencies. Heterogeneity analysis by the risk of being at the credit line limit supports the SME motive to preserve financial flexibility.

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1 Introduction

Financial frictions are a central topic in finance and macroeconomics (see Stein (2003) for a survey and Catherine et al. (2022) for a recent example). Theory points to several frictions that may hamper firms' access to finance, especially for small-and-medium enterprises (SMEs), such as information frictions and collateral constraints (Stiglitz and Weiss, 1981). Governments worldwide spend aggressively to facilitate SME funding, with such programs having been ramped up to an unprecedented scale in the aftermath of the pandemic era. Yet, there is an active debate on whether and to what extent SMEs are truly unable to borrow, with recent evidence that SMEs maintained ample financial slack even in the Covid-19 crisis (Chodorow-Reich et al., 2022). How do SMEs manage their financing needs over time? How do they trade off different financial instruments? And what is the nature of the frictions that actually limit SMEs' borrowing? Our goal is to answer these questions, which are crucial for designing policies aimed at strengthening firms' financial well-being and for gaining a better understanding of the frictions that may limit firm growth.

Combining a field experiment that randomly expanded debt capacity on business credit lines with novel administrative data capturing SMEs' monthly credit line usage and spending patterns, this paper shows that seemingly unconstrained SMEs with substantial financial slack borrow and invest *as if* they are financially constrained. We first document that most SMEs maintain debt levels far below their borrowing limit. Even so, our experiment-generated debt capacity expansion leads to large and persistent increases in borrowing and investment even for firms with the most financial slack before the experiment, contrary to the predictions of the canonical (static) theory of financing constraints.[1] We provide supporting evidence that SMEs' desire to preserve financial flexibility is the key friction that shapes their borrowing decisions. Our main contributions are to enrich the understanding of the size and nature of financing constraints that SMEs face and to provide the first experimental evidence on the real effects of financing in the context of firms in the formal sector making high-stakes financing and production decisions.

We collaborated with a large European retail bank in Türkiye (henceforth *our bank*) to conduct this study. Our bank periodically identifies SMEs eligible for a debt capacity increase from their *existing* users of business credit lines using proprietary underwriting criteria that trades-off a potential increase in revenues with the risk of default. Our bank identified 3,169 SMEs that were pre-approved for debt capacity increases. Among this pre-approved group, we randomly offered unexpected, surprise debt capacity increases to 2,414 SMEs (i.e., the "treated" group) and withheld capacity increases for the remaining 755 firms (i.e., the "control" group). The treatment assignment was applied *automatically* and communicated to the firm via phone or text. The intervention did *not* affect the cost of borrowing due to the interest rate cap in Türkiye, which was binding for all firms and did not vary over time.

The range of our experimental sample covers the bottom half of the firm size distribution in the universe of Turkish SMEs, including the median. These businesses have up to 10 employees and operate in a wide range of sectors including retail (brick-and-mortar stores), services (repair shops), food and beverage (restaurants), wholesale, and professional services (e.g., law or dental practices). While these businesses tend to be on the smaller end of the SME sector, they capture established businesses with employees in the formal sector that

[1]See Stein (2003) for a comprehensive survey of the standard theory of financing constraints considered in earlier work. In essence, firms choose investment levels subject to the budget constraint, comprised of internal and external financing. Raising external financing is costly due to financing frictions, and these frictions lead to underinvestment. Thus, if firms already had enough financial slack to fund investment, expanding their debt capacity should not have any real effects.

hold the potential for income and productivity growth (Akcigit et al., 2021). Using statistics obtained from the Central Bank of Türkiye, we also verified that the business credit line usage behavior of our experimental sample looked similar to that of the universe of Turkish SMEs.

The key strength of our research design is that it helps to overcome endogeneity challenges that complicate the identification of the causal effects of financing. Two types of endogeneity are particularly problematic: (1) factors that affect financing, such as cash flows, cost of capital, or economic conditions, also influence investment opportunities (i.e., correlated confounds)[2] and (2) firms seek financing if they expect needing it (i.e., selection). We tackle the first challenge by randomizing treatment assignment and comparing businesses that are observationally identical in every respect except for their treatment assignment. We confirm that the randomization successfully balanced the characteristics of the treated and control businesses, with both groups having similar levels and trends in debt capacity and utilization as far back as three years preceding the intervention. Second, the lender-initiated capacity expansion was applied to the customers' accounts automatically as a "surprise" treatment without prior knowledge. This feature minimizes selection concerns and creates an ideal setting to examine the real effects of financing, holding expectations about future debt capacity and information about its own investment opportunities fixed.

In our setting, businesses have two ways to draw on the *same* credit line – as revolving debt or as term debt. If firms choose to draw revolving debt – a standard way to draw on business credit lines – they can borrow up to a pre-set capacity limit. Businesses can repay the drawn amount in full at the end-of-billing cycle or revolve the unpaid balance to the next billing cycle and accrue interest on the unpaid balance. If firms instead choose to draw on these lines as term debts – a unique feature of our setting – they borrow a fixed sum and make preplanned payments until the loan is paid off, much like point-of-sale financing in the U.S. Overall, the key differences between revolving and term debt are the (1) the pricing and (2) the repayment schedule. Revolving debt is expensive, whereas term debt is (almost always) interest-free – our bank accepts fees from participating vendors and originates these loans without conducting a separate credit check. Firms can repay revolving debt flexibly at their discretion, whereas term debt requires "rigid" regular, monthly repayments over 4 to 12 months.[3]

We start by analyzing SMEs' credit line use before the intervention and document two facts. First, most SMEs have debt levels far below their capacity limits. In the month before the intervention, less than 10 percent of SMEs were truly financially constrained in the sense that they exhausted nearly all of their capacity and could no longer borrow (utilization ratio of more than 98 percent). An average firm used 39 percent of its debt capacity and a median firm 33 percent, with 10 percent of firms not having any outstanding debt on their credit lines. Second, despite revolving debt being markedly more expensive than term debt, most SMEs relied on revolving debt. Nearly 50 percent of all firms used a mix of revolving and term debt or depended solely on revolving debt (20 percent), whereas less than 20 percent of firms only used term debt. In summary, most SMEs had substantial financial slack before the intervention, and they *did not* minimize the cost of financing by relying solely on term debt. We next explore how randomly offering debt capacity increases affect their financing and investment decisions.

[2]These concerns are well-established in the literature on cash flow-financing sensitivity (Fazzari et al., 1988; Kaplan and Zingales, 1997; Rauh, 2006; Lewellen and Lewellen, 2016).

[3]Another key feature of term debt is that it can only be used only to finance durable goods, such as electronics and machinery, or professional business services. Moreover, term debts can only be issued in-store at purchase and cannot be refinanced. Thus, we infer businesses' investment from the usage of term debts. We discuss the contract features in greater detail in Section 2.1.

The treatment assignment generated a strong first-stage for debt capacity. Treated firms' debt capacity increased by 50 percent after 12 months and 55 percent on existing debt capacity after 36 months of the experiment compared to the control group, representing an economically meaningful change. The strong-first stage and the monotonic effect of treatment assignment on debt capacity allows us to use the treatment assignment, $\mathbb{Z}_i$, as an instrument for the change in debt capacity. Our primary intent-to-treat (ITT) outcome is the change in total debt carried across periods, or the sum of revolving and term debt. This outcome excludes debt balances that are paid off at the end of the billing cycle. We use this instrument to estimate the Local Average Treatment Effect (Angrist and Imbens, 1994), capturing how much firms borrowed per dollar increase in debt capacity. We refer to this magnitude as the "treatment effect."

We report three main findings. First, even though most SMEs had substantial financial slack before the experiment, higher debt capacity had large and positive effects on borrowing both in the short- (i.e., 12 months after the intervention) and in the long-run (i.e., 36 months after). Treated firms increased borrowing by 61 percent relative to the pre-experimental mean after 12 months. The Wald estimator capturing the treatment effect of the capacity expansion implies that firms used 35 cents out of a dollar increase in debt capacity. We conduct a battery of robustness tests to confirm that the drawdown response does not simply reflect (1) businesses shifting their sources of financing, either via substituting across different bank accounts or by shifting from cash use to credit lines; (2) unusual inflation or exchange rate patterns; or (3) noise arising from firms being small. Reweighting our sample to match the distribution of the universe of Turkish SMEs delivers qualitatively similar estimates (i.e., 0.35 in our sample vs. 0.31 reweighted), suggesting that our results can be generalized to a broader population of Turkish SMEs.[4]

The increase in debt capacity led to a persistent increase in borrowing in the long-run, even for businesses with the most substantial slack before the experiment. Treated firms drew down 44 cents after the second year and 55 cents on the dollar of debt capacity after 3 years. To better assess whether the large treatment effect is driven by firms that were most financially constrained before the experiment, we examine heterogeneous treatment effects by grouping firms into quintiles of average pre-experiment utilization rate. In the short-run, more financially constrained businesses exhibited larger treatment effects relative to the least constrained firms (i.e., 0.21 vs. 0.46), although the most constrained group (i.e., pre-experimental utilization of more than 60 percent) showed a relatively muted response of 0.38. In the long-run, all businesses exhibited a large treatment effect of at least 0.43, including firms with the most financial slack (i.e., those that used less than 20 percent of debt capacity). Overall, these results suggest that SMEs increased borrowing in response to debt capacity increases irrespective of their financial slack before the intervention.

Second, the financing and spending patterns suggest that treated SMEs used a mix of revolving and term debt to finance working capital and investment in the short-run, and they directed the entirety of their borrowing to financing investment using term debt in the long-run. Decomposing treatment effects into types of financing shows that treated SMEs drew a mix of high-cost revolving debt and interest-free term debt in the short-run, but strictly relied on term debt in the long-run. Out of the 35 cent increase in borrowing per dollar of capacity expansion after 12 months, 43 percent was drawn using revolving debt and 57 percent in term debt. Given that firms held, on average, 40 percent of total debt in

[4] We also provide direct evidence that our research design helps address the endogeneity challenge in estimating the causal effects of financing by comparing the magnitude of our experimental estimate to that obtained from non-experimental econometric methods. Specifically, we show that covariate-controlled estimates from a pre-experimental period are half as large as the experimental estimates (18 cents vs. 35 cents), suggesting that randomization helps mitigate downward bias.

revolving and 60 percent in term debt before the experiment, treated SMEs simply expanded their existing financing structure in response to debt capacity increases in the short-run. In the long-run, SMEs gradually phased out revolving debt and ramped up drawdowns using term debt. Term debt accounted for 58 percent of total drawdowns in the first year, 84 percent in the second year, then 100 percent of drawdowns after three years.

How do businesses use different types of debt? Decomposing finer *spending* categories for each type of financing reveals that firms used revolving debt to cover day-to-day operating expenses, while they used term debt to finance new investments. Our bank categorizes detailed transactions on business credit lines into seven spending categories: auto parts, gas/auto repair, durable, non-durable, business services (e.g., advertising/consulting), insurance/other services, and cash advances. We exploit this feature to examine how businesses use different types of debt. Two-thirds of revolving debt is used on non-durable expenses, such as gas and auto repair, whereas term debts are primarily used for durable equipment and machinery. We thus infer firms' investment from the use of term debt. Taken together, our results indicate that SMEs take, on average, two years to ramp up investment and three full years to commit their financing to investment. Despite the large increase in drawdowns, treated businesses were not more likely to fall into financial distress relative to control businesses after three years, as measured by delinquency and restructuring rates. These results indicate suggest that (1) treated firms must have generated sufficient returns to capital because higher debt did not lead to greater financial distress; and that (2) our bank may have been too conservative in extending credit lines to firms with growth potential.

Finally, we provide corroborating evidence that the financial flexibility channel best explains our main findings. Our findings raise several seemingly puzzling firm behaviors: why do firms with substantial financial slack increase drawdowns after debt capacity expansions when they could have borrowed previously? And why do firms rely on revolving debt at all when interest-free term debt is available? The financial flexibility channel posits that the firm is forward-looking and makes investment and financing decisions in anticipation of future financing needs (Froot et al., 1993; Midrigan and Xu, 2014). Thus, the desire to preserve financial flexibility leads firms to (1) use debt conservatively even when they have substantial slack and (2) to manage short-term liquidity needs by choosing financial contracts that provide the option to revolve even if they are costly. This channel is particularly plausible in a country such as Türkiye, where the volatile business and political environment creates strong precautionary motives. We confirm the relevance of this channel by showing that SMEs that face a greater risk of being at the credit limit – that is, those that maintained substantial slack on average but frequently used more than 75 percent of their debt capacity before the intervention – have the highest treatment effect. Additional tests show that (1) firms with higher pre-intervention unpredictable spending volatility have a higher demand for flexibility (i.e., untapped capacity), and (2) firms with no alternative sources of financing exhibit a larger drawdown response, consistent with precautionary motives to preserve a financial buffer being more pronounced for this group.

We also explore the role of other potential mechanisms. One possibility is that the expanded debt capacity allows firms to finance large investments that they could not have afforded before. However, 77 percent of firms in our sample could have afforded new borrowing incurred within the first 12-months of the experiment with their existing capacity. Another possibility is that firms borrow more after the intervention because they are "encouraged" by the lender-initiated capacity increases and perceive themselves to be more profitable. This channel predicts that treatment effects should be the largest for firms that are least aware of their own quality as they are marginal borrowers that would be most "encouraged" by capacity expansions. However, we do not find a clear cut treatment effect gradient by firms' awareness of their own quality, which we proxy by the number of capacity increases before the intervention. The use of high-cost revolving debt in the short- but not in the long-run may be explained by firms making suboptimal financing decisions (i.e., mistakes) and learning how to use credit lines optimally over time. For example, Rema et al. (2014), Bruhn et al. (2018), and Gertler et al. (2023) provide evidence that small firms exhibit behavioral biases when they make managerial decisions. This channel predicts that inexperienced credit line users should rely more heavily on revolving debt in the short-run as they would be more prone to make mistakes than experienced credit line users. However, we do not find a clear cut gradient in firms' reliance on revolving debt by account age.

To the best of our knowledge, this is the first experimental evidence on how SMEs in the formal sector use business credit lines – the most common form of bank lending to small firms in industrialized economies (Kashyap et al., 2002) – to make high-stakes financing and investment decisions.[5] A small, but growing number of studies examine the financing effects of formal credit contracts on SMEs in emerging markets, such as trade credit (Breza and Liberman, 2017) or bank loans (Banerjee and Duflo, 2014; Ponticelli and Alencar, 2016; Fonseca and Matray, 2022), exploiting policy reforms that generated differential credit supply shocks or restrictions on contract terms. However, experimental evidence involving formal sources of financing remains rare.[6] Our contribution to this literature is twofold. First, we provide well-identified causal effects of high-stakes credit provisions on the dynamics of SME borrowing, financing choices, spending decisions, and timing of investment. While prior research documents the effects on take-up of financing contracts (see, for example, Barboni and Agarwal (2023)), there is much less evidence on *which* types of financing contracts stimulate investment and *when*. Second, our high-quality, administrative panel data capturing SMEs' credit use and spending decisions allow us to improve the measurement and precision of financing effects and to explore rich heterogeneity analysis. Specifically, our study is the first to track firms' high-frequency spending breakdowns in the emerging markets context, which helps shed light on whether firms use their capital productively and how quickly they ramp up investment.

We contribute to the literature on the real effects of financing on SMEs by enriching our understanding of the size and nature of financing constraints, and, more specifically, of how SMEs dynamically manage their debt capacity. Financing frictions are well-known barriers to growth for SMEs, because small firms face greater costs in raising external capital (Petersen and Rajan, 1994; Berger and Udell, 2002; Robb and Robinson, 2014) and are disproportionately sensitive to macroeconomic fluctuations and credit cycles than are large firms (Davis et al., 1996; Kim et al., 2020). Consistent with this, prior studies show that alleviating financing constraints fosters a process of creative destruction (Bertrand et al., 2007; Kerr and Nanda, 2009; Adelino et al., 2015; Schmalz et al., 2016) and job creation (Brown and Earle, 2017), although it may come at the cost of a higher likelihood of firms going bankrupt (Lelarge et al., 2019) and the misallocation of workers (Barrot et al., 2021). Yet, despite the

[5]Our research design is similar in spirit to experimental studies in the development and finance literature that test the existence of credit and liquidity constraints for small firms. However, it is crucially different in terms of institutional setting and the type of financing considered. Most prior work has focused on the impacts of small cash grants or microcredit ($200 or so) extended to informal, subsistence micro-entrepreneurs (de Mel et al. (2008), Field et al. (2013), Banerjee et al. (2015)). A recent exception is McKenzie (2017), which evaluates effects of offering large grants of roughly $50,000 per recipient. By contrast, our focus falls on how established firms in the formal sector use high-stakes credit provisions that are substantially larger in size and involve complex intertemporal borrowing decisions. It is important to have solid evidence of how established firms make investment and financing decisions given that such firms tend to be transformational entrepreneurs who hold the potential for income and productivity growth and contribute materially to the aggregate economy in emerging markets (Schoar, 2010). See Armendariz de Aghion and Morduch (2005) and Banerjee and Duflo (2005) for a comprehensive overview of the microcredit literature.

[6]A recent exception is Cai and Szeidl (2023), which documents the effects of randomly advertising new loan products (i.e., unsecured working capital loans) to SMEs in China.

large emphasis on understanding the effects of financing frictions, there is relatively little direct evidence on the size of financing constraints and the channel through which financing frictions translate to real effects.[7] Our contributions are to provide (1) direct evidence that seemingly unconstrained SMEs with substantial untapped debt capacity are in effect financially constrained and to illustrate that (2) demand for financial flexibility is a key channel that shapes SMEs' financing and investment decisions. An implication of these findings is that standard measures of financing constraints (e.g., utilization) may not capture firms' true need for capital because "seemingly" unconstrained firms may have high "shadow" constraints (Froot et al., 1993).

One form of these "shadow" constraints can arise in a dynamic contracting setting, where forward-looking firms may not invest today to preserve debt capacity in anticipation of future borrowing constraints (Clementi and Hopenhayn, 2006; DeMarzo and Fishman, 2007; Rampini and Viswanathan, 2010). Our finding that firms that face biding constraints more frequently before the intervention show the largest treatment effect supports this class of models. As such, policies aimed at spurring firm investments can consider expanding debt capacity even to firms that appear to have ample borrowing power.

