Corporate Liquidity Supply from Non-Bank Intermediaries and the Real Effects of Factoring*

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Abstract: We show that short–term fluctuations in firms' ability to convert trade credit receivables into liquidity through factoring have large and persistent real effects, with limited substitution from other financing sources nor adjustments in trade credit terms. In Brazil, specialized non–bank intermediaries (FIDCs) securitize receivables and are key providers of working–capital liquidity. Using novel transaction–level data linking all factoring and credit operations, invoices, payments, and employment records, we exploit investor inflows to FIDCs in a shift–share design to identify exogenous variation in factoring supply. A one–percentage-point decline in factoring rates increases factoring volumes by 16%, revenues by 6%, and intermediate input expenditure by 4%, with effects persisting for several months. Firms expand permanent employment and temporarily demand less temporary labor. A model of corporate liquidity management rationalizes these findings: factoring endogenously transforms production into collateral, tying firms' real and financial marginal decisions in a self–reinforcing liquidity–productivity loop. Model–implied macro–elasticities indicate that lowering economy–wide factoring spreads by 1 percentage point would raise aggregate output and wages by 0.3 to 0.5 percentage points.

JEL Codes: E44, G30, D22, E22, E24, J23, O16

The views expressed in this working paper are those of the authors and do not necessarily reflect those of the Central Bank of Brazil.

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1 Introduction

How important is working capital financing in bridging the gap between firms' upfront payments, to employees and suppliers, and firms' future payments from customers? How responsive are firms' production, employment, supply chain, and financial decisions to working capital financing terms? Due to the ubiquity of trade credit and intermediated working capital financing across the firm size distribution, these questions matter to policymakers evaluating reforms to corporate liquidity supply. In particular, small and medium enterprises (SMEs) rely more heavily than large firms on working capital financing because SMEs lack cash buffers and sophisticated corporate treasury, yet SMEs also face frictions in acquiring financing due to limited collateral and credit history (BIS, 2023). This paper studies how marginal changes in the price of factoring, the main type of intermediated financing of trade credit, affect firms' decisions and outcomes using a comprehensive dataset covering the entire firm size distribution.

The most common form of working capital financing worldwide is trade credit, defined as suppliers allowing buyers to pay at a later time than the time of transaction. Formally, a trade credit contract consists of an upfront transaction in which the supplier records a receivable, and a settlement transaction in which the buyer pays and the receivable is retired. Suppliers who want cash before payment clearing can sell the receivable to a financial intermediary called a factor, and this type of sale is called factoring. Factoring is an increasingly important way for suppliers to extend long trade credit terms while ensuring liquidity for short–term payment obligations. The worldwide factoring share of receivables increased from 7% in 1997 to 24% in 2017 (Boissay et al., 2020). In Brazil, the setting of this paper, factoring is the highest volume form of intermediated working capital financing. Few papers have estimated the impact of working capital financing terms on firms' outcomes, and none uses a dataset encompassing all firms in an economy.

The Brazilian setting is well–suited to this topic due to specialized mutual funds called FIDCs, which purchase and securitize firms' receivables, selling debt tranches to institutional investors. FIDCs are similar to fintechs in their use of algorithms and big data to target and receivables that banks are reluctant to purchase. FIDCs' share of all factoring in Brazil has grown from 7% in 2015 to 32% in 2023, reflecting the growth of fintech and rising investor demand for securitized receivables. FIDCs' share will likely continue to increase as ongoing reforms broaden the set of eligible investors and reduce the informational advantage of banks over FIDCs in assessing receivables risk for factoring. FIDCs' regulatory structure mandates them to primarily purchase receivables, along with short–term Brazilian Treasury notes for liquidity management, so portfolio inflows to FIDCs mechanically translate into changes in corporate liquidity supply. FIDCs' main investors are broad market mutual funds and pension funds who face constraints on asset allocation, so there is a liquidity–driven component of flows to FIDCs. In turn, there are sticky relationships between FIDCs and firms due to costly screening: the risk of a firm's receivables depends on the firm's customers in addition to the firm's own creditworthiness, and firms must establish and manage escrow accounts in FIDCs. We use FIDCs' past receivables purchases and current flows to instrument for firms' factoring interest rate, and we are the first to estimate causal responses of firms' decisions and outcomes to the factoring interest rate. Our instrument is valid because institutional investors cannot observe the identities of the numerous firms whose receivables are held by FIDCs, the flows to FIDCs have a liquidity–driven rebalancing component, and FIDCs' demand for receivables necessarily adjusts to fund flows because of their capital allocation constraints.

We construct a large new dataset using several restricted–access databases at the Central Bank of Brazil (BCB). The dataset is comprehensive in several dimensions. Our dataset contains all factoring transactions from banks and FIDCs, for all formally registered firms in Brazil that have ever sold their receivables. We are also the first to use the universe of transaction–level boleto contracts to infer trade credit payment terms. We complement the boletos with the universe of other transaction–level electronic payments, with terabytes of data in total. We merge the factoring data, at the firm by month level, to employer-employee records (RAIS), payments, and boletos. There are three main takeaways from our summary statistics: (i) firms have greater cash inflow volatility than cash outflow volatility; (ii) firms that are smaller and riskier tend to factor a larger share of receivables; (iii) FIDCs tend to purchase receivables from riskier firms. Our interpretations are as follows. The differences in cash flow volatility generate firms' demand for short–term liquidity through working capital financing. Firms that face tighter financing constraints rely more on factoring, since factoring is inherently available to any firm that offers trade credit, and most firm-to-firm transactions in Brazil feature trade credit, while bank financing is expensive for SMEs with limited collateral and reputation.

In light of these facts, the results from our regressions can be interpreted as a local average treatment effect for firms that factor as their marginal source of liquidity. In the first stage, we use local projections to show that a firm's exposure to net fund inflows leads to a decrease in the factoring interest rate that mostly decays to zero after four months. In the IV regressions, we show that a flow-induced one percentage point decrease in the interest rate leads to large contemporaneous increases in factoring volume (16.2%), revenue (6.1%), and intermediate input expenditure (3.6%). We estimate an increase in permanent contract labor (1.1%) and a contemporaneous decrease in temporary contract labor (2.1%). The IV local projections show that factoring volume reverts to the previous level after several months, following the reversion of the interest rate, but revenue and intermediate input expenditure persist 1 to 3 percentage points above the previous level.

The increase in permanent labor persists at around 1%, as expected. However, the impact on temporary labor reverts after two months; cheaper factoring leads to greater use of temporary labor as well in the long term. We explain the contemporaneous effect through the lens of cash flow volatility, in which hiring labor with flexibility is an imperfect substitute for factoring, and the long term effect through the lens of growth with loosened financial frictions.

We build a model of factoring to explain how cash flow volatility affects firms' outcomes and how cheaper factoring can have real consequences, including on aggregate output in general equilibrium. Firms' cash inflow volatility arises from the timing of customers' payments and uncertain demand. Factoring directly eliminates volatility from the timing of payments, while other forms of financing do not. When factoring is more expensive, firms not only substitute towards other financing, but also demand more temporary labor to match the fluctuation in cash outflows to cash inflows. In the presence of fixed capacity costs or efficiency costs of temporary versus permanent labor, it is more efficient for firms to factor rather than fluctuate production. We calibrate the model using moments in the data, and apply it to two counterfactuals of how firms' outcomes and aggregate output would respond to a decrease in the factoring interest rate. The first counterfactual is analogous to partial equilibrium, where we only change factoring interest rate for an infinitesimal subset of firms, holding constant aggregate prices and allocations. The second counterfactual is analogous to general equilibrium, where we reduce the factoring interest rate for all firms and allow aggregate prices and allocations to adjust. We motivate the general equilibrium counterfactual through three broad trends: the increased use of fintech in factoring to reduce transaction costs, the introduction of receivables registries to reduce search and verification costs, and regulatory changes that increase demand for receivables through expanding investor access to FIDCs. We find that the model-generated partial equilibrium response is similar in magnitude to the regression results, with elasticities around 3.1, while the general equilibrium response is an order of magnitude smaller, with elasticities of 0.3 to 0.5. General equilibrium dampening arises from higher prices, particularly for permanent contract wages.

This paper relates to several strands of literature in corporate finance, intermediation, and macro-finance. The literature on the real effects of credit supply shocks has shown large cross-sectional impacts on employment and output, primarily using data on large firms. Our regression estimates have similar magnitudes to those of Chodorow-Reich (2014), where working capital loans comprise a large share of the credit supply shock. Our estimates of the long term impacts on wage bill are comparable to those of Huber (2018), and our aggregate elasticities are comparable to those of Herreno (2023). Our contribution is threefold: first, we provide the first causal estimates of elasticities of real outcomes to factoring, an important and under-studied type of financing; second, we are the first to show heterogeneity across the entire distribution of firm size and other attributes; and third, we show that there are small effects on financial outcomes, both for trade credit and for intermediated financing.

In the literature on working capital financing, Lian and Ma (2021) show that borrowing constraints based on cash flows is one channel for real effects of working capital financing terms. Several papers have shown that the debt portfolios of small and medium enterprises (SMEs), and SMEs' responses to financing shocks, are systematically different from those of large firms (Custódio et al., 2013; Bahaj et al., 2022; Chodorow-Reich et al., 2022), with an important role for collateral (Luck and Santos, 2019). Caglio et al. (2022) show that while large public firms primarily rely on unsecured credit lines, all other types of firms rely heavily on accounts receivable backed financing. In our setting, factoring is the main form of working capital financing for all but the largest firms, and small firms factor a larger share of receivables, yet all firms have significant responses in real outcomes to the factoring interest rate. Hahn et al. (2024) show that a decrease in the flexibility of temporary labor reduces firms' cash holdings; we show the converse, that cheaper financing through factoring leads to substitution away from temporary labor. Almeida et al. (2024) compare the investment and output responses to working capital financing shocks across more versus less constrained firms; our contribution is that we instrument the financing shock, we demonstrate labor substitution patterns that are key to understanding the mechanism for working capital financing terms to have real effects, and we have rich microdata that allow us to study the impact of firm-level shocks with firm-to-firm trade credit, rather than industry-level shocks on firms' total trade credit exposure.

The long literature on trade credit discusses how firms use trade credit for risk sharing (Yang and Birge, 2018) and reserve liquidity (Amberg et al., 2021), with high substitutability for bank loans (Restrepo et al., 2019). There is a higher demand for trade credit in environments with weaker creditor protection due to the information advantage of suppliers versus other creditors (Fabbri and Menichini, 2010), and trade credit eases bank credit constraints (Adelino et al., 2023; Garcia-Martin et al., 2023; Skrastins, 2021). Through the interplay of trade credit and bank credit, trade credit can amplify or dampen aggregate fluctuations (Altinoglu, 2021; Reischer, 2024; Bocola and Bornstein, 2023), both through production linkages and through default risk (Jacobson and Von Schedvin, 2015; Mateos-Planas and Seccia, 2021). However, the empirical literature on the financial intermediation of trade credit is nascent, comprising of three papers that have crucial differences with this paper. The closest paper is Bottazzi et al. (2023), who use a one-time shock to the supply of factoring services and show that factoring alleviates financial constraints. In comparison, our dataset contains the factoring interest rate and leverages quasi-exogenous variation in the interest rate, allowing us to estimate financing semi-elasticities, while Bottazzi et al. (2023) only measure the total effect of the shock on factoring share and firms' outcomes. In addition, our dataset is much larger, with 1.03 million firms in our dataset versus 2,663 firms in Bottazzi et al. (2023), and our dataset includes the numerous small firms that rely most heavily on factoring. By comparison, most papers in the literature on trade credit and working capital financing only have data on large firms. Amberg et al. (2024) study supply-chain finance (SCF), which is buyer-initiated unlike supplier-initiated factoring, and similarly to Bottazzi et al. (2023) study the total effects of SCF enrollment, rather than marginal changes to interest rates. In our setting in Brazil, factoring volume is far higher than SCF volume. Yu (2023) study accounts receivable backed lending in the US, which is the primary form of working capital financing for the set of 695 sellers and 527 buyers in the Yu (2023) sample of publicly traded firms, and focuses on the moral hazard motivation for trade credit rather than cash flow volatility. As Caglio et al. (2022) show, large publicly traded firms differ from most other firms in their composition of working capital financing, primarily comprising of lines of credit, loans, and bonds rather than trade credit and factoring. In relation to the trade credit and factoring literature, our contribution is to show empirical facts that motivate the importance of factoring for trade credit, estimate the heterogeneous impact of factoring on trade credit terms, and model how factoring enhances trade credit by alleviating the cash flow variation that arises from extending financing through trade credit. We are the first to estimate the causal impact of a change in the factoring interest rate on firms' outcomes, and the first to document the heterogeneous impacts across the distribution of firms.