We contribute to the financial intermediation literature that examines the role of business credit lines by providing micro-evidence of the *funding role* of credit lines in normal times. In addition, we also show how SMEs trade off different sources of debt financing (i.e., term debt vs. revolving debt), which are unique features of our experiment. Existing literature has emphasized the role of credit lines as *contingent liquidity* that allows firms to alleviate liquidity shocks (Boot et al., 1987; Shockley and Thakor, 1997; Holmström and Tirole, 1998; Sufi, 2009). For example, prior studies show that firms draw heavily on credit lines during economic downturns (Ivashina and Scharfstein, 2010; Campello et al., 2010), and this "run" on credit lines is particularly concentrated among large or risky firms (Greenwald et al., 2023; Acharya and Steffen, 2020). SMEs draw extensively on their credit lines following unexpected cash-flow shocks (Brown et al., 2021), although lenders have substantial discretion in granting funds to small firms and may not honor all drawdowns (Chodorow-Reich et al., 2022). These studies mainly highlight the role of credit lines as a source of contingent liquidity by analyzing firms' drawdown behavior in response to negative liquidity shocks. By contrast, we show that credit lines serve as a primary source of funding even in normal times and is particularly useful for firms that have prefer financial and debt repayment flexibility. This "funding role" of credit lines has been emphasized in the dynamic optimal contracting framework (Hennessy and Whited, 2005; Gamba and Triantis, 2008; Rampini and Viswanathan, 2010; DeAngelo et al., 2011; Nikolov et al., 2019), but micro-evidence supporting this mechanism remains scant. The gradual adjustment in the level and the speed of borrowing that we document supports the empirical predictions from the structural literature.

While our study provides well-identified experimental evidence on SME financing, it raises the question of whether our findings can be generalized to a broader setting, such as the U.S. or other developed countries. We believe that our findings provide novel insights about SMEs that are generalizable for several reasons. First, the type of privately-held bank-dependent SMEs considered in this paper is highly prevalent, accounting for more than 80 percent of firms in the U.S. and 90 percent of businesses worldwide (SBA, 2019; The World Bank, 2023). Second, business credit lines are the most common form of bank lending in industrialized economies, and the size of SME financing constraints we document is comparable to that in other settings. For example, Chodorow-Reich et al. (2022) shows that in

[7] Prior evidence highlights the role of the covenant (Chava and Roberts, 2008; Chodorow-Reich and Falato, 2022), collateral (Schmalz et al., 2016; Catherine et al., 2022), information (Bernstein et al., 2016), and internal cash flow (Fazzari et al., 1988; Kaplan and Zingales, 1997) channels in alleviating financial frictions.

the U.S., more than 50 percent of SMEs in the bottom half of the firm size distribution utilize less than half of the available debt capacity on business credit lines. Finally, financial flexibility plays a universally central role in firm production decisions. For example, U.S. corporations point to financial flexibility as the most important determinant of debt policy (Graham and Harvey, 2001). Thus, credit lines and the associated motive for flexibility are likely to be relevant for SMEs in other countries, including the U.S.

2 Experimental Context and Design

This section describes the institutional setting and details of the experimental design.

2.1 Institutional Background

SMEs in Türkiye. SMEs form the backbone of the Turkish economy. They provide a major source of income for low-income, urban households and account for half of the country's total value added (Turkish Statistical Institute, 2021). Türkiye pursued ambitious reforms beginning in the 2000s that propelled dramatic economic growth and halved the share of people below the poverty line between 2006 and 2020 (The World Bank, 2023). SMEs were at the forefront of this economic agenda, prompting the Turkish government to implement one of the largest credit guarantee programs in the world (7.6% of GDP) in 2017 to foster SME growth (OECD, 2019; Akcigit et al., 2021). As of 2023, Türkiye stands as the world's 19^{th} largest economy, ranking just below the Netherlands (18^{th}) and above Switzerland (20^{th}). See Table A.1 for how Turkey compares to the US, Europe, and other emerging markets.

Despite SMEs' central role in the Turkish economy, financial access remains a major impediment for Turkish businesses. In 2019, access to finance was the biggest business obstacle in Türkiye across all business sizes. Whereas only 15 percent of SMEs in Europe and Central Asia stated access to finance was the most important constraint (The World Bank, 2019), a third of Turkish businesses indicated financing was the most important hurdle, more than other challenges such as tax rates and political instability. SMEs rely exclusively on bank lending and face greater costs in raising external capital (Berger and Udell, 2002), making them disproportionately sensitive to macroeconomic fluctuations and credit cycles. Given the importance of financing, the experiment generates high-stakes opportunities for participating businesses.

Figure A.1 plots annual inflation, GDP growth rate, and the exchange rate with U.S. dollars. Macroeconomic conditions in Türkiye were relatively stable during our experimental period. In our analysis, we conduct robustness tests by measuring key outcomes in real Turkish Lira and US dollars to confirm that our results are not driven by inflation or exchange rate depreciation.

Lines of Credit. Lines of credit are an instrumental form of financing for SMEs, constituting 70 percent of all bank lending to small firms (Kashyap et al., 2002). Lines of credit are used to finance investments when profitable opportunities arise and for smoothing cash flow shocks to access liquidity in bad times and avoid financial distress (Chodorow-Reich et al., 2022). The 'flexibility' to borrow on-demand is the key feature that makes lines of credit particularly valuable for businesses with high hedging needs (Froot et al., 1993; Acharya et al., 2007).[8] In our sample, businesses extensively utilize bank lines of credit. We display the capacity utilization histogram in Figure 2.

[8]See, for example, Shockley and Thakor (1997), DeMarzo and Sannikov (2006), Sufi (2009), Jiménez et al. (2009) and Lins et al. (2010) for discussions on the importance of business lines of credit as a provision of bank liquidity. Holmström and Tirole (1998) provided a theoretical framework highlighting that a committed line of credit can relieve financial constraints by providing liquidity insurance.

Our bank underwrites covenant-free, unsecured lines of credit based on business income and risk. After establishing the line of credit, our bank charges an up-front commitment fee to allow SMEs to draw down any amount up to the specified debt capacity at any time. These contracts typically last 3 to 5 years and are renewed at expiration.

Businesses can draw down on the *single* capacity on the line of credit in two ways either as a flexible-payment revolving debt or as a fixed-payment term debt. If businesses draw revolving debt, they can borrow up to their debt capacity over a billing cycle and decide whether to pay off the debt (partially or in full) or carry debt across pay periods by paying a pre-set interest rate on the unpaid billing-end balance. Businesses can roll over revolving debt provided their line of credit is active. The interest rate (i.e., APR) is capped at 24 percent by the regulator, and this maximum is binding for all businesses. Thus, all businesses in our experiment face the same interest rate, and this rate does not vary over time or across firms.

Alternatively, businesses can draw down term debts and make fixed payments until the principal and interest are paid off. In our setting, all term debts are point-of-sale (POS), in which businesses purchase at a participating vendor and pay for those purchases over up to 12 months, usually with no or near-zero interest.[9] Our bank accepts fees from participating vendors and originates these loans without conducting a separate credit check. Term debts can only be issued in-store at purchase and cannot be refinanced. The change in term debt is defined through an accounting identity to the new spent financed with term debt minus due payments for existing term debt. Moreover, their use is restricted to financing durables or business services (e.g., machinery, auto parts, etc.). Hence, an increase in term debt always reflects new spending and never a refinancing or modification of the existing financing structure. Total debt equals the sum of revolving and term debt components.

Several reasons explain why term debts are less expensive than revolving debt. From the perspective of our bank, term debts are effectively subsidized by participating vendors because they pay a transaction fee each time businesses draw down term debt on lines of credit to finance their purchases. Whereas term debts are not technically collateralized, they can be considered a secured debt because our bank can seize the durable asset purchased with term debt in the event of bankruptcy. Finally, term debts tend to have lower expected losses than revolving debt.

2.2 Research Design

Collaborator. We collaborate with one of the largest commercial banks in Türkiye that offers retail banking products to SMEs with 0-10 employees. Our bank holds 17 percent of the market share in the local private lending market, serving more than 13 million businesses that are representative of the population that participates in the local banking system.[10]

Sample. The experiment's participants include 3,169 businesses approved for a capacity increase in the summer of 2014. These businesses are identified by the bank, and they are *not* applicants that sought out more credit. Our bank periodically assesses existing clients' capacities in real terms to identify businesses with depleted real debt capacity. Specifically, proprietary underwriting criteria are used to predict the bank's revenue and costs based on factors such as the businesses' capacity utilization and risk of default. Businesses that recently (i.e., within the last six months) opened accounts or received a capacity increase are

[9] The vendor facilitates the loan, but the bank disburses and ultimately backs it. This arrangement benefits both parties, as it boosts sales for both vendors and banks. Businesses can always purchase outright (and revolve later), but not vice versa.

[10] Our bank's retail banking market share is comparable to that of JPMorgan Chase in the US (Statista, 2023).

eliminated from consideration. This process led to 3,169 businesses eligible for automatic credit increases.[11]

Randomization Next, approved businesses are stratified into equal-width bins with respect to end-of-billing cycle balances over debt capacity. A random subsample is drawn from each stratum using a random number generator. This group, which we denote $\mathbb{Z}_i = 1$, receives an automatic capacity increase. The control group ($\mathbb{Z}_i = 0$) is excluded from the lender-initiated capacity increase. Note that although the assignment to the treatment group, $\mathbb{Z}_i$, is random, the magnitude of the capacity increase is not randomized. See Figure 1 for the experimental timeline.

Other Features. The experiment is conducted in a natural, real-life setting. Because the approval process is part of our bank's normal business operation, the experimental sample is unaware they were participating in an experiment. The issuer pushes the capacity increases without preannouncement or a request from the business. The capacity increases are also difficult to predict using a comprehensive econometric prediction based on repeat learning and calibration. Treated businesses are notified of their debt capacity change through their statements and their preferred method of notification. This "surprise" treatment is ideal for examining businesses' behavior because the treated and control businesses have similar expectations about their future debt capacity.

As discussed in Section 2.1, the intervention only affects debt capacity without affecting other contract terms, such as maturity and pricing. The "surprise" treatment and uniform pricing minimizes selection, moral hazard, substitution, and wealth effects. Thus, treatment effects should capture businesses' response to a truly exogenous increase in debt capacity. Due to our bank's institutional constraints, the treatment assignment is rolled out over two calendar months.

2.3 Data

We obtain administrative credit line usage data covering three years before and after the onset of the experiment. The data contains detailed information on the businesses' debt capacity, balances for each type of debt (e.g., revolving vs. term), spending amount and categories by financing type (e.g., durable investment or operating expenses), and basic information on liquid assets (e.g., checking balances). We supplement this data with information on distress delinquency, and restructuring. The unit of observation is business-by-month.

Overall, this dataset allows us to track how much firms drawdown on their business credit lines, which financing contracts they choose, where firms spend money using credit lines (i.e., spending), and their likelihood of default at monthly frequency. We do not observe firm demographic (e.g., industry, ownership structure, risk scores, etc) or financial information (e.g., cash flows, sales, profit, etc) beyond those that can be tracked by credit line usage activity. We also do not observe SMEs' financial activities at other financial institutions if firms bank with multiple banks. However, the credit line usage activity we capture is likely to provide a comprehensive financial activity of SMEs because (1) our bank only considered active users of credit lines at our bank for this experiment; and (2) only 11 percent of the universe of Turkish firms in our size distribution bank with multiple financial institutions, making substitution across banks unlikely to affect our main estimates.

[11] The businesses in our sample capture various sectors, including retail (e.g., brick-and-mortar stores); services (e.g., repair, hair salon); food and beverage (e.g., restaurants, bakeries); hospitality, small-scale manufacturing, wholesale, professional services (e.g., lawyers, accountants, dentists); and agricultural.

Representativeness. How do our sample of businesses compare to the national distribution? To assess the representativeness of our sample, Table 2 reports summary statistics using administrative credit registry data maintained by the Central Bank of Türkiye. This Table describes the business line of credit usage for the universe of Turkish SMEs at the onset of the experiment. The range of our businesses covers the bottom half of the firm size distribution in the universe of Turkish SMEs, including the median. Specifically, the top 5 percent of businesses in our sample in terms of debt capacity our proxy for firm size match the debt capacity of a median firm in the universe of Turkish SMEs. Thus, the businesses we study capture the behavior of firms that generate meaningful economic value.

2.4 Randomization Assessment and Estimation Framework

Balance. The random assignment successfully balanced the characteristics of treated and control businesses. To visualize the balance of covariates, we plot key outcomes for the treated and control groups before the experiment. Figure 3 displays the pre-trends by $\mathbb{Z}_i$. The trends in credit usage and debt levels of the treatment and control groups are similar as far back as three years preceding the intervention. Table 3 further reports statistical tests on key outcome variables to assess the validity of randomization for the four quarters preceding the intervention. The null hypothesis for the treatment and the control groups being statistically indistinguishable has a minimum p-value of 0.15.

Estimation Framework. The randomization procedure makes $\mathbb{Z}_i$ an exogenous instrument for econometric evaluation. We use this feature to examine the causal effect of capacity using a two-stage least squares (2SLS) procedure.

We first focus on the short run, the first year of the experimental period. We estimate first-stage (FS), intent-to-treat (ITT), and treatment effect (2SLS) using simple regressions of the form

$$Y_i = \beta X_i + f_s + \epsilon_i \tag{1}$$

where i denotes a business and f_s stands for randomization strata fixed effects. The FS and ITT specifications compare the average change in capacity and debt between the treatment group and the control group over a period τ using ordinary least squares (OLS). In these specifications, X_i is set to $\mathbb{Z}_i$, which is orthogonal to measurement error, omitted variables, and the residual, such as shocks to cash flows and investment opportunities.

The Wald estimator of the treatment effect is calculated as the ratio of the ITT and FS effects:

$$\beta_\tau^{\text{Wald}} = \frac{\beta_\tau^{\text{ITT}}}{\beta_\tau^{\text{FS}}} = \frac{\mathbb{E}\left[\Delta^\tau \text{ Debt}_i | \mathbb{Z}_i = 1\right] - \mathbb{E}\left[\Delta^\tau \text{ Debt}_i | \mathbb{Z}_i = 0\right]}{\mathbb{E}\left[\Delta^\tau \text{ Capacity}_i | \mathbb{Z}_i = 1\right] - \mathbb{E}\left[\Delta^\tau \text{ Capacity}_i | \mathbb{Z}_i = 0\right]}$$

and captures the local average treatment effect (LATE) of increased debt capacity. As the model is exactly identified, the Wald estimate overlaps with the treatment effect obtained using a two-stage least-squares (2SLS) framework, in which changes in capacity and debt are used, respectively, as endogenous and outcome variables, with $\mathbb{Z}_i$ as an instrument for the change in debt capacity.

For β_τ^{Wald} to have a causal interpretation, $\mathbb{Z}_i$ must be (1) independent of potential outcomes; (2) have a clear, monotonic effect on debt capacity; and (3) influence business behavior only through its impact on debt capacity. The experiment features partial compliance because our bank did not prevent control businesses from obtaining higher debt capacity if they requested a capacity increase (i.e., ”always-takers”) nor did they prevent treated businesses from opting out (i.e., ”never-takers”).[12] The LATE framework computes the average

[12] After 12 months, 77% of the treatment, 24% of control always-takers received a capacity increase; and 22 percent

treatment effect by computing the weighted average of effects on the compliant subpopulation (Angrist and Imbens, 1994).

We also examine long-run dynamics using the following distributed lag specification:

$$Y_{it} = \sum_{j=1}^{T} \gamma_j X_{ij} + f_t + f_s + \epsilon_{it} \tag{2}$$

where f_t and f_s denote time and strata fixed effects, respectively. For FS and ITT specifications, the instruments (i.e., X_{ij}) are set to be the treatment assignment $\mathbb{Z}_i$ interacted with time dummies $\times f_{t=j}$. We obtain long-run cumulative first-stage and intent-to-treat coefficients, $\Gamma_\tau^{\text{FS}} = \sum_{j=1}^{\tau} \gamma_j^{\text{FS}}$ and $\Gamma_\tau^{\text{iTT}} = \sum_{j=1}^{\tau} \gamma_j^{\text{ITT}}$, by cumulatively summing the point-in-time coefficients. Cumulative treatment effects of a unit change in capacity, over τ quarters since the capacity increase are similarly obtained by cumulatively summing the point-in-time treatment effects, $\Gamma_\tau^{\text{TE}} = \sum_{j=1}^{\tau} \gamma_j^{\text{TE}}$, where γ_j^{TE} are estimated using 2SLS. For the long-run analysis, we collapse data into quarterly and estimate effects on NxT = 3,169 x 12 participant-quarter observations. Robust standard errors are corrected for clustering at the business level.

Table A.2 summarizes the estimation framework. Panel A reports the estimation framework for short-run point-in-time estimates, whereas Panel B reports the framework for long-run dynamic effects.

2.5 Pre-Experimental Borrowing and Debt Capacity

Before we examine the impact of debt capacity expansions, we first assess how our experimental sample looks before the intervention and establish that most SMEs we study do not appear to be financially constrained. Table 1 displays summary statistics. Before the experiment, the average line of credit capacity and debt (stock) were 4,662 and 1,569 TRY, respectively. Roughly 44 percent of outstanding debt represented expensive revolving debt; 56 percent were less expensive term debts. The average monthly spending (flow) using lines of credit was 823 TRY. Three-quarters of spending is used to cover operating costs (regular spending), while a quarter is spent on financing investments using term debts. Businesses, on average, have 1,248 TRY in liquid cash deposited at our bank.

Financial Slack. We further assess SMEs' pre-experimental credit usage and financing choice and document two novel facts. First, most SMEs have debt levels far below their capacity limits. Figure 2a illustrates this point visually. In the month before the intervention, less than 10 percent of SMEs were truly financially constrained in the sense that they exhausted nearly all of their capacity and could no longer borrow (utilization ratio of more than 98 percent). An average firm utilized 39 percent of their debt capacity and a median firm 33 percent, with roughly 13 percent of firms not having any outstanding debt on their credit lines.