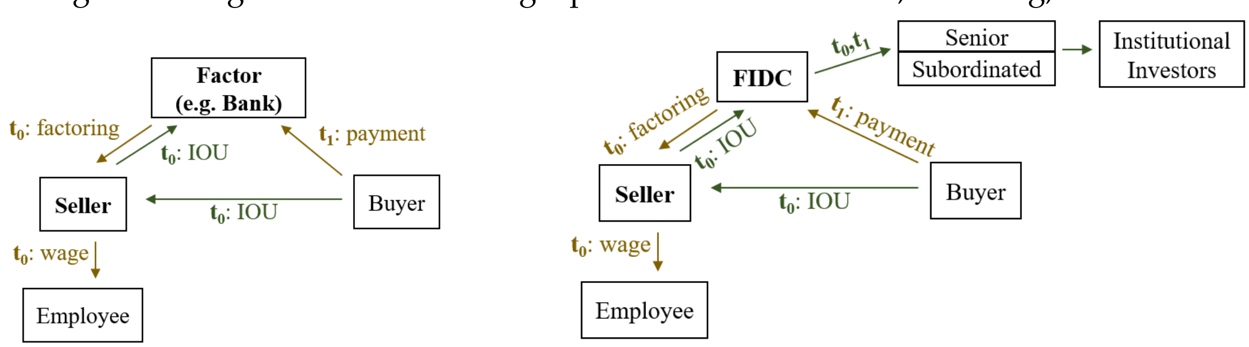
The importance of FIDCs to factoring, through investors' asset demand for receivables, relates to the literature on non-bank credit supply, specifically through fintechs and funds. Our instrument is inspired by flow-induced trading, namely that firms buy or sell assets in proportion to their holdings, rather than in order of liquidity or in the same allocation as the market portfolio (Coval and Stafford, 2007; Edmans et al., 2012; Wardlaw, 2020; Van der Beck, 2022; Dou et al., 2022; Darmouni et al., 2022). While the literature focuses on equity and bond funds, we adopt the intuition of flow-induced trading to the factoring setting, featuring short maturity and a high rate of recurring purchases, by using past issuance rather than lagged holdings as the measure of a firm's exposure to a fund. The primary justification for the exclusion restriction, that fund flows only affect firms' outcomes through funds' asset purchases, is that flows arise from liquidity or asset class rebalancing motives, rather than expectations of firm-level future returns, for instance from productivity shocks. In our setting, almost all factoring goes to firms whose assets are otherwise not exposed to rebalancing because they are not publicly traded, they do not issue bonds, and there are no analogous funds to FIDCs for long-term debt. Also, most FIDCs purchase receivables from thousands of firms, and neither the firms seeking factoring nor their buyers with payment obligations are reported to investors, so it is unlikely that FIDC flows respond to specific productivity shocks. For these reasons, we believe that the exclusion restriction is more plausible in our setting than in the literature.

We organize the remainder of the paper as follows. Section 2 describes the institutional setting of factoring and FIDCs. Section 3 describes the data and the key facts. Section 4 introduces the methodology and discusses the regression results. Section 5 interprets the results in the lens of a model of factoring and discusses the results from the counterfactuals. Section 6 concludes.

2 Factoring and FIDCs

When firms transact, they choose payment terms jointly with the price and quantity of the good or service. These payment terms stipulate the payment date or dates, often in relation to the contract date. When the payment date t_1 is later than the contract date t_0, the seller has offered trade credit to the buyer. We represent this in Figure 1a with an arrow from the buyer to the seller labeled with "IOU." The contract that the buyer signs, stipulating the payment terms, creates an account receivable, which is an asset on the seller's balance sheet. Its maturity equals the difference between the payment date t_1 and the contract date t_0. The discrepancy between cash inflows at t_1 and cash outflows at t_0, as well as greater volatility for cash inflows relative to outflows,[5] generates firms' demand for working capital financing.

Figure 1: Diagram of the Financing Operations: Trade Credit, Factoring, and FIDCs



(a) Typical Factoring

(b) Factoring to a FIDC

Notes: These diagrams show the sequence of transactions for factoring and FIDCs in our setting. On the left is the typical environment for factoring around the world, where the seller extends trade credit to the buyer upon the transaction at time t_0, and the buyer repays at time t_1. If the seller wants cash before t_1, the seller can sell the receivable "IOU" to the factor, receiving the discounted value of the receivable. The discount can be converted into the factoring interest rate. The buyer directly repays the factor through an escrow account set up by the seller. The diagram on the right shows the institutional setting in Brazil when the factor is a FIDC: there is an additional step of securitization where the buyers' payments flow to the standardized share classes held by institutional investors.

After providing trade credit, the seller can choose whether to retain the receivable on its balance sheet or sell the receivable at a discount to a financial intermediary. Factoring

[5]See Figure A2 in the appendix for empirical evidence of the volatility mismatch.

is defined as the sale of the receivable, and the factor is the financial intermediary who purchases the receivable. By factoring the receivable, the seller obtains cash upfront that the seller can use to pay its employees, while still providing trade credit to its buyer for various reasons, such as alleviating moral hazard.

Both factoring and trade credit are widely used around the world (Boissay et al., 2020). A unique feature about the Brazilian institutional setting is the receivables fund, written in Portuguese as the Fundo de Investimento em Direitos Creditórios (FIDC). The regulation that enabled the creation of FIDCs was Instruction 356 from the Securities and Exchange Commission of Brazil (CVM), passed in December 2001. In the subsequent two decades, FIDCs have steadily grown to become a major asset class. Similarly to other types of funds, net asset value (NAV) is the primary metric of fund size. From January 2013 to January 2024, total FIDC NAV grew from 46 billion US dollars (USD) to 111 billion USD,[6] while the total number of FIDCs grew from 396 to 2,551. All FIDCs must have at least 50% of their NAV invested in receivables at all times. However, a large share of the growth in the number of FIDCs has come from funds that purchase distressed debt, much of which is consumer debt, including credit card receivables. This paper focuses on the 762 FIDCs that primarily purchase firms' receivables, specifically recourse factoring.[7] These FIDCs have combined NAV of 17.7 billion USD, purchasing 4.1 billion USD of firms' receivables per month.

The purpose of FIDCs is to securitize receivables for institutional investors, who wish to have exposure to short–term corporate debt for a wide cross-section of firms in a standardized asset.[8] As the debtors repay the FIDCs, the payments first go to senior shareholders, then to subordinated shareholders, with greater risk but also higher returns for subordinated shares. See Figure 1b for a visual depiction of the process. FIDCs are similar to fintechs in their use of additional sources of data besides credit bureaus' scores and patchy credit history, along with sophisticated algorithms, to price receivables. As we show later, FIDCs target higher-risk receivables that banks are reluctant to purchase.

The primary types of factoring are recourse, where the seller retains residual liability to the factor, and non-recourse, where only the buyer is liable. This paper focuses on recourse factoring, both because of data quality and because FIDCs primarily purchase receivables via recourse factoring.

[6] All monetary figures in this paper are expressed in current (September 2024) US dollars.

[7] See Figure A8 for the distribution of FIDC size.

[8] There are 251 thousand firms in Brazil whose receivables were purchased by FIDCs during our study period. By comparison, there are around 1,500 firms that issued corporate bonds, and fewer than 400 firms that are publicly traded, i.e. have easily accessible equity exposure.

3 Data and Summary Statistics

We use a novel combination of transaction–level datasets from the BCB. These datasets cover the universe of trade credit, electronic payments, and intermediated credit operations in Brazil. We measure trade credit payment terms using boletos, the standardized form of invoices in Brazil. Almost all firm-to-firm transactions use boletos, which can be settled using bank transfers, cash, and other payment rails. The supplier and buyer both observe and stamp the boleto, which the supplier's bank registers with a notary and reports to the BCB. In the boletos data, we observe identifiers for buyer and seller, date of invoice, the due date of payment, the actual date of payment, the amount due, the amount paid, and the reason for delay. The electronic payments dataset includes all payments associated with boletos, usually via bank transfer or cash, as well as all interbank transfers and instant payments. For tractability, we aggregate the terabytes of transaction–level data on boletos and payments to the firm by firm by month level.

The other major component of our dataset is the registry of credit operations (SCR). SCR includes all debt financing for firms whose total debt since June 2016 exceeds 200 Brazilian reais (BRL), equal to around 40 USD at current exchange rates. In SCR, we observe numerous small firms, including firms with annual revenue under 10 thousand USD per year and firms without full-time employees, so we are not concerned about the coverage of the 200 BRL threshold. We are the first to recognize the unique structure of the factoring data in the SCR and to correctly use the factoring data for all firms in SCR. We are also the first to construct the dataset of FIDC operations in SCR, combining direct purchases of receivables from firms with bulk purchases of receivables from other financial intermediaries. The SCR also contains transactions and snapshots for lines of credit and loans backed by accounts receivable as the main alternative forms of working capital financing. Finally, using firm identifiers, we have the location and sector from the tax registry, and labor variables at the monthly level from the matched employer-employee dataset (RAIS).

Our final dataset consists of almost all formally registered firms in Brazil from November 2018 to March 2024. While there are over 6 million registered firms in Brazil, a large majority do not appear active in any given month, where we define activity by sending or receiving payment, or initiating any financing. There are 1.03 million firms in Brazil whose receivables are ever purchased by a FIDC. Under the definition of the instrument, this is a superset of the firms for the firm-by-month level dataset in the regressions, since firms who never have receivables purchased by FIDCs have instrument value equal to zero and are dropped from the regression via the firm fixed effects. These 1.03 million firms receive an average of $68.2 billion USD of trade credit per month, of which $6.9 billion (10%) is factored with recourse, and another $10.5 billion (15%) is financed through other means. By comparison, total issuance of all other working capital financing, comprising of credit lines, short–term loans, and short–term bonds, sums to $4.7 billion USD per month.