Financing Choice. Second, despite revolving debt being markedly more expensive than term debt, most SMEs rely on revolving debt. Figure 2b plots the distribution of financing choice or the ratio of expensive revolving debt to the total debt on the line of credit. Three mass points stand out 13 percent of businesses do not borrow at all; 17 percent exclusively borrow on term debts that can only be used to finance investment; and 14 percent

of treatment did not receive a capacity increase never-takers. The partial compliance reflects the fact that some treated firms are never-takers who did not consent to receive promotional offers, and some control firms are always-takers who requested a capacity increase. Partial compliance is a standard feature of RCTs, and the Instrumental Variables (IV) addresses this concern by identifying effects on compliers (Angrist and Pischke, 2009).

exclusively borrow expensive revolving debt, which is used primarily to cover the operating costs of running a business. The remaining 56 percent of the businesses use a mix of revolving and term debts to finance day-to-day operations and investment.

3 The Effect of Capacity Expansions on Debt

This section examines the effect of treatment assignment on capacity (first-stage) and debt (intent-to-treat), the effect of debt capacity expansion on debt (treatment effect), and heterogeneous treatment effects. Section 3.1 and Section 3.2 present first-stage, short-run (up to 12-months) and long-run (up to 36-months) ITT and TE. Section 3.3 reports heterogeneous treatment effects, and Section 3.4 reports robustness analysis.

3.1 The First-Stage Effect on Capacity

The random assignment $\mathbb{Z}_i$ had a large and monotonic effect on debt capacity. To visualize how debt capacity for the treated and the control group evolved over time, Panel A of Figure 4 plots the first 12 months effects and shows that treated SMEs' debt capacity increased sharply in the first two months and remained high after 12 months. Panel B long-run effects over 36 months after the intervention. The difference in debt capacity between the treatment and the control group remained wide and did not attenuate in the long-run. Control businesses' debt capacity also increased slightly over the same period, consistent with partial compliance discussed in Section 2.2. Panel B of Figure 4 shows first-stage response adjusting for inflation.

The first-stage effects are economically large and statistically significant. To assess the economic significance of the first-stage effect more effectively, the first row in Table 4 reports average effects using the short-run specification 1. The experimental assignment is associated with a first-stage effect of 2,562 TRY after three months and 2,351 TRY after 12 months, which constitutes a 50% increase in pre-experiment capacity. The F-statistic for these first-stage regressions are 95 and 104, respectively, indicating that $\mathbb{Z}_i$ is a strong instrument for debt capacity.The change in debt capacity corresponds to $1,041 in US dollars. These effects persist in the long-run, as shown in Table 5.

3.2 Intent-to-Treat and Treatment Effects on Debt

Short-Run Effects. The randomized debt capacity expansions led to a large and immediate borrowing response for treated SMEs. Figure 5a illustrates that treated SMEs' borrowing increased sharply in the first five months of the experiment and leveled off at high levels six months into the experiment.

The ITT effects on drawdowns are large and economically meaningful. The second row of Table 4 shows that relative to the control group, treated businesses borrowed 538 TRY more after three months and 820 TRY more after 12 months. The magnitude of the 12-month debt response corresponds to a 52 percent increase in the pre-experiment capacity mean. Both estimates are highly statistically significant (p=0.008 and p=0.003). The 12-month response corresponds to $363 in US dollars. The third row of Table 4 reports the treatment effect, $\beta_{\tau}^{\text{Wald}}$. For a dollar of debt capacity increase, businesses spent 21 cents (i.e., $538/2,562 = 0.21$) after 3-months and 35 cents after 12-months.

Overall, treated SMEs exhibited a large drawdown effect in response to debt capacity expansion in the short-run. However, whether these drawdown effects are temporary because firms are pulling expenditures forward or long-lasting because they commit their debt capacity to financing projects in the long-run is an open question.

Long-run Dynamics. We track ITT and TE over three years to examine long-run dynamics. Given that the experiment created long-run differences in debt capacity, the persistent first-stage effect allows for an investigation of long-run effects. We use a dynamic quarterly specification shown in eq. (2) to assess the economic magnitude.

Higher debt capacity had a persistent effect on business drawdowns. Figure 5b shows these results visually. The increase in drawdowns remain high well beyond the first year and persist until 36 months after the intervention. To better assess the economic magnitude, the first four columns of Table 5 report cumulative estimates, and the last three report point-in-time estimates to capture delayed response during the first year after the first quarter, second year, and third year of the capacity increase. Treated businesses cumulatively drew down 902 TRY and 1,296 TRY more after 8 and 12 quarters, respectively, relative to control businesses. The treatment effects are large and meaningful, with businesses cumulatively borrowing 44 cents after 8 quarters and 55 cents after 12 quarters out of a dollar increase in debt capacity over the same time horizon. Figure 6 plots the long-run cumulative coefficients Γ_τ^{FS}, Γ_τ^{ITT}, and Γ_τ^{TE} and tracks how treatment effects build up over time.

Overall, the effect of debt capacity expansion of SME borrowing is large and persistent. These results are surprising given that an average firm in our sample has substantial financial slack. To assess whether the large drawdown response is mainly driven by businesses that were financially constrained before the intervention, the next section examines heterogeneous treatment effects.

3.3 Heterogeneity by Financial Slack

To document heterogeneous treatment effects, we group businesses into four equal-sized groups ($K = 4$) based on their average utilization (i.e., debt-to-capacity) ratio over the 12-month period before the onset of the experiment and estimate a variant of the simple specification Equation (1):

$$Y_i = \sum_{k=1}^{K=4} \psi_{jk} \cdot X_{ij} \times f_k \; + f_s + \epsilon_i \tag{3}$$

where k denotes a bin and f_k stands for bin fixed effects. Figure 2a (right) displays the histogram of utilization over this period.[13]

The short-run estimates reveal that financially constrained businesses exhibit a higher drawdown response. Panel A of Figure 7 displays 12-month treatment effects for subsamples of SMEs grouped by their baseline capacity utilization. The figure shows a clear gradient in the their drawdown response, with more constrained businesses exhibiting higher TE relative to less constrained (i.e., 0.2 vs. 0.49). One exception is the most constrained group in the top quartile, which exhibits a large TE of 0.36 but not as large as those in the third quartile. We conjecture that precautionary motive to preserve debt capacity may override the financing needs for SMEs in the top quartile.

The long-run estimates show that while more constrained businesses exhibit large and persistent treatment effect, even businesses with substantial financial slack exhibit a large drawdown response. Panel B of Figure 7 displays 36-month TEs by baseline utilization ratio. The most constrained SMEs (top quartile) exhibited 50 percent higher drawdown response relative to the least constrained SMEs (bottom quartile). While constrained SMEs borrowed

[13] We assume that utilization is 0 for months that a business does not have any outstanding debt balance on their lines of credit and that it's 1 for months that a business has not yet opened a line of credit. The latter assumption applies to 11 percent of businesses that opened a new account within a year of the onset.

more than less constrained SMEs, even those with substantial financial slack drew down significantly of at least 0.4 on the dollar of expanded debt capacity.

In summary, while the large drawdown response can be attributed to SMEs that were more financially constrained in the short-run, all SMEs exhibited a large borrowing response irrespective of their financial slack in the long-run.

3.4 Robustness and Magnitude Assessment

We provide a battery of robustness checks to ensure that our main TEs are not simply driven by inflation, nature of firms we study, and balance shifting. In Panel A of Table 6, we conduct robustness tests using US dollars and real TRY to ensure that fluctuations in the exchange rate or inflation do not drive our results. The first row uses the dollar value of debt as a left-hand-side variable. The second row uses the real value of debt as a left-hand-side variable, deflated using the price deflator for personal consumption expenditures. The estimates remain quantitatively consistent compared to our main short-run estimate of 35 cents. See Table A.4 for long-run TEs in Euros and USD.

We ensure that our results are generalizable to the broader population of Turkish SMEs and do not simply reflect a large number of very small firms exhibiting large drawdown responses. In the first row of Panel B, we reweight the sample to match the distribution of the universe of Turkish SMEs in terms of capacity utilization rate. In the second row, we restrict our analysis to the largest 5% of firms in our sample that look like a median SMEs in the economy in terms of average debt capacity. The sample re-weighting generates quantitatively similar estimates, and restricting our sample to the largest SMEs in the sample deliver estimates that are even larger than our baseline estimate of 35 cents.

An important concern is that our estimates do not identify SMEs' net propensity to spend but rather their propensity to substitute financing elsewhere. In this case, the large drawdown response would reflect a substitution between financing that does not lead to real effects. In Panel C of Table 6, we provide evidence that our treatment effect does not simply reflect substitution across accounts. The first row reports treatment effects restricting the 74 percent of SMEs that do not have a bank account elsewhere, and the second row restricts the sample to 41 percent of SMEs that do not have a cash account at our bank. Both sample restrictions deliver estimates quantitatively similar to our baseline estimates. In the last row, we directly confirm that firms do not change their cash use using 59 percent of firms in our sample with checking accounts at our bank. Overall, our estimates do not appear to reflect balance shifting across accounts or across types of financing (cash vs. credit lines). This is not surprising given that only 11 percent of the universe of Turkish firms in our size distribution bank with multiple financial institutions, making substitution across banks unlikely (see Panel B of Table 2).

Magnitude Assessment. To what extent does randomization help us document accurate financing effects? Randomized control trials (RCTs) are considered the ”gold standard” for causal inference (Floyd and List, 2016), but the extent to which it helps to address identification challenges that financing is not independent of investment opportunities and their correlated confounds is not well-understood.

We demonstrate that randomization mitigates downward bias when estimating financing effects. In the spirit of Lalonde (1986) and Angrist et al. (2015), we compare treatment effects from non-experimental analysis to our experimental benchmark to gauge the size and the direction of bias one would obtain in the absence of the experiment – i.e., fixing our sample, how different would our estimates be if we did not use an experimental approach? Using data from three years before the intervention, we document a 12-month effect of having a higher debt capacity by comparing businesses with more versus less debt capacity using observational data. Because all debt capacity changes before the intervention were not randomized, naively comparing businesses with more versus less debt capacity captures bias arising from correlated confounds and self-selection.

Using non-experimental methods delivers estimates that are half as large as our experimental estimate, indicating that randomization helps to address the downward bias in estimating the financing effect. Table A.3 report the 12-month first-stage, ITT, and treatment effects using various covariate-controlled and selection-on-observables methods (i.e., variants of propensity score matching). See Section A for estimation details. Compared to our experimental benchmark of 35 cents, non-experimental methods deliver estimates of 18 to 21 cents on the dollar. We conjecture two potential reasons for this downward bias. First, businesses that seek more financing are not necessarily looking to invest but are simply asking for a higher capacity as a precautionary motive. Second, our bank might have only approved higher lines for firms that were more financially stable and lower marginal propensity to drawdown on expanded debt capacity before the experiment.

Overall, this exercise illustrates the importance of having a credible, exogenous instrument for financing. The fact that we get a substantially different estimate *for the same set of firms* illustrates that randomization effectively addresses selection bias in estimating financing effects from observational data. Instead, we illustrate that a naive comparison between businesses with more versus less financing introduces a downward bias and that this bias can reduce the magnitude of the experimental benchmark by half.

4 Financing Choice and Spending

So far, we have shown that SMEs exhibited a large and persistent drawdown response to exogenous debt capacity increases although most SMEs had substantial financial slack before the intervention. To better understand how SMEs use their expanded debt capacity, we next analyze SMEs' financing contract choice and spending. Section 4.1 examines businesses' financing choices (i.e., revolving vs term debts) and Section 4.2 explores where businesses direct the new debt. Section 4.3 discusses the effects on financial distress.

4.1 Types of Financing Contract

As discussed in Section 2.1, SMEs can draw on the *same* credit line as high-cost, flexible-payment revolving debt or interest-free, fixed-payment term debt. We decompose treatment effects – i.e., how much SMEs borrowed per dollar of expanded debt capacity – into its revolving and term debt subcomponents to examine SMEs' financing choice.

SMEs used a mix of high-cost revolving and interest-free term debt in the short-run but gradually moved away from revolving debt over time and relied strictly on term debt in the long-run. Figure 8 provides visual insight into the dynamics of financing choice by decomposing total debt response into its revolving and term debt subcomponents. Panel A shows that treated SMEs increased their use of revolving and term debt in the short-run. Over the 36 months period after the intervention, Panel B shows that that treated firms continued to increase their use of term debt over time, while the increase in revolving debt levels off and starts to decrease after the second year of the experiment until it becomes statistically indistinguishable from that of the control group.

To get precise estimate of the size of the decomposition, Table 7 and 8 report short-run and long-run effects for each financing type. In the first three months, out of 21 cent increase in borrowing per dollar of expanded debt capacity, revolving debt accounted for 29 percent (6 cents) whereas term debt accounted for 71 percent (15 cents). After 12 months, revolving debt accounted for 43 percent (15 cents out of 35 cents increase) whereas term debt accounted for the remaining 57 percent, suggesting a temporary increase in the use of revolving debt in the short-run. SMEs exclusively relied on term debt in the long run. Decomposing treatment effects into its revolving and term counterparts, Table 8 shows that term debts accounted for 58 percent of total drawdowns in the first year, 84 percent in the second year, then 100 percent of treatment effect after three years.

In summary, although businesses use a mix of high-cost revolving debt and low-cost term debts in the short run, they resort more heavily to term debt in the long-run. Specifically, revolving and term debt, respectively, accounted for 43 percent and 57 percent of total new debt after 12 months, and these shares converge to 0 percent and 100 percent after 36 months. At first glance, SMEs' financing choice is somewhat puzzling. Since term debts are interest-free, SMEs should in theory minimize their cost of financing by only drawing term debts. To better understand why firms used a mix of expensive revolving debt and inexpensive term debt, we next analyze where firms direct the each type of financing.

4.2 Spending Composition

We exploit our bank's categorization of purchase transactions by financing type to examine where firms spent their money using each financing type. Our bank categorizes purchase transactions into eight mutually exhaustive categories based on the transaction counterparty's point-of-sale identifier. Table A.5 summarizes how we aggregate detailed purchase categories.

SMEs used high-cost revolving debt to primarily finance working capital. Figure 10 shows 12-month cumulative effect on purchase transactions and the associated contribution of each spending category to each financing type. Figure 10a shows that the majority (75 percent) of revolving debt is used to finance day-to-day operating expenses. Specifically, auto and gas spending accounted for 31 percent of the response; cash advances (conversion of debt capacity to checking balances) 27 percent; fixed payments like insurance and utilities account for 15 percent; and the remainder were durable investments, such as electronics and machinery.

On the other hand, SMEs resort to term debt to finance investments. Figure 10b shows that more than 60 percent of term debt is used to finance durable investment, while the remainder is used for investment in marketing and business strategy. Specifically, 53 percent of the term debt is directed toward electronics and machinery, and 38 percent is directed toward business services.

Overall, spending patterns reveal that firms used high-cost revolving debt to finance working capital, whereas they resorted to inexpensive term debt to finance durable investments or professional business services. This finding, combined with the fact that firms gradually resort to term debt suggest that firms take time to invest. One possibility is that SMEs rely on revolving debt to smooth out day-to-day cash flows in the short-run, and once they are financially stable and can commit to a fixed repayment schedule, they resort to term debts to finance investment.

4.3 Financial Distress

Although the increase in debt capacity boosts investment, it can also increase the likelihood of financial distress. To examine whether treated businesses are more likely to experience financial distress, we supplement our data with loan performance data and consider two measures of financial distress: (1) an indicator for whether a debt is non-performing (i.e., delinquent) and (2) an indicator for whether a debt is renegotiated and restructured. Our bank considers credit line accounts as non-performing or ”delinquent” if payments have not been made for 90 days or more. In addition, since debt can be restructured before becoming non-performing, the renegotiation measure provides a less conservative measure of financial distress.

SMEs do not appear to incur high distress costs from increased borrowing. Figure 11 plots cumulative effects on delinquency and restructuring rates over 36 months following the experiment. Both the treated and control businesses are equally likely to fall into financial distress. The delinquency chart shows that as high as 10 percent of all lines fall into delinquency after three years of the experiment. However, delinquency rates are not statistically higher for treated businesses relative to control businesses. Similarly, the restructuring chart shows that the restructuring rate reaches up to more than 5 percent after three years, but treated businesses are not more likely than control businesses to restructure their debt. While we do not directly observe SMEs' returns to capital due to data limitations, the limited evidence of distress suggests that treated SMEs must have generated sufficient returns on investment to cover financing costs.

5 Economic Mechanisms

So far, we have shown that treated SMEs exhibited a large and persistent drawdown response to exogenous debt capacity expansions even though most SMEs had substantial financial slack before the intervention. SMEs did not minimize the cost of financing: they relied on high-cost revolving debt in concert with inexpensive term debt in the short-run. Higher borrowing did not lead to greater financial distress.

What economic mechanism explains these results? These results are somewhat puzzling from the *static* view of financial constraints, which suggests that only firms that are unable to borrow at a reasonable cost should respond to debt capacity expansions. In this section, we clarify the economic mechanism that explains our findings. Section 5.1 discusses the role of the financial flexibility channel and Section 5.2explores other potential channels that could explain our findings.

5.1 The Financial Flexibility Channel

We conjecture that SMEs' preference for preserving financial flexibility is the key economic mechanism that explains our findings. Under the *dynamic* view of financial constraints where firms trade off the benefits of borrowing more today against a higher expected cost of facing liquidity risks tomorrow, SMEs have incentives to preserve their debt capacity to insure against negative shocks and to readily fund investment when profitable opportunities arise (Gamba and Triantis, 2008). Thus, even firms that appear to have substantial financial slack in the static sense may face high dynamic financing constraints because firms optimally choose to borrow less today if they expect to face high uncertainty and high marginal cost of borrowing in the future (Amberg et al., 2023). Such ”hedging motive” (Froot et al., 1993) is the central economic force behind the dynamic investment models with costly external financing (Hennessy and Whited, 2005; DeAngelo et al., 2011; Nikolov et al., 2019), but this channel has received less attention in the empirical SME literature.

The financial flexibility channel helps to reconcile our (seemingly puzzling) empirical findings. First, since firms with a large distance between debt capacity and actual borrowing (i.e., lower utilization rate) can be interpreted as facing tight financing constraints under the dynamic view of financing constraints, this channel helps to rationalize why firms that appear to have substantial financial slack exhibit a high drawdown sensitivity when they experience debt capacity increases. Second, SMEs' reliance on high-cost revolving debt in the short-run when inexpensive term debt is available is consistent with the liquidity management strategy in which firms optimally choose flexible repayment contracts (i.e., revolving debt) in the short-run to manage volatile cash flows. Under this view, a possible interpretation of the greater reliance on term debt over time is that firms rely on high-cost revolving debt to strengthen their financial health in the short-run until they can commit to making regular, fixed repayment (i.e., term debt) in the long-run. Finally, the fact that higher borrowing does not lead to greater financial distress simply reflects firms' conservative borrowing behavior to preserve financial flexibility.

Smell Test We document three sets of evidence supporting the relevance of the flexibility channel. First, a large share of SMEs face a risk of hitting the binding financial constraint. Firms' desire to preserve flexibility stems from the expectation of incurring high cost of financial distress in the future. Thus, firms should face some risk of being unable to borrow in practice to have precautionary motives. Column 1 of Table A.6 reports that 63 percent of firms utilized more than 75 percent of their credit lines at least once in the 12-month period before the intervention. Columns 2 and 3 show that treatment assignment reduced this probability by 4 percentage point (ppt) in the short-run and 1 ppt in the long-run. In a related result, Table 6 shows that firms with no alternative sources of financing exhibit a larger drawdown response, consistent with precautionary motives to preserve a financial buffer being more pronounced for this group.

Second, firms with less financial slack before the intervention relied more heavily on revolving debt in the short-run, consistent with the interpretation that the take-up of revolving debt reflects firms demand for repayment flexibility. Figure 12 decomposes heterogeneous treatment effects by baseline financial constraints (i.e., Figure 7) into debt types. There is a positive, monotonic relationship with pre-experimental utilization rate and the share of revolving debt out of total borrowing (panel A), although all firms exclusively use term debt in the long-run (Panel B). Consistent with firms taking time to strengthen their financial health until they can commit to making fixed repayment, Table A.7 confirms that treated SMEs' spending volatility decreased by 33 percent (i.e., 0.09/.27) in the short-run.[14] Under the assumption that revolving debt carried interest during the entire 36-month period, we estimate that firms paid 179 TRY, or as large as 11 percent of total debt before the intervention, for repayment flexibility.

Finally, we show that firms with more spending volatility have lower utilization rate and higher unused debt capacity, consistent with firms keeping 'dry powder' when faced with high future uncertainty and distress cost. Table 9 documents the correlation between spending volatility and demand for flexibility. We infer the magnitude of uncertaintyâthe businesses' spending volatilityâfrom the variance of *unexpected* spending after residualizing predictable components of spending, such as time-effects (e.g., seasonality) and time-invariant firm-effects (e.g., some firms have higher fixed cost than others). Table 9 shows that firms with higher unexpected spending volatility have lower utilization rate and higher unused debt capacity. For example, columns 3 and 7 show that a standard deviation increase in spending volatility lowers capacity utilization by 1.5 ppt and increases available capacity by 15 percent; and moving from the 10th to 90th percentile of volatility leads to utilization reduction by 3.5 ppt, increase in unused capacity by 35 percent.

[14] We use spending volatility to proxy for firms' financial health and performance since we do not observe cash flow volatility.

Predictions of the Flexibility Channel We test the prediction of the financial flexibility channel directly by estimating heterogeneous treatment effects by the number of times firms faced binding constraints before the intervention. To the extent that precautionary motives shape how firms use credit lines, SMEs that face a higher risk of being in the strict no-borrowing kink should exhibit a higher borrowing response to debt capacity expansions. Even though firms on average maintain debt levels far below the credit limit, Figure A.2d shows that a large share of firms utilized more than 75 percent of their credit limits frequently. We take advantage of this feature to document heterogeneous treatment effects by the likelihood of firms facing binding constraints.

We document a striking, monotonic increase in treatment effects by the number of times firms hit binding constraints, defined as firms utilizing more than 75 percent of their capacity. Figure 13 shows short-run (top) and long-run (bottom) treatment effects by the number of times SMEs faced binding constraints before the experiment. Treatment effects are 140 percent larger (0.21 vs. 0.51) for firms that faced binding constraints more than 8 times relative to those that did not have any borrowing before the intervention in the short-run; and 265 percent larger (0.2 vs. 0.73) in the long-run. The magnitude of treatment effects monotonically increases with the number of times that firms hit the binding constraints, suggesting that the risk of facing financial distress plays a central role in shaping firms' borrowing decisions.

The reliance on revolving debt increases with the number of times firms hit binding constraints. Figure 14 decomposes Figure 13 into its revolving and term debt subcomponents. The share of revolving debt to total is 8 times as large (0.03 vs. 0.24) for firms that face the highest risk of hitting binding constraints relative to firms that do not borrow in the short-run. In the long-run, all firms move away from their use of revolving debt, irrespective of their likelihood of facing binding constraints. These findings are consistent with the interpretation that revolving debt contracts provide repayment flexibility, and that these contracts are particularly useful for firms that face the highest risk of illiquidity in the future.

5.2 Other Mechanisms

We explore three other economic mechanisms – lumpiness in investment, encouragement, and learning – and show limited role of these channels.

Lumpy Investments Unconstrained firms could have borrowed more in response to debt capacity expansion because higher capacity allowed them to make large investments that they couldn't have afforded before with existing debt capacity. Since investments tend to be lumpy (Doms and Dunne, 1998; Cooper et al., 1999), prior research shows that external financing can affect the timing and size of investment projects (Whited, 2006).

We confirm that lumpy investments are *not* the primary channel that explains our results. First, we confirm that 77 percent of firms in our sample could have afforded new borrowing incurred within the first 12-month of the experiment with the existing debt capacity. Treated firms do not increase their utilization rate more than control firms (see Table A.7), indicating that SMEs do not suddenly increase their utilization to finance goods they could not afford before. To better understand how the size of lumpy *investments* (rather total borrowing, which captures investments and working capital) affects ITT, we examine the probability of firms making lumpy investments and decompose the 12-month treatment effects by lumpy and non-lumpy investments. We define "lumpy" investment as an indicator that equals one if the maximum spending using term debt in the first 12 months of the experiment – i.e., our proxy for investment as discussed in Section 4.2 – on a specific category (i.e., equipment or electronics) is greater than the firm's unused debt capacity at the onset. Since our data does not capture information on granular item-by-item purchases, our measure overstates the size of ”lumpy” investments. Despite this, Table A.8 confirms the limited role of the lumpy investment channel – while the treatment assignment increases the likelihood of firms making lumpy investments by 4.3 ppt (Col 1), 74 percent of ITT (585/795) effect is driven by non-lumpy spending.

Encouragement A possible alternative interpretation behind why firms with substantial financial slack respond is that they may be ”encouraged” by the lender-initiated limit increases and perceive themselves to be profitable. Under this interpretation, firms that never experienced limit increases before the intervention should have larger treatment effects than those that experienced limit increases multiple times because ”encouragement effect” is likely to be more salient for firms that may be less aware of their own quality. However, Figure A.3 shows that there is no clear cut gradient in treatment effect by the number of capacity increases before the intervention either in the short- or in the long-run, suggesting that the encouragement effect is unlikely to the primary driver.

Learning Prior research documents that small firms exhibit behavioral biases when they make managerial decisions (Rema et al., 2014; Bruhn et al., 2018; Gertler et al., 2023). Thus, an alternative interpretation behind why firms rely on expensive revolving debt in the short-run but not in the long-run may be explained by the learning channel – i.e., firms make sub-optimal financing decisions (i.e., mistakes) in the short-run and they learn how to optimally utilize credit lines over time. Under this channel, inexperienced users of credit lines should rely more heavily on revolving debt as they have the most scope for ”learning” how to use credit lines relative to more experienced users. However, Figure A.3 shows that youngest users of credit lines are equally likely to rely on revolving debt as very experienced users, indicating the limited role of the learning channel. Table A.9 summarizes our findings and the predictions of competing mechanisms.

6 Conclusion

Contrary to the widespread notion that small firms are unable to raise sufficient external funds at a reasonable cost, we show that a large share of SMEs have sufficient financial slack. Using a field experiment that randomly expanded debt capacity to some SMEs but not to others with otherwise similar characteristics, we show that SMEs exhibit a large and persistent increase in drawdown response, even those that had the most financial slack before the intervention. Firms used a mix of high-cost revolving debt and interest-free term debt in the short-run, and they exclusively rely on term-debt in the long-run. Firms use revolving debt to finance working capital, while they use term debt is used to finance investment, suggesting that debt capacity expansion gradually increases firm investment.

We interpret our findings through the lens of the financial flexibility channel, in which firms’ desire to preserve financial flexibility shapes their financing choice and investment timing. This channel predicts that firms with a greater demand for flexibility should exhibit larger treatment effects, because debt capacity expansion is more valuable to these marginal firms. We test this prediction directly by exploiting the fact that a large share of firms in our sample frequently faced binding financial constraints (i.e., used more than 75 percent of their capacity limits) before the intervention, even though they maintained substantial financial slack on average. Consistent with the flexibility channel, we document a clear, positive gradient in treatment effects by the frequency of SMEs facing binding constraints before the intervention. Our back-of-the-envelope calculation shows that firms are willing to pay up to 10 percent of total borrowing in interest expense to have a flexible repayment contract.

Our economic interpretation resonates with Graham and Harvey (2001, p. 189): "*the most important factors affecting debt policy are financial flexibility...*"; and Modigliani and Miller (1963, p. 442): "*additional considerations, which are typically grouped under the rubric of the need for preserving flexibility, will normally imply the maintenance by the firm of a substantial reserve of untapped borrowing power* ." SMEs cautiously manage their liquidity by trading off the benefits of borrowing more today against a higher expected cost of facing liquidity risks tomorrow. This dynamic view of financing constraints enriches our understanding of SMEs' financing choice and investment timing, as firms take time to strengthen their financial health until they can fully commit their expanded debt capacity to financing investment.

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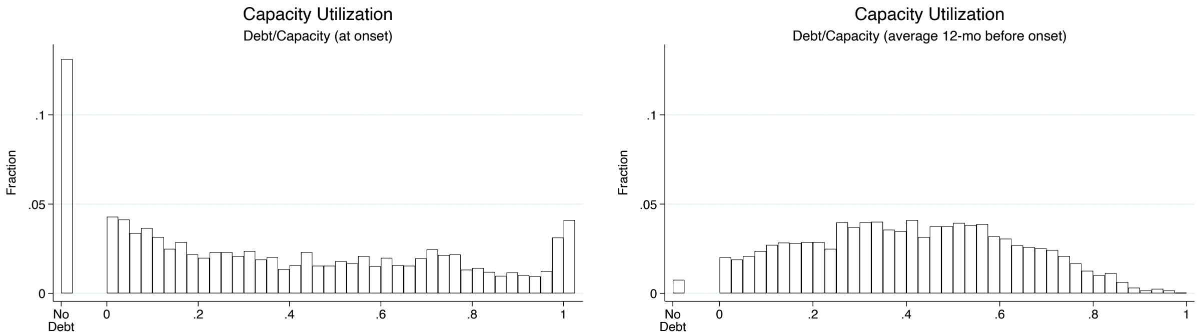
Figure 1: Experimental Timeline

Selection	→	**Randomization**	→	**Intervention**
Participants (N=3,169) pre-approved for increase ΔC_i		$\mathbb{Z}_i \in \{0,1\}$		$\mathbb{Z}_i = 1$: Treatment (N=755) pushed ΔC_i $\mathbb{Z}_i = 0$: Control (N=1,874) withheld from ΔC_i

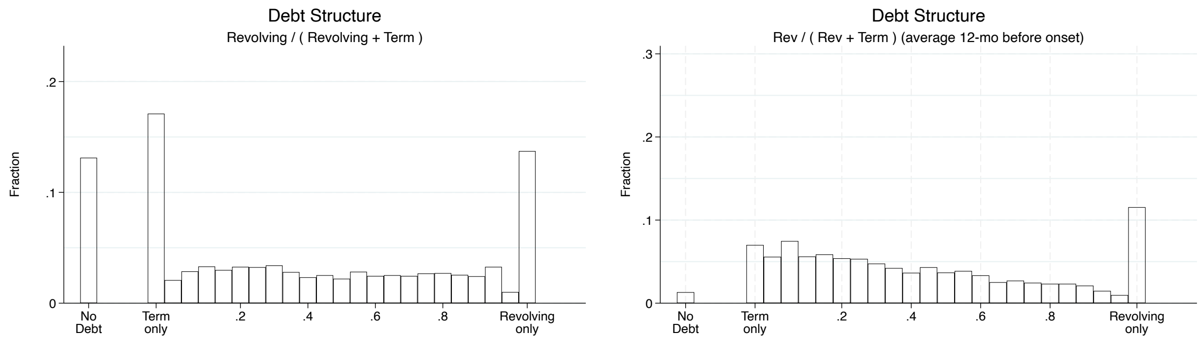
Note. This figure summarizes our randomization timeline.

Figure 2: Pre-Experimental Capacity Utilization and Financing Choice

(a) Histogram of Capacity Utilization

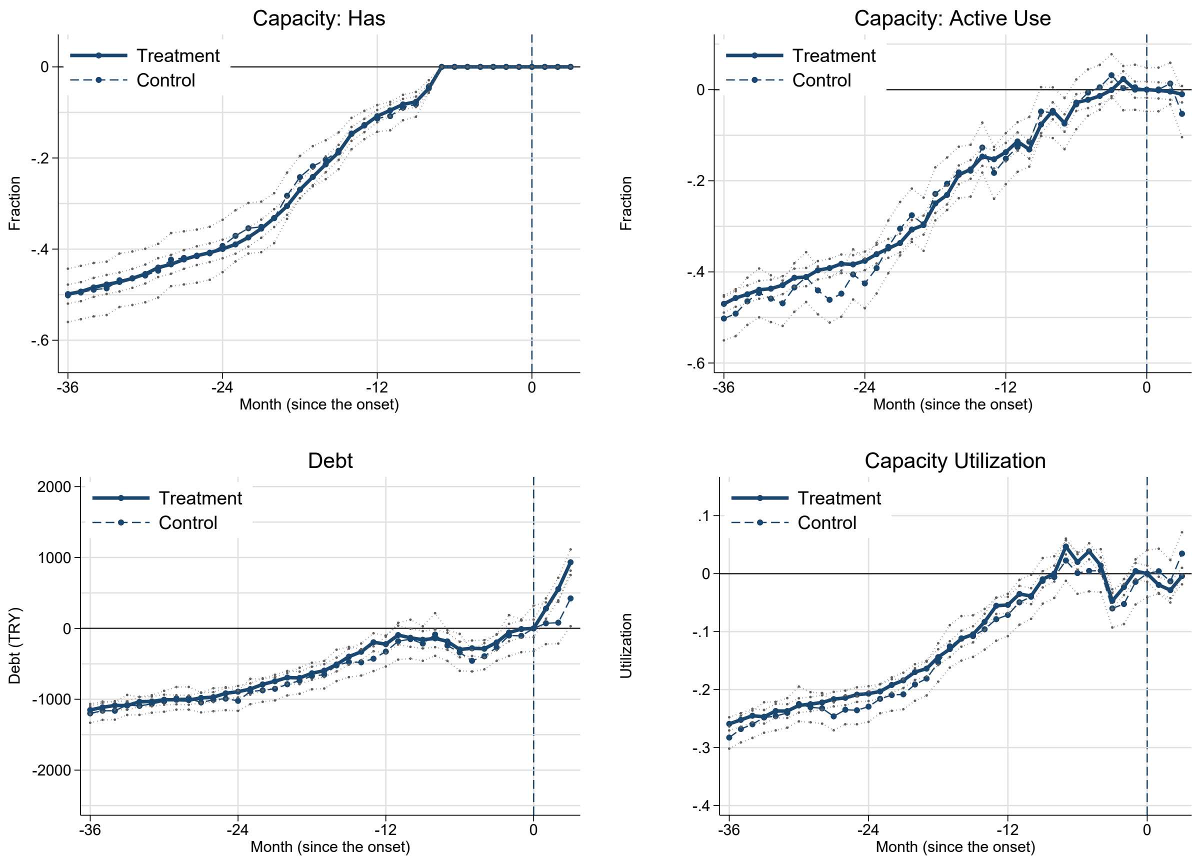


(b) Histogram of Debt Structure



Note. This figure plots the histogram of pre-experimental capacity utilization and debt structure. In each panel, the left chart plots histogram at the onset (i.e., month before the intervention) and the right chart plots outcomes averaged over the 12-month period before the intervention. In both panels, the left-most bar shows the share of businesses with no outstanding debt. Figure 2a plots the histogram of utilization rate, measured as the outstanding debt balances divided by debt capacity. Figure 2b plots the the distribution of revolving debt as a share of the total debt among businesses with outstanding debt. If the share is 0 (1), all outstanding debt is drawn in the form of term debts (revolving debt).