Table 1: Annual Means of Trade Credit, Factoring, and Other short–term Debt

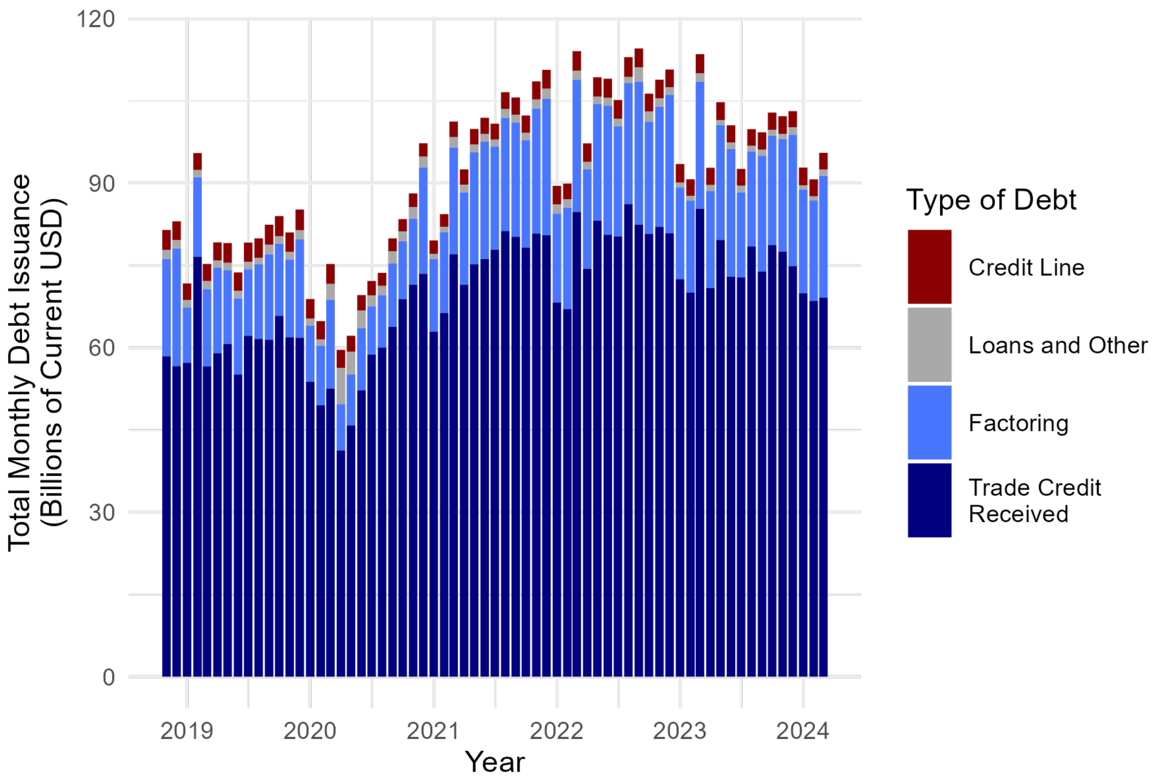
	Mean Overall	Mean Small Firms	Mean Medium Firms	Mean Large Firms
Panel A: Trade Credit Received, by Seller				
Volume (Million USD)	1.32	0.42	6.17	44.32
Maturity (Days)	30.36	33.99	29.67	28.22
Panel B: Recourse Factoring, by Seller				
Volume (Million USD)	0.13	0.08	0.56	1.97
Interest Rate (%)	19.42	18.35	21.58	19.52
Maturity (Days)	121.19	138.49	95.77	105.06
Panel C: Non-Recourse Factoring, by Buyer				
Volume (Million USD)	0.15	0.01	0.50	9.12
Interest Rate (%)	13.04	15.54	12.50	13.07
Maturity (Days)	79.86	94.81	86.48	77.17
Panel D: Secured Credit Lines				
Volume (Million USD)	0.04	0.02	0.26	0.72
Interest Rate (%)	30.63	45.13	23.24	18.67
Maturity (Days)	66.10	57.22	72.86	69.14
Panel E: Unsecured Credit Lines				
Volume (Million USD)	0.02	0.01	0.07	0.17
Interest Rate (%)	332.07	356.74	316.49	206.32
Maturity (Days)	42.20	41.01	44.82	43.89
Panel F: Other short–term Debt (Maturity Under 1 year)				
Volume (Million USD)	0.03	0.00	0.13	1.20
Interest Rate (%)	7.04	22.24	10.09	6.65
Maturity (Days)	187.61	181.17	176.71	188.82

Notes: The data are from the Central Bank of Brazil, covering 627,540 firms over the 65 months from November 2018 to March 2024 that report employment data in at least one month. There are 40,790,100 firm-by-month observations. We define the mean number of employees at the firm level, averaging across months, then classify firms as small (0 up to 50 mean employees), medium (50 up to 500 mean employees), or large (500 or more mean employees). The data on number of employees is from RAIS and covers the period from November 2018 to December 2022. Under this classification, there are 579,361 small firms, 40,627 medium-size firms, and 7,552 large firms. The mean annual revenue of firms in each bin, as proxied by payment inflows, are 539 thousand USD for small firms, 15.4 million USD for medium-size firms, and 269 million USD for large firms. In Panel A, the trade credit means are at the *debtor* firm level. We measure trade credit using boletos, and we measure revenue using the sum of boletos and interfirm electronic payments. In our sample, there are 1.69 billion trade credit transactions per year, an average of 2,687 per debtor per year. In Panel B, for recourse factoring, the debtor is the seller, who initiates the factoring. In our sample, there are 39.3 million recourse factoring transactions per year. In Panel C, for non-recourse factoring, the debtor is the buyer, and we do not always observe the seller who initiates the factoring. In our sample, there are 17.3 million non-recourse factoring transactions per year. In Panel D, there are 1.72 million drawdowns of secured credit lines per year. In Panel E, there are 7.64 million drawdowns of secured credit lines per year. In Panel F, there are 3.57 million other working capital financing transactions per year. For comparison of interest rates, the mean federal funds rate in Brazil (SELIC) during the sample period was 7.83%. The set of other short–term debt in Panel F includes government-subsidized loans, while the other categories of financing almost never receive government subsidies. For factoring, in Panels B and C, the main risk is non-payment by the buyer, so interest rates do not vary as much over the distribution of debtor size as for other types of financing.

Table 1 shows summary statistics about the comprehensive contract-level data for trade credit, factoring, and other short–term financing in Brazil. There are two main takeaways from Table 1: trade credit is the largest form of short–term lending in Brazil, and factoring is the majority of intermediated capital financing in Brazil.

Figure 2 shows that factoring has consistently been the primary type of intermediated working capital financing over time. Note that trade credit is not intermediated. Of the total monthly working capital volume that varied from a trough of $60 billion in April 2020 to a peak of $114 billion in March 2022, 70% consisted of trade credit that was not factored, i.e. receivables that suppliers held on their balance sheets. Another 24% was trade credit that was factored, 3% was secured credit lines, and 1% was unsecured credit lines, and the remaining 2% were short–term loans and bonds.[9]

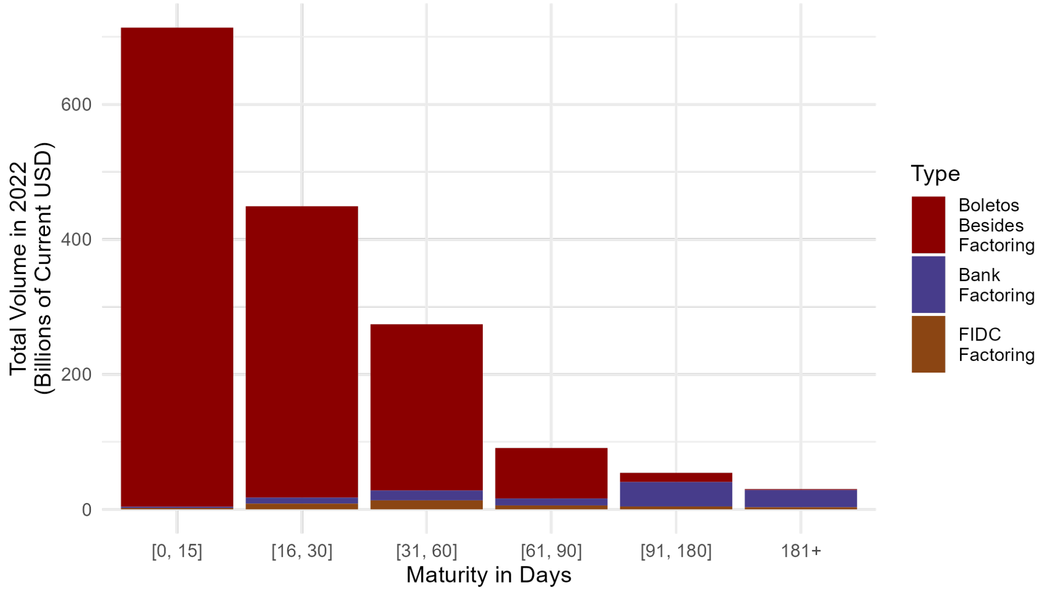
Figure 2: Time Series of Working Capital Financing in Brazil