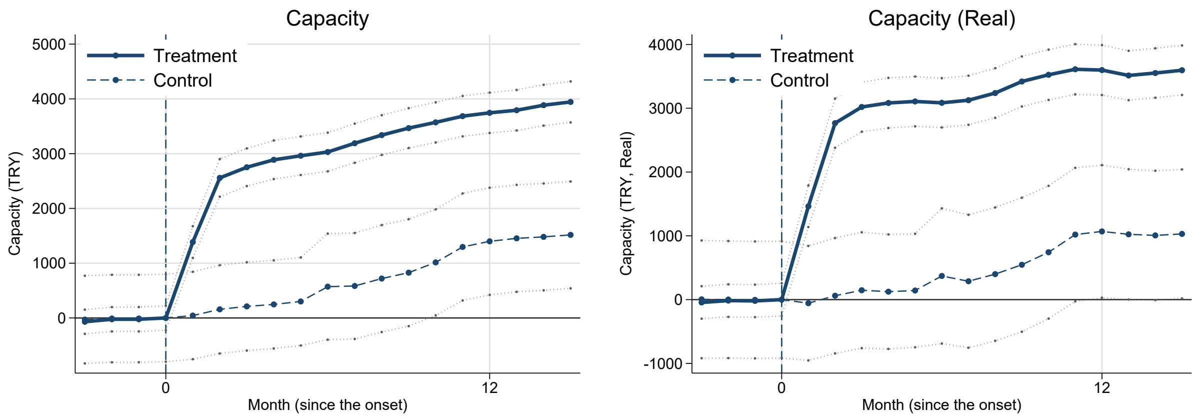
Figure 3: Covariate Balance Pre-trends



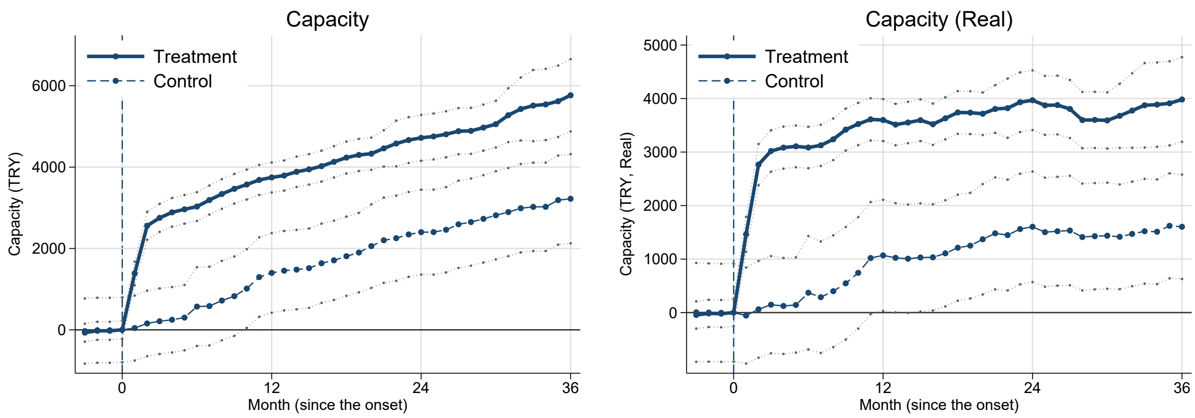
Note. Figures provide visual assessment of pre-trends by plotting covariates for treated and control group $\mathbb{Z}_i$ over 36-months preceding the experiment. The blue dashed line denotes the start date of the experiment. The y-axis is normalized to have levels equal to zero at the onset of the experiment. Dashed lines indicate 95% confidence intervals for the estimate of the mean.

Figure 4: First-Stage Effect on Debt Capacity

(a) Short-run: Nominal and Real



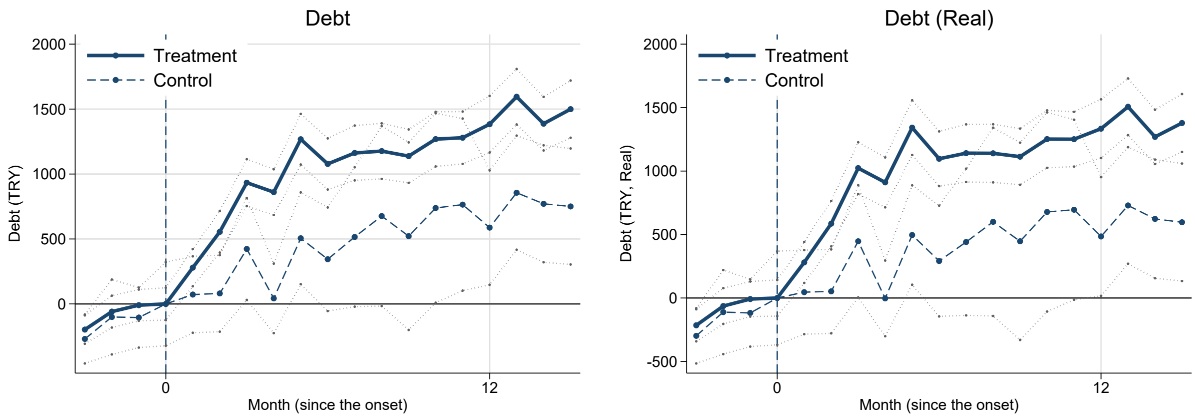
(b) Long-run: Nominal and Real



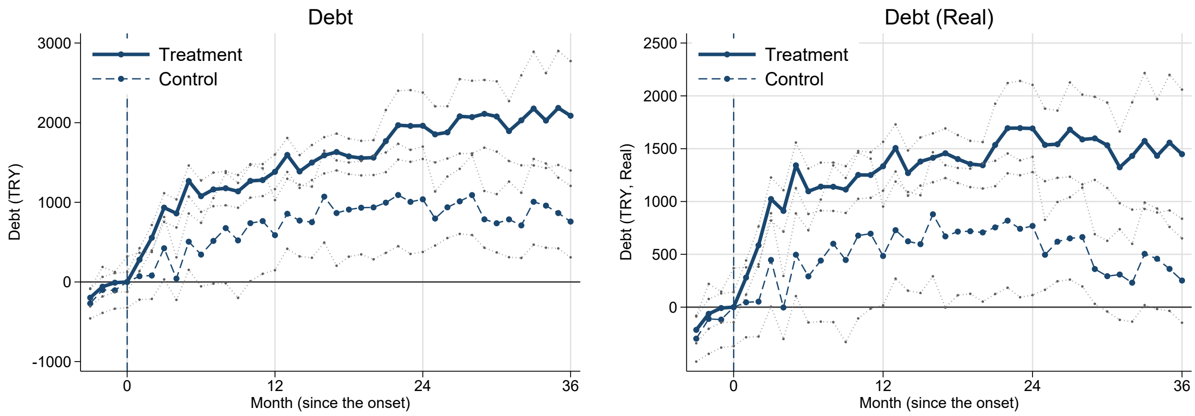
Note. In each panel, the left chart plots outcomes in nominal Turkish Lira (TRY) and the right chart plots outcomes in real TRY. Real levels are calculated using the implicit price deflator for personal consumption expenditures. Panel 4a plots short-run effects over 12 months since the onset of the experiment. Panel 4b plots long-run effects over 36 months since the onset. The y-axis is normalized to have levels equal to zero at the onset of the experiment. The blue dashed line denotes the start date of the experiment. Dashed lines indicate 95% confidence intervals for the estimate of the mean.

Figure 5: Intent-to-Treat Effect on Debt

(a) Short-run: Nominal and Real



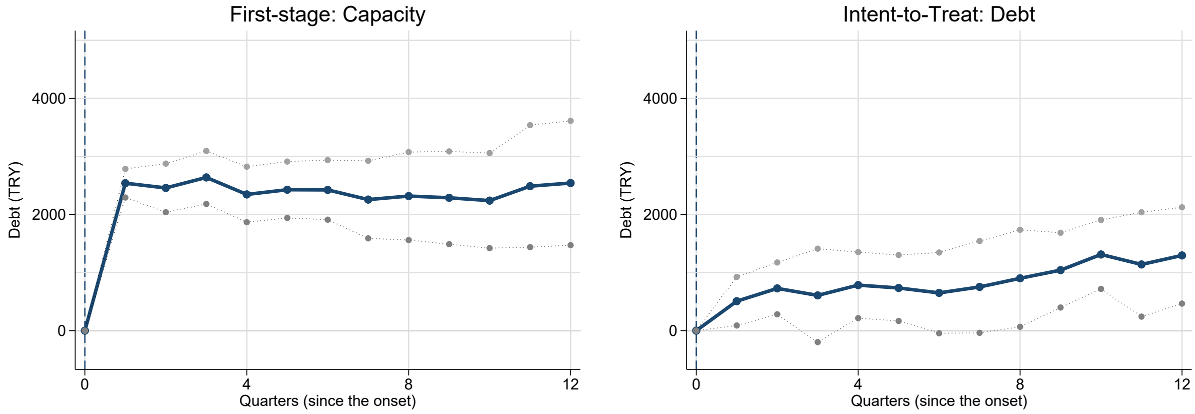
(b) Long-run: Nominal and Real



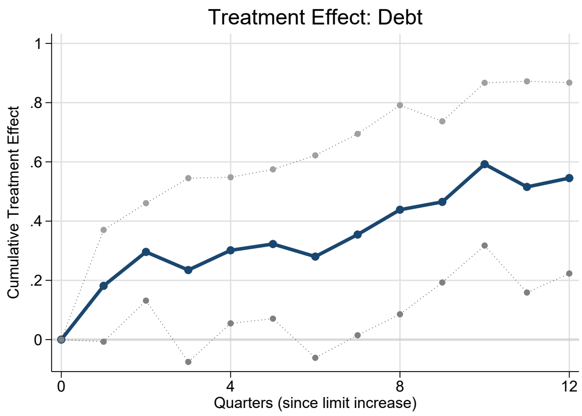
Note. In each panel, the left chart plots outcomes in nominal Turkish Lira (TRY) and the right chart plots outcomes in real TRY. Real levels are calculated using the implicit price deflator for personal consumption expenditures. Panel 5a plots short-run effects over 12 months since the onset of the experiment. Panel 5b plots long-run effects over 36 months since the onset. The y-axis is normalized to have levels equal to zero at the onset of the experiment. The blue dashed line denotes the start date of the experiment. Dashed lines indicate 95% confidence intervals for the estimate of the mean.

Figure 6: Long-run Effects on Capacity and Debt

(a) First-stage and Intent-to-treat



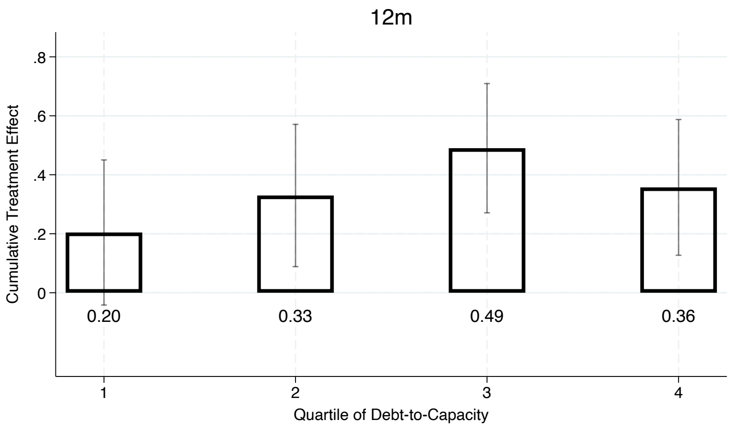
(b) Estimates: Long-run Treatment Effect



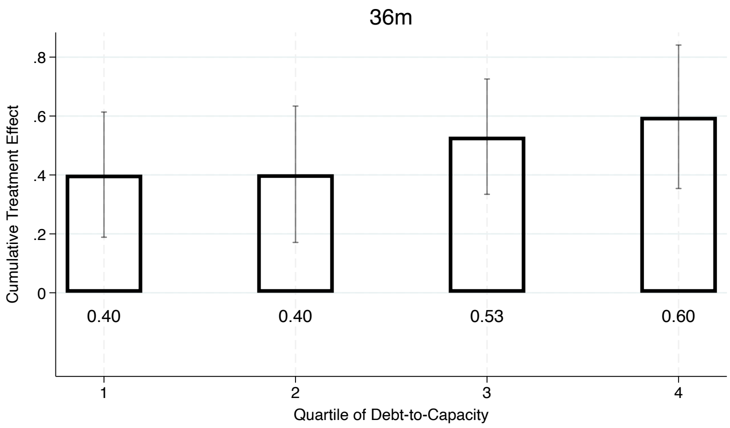
Note. Figure 6a plots first stage and intent-to-treat effects on debt capacity and total drawdowns, and Figure 6b plots treatment effects over 12 quarters since the onset of the experiment. Estimates are obtained from running Equation (2), which uses data on NxT = 3,169 x 12 firm-quarter observations and captures cumulative long-run dynamics. The ITT effects are shown in Turkish Lira (TRY). Treatment effects can be interpreted as a change in spending response per dollar (lira) increase in debt capacity. Blue dashed line denotes the onset of the experiment. Dotted lines denote 95% confidence intervals.

Figure 7: Heterogeneous Treatment Effects by Capacity Utilization

(a) Short-run: 12-month



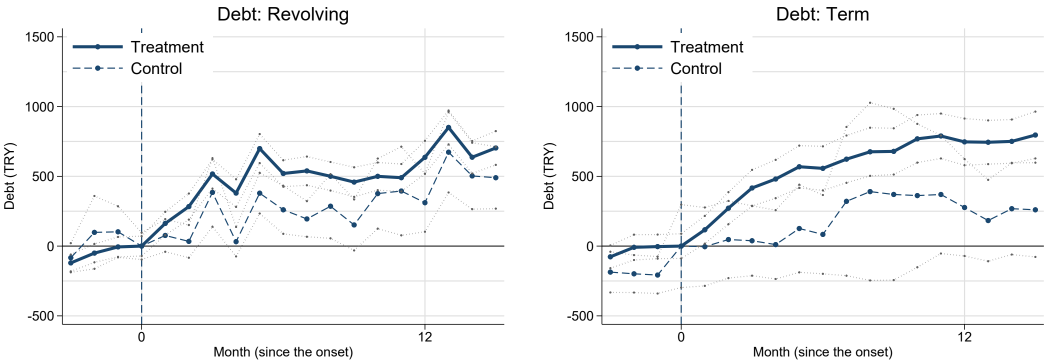
(b) Long-run: 36-month



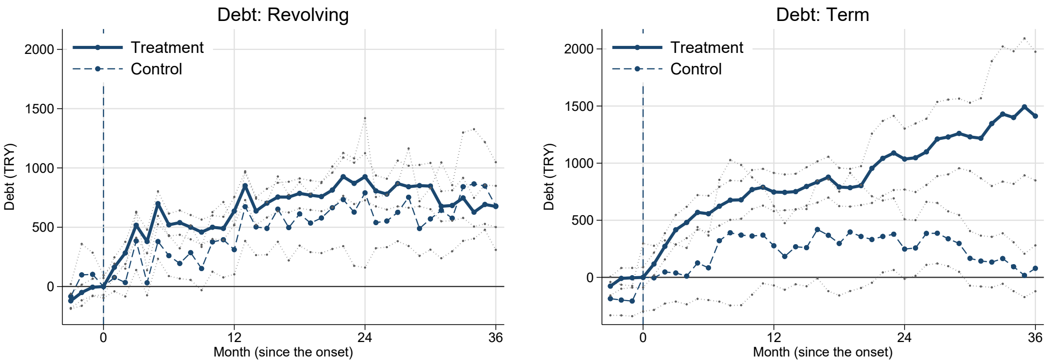
Note. The figure plots treatment effect heterogeneity by baseline (i.e., pre-experimental) capacity utilization rate. Firms are grouped into four bins based on the distribution of average utilization rate over the 12-month period before the intervention. Figure 2a (right) displays the histogram of utilization over this period. Heterogeneous treatment effects are obtained using Equation 3. Whiskers denote 95% confidence interval. Treatment effects are annotated below each bar.

Figure 8: Short-Run and Long-Run Effects on Financing Choice

(a) Short-Run Intent-to-Treat



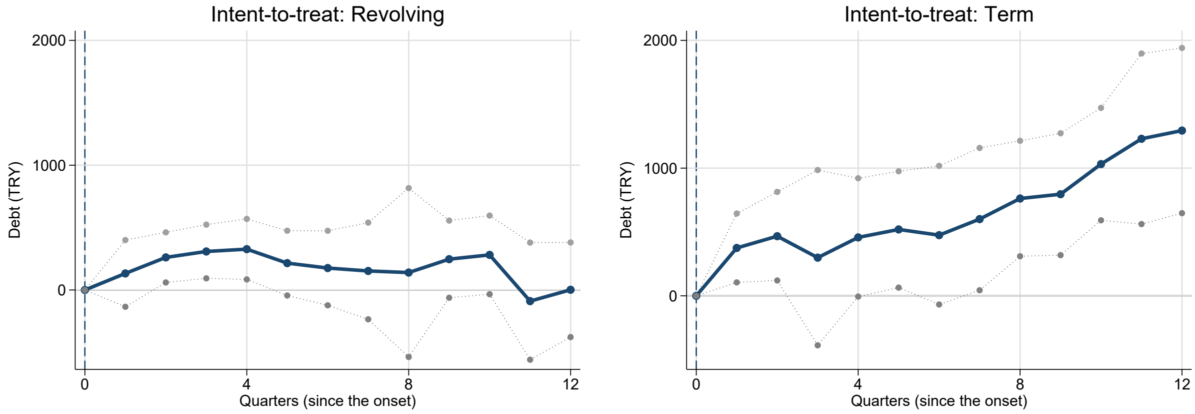
(b) Long-Run Intent-to-Treat



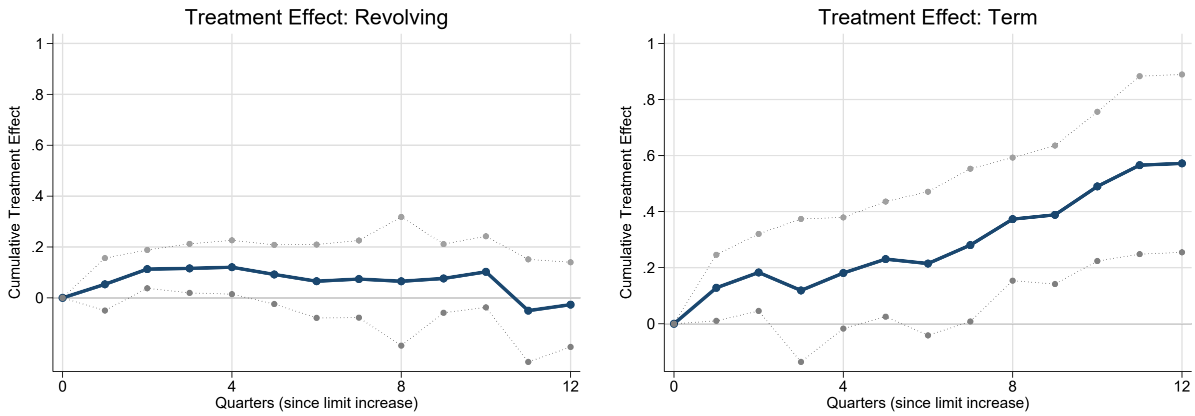
Note. Figures plot revolving and term debt by treatment status over the first 12-months (Figure 8a) and 36-months (Figure 8b) of the experiment. Firms can draw on the *same* credit line as revolving or term debt without additional approval process. Revolving debt is high-cost, interest-accruing debt and term debt is a point-of-sale term debt offered at 0% APR. See Section 4.1 for a detailed discussion on the types of debt. The sum of the two types of debt show in this figure corresponds to total debt shown in Figure 5. Outcomes are shown in Turkish Lira (TRY) and normalized to have levels equal to zero at the onset of the experiment. Blue dashed line denotes the onset of the experiment. Dotted lines are the 95% confidence intervals for the estimate of the mean.

Figure 9: Long-run Effects on Financing Choice

(a) Intent-to-treat



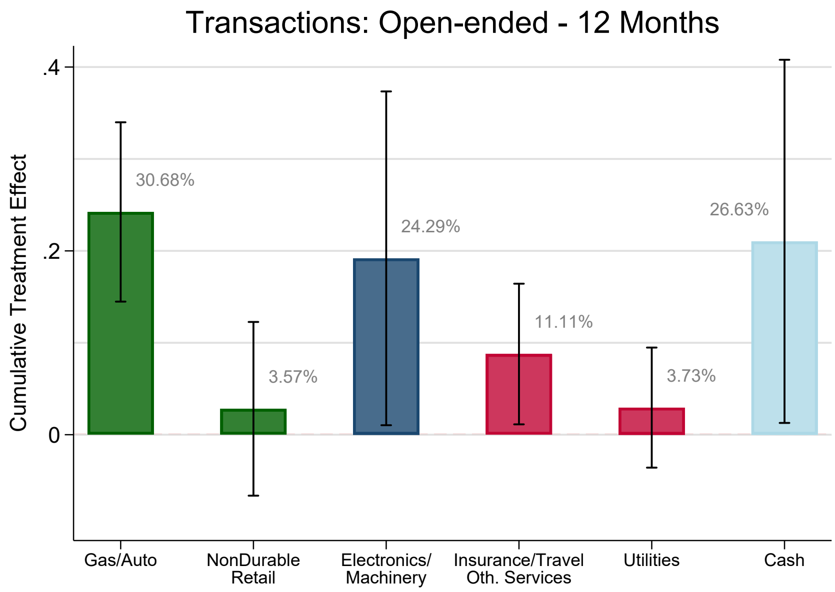
(b) Treatment Effect



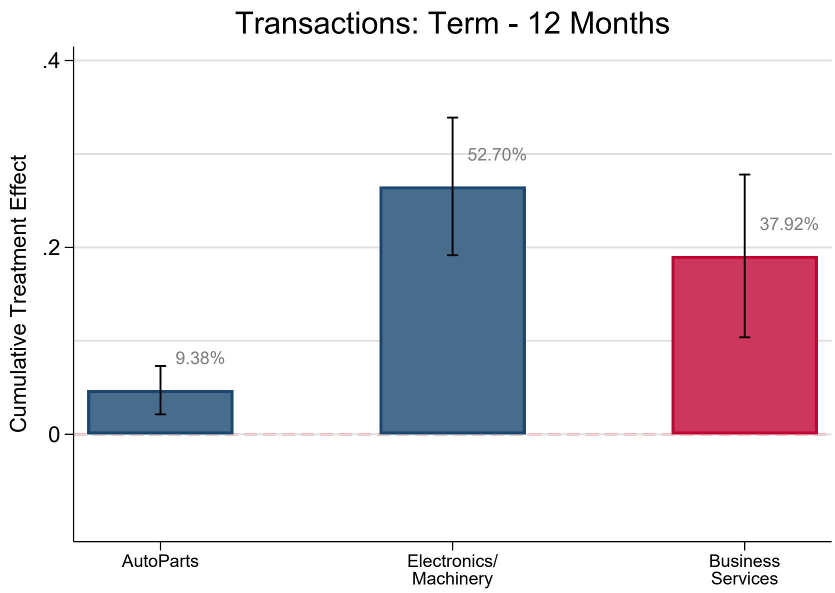
Note. Figure 9a and Figure 9b plot intent-to-treat and treatment effects, respectively, on revolving and term debt over 12 quarters since the onset of the experiment. Estimates are obtained from running Equation (2), which uses data on NxT = 3,169 x 12 business-quarter observations and captures cumulative long-run dynamics. The ITT effects are shown in Turkish Lira (TRY). Treatment effects can be interpreted as a change in spending response per dollar (lira) increase in debt capacity. Blue dashed line denotes the onset of the experiment. Dotted lines denote 95% confidence intervals.

Figure 10: Decomposition of Spending Type by Financing Choice

(a) Transactions on Revolving Debt

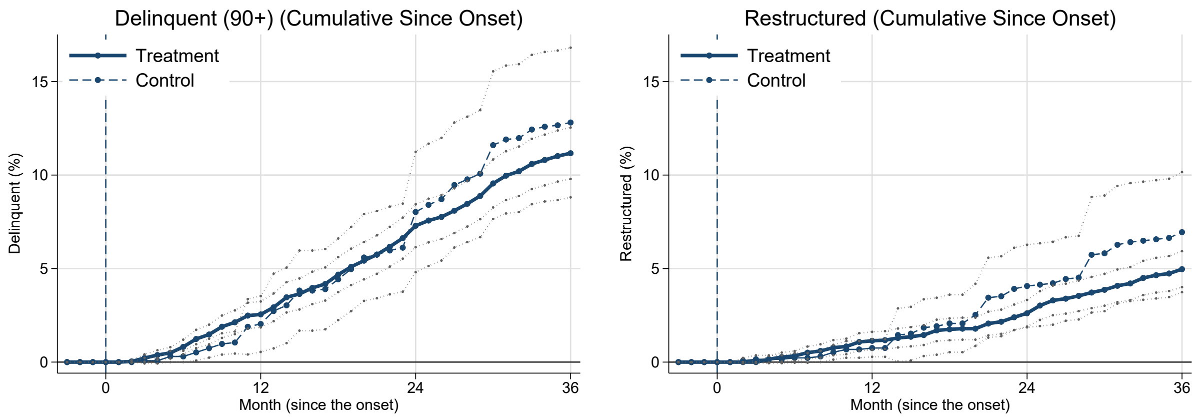


(b) Transactions on term debt



Note. This figure plots 12-month treatment effects on detailed spending categories transacted using revolving and term debt. The share of spending on each spending category relative to total transactions is shown in gray. For example, the left-most bar in Figure 10a shows that spending on gas and auto services (e.g., auto repair, car wash, inspection, etc) represents 31 percent of total transactions incurred using revolving debt. Spending on non-durable goods are shown in green; durable goods in dark blue; services in red; and cash advance in a light blue bar. term debt only captures spending on durable goods and business services, as regulations in Türkiye prohibit the use of term debt to finance strict nondurable goods. See Table A.5 for examples of transactions included in each spending category. Whiskers show 95 percent confidence intervals.

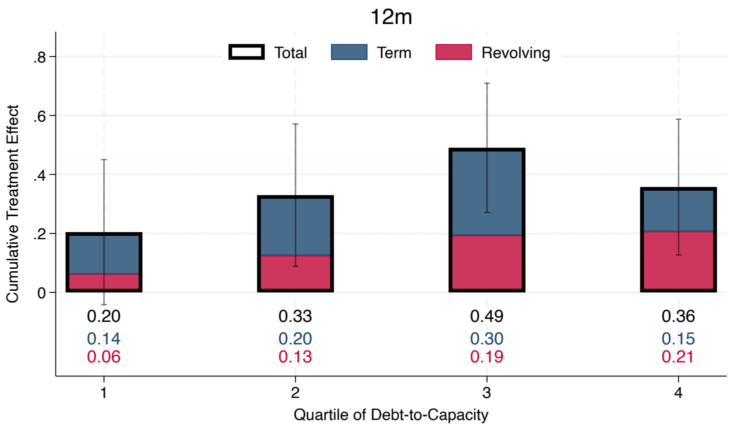
Figure 11: Event Study: Distress and Renegotiation



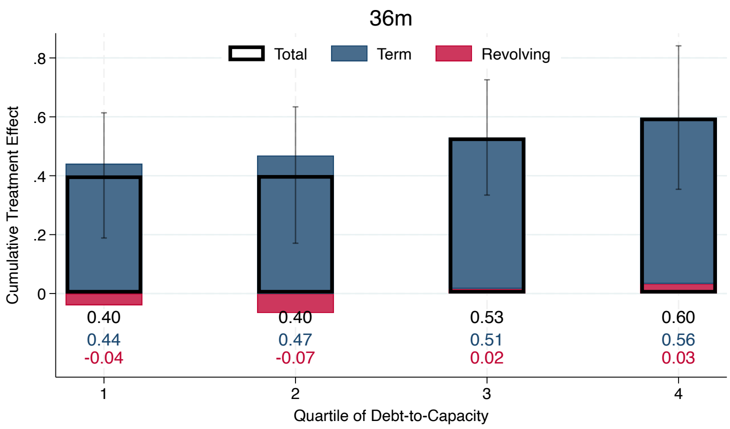
Note. Figures plot the share of businesses with non-performing (i.e., "delinquent") loans and with restructured debt by treatment status over 36 months since the onset of the experiment. A credit account is considered to be non-performing if payments have not been made for 90 days or more. Outcomes are normalized to have levels equal to zero at the onset of the experiment. Blue dashed line denotes the onset of the experiment. Dotted lines denote 95% confidence intervals.

Figure 12: Heterogeneous Treatment Effects by Capacity Utilization: Revolving Debt vs. Term Debt

(a) Short-run: 12-month



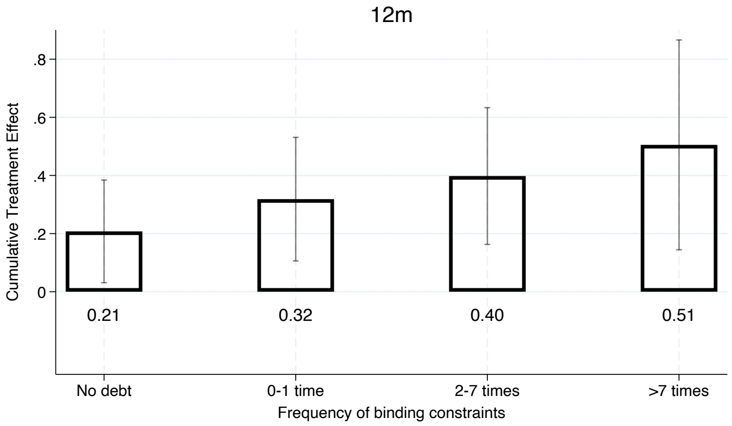
(b) Long-run: 36-month



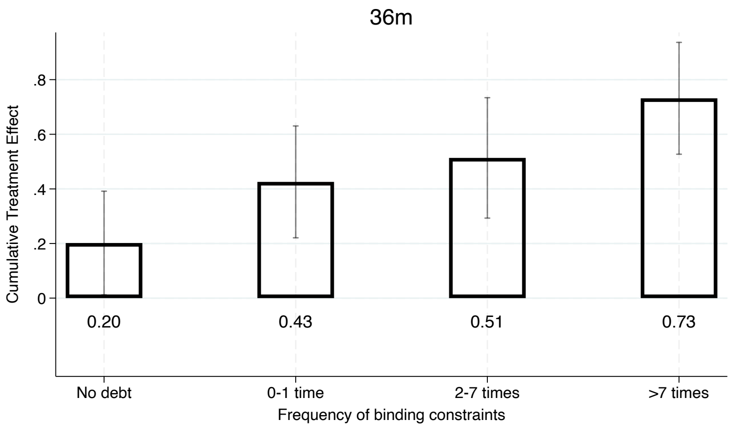
Note. The figure decomposes Figure 7 – i.e., heterogeneous treatment effects by utilization rate – into its revolving and term debt subcomponents. Firms are grouped into four bins based on the distribution of average utilization rate over the 12-month period before the intervention. Heterogeneous treatment effects are obtained using Equation 3. Whiskers denote 95% confidence interval. Treatment effects are annotated below each bar.

Figure 13: Decomposition of Heterogeneous Treatment Effects by the Frequency of Firms Facing Binding Constraints

(a) Short-run: 12-month



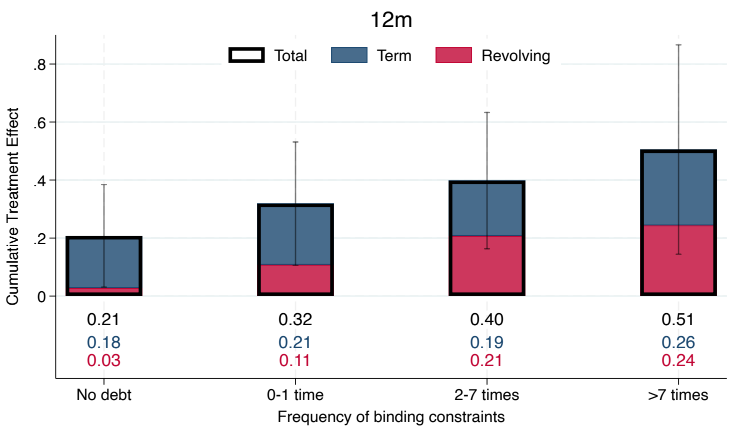
(b) Long-run: 36-month



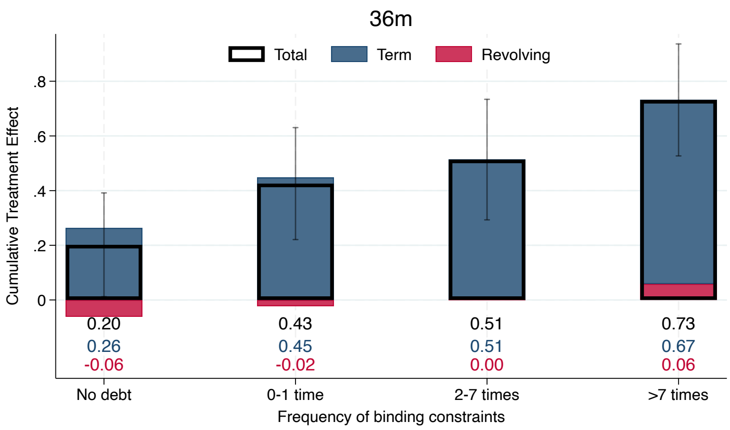
Note. The figure plots treatment effect heterogeneity by baseline (i.e., pre-experimental) the number of times firms face binding financial constraints (i.e., utilization rate > 0.75). Firms are grouped into four bins based on the number of times firms face binding constraints over the 12-month period before the intervention. These groups are firms that: (1) don't carry balance across periods; (2) hit binding constraints at least once or less; (3) hit binding constraints 2-7 times; (4) more than 8 times. Figure A.2d displays the histogram of number of times firms face binding constraints. Heterogeneous treatment effects are obtained using Equation 3. Whiskers denote 95% confidence interval. Treatment effects are annotated below each bar.

Figure 14: Decomposition of Heterogeneous Treatment Effects by the Frequency of Firms Facing Binding Constraints

(a) Short-run: 12-month



(b) Long-run: 36-month



Note. The figure decomposes Figure 13 – i.e., heterogeneous treatment effects by binding constraints – into its revolving and term debt subcomponents. Firms are grouped into four bins based on the number of times firms face binding constraints over the 12-month period before the intervention. These groups are firms that: (1) don't carry balance across periods; (2) hit binding constraints at least once or less; (3) hit binding constraints 2-7 times; (4) more than 8 times. Heterogeneous treatment effects are obtained using Equation 3. Whiskers denote 95% confidence interval. Treatment effects are annotated below each bar.

Table 1: Summary Statistics

	N (1)	Mean (2)	SD (3)	p10 (4)	p25 (5)	p50 (6)	p75 (7)	p90 (8)
lines of credit								
Capacity (TRY)	3,169	4,662	5,374	800	1,250	3,000	5,700	10,700
Debt (TRY)	3,169	1,569	2,626	0	190	784	1,891	3,690
Revolving	3,169	684	1,643	0	0	86	778	1,703
Term	3,169	885	1,845	0	0	243	977	2,430
Debt-to-Capacity	3,169	0.39	0.33	0	0.07	0.33	0.69	0.91
Unused Capacity (TRY)	3,169	3,100	4,420	137	500	1,500	3,802	7,399
Transactions (TRY)	3,169	1,050	1,968	0	77	389	1,163	2,754
Revolving	3,169	817	1,678	0	29	276	950	2,082
Term	3,169	233	914	0	0	0	0	568
Balance sheet								
Has Assets?	3,169	0.59	0.49	0.00	0.00	1.00	1.00	1.00
Checking (Bank) (TRY)	1,883	1,248	4,340	0	0	2	180	1,613

Note. Statistics based on the month before the experiment. Nominal variables expressed in Turkish Lira (TRY). Statistics represent raw distribution not adjusted by strata.

Table 2: Summary Statistics: Universe of SMEs

	Panel A: All SMEs			*Panel B*: SMEs below p50		
TRY	Capacity (1)	Debt (2)	Utilization (3)	Capacity (4)	Debt (5)	Util (6)
p5	1,480	0	0.000	668	0	0.000
p25	10,000	0	0.000	4,500	0	0.000
p50	26,500	588	0.032	10,000	0	0.000
p75	75,418	24,200	0.535	20,000	1,805	0.267
p95	337,414	124,200	1.000	25,000	15,000	1.000
Multiple Banks?		0.361			0.116	
N	3,439,077	3,439,077	3,439,077	1,719,477	1,719,477	1,719,477

Note. Source: Central Bank of Türkiye. Statistics based on the month before the experiment. Panel B based on businesses with capacity below 26,500 (i.e., the median capacity for the universe).