Notes: The data are from the Central Bank of Brazil. This figure shows the composition of firms' short term financing, with maturity under 1 year, among the 1 million firms in our sample. In dark blue is the value of trade credit that a firm receives from its suppliers. In light blue is factoring, the sale of receivables from the trade credit that a firm offers its customers. In red are credit lines, which generally require firms to post collateral. In gray are working capital loans and bonds.

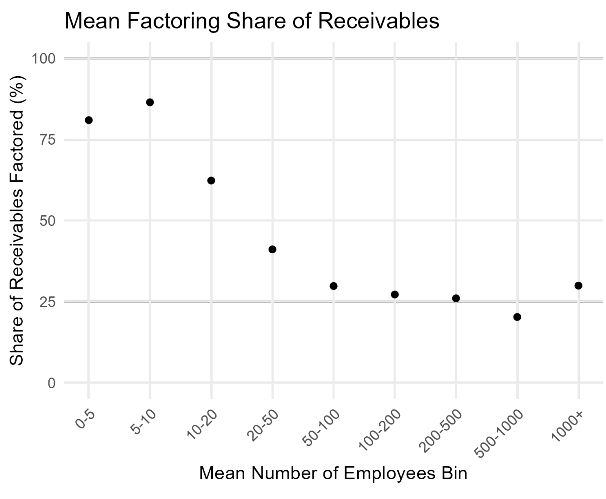
[9]Figure A1 shows that the relative importance of each type of working capital financing is invariant across the distribution of firms' credit score, although the exact magnitudes vary across the distribution.

Figure 3: Distribution of Maturity for Trade Credit and Factoring

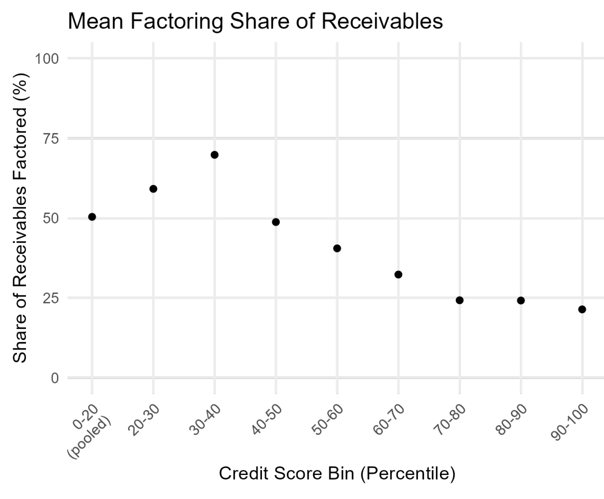


Notes: The data are from the Central Bank of Brazil. This figure partitions factoring and trade credit at the contract level by the maturity bin, then sums the contract value by bin. We measure the maturity of trade credit and receivables by the contract dates and due dates from the boleto transactions. The red bars are receivables that the sellers retain and do not factor. The purple bars are factored to banks, and the brown bars are factored to FIDCs, who largely purchase receivables in the 31 to 60 day maturity bin.

Figure 4: Factoring Share of Payment Inflows



(a) Factoring Share by Number of Employees



(b) Factoring Share by Credit Score

Notes: The data are from the Central Bank of Brazil. The denominator is the issuance volume of all receivables, and the numerator is the volume of receivables that the sellers factor. Each subfigure partitions firms into bins along the horizontal axis. On the left, we classify firms by the mean number of employees across all months, where each bin includes the lower bound and excludes the upper bound. On the right, we classify firms by deciles of credit score in June 2023, the only month with available data. The bottom 19% of firms have a credit score of 0, generally signaling a lack of any credit history, so we pool together the bottom two deciles.

Figure 3 shows that the factoring share increases over the maturity of the receivable. Most receivables have short maturity, and the seller retains most short-maturity receivables. By comparison, almost all long maturity receivables are factored.

Figure 4 is a bin-scatter plot that shows that the share of receivables that are factored is greater for firms with few employees (left) and low credit score (right). Each dot represents the revenue-weighted share of receivables that are factored for a bin of firms, by the mean number of employees across all months on the left, and by credit score decile on the right. The credit scores are a one-time snapshot in 2023 from the largest corporate credit scoring agency in Brazil.

Receivables funds (FIDCs), who purchase and securitize receivables by offering shares at different seniorities, are one reason for the high rate of factoring in Brazil. The CVM Instruction 356 in December 2001 defined the FIDC and set common standards. The number of FIDCs grew steadily over the 2000s and 2010s. Figure A5 in the appendix shows that FIDCs now comprise over 30% of all recourse factoring, a share that has increased over time. Flows to funds explain some of the variation in factoring prices across firms and across time. FIDC flows have weak autocorrelation of 0.21 from month to month. Table 2 shows summary statistics on FIDCs:

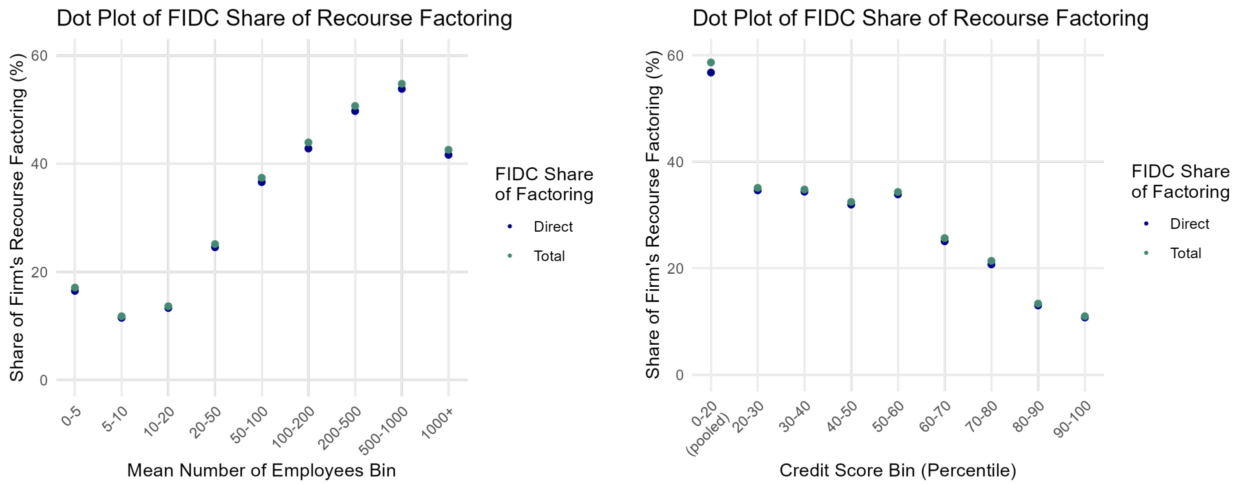
Table 2: Summary Statistics on FIDCs at the FIDC by Month Level

	Mean	**Std. Dev.**	**10th Percentile**	**Median**	**90th Percentile**
Net asset value	23.59	51.36	1.14	7.78	51.22
Monthly recourse factoring	4.48	11.45	0.00	0.94	11.86
Annualized net return (%)	13.83	22.66	-4.04	11.88	34.37
IR recourse factoring (%)	32.75	61.22	10.87	36.97	76.10
Monthly net flow | positive	1.27	6.28	0.00	0.12	2.53
Monthly net flow | negative	-1.09	5.58	-2.04	-0.07	-0.00

Notes: The data are from the Securities and Exchange Commission of Brazil (CVM). The net asset value, monthly recourse factoring, and flow variables are expressed in millions of USD. The interest rate (IR) is an issuance volume weighted average. The net flow is defined to be the difference between current net asset value NAV_t and net return adjusted previous month net asset value $\mathrm{NAV}_{t-1}(1+\tilde{r})$, where $\tilde{r}$ is the net return. "Monthly net flow | positive" is the subset of FIDC by month observations with positive net flow, while "Monthly net flow | negative" is the subset of FIDC by month observations with negative net flow. The difference between the factoring interest rate and the net return is explained by funds' holdings of low yield Brazilian Treasury bills for liquidity, performance fees, and default, usually in the form of delayed payment. The net asset value, recourse factoring purchase, and net flow are reported in millions of USD.

Figure 5 is a bin-scatter plot that shows that FIDCs tend to purchase receivables from firms with many employees (left) yet with low credit score (right). Although larger firms tend to have higher credit scores, each decile of credit score features firms across most of the size distribution. In each plot, we categorize each firm into a bin, then compute the mean share of factored receivable volume that is purchased by FIDCs rather than banks.

Figure 5: FIDC Share of Factoring



(a) FIDC Share by Number of Employees

(b) FIDC Share by Credit Score

Notes: The data are from the Central Bank of Brazil. Each subfigure partitions firms into bins along the horizontal axis. On the left, we classify firms by the mean number of employees across all months, where each bin includes the lower bound and excludes the upper bound. On the right, we classify firms by deciles of credit score in June 2023, the only month with available data. The bottom 19% of firms have a credit score of 0, generally signaling a lack of any credit history, so we pool together the bottom two deciles. In both plots, the denominator is all recourse factoring volume, and the numerator is recourse factoring volume in which the factor is the FIDC. The lower dots are FIDC purchases of receivables directly from firms, while the upper dots are total FIDC purchases of receivables, including from banks.

The main takeaways about the setting for working capital financing in Brazil are that trade credit is by far the most common type of firm-to-firm borrowing in Brazil, small and low credit score firms factor a large share of trade credit, and factoring volume is much higher than other types of intermediated working capital financing. FIDCs purchase a larger share of receivables for low credit score and large firms than for other firms.

4 Empirical Analysis

The ideal experiment would be to randomize the price offered to each receivable, across banks and funds (asset demand) and across firms (asset supply). This would allow us to trace out the financing demand curve of factoring, and for each marginal increment along the curve, compare firms' input demand, revenues, trade credit and other firm-to-firm decisions to compute elasticities with respect to the factoring interest rate. However, such an experiment is logistically difficult, and infeasible at the scale of the Brazilian economy, so we use an instrumental variable strategy instead.

4.1 First Stage

The first stage regression has factoring interest rate $r^{\text{Fac}}_{j,t}$ on the left hand side and firm-level expected flow-driven "exposure" (net purchases of receivables) on the right hand side, constructed as follows: $x^{\text{Fac}}_{j\to f,t}$ is fund f's exposure to firm j's recourse factoring, either directly purchasing receivable from firm j or from a bank/fintech, in month t. $X_{f,t}$ is fund f's total purchases of assets. $F_{f,t}$ is the net inflow to fund f, based on net asset value (NAV) following the literature: $F^{\text{NAV}}_{f,t} := \frac{\text{NAV}_{f,t}-\text{NAV}_{f,t-1}R_{f,t}}{\text{NAV}_{f,t-1}}$. We then define fund by factoring type by month exposure $e^{\text{Fac}}_{j,t}$ to funds' flows is the firm's share of 3-month lagged fund receivables purchases, scaled by the flow to the fund

$$e^{\text{Fac}}_{j,t} := \sum_f \frac{x_{j\to f,\underline{t}}}{X_{f,\underline{t}}} F_{f,t},$$

We normalize exposure $e^{\text{Fac}}_{j,t}$ so that its units are standard deviations from the mean. Then the first stage regression is

$$r^{\text{Fac}}_{j,t} = \alpha_j + \alpha_t + \gamma_1 e^{\text{Fac}}_{j,t} + \varepsilon_{j,t}. \tag{1}$$

The outcome variable of the first stage is the overall interest rate (IR) on factoring, shown in column 1 of Table 3. The interpretation is that a one standard deviation increase in expected fund purchases of receivables, due to net fund inflows, leads to a 0.12 percentage point decrease in the firm's factoring interest rate. The first-stage F-statistic is 91.1.