Table 3: Covariate Balance

	Panel A: Levels				Panel B: Changes			
	Capacity	Rev.	Inst.	Check	Capacity	Rev.	Inst.	Check
γ_{-1}	-451	37	-2	-68	-449	42	-5	-235
	(405)	(59)	(83)	(397)	(212)	(87)	(65)	(310)
γ_{-2}	42	-1	5	165	-122	-36	30	80
	(312)	(83)	(87)	(164)	(183)	(86)	(84)	(140)
γ_{-3}	206	39	-22	82	156	33	-79	-37
	(366)	(33)	(129)	(177)	(186)	(43)	(101)	(190)
γ_{-4}	94	9	59	117	-54	42	-8	32
	(490)	(38)	(111)	(207)	(107)	(74)	(84)	(193)
p	0.15	0.8	0.93	0.7	0.23	0.76	0.89	0.9

Note. Estimates from Equation (2) use data on the 4 quarters prior to the start of the experiment for the N=3,169 participants. The bottom row displays p-values for the null hypothesis that γ_j are jointly equal to zero.

Table 4: Short-Run Effects on Capacity and Debt

	Baseline Level (1)		*3m* (2)	*6m* (3)	*12m* (4)
ΔCapacity (TRY)	4,662	First Stage (OLS)	2,562	2,480	2,351
			(122)	(206)	(240)
		F-stat	95	96	104
ΔDebt (TRY)	1,569	Intent-to-treat (OLS)	538	770	820
			(201)	(216)	(280)
		Treatment Effect (Wald)	0.21	0.31	0.35

Note. This table presents first-stage (FS), intent-to-treat (ITT), and treatment effects over different time horizons after the onset of the experiment. Estimates are obtained from running Equation (1), which captures the average effect of receiving a debt capacity increase, $\mathbb{Z}_i = 1$. Since outcomes are stock variables, estimates represent the total effect on outcomes relative to the control group at different points in time. The treatment effect is obtained from 2SLS-IV procedure described in Section 2.4 and captures the change in spending per dollar (lira) of expanded debt capacity. Column 1 reports the pre-experiment mean of the outcome variables. FS and ITT effects are shown in Turkish Lira (TRY). Robust standard errors clustered at the business-level and reported in parentheses.

Table 5: Long-Run Effects on Capacity and Debt

		Cumulative				Point-in-time		
		$1q$	$4q$	$8q$	$12q$	$\sum_{j=2q}^{4q}$	$\sum_{j=5q}^{8q}$	$\sum_{j=9q}^{12q}$
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Capacity (TRY)	First-stage (OLS)	2,540 (126)	2,346 (244)	2,318 (387)	2,542 (546)	-194 (214)	-28 (295)	224 (276)
Δ Debt (TRY)	Intent-to-treat (OLS)	508 (213)	785 (290)	902 (426)	1,296 (423)	277 (201)	117 (302)	394 (424)
	Treatment Effect (2SLS)	0.18 (0.10)	0.31 (0.13)	0.44 (0.18)	0.55 (0.16)	0.12 (0.10)	0.14 (0.12)	0.11 (0.16)

Note. This table presents first-stage (FS), intent-to-treat (ITT), and treatment effects over different time horizons after the onset of the experiment. Estimates are obtained from Equation (2) using data on $N \times T$ = 3,169 x 12 business-quarter observations. Columns 1 to 4 show cumulative effects, $\gamma_\tau = \sum_{j=1}^{\tau} \gamma_j$, since the onset of the experiment. Columns 5 to 7 report cumulative point-in-time estimates. FS and ITT effects are shown in Turkish Lira (TRY). The Wald estimator of treatment effect is calculated as the ratio of FS to ITT estimates, and captures the change in spending per dollar (lira) of expanded debt capacity. Robust standard errors clustered at the business-level and reported in parentheses.

Table 6: Short-Run Effects on Capacity and Debt Robustness

	Y		N (1)	$3m$ (2)	$6m$ (3)	$12m$ (4)
	Δ Debt	Main IV Estimate as in Table 4	3,169	0.21 (0.08)	0.31 (0.09)	0.35 (0.09)
Panel A: Real Terms	Δ Debt	USD Terms Debt in U.S. Dollars	3,169	0.21 (0.08)	0.30 (0.09)	0.33 (0.12)
		Real Terms Debt deflated by CPI	3,169	0.21 (0.08)	0.31 (0.09)	0.34 (0.11)
Panel B: External Validity	Δ Debt	Weighted for External Validity to Match SME Universe	3,169	0.18 (0.08)	0.32 (0.08)	0.31 (0.10)
		Subsample Largest 5% by Capacity to Match the Median SME in Universe	156	0.39 (0.09)	0.46 (0.12)	0.49 (0.13)
Panel C: Balance Shifting	Δ Debt	Subsample No Account on Other Banks Ensure no shifting on Other Banks	2,352	0.24 (0.08)	0.35 (0.09)	0.39 (0.11)
	Δ Debt	Subsample No Cash Account Ensure no shifting on Cash	1,286	0.23 (0.09)	0.30 (0.10)	0.40 (0.12)
	Δ Cash	Cash Balances Ensure no shifting on Cash	1,883	-0.002 (0.17)	-0.01 (0.11)	-0.02 (0.25)

Note. This reports treatment effect robustness over different time horizons after the onset of the experiment. The first row reports IV estimates as shown in Table 4. Panel A reports estimates in U.S. dollars and real Turkish Liras. Real terms are deflated using the price deflator for Consumer Price Index. The first row of Panel B reports estimates reweighting the experimental sample to match the distribution of the universe of SMEs in Türkiye using utilization bins reported in Table 2. The second row of Panel B reports estimates restricting the sample to the largest 5 percent of SMEs using capacity utilization. The first two rows of Panel C reports estimates restricting the sample to subsample with no account at other banks (first row) and to those with no checking account at our bank (second row). The last row uses cash spending as an outcome for a sample of firms with checking accounts at our bank. Robust standard errors clustered at the business-level and reported in parentheses.

Table 7: Short-Run Effects on Financing Choice

	Baseline Level (1)		*3m* (2)	*6m* (3)	*12m* (4)
ΔRevolving	684	Intent-to-Treat	149	287	343
			(131)	(97)	(118)
		Treatment Effect	0.06	0.12	0.15
ΔTerm	885	Intent-to-Treat	389	483	477
			(130)	(170)	(229)
		Treatment Effect	0.15	0.19	0.20
		Revolving Share	0.28	0.37	0.42

Note. This table presents intent-to-treat (ITT) and treatment effects on revolving and term debt over different time horizons after the onset of the experiment. Estimates are obtained from running Equation (1), which captures the average effect of receiving a debt capacity increase, $\mathbb{Z}_i = 1$. Since outcomes are stock variables, estimates represent the total effect on outcomes relative to the control group at different points in time. Column 1 reports the pre-experiment mean of the outcome variables. Revolving share is defined as the ratio of revolving debt to the sum of revolving and term debt. Robust standard errors clustered at the business-level and reported in parentheses.

Table 8: Long-Run Effects on Financing Choice

		Cumulative				Point-in-time		
		1q (1)	*4q* (2)	*8q* (3)	*12q* (4)	$\sum_{j=2q}^{4q}$ (5)	$\sum_{j=5q}^{8q}$ (6)	$\sum_{j=9q}^{12q}$ (7)
ΔRevolving	Intent-to-treat (OLS)	133	327	140	2	195	-187	-138
		(136)	(124)	(345)	(193)	(157)	(315)	(375)
	Treatment Effect (Wald)	0.05	0.12	0.07	-0.03	0.07	-0.06	-0.09
ΔTerm	Intent-to-treat (OLS)	375	457	762	1,294	83	305	532
		(137)	(236)	(231)	(330)	(193)	(216)	(224)
	Treatment Effect (Wald)	0.13	0.18	0.37	0.57	0.05	0.19	0.20
	Revolving Share	0.26	0.42	0.16	0.00	0.70	-1.60	-0.35

Note. This table presents intent-to-treat (ITT) and treatment effects on revolving and term debt over different time horizons after the onset of the experiment. Estimates are obtained from Equation (2) using data on NxT = 3,169 x 12 business-quarter observations. Columns 1 to 4 show cumulative effects, $\gamma_\tau = \sum_{j=1}^{\tau} \gamma_j$, since the onset of the experiment. Columns 5 to 7 report cumulative point-in-time estimates. FS and ITT effects are shown in Turkish Lira (TRY). The Wald estimator of treatment effect is calculated as the ratio of FS to ITT estimates, and captures the change in spending per dollar (lira) of expanded debt capacity. Revolving share is defined as the ratio of revolving debt to the sum of revolving and term debt. Robust standard errors clustered at the business-level and reported in parentheses.

Table 9: Spending Uncertainty and Flexibility

Y: Effect on	*Panel A*: Debt / Capacity				*Panel B*: log (Capacity - Debt)			
X: Type of Uncertainty	Past Investment	Futu. Investment	Past Working-Cap	Futu. Working-Cap	Past Investment	Futu. Investment	Past Working-Cap	Futu. Working-Cap
β: Effect of one unit Uncertainty	-0.06 (0.07)	-0.21 (0.06)	-0.32 (0.13)	-0.12 (0.08)	0.058 (0.005)	0.027 (0.004)	0.032 (0.008)	-0.0001 (0.005)
α: Base Flexibility	39.2 (0.9)	41.0 (1.0)	40.3 (0.9)	39.5 (0.8)	6.5 (0.06)	6.7 (0.06)	6.9 (0.06)	7.1 (0.05)
Effect p value	0.41	0.001	0.012	0.13	$<$0.001	$<$0.001	$<$0.001	0.98
Effect of one σ	-0.5	-1.9	-1.5	-0.9	0.47	0.25	0.15	-0.002
Effect from $p90$ to $p10$	-1.3	-5.0	-3.5	-2.0	1.20	0.66	0.35	-0.004

Note. Table reports estimates from a regression $Y_i = \alpha + \beta X_i + \epsilon_i$, where X_i is a measure of spending uncertainty. In Panel A, Y is the debt-to-capacity ratio at the onset. In Panel B, Y is the log of capacity minus debt (in nominal terms). X is the magnitude of spending volatility, proxied by the variance of residuals from a regression of log-quarterly-spending on calendar-date dummies and firm fixed-effects. The spending volatility captures unpredictable variation in spending after accounting for seasonality and time-invariant firm-specific spending patterns. Two types of spending is considered at two different time points: spending on investment (using term debt) and on working capital (using revolving debt) 12 quarters before the intervention ("past") and after the intervention ("future"). Estimates are obtained using data on NxT = 3,169 x 12 business-quarter observations. p value is for the coefficient β. The bottom two rows display the effect of an increase in one standard deviation of risk or going from the 10th 90th percentile of risk on the size of the flexibility.

A Evaluating Non-Experimental Methods

Let D_i denote firms having a higher debt capacity today relative to 12 months before. We examine the effect of D_i (rather than Z_i) on debt capacity and firm drawdowns 3 years before the experiment. Non-experimental estimates should be similar to our experimental estimate of 0.35 in the absence of selection bias. We use the following methods:

1. Raw correlation
$$\rho = E[Y_1 - Y_0] + bias$$

2. Including strata fixed-effects (i.e., pre-experimental utilization bins).
$$\rho = E[Y_1 - Y_0|x] + bias$$

3. Including strata fixed-effects + firm controls
$$\rho = E[Y_1 - Y_0|\mathbf{X}] + bias$$

4. Strata matching à la Angrist (1998) that computes the average of conditional treatment effects using the conditional probability of treatment within strata $\lambda_x = E[D|x]$:
$$\rho = E\left\{\frac{\lambda_x(1-\lambda_x)}{E[\lambda_x(1-\lambda_x)]}\delta_x\right\}$$
where $\delta_x = E[Y_1 - Y_0|x]$+ bias

5. Propensity score weighting à la Hirano et al. (2003)
$$\rho = E\left[\frac{yD}{\lambda_x}|\mathbf{X}\right] - E\left[\frac{y(1-D)}{(1-\lambda_x)}|\mathbf{X}\right] + bias$$
where $\lambda_x = E[D|\mathbf{X}]$ is the conditional-on-covariates probability of treatment.

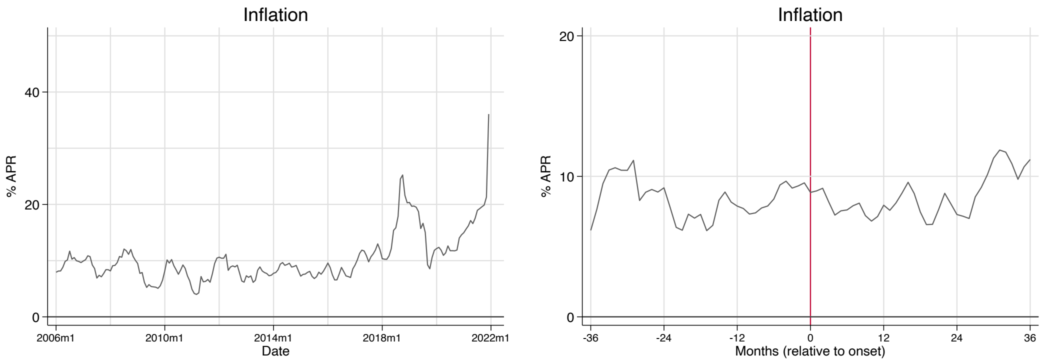
6. Hybrid weighting/reweighting procedure suggested by Kline (2011).

$$\rho = (\beta_1 - \beta_0)' E[\mathbf{X}] + bias$$

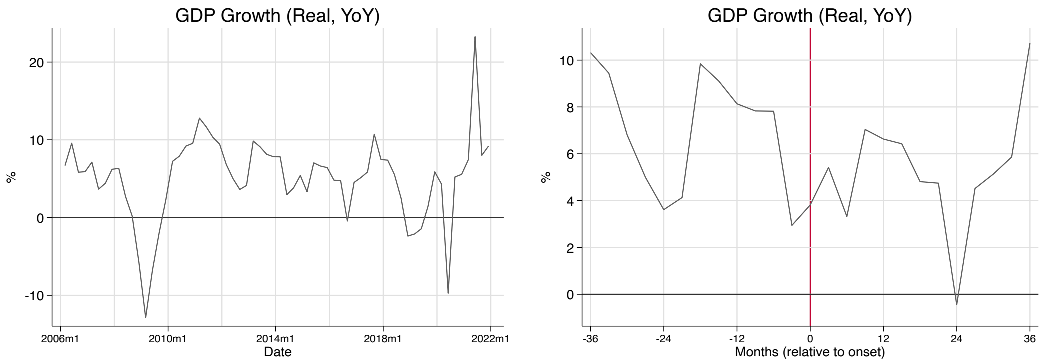
where $E[Y_0|\mathbf{X}] = E[y|\mathbf{X}, D = 0] = \mathbf{X}'\beta_0$ and $E[Y_1|\mathbf{X}] = E[y|\mathbf{X}, D = 1] = \mathbf{X}'\beta_1$.

Figure A.1: Macroeconomic Environment in Türkiye

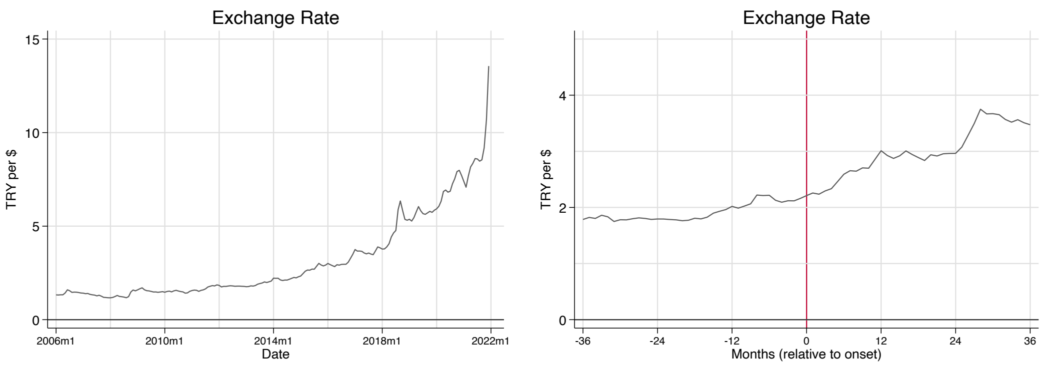
(a) Inflation



(b) Real GDP Growth (quarterly %)

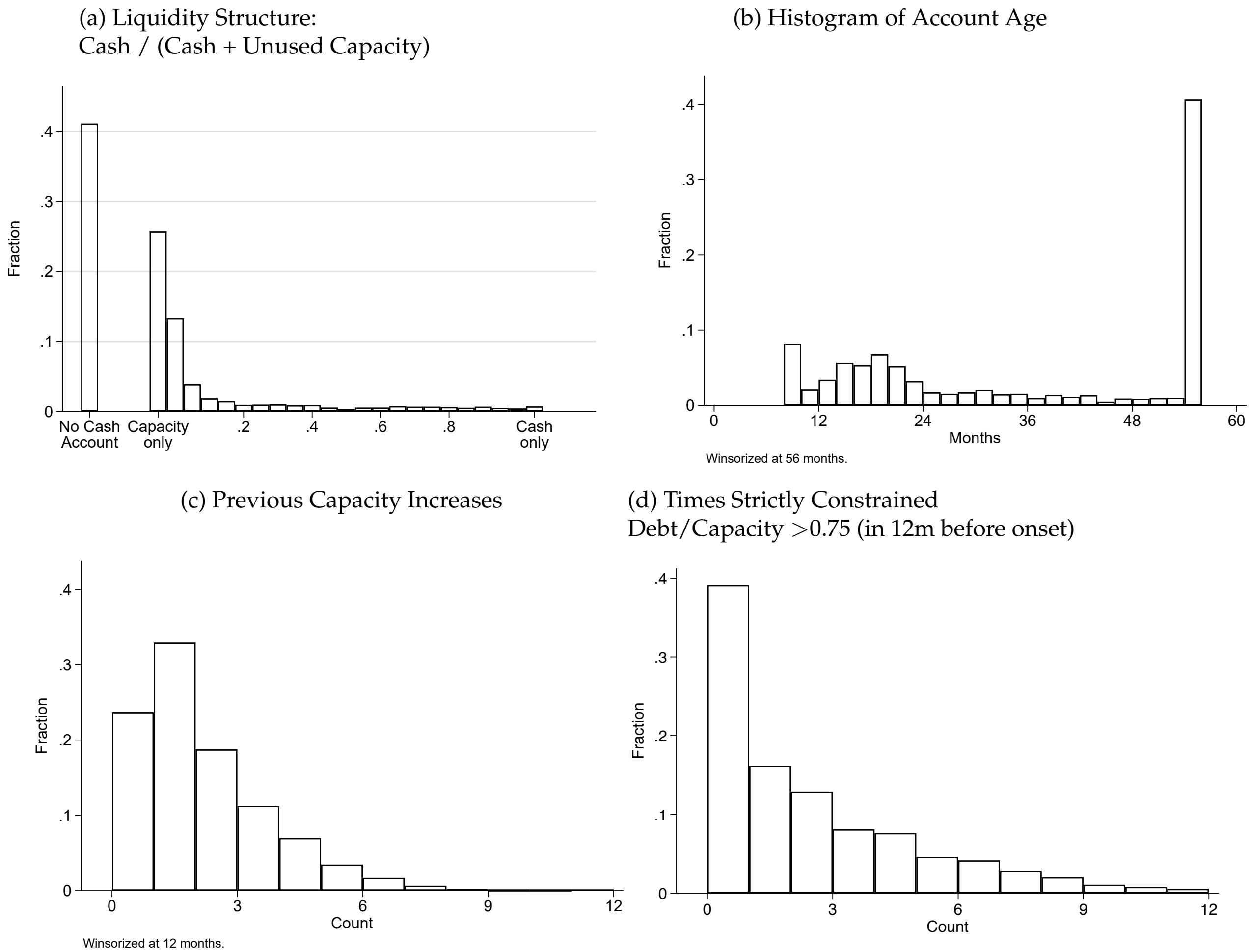


(c) USD/TRY Exchange Rate



Note. Figures plot annual inflation, GDP growth, and USD/TRY exchange rate. In each panel, the chart to the left plots the outcome between 2006 and 2022, whereas the chart to the right plots outcomes 36 months around the experiment. Source: Turkstat via Türkiye Data Monitor.

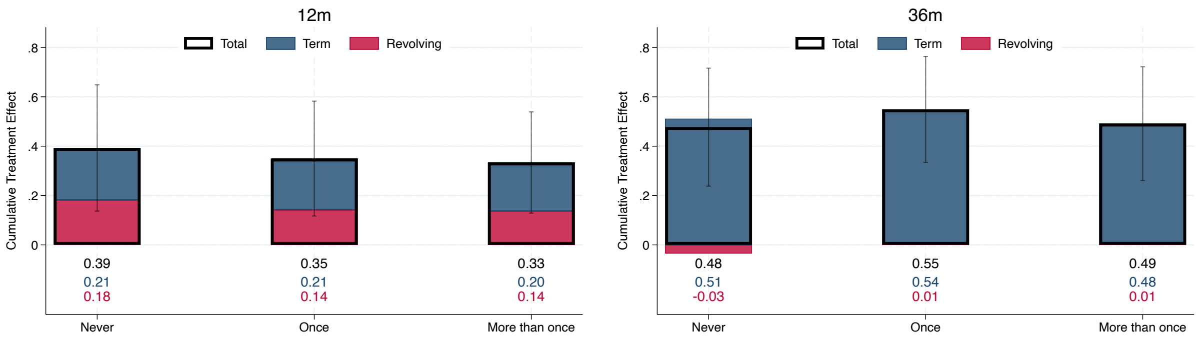
Figure A.2: Other Firm Characteristics



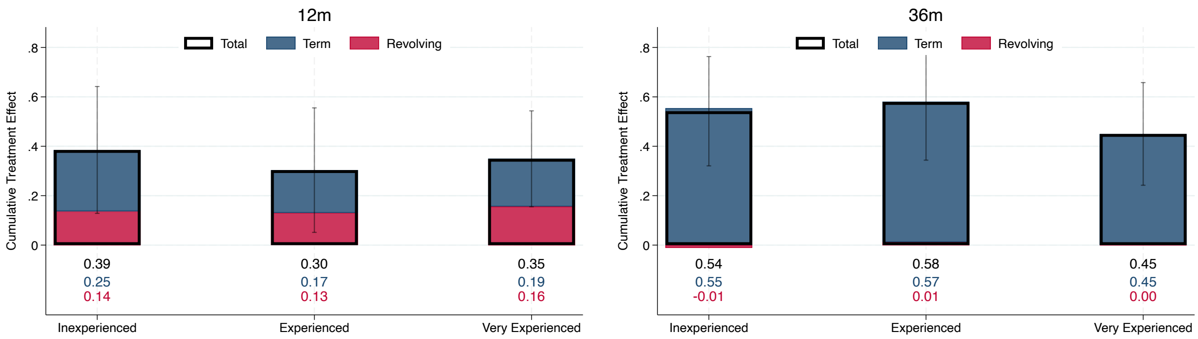
Note. Figures plot the distribution of liquidity structure, account age, frequency of capacity increases firms experienced, and number of times that firms face binding constraints. before the intervention. Liquidity structure is measured as the share of cash to the sum of cash and available capacity at the onset. The left-most bar shows the share of businesses with no cash account. Account age is measured as the number of months that an account has a positive debt capacity and is truncated at the top – these firms have account age of over 60 months. Capacity increases before the experiment captures non-experimental increases in debt capacity, which captures both lender- and borrower-initiated changes. Binding constraint is measured as firms having utilization ratio greater than 75 percent.

Figure A.3: Heterogeneous Treatment Effects by Previous Capacity Increases, Account Age, Firm Size

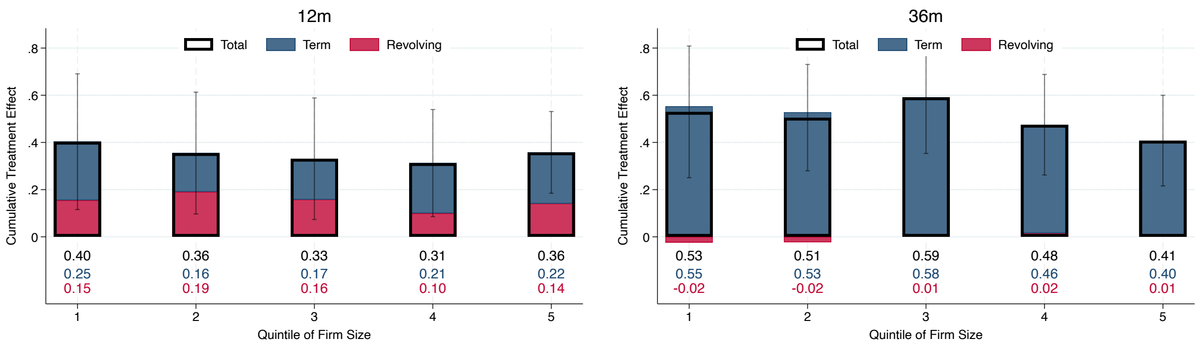
(a) By the Number of Capacity Increases



(b) By Account Age at Onset



(c) By Baseline Firm Size



Note. The figure shows heterogeneous treatment effects by the number of capacity increases, account age at onset, and firm size proxied by the size of the credit limit. Firms are grouped into subsample bins based on the distribution of average subsample split variable over the 12-month period before the intervention. Number of capacity increases are grouped into three bins: (1) Never experienced; (2) experienced one limit change before; and (3) more than once. Account age bins are grouped into age terciles: firms that had an active credit line account for (1) 8 to 19 months; (2) 20 to 55 months; and (3) more than 56 months. Firm size bins are grouped into 5 bins based on quintiles: (1) 100-1,000; (2) 1,050 to 2,100; (3) 2,200 - 3,600; (4) 3,650 - 6,200; (5) 6,300 or over. Heterogeneous treatment effects are obtained using Equation 3. Whiskers denote 95% confidence interval. Treatment effects are annotated below each bar.

Table A.1: Macroeconomic Indicators

	TR	SE As IN+CN+ID	Lat Am MX+BR+AR	SE Eu GR+BG+RO	S Eu IT+ES+PT	US	EU28
GDP per capita (PPP)	24.6	8.9	19.5	23.5	35.4	57.3	39.9
GDP growth	4.9	6.6	0.3	1.9	0.7	2.3	1.6
Poverty	2.2	26.6	7.6	6.9	1.6	1.5	-
Borrowed	0.36	0.14	0.26	0.18	0.39	0.65	0.42

Note. In this Table, we compare Türkiye (TR) to the United States (US), the European Union 28 (EU28), as well as comparable countries based on geographic and economic clusters: Southern Europe (Italy, Spain, and Portugal), Southeast Europe (Greece, Bulgaria, and Romania), Southeast Asia (India, China, and Indonesia), Latin America (Mexico, Brazil, and Argentina). Source: World Bank and OECD. GDP per capita PPP is constant in 2017 international \$. Poverty is the headcount ratio at \$3.65 a day (2017 PPP, % of the population).

Table A.2: Estimation Framework

	Panel A: Equation (1)			*Panel B: Equation (2)*		
	$Y_i = \beta X_i + f_s + \epsilon_i$			$Y_{it} = \sum_{j=1}^{T} \gamma_j X_{ij} + f_t + f_s + \epsilon_{it}$		
	Z_i	X_i	Y_i	Z_{it}	X_{ij}	Y_{it}
First-stage	$\mathbb{Z}_i$	$\mathbb{Z}_i$	Δ^τ Capacity$_i$	$\mathbb{Z}_i \times f_t$	$\mathbb{Z}_i \times f_t$	Δ Capacity$_{it}$
Intent-to-treat	$\mathbb{Z}_i$	$\mathbb{Z}_i$	Δ^τ Debt$_i$	$\mathbb{Z}_i \times f_t$	$\mathbb{Z}_i \times f_t$	Δ Debt$_{it}$
Treatment Effect	$\mathbb{Z}_i$	Δ^τ Capacity$_i$	Δ^τ Debt$_i$	$\mathbb{Z}_i \times f_t$	Δ Capacity$_{it-j+1}$	Δ Debt$_{it}$

Note Y, X, and Z stand for the left-hand-side variable, right-hand-side variable, instrument. C stands for capacity, and D for debt. $\mathbb{Z}_i$ denotes experimental assignment. f_t and f_s stands for calendar date and randomization strata fixed effects.

Table A.3: Econometric Evaluations of Non-Experimental Methods

12-month effect	Raw Correlation (1)	Strata-adj OLS (2)	Strata-adj OLS + Controls (3)	Strata Matching (4)	HIR (5)	Oaxaca-Blinder (6)
First-stage (TRY)	1,906	1,895	1,905	1,934	1,522	1,923
	(110)	(108)	(96)	(104)	(134)	(65)
Intent-to-treat (TRY)	394	391	396	423	279	344
	(73)	(72)	(102)	(62)	(50)	(92)
Treatment Effect	0.21	0.21	0.21	0.22	0.18	0.18

Note. This table reports 12-month first-stage, intent-to-treat, and treatment effects using (endogenous) debt capacity increase $\mathbb{D}_i$ – rather than (exogenous) treatment assignment, $\mathbb{Z}_i = 1$ as an instrument to demonstrate selection bias that could arise from employing non-experimental methods. The estimates are obtained using the pre-experimental period (i.e., evaluated 36 months before the intervention). Column 1 reports raw correlation between Y and D. Column 2 controls for randomization strata, f_s, which corresponds to fixed effects for 10 different utilization bins. Column 3 adds pre-experimental business characteristics to Column 2. Column 4 estimates treatment effects weighted by the conditional probability of treatment within strata à la (Angrist, 1998). Column 5 estimates average treatment effect by swapping propensity score weights for strata fixed effects à la (Hirano et al., 2003). Column 6 uses a reweighting procedure suggested by (Kline, 2011). Bootstrap iterations for columns 4 and 5 are set to 1,000.

Table A.4: Long-Run Effects on Capacity and Debt EUR and USD

	Baseline Level (1)		*6m* (2)	*12m* (3)	*18m* (4)	*24m* (5)	*30m* (6)	*36m* (7)
		A. Euro (EUR)						
ΔCapacity	1,641	First-stage (OLS)	886	712	766	709	614	640
			(75)	(70)	(79)	(113)	(109)	(134)
ΔDebt	552	Intent-to-treat (OLS)	276	242	205	270	340	307
			(77)	(88)	(110)	(126)	(85)	(108)
		Treatment Effect (Wald)	0.31	0.34	0.27	0.38	0.55	0.48
			(0.09)	(0.12)	(0.14)	(0.17)	(0.11)	(0.11)
		B. U.S. Dollar (USD)						
ΔCapacity	2,154	First-stage (OLS)	972	812	885	812	676	765
			(77)	(82)	(92)	(130)	(125)	(162)
ΔDebt	725	Intent-to-treat (OLS)	296	270	233	303	362	363
			(87)	(103)	(129)	(145)	(98)	(129)
		Treatment Effect (Wald)	0.30	0.33	0.26	0.37	0.54	0.47
			(0.09)	(0.12)	(0.14)	(0.17)	(0.12)	(0.11)

Note. This table presents first-stage (FS), intent-to-treat (ITT), and treatment effects over different time horizons after the onset of the experiment in Euros and U.S. dollars. Estimates are obtained from running Equation (1), which captures the average effect of receiving a debt capacity increase, $\mathbb{Z}_i = 1$. Month-end exchange rates converting TRY to EUR and USD are obtained from Datastream and applied to transform outcome variables.

Table A.5: Transaction Categories and Aggregation

Type (1)	Group (2)	Category (3)	Subcategory Examples (4)
		A. Investment	
Durable	Auto Parts	Auto Parts	Tires, spare parts, etc
Durable	Electronics/ Machinery	Appliances, electronics, furniture	Major appliances, computer, cell phones, equipment, furniture, building materials
Services	Business Svcs	Advertising, consulting, misc biz svcs	Ads, consulting, IT, security
		B. Operating Expenses	
Cash	Cash	Cash advance	–
Nondur	Gas & Auto	Fuel, auto repair	Gas, car wash, protection
Nondur	Nondur Retail	Retail, recreation, restaurants, hobbies, stationary	Department store, sports acticvities, resturant, printing, office supplies
Services	Insurance/ Travel/Other Services	Insurance, travel, health, education	Insurance, hotel, resorts, car rental, schools, hospitals, laboratories
Services	Utilities	Utilities	Natural gas, electricity, water, telecomm

Note. This table reports examples of detailed categories included in different spending types.

Table A.6: Probability of Facing Binding Constraints

	Y = 1(Binding Constraints)		
	Onset	*12m*	*36m*
	(1)	(2)	(3)
Z	–	-0.04	-0.01
		(0.03)	(0.03)
Constant	0.630	0.626	0.755
	(0.01)	(0.03)	(0.03)

Note. This table examines the probability of firms facing binding financing constraints. The outcome is an indicator variable that equals one if firms utilize more than 75 percent of their debt capacity. Column 1 reports the probability of firms ever being in the "binding" region of utilization ratio 12 months before the experiment. Columns 2 and 3 report the effect of treatment assignment on the probability of firms facing binding constraints in the short-run and long-run.

Table A.7: Spending Volatility, the Cost of Flexible Contracts, and Utilization

	Spending Volatility		The Cost of using Flexible Contracts		Utilization	
	12m	*36m*	*12m*	*36m*	*12m*	*36m*
	(1)	(2)	(3)	(4)	(5)	(6)
Z	-0.090	-0.072	75.90	178.5	-0.002	0.04
	(0.01)	(0.01)	(4.07)	(2.59)	(0.02)	(0.02)

Note. This table examines the effect of treatment assignment on spending volatility, total interest accrued on revolving debt, and utilization rate. The outcome used in the first two columns is the standard deviation of change in spending using revolving debt scaled by debt capacity. Since revolving debt is primarily used to finance working capital, we use the change in revolving debt as a proxy for spending volatility. The last two columns use the total interest expense accrued on revolving debt as the outcome. Since we do not directly observe interest expense, we assume that the firm accrues 24 percent APR whenever revolving debt is positive. The last two column reports effects on utilization rate, measured as revolving debt balance to total debt capacity.

Table A.8: Lumpy Investments

12m	Outcomes: 1(Lumpy)	Outcomes: Change in Debt	
	(1)	(2)	(3)
Z	0.042 (0.01)	820 (280)	
Z x non-Lumpy			615 (280)
Z x Lumpy			4,132 (781)
N	3,169	3,169	3,169

Note. This table examines the effect of treatment assignment on lumpy investments and decomposes 12-month ITT effect into lumpy and non-lumpy investments. Column 1 uses the indicator "Lumpy" as the outcome, which equals one if the maximum spending using term debt on a specific category of goods (e.g., equipment) is greater than the unused (available) debt capacity at the onset. Since our data does not capture item-by-item investment spending, our measure of lumpy investment may overstate total lumpy investment spending. For example, this measure captures total spending on total equipment rather than spending on toaster oven vs. fridge, etc. Columns 1 and 2 decomposes ITT effects into change in debt driven by non-lumpy and lumpy investments.

Table A.9: Competing Models and Testable Predictions

#	Outcome		Finding— In response to an exogenous capacity shock:	Table	Figure	Static Financial Frictions	Flexibility	Lumpy Investment	Encouragement	Mistakes and Learning
1	Total Debt	Short-run	increase debt	4, 6	5a	✓	✓	✓	✓	✓
2		Long-run	with effect building up with a lag	5	5b, 6		✓		×	×
3		Heterogeneity	even if have financial slack		7	×	✓	✓	✓	✓
4	Types of Debt	Short-run	use a mix of high-cost and low-cost debt	7	8a		✓			✓
5		Long-run	minimize cost of financing	8	8b, 9		✓			✓
6	Spending		invest, in non-lumpy increments		10		✓	×		
7	Defaults		no diff. effect on financial distress		11		✓			×

Note. This table summarizes our findings and whether they are consistent with various model predictions.