Table 3: First Stage Regression and its Decomposition into Bank vs FIDC

	First Stage	Decomposition	
	IR Factoring Issuance (All)	IR Factoring Issuance (Funds)	IR Factoring Issuance (Banks)
	(1)	(2)	(3)
$e_{j,t}$	$-$**0.1212*****	-0.1957^{***}	-0.0530^{***}
	(0.0127)	(0.0172)	(0.0068)
Num. Obs.	4,146,540	1,734,458	2,424,888
Num. Firms	511,896	251,391	313,390
Num. Months	65	65	65

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Notes: These regressions use data from the Central Bank of Brazil. The dataset is at the firm by month level, with firm and month fixed effects, and *standard errors are clustered at the firm level and shown in parentheses*. **The first stage coefficient is in column 1**. This is equal to a receivables value weighted average of interest rates from fund issuance (column 2) and bank issuance (column 3), where factoring issuance is the purchase of receivables. If a firm does not factor in a given month, then the interest rate is undefined, and the observation is dropped from the regression.

The column 1 interest rate is a value-weighted average of the interest rates on receivables purchased directly by funds (column 2) and by banks (column 3). Banks retain most of the receivables that they purchase; banks only re-sell 1.04% of the face value of receivables to funds, usually on the same day. We interpret column 3, the bank interest rate, as an equilibrium object; under our hypothesis, banks only change the interest rate because of competition with funds or the prospect of re-selling to funds.

The exclusion restriction states that fund flows only affect firms' revenues, expenditures, and trade credit decisions through the factoring interest rate, and are not a sign of expectations of firms' creditworthiness nor higher returns conditional on fixed effects. Because we focus on FIDCs, who are mandated to hold the majority of asset value in receivables and purchase negligible amounts of other corporate debt, we do not believe that there is contamination through other corporate interest rates. FIDCs' asset values and flows are a tiny share of total fund asset values and flows,[10] so we believe that FIDC flows are not large enough to affect monetary policy.

We argue that reverse causality, arising from flows chasing firms with high expected returns, is not a concern for three reasons. First, we do not believe that investors select FIDCs based on specific exposure. There are 762 FIDCs in our sample, and there are 251 thousand non-financial firms who sell receivables to FIDCs, with the majority of firms selling receivables to multiple FIDCs, so most FIDCs purchase receivables from thousands of firms. FIDCs do not report the identities of the firms, so investors cannot select FIDCs based on exposure to specific firms. We also believe that sectoral selection is not strong, as FIDCs tend to be diversified (see Figure A9). We show in Section A.3 that our results are robust to inclusion of sector-time and location-time fixed effects that capture many of the potential sources of fundamental shocks that could threaten identification. Of the 762 FIDCs, 651 of them purchase receivables from multiple high-level sectors,[11] and 430 have at least 20% AUM share in multiple sectors. Second, we believe that flows to FIDC are largely driven by institutional investors' portfolio allocation constraints across broad asset classes, like receivables versus equity and fixed income. Third, we show in Table 9 that firms' characteristics are balanced across firm-by-month observations with positive flows, negative flows, and flows near zero. To further assuage endogeneity concerns, we run a falsification test in Section A.4: we regress lagged outcomes on the current shock with current period fixed effects in Table 15 to test for anticipation effects.

[10] In March 2024, there are 18 billion USD of assets under management for FIDCs that primarily purchase firms' receivables, the focus of this paper. In comparison, there are 129 billion USD of assets under management for fixed income funds, and the total stock market capitalization is 972 billion USD.

[11] We define the high-level sectors to be manufacturing, retail, wholesale, transport, professional services, and other sectors.

4.2 IV Regression

The structural regressions estimate the contemporaneous impact of the recourse factoring interest rate, fitted on the FIDC flows, on a variety of response variables:

$$y_{j,t} = \alpha_j + \alpha_t + \beta_1 r^{Fac}_{j,t} + \varepsilon_{j,t} \tag{2}$$

The main response variables are shown in Table 4, which shows that a one percentage point increase in the factoring interest rate causes a large decrease in firms' contemporaneous revenue of 6.1 log points from column 1, a moderate decrease in intermediate input expenditure of 3.6 log points in column 2, and small decrease in expenditure on labor of 0.56 log points in column 3.[12] We decompose the decrease in labor expenditure into a decrease in labor demand for permanent employees and an increase in labor demand for temporary employees, with small increases in wages that likely reflect composition effects. Column 4 shows that the number of hours worked by permanent employees decreases by 1.1 log points, while column 5 shows that the number of hours worked by temporary employees increases by 2.1 log points. The average number of permanent employees per firm is 46.6, while the average number of temporary employees is 4.3; this differrence explains why employment and the wage bill decrease despite a larger percentage change in temporary labor than permanent labor. The mean number of weekly working hours for permanent employees is 41.8 and for temporary employees is 37.4, including overtime work, so the employment results vary little when measured by number of employees instead of hours. See Table 6 and Table 10 for the decomposition of the impact on labor market variables.

[12]We proxy for revenue and intermediate input expenditure using all boleto transactions, including transactions where the counterparty is a consumer. Since boleto transactions can be settled by cash, bank transfer, PIX, or other means, we believe that our proxy is representative of firms' real outcomes.

Table 4: IV Regressions of the Main Outcomes on the Factoring Interest Rate

	(1)	(2)	(3)	(4)	(5)
	Log Revenue	Log Expenditure	Log Wage Bill	Labor Demand (Log Hours, Permanent)	Labor Demand (Log Hours, Temporary)
$r^{Fac}_{j,t}$	-0.0614^{***}	-0.0357^{***}	-0.0056^{*}	-0.0110^{***}	0.0212^{***}
	(0.0093)	(0.0056)	(0.0023)	(0.0023)	(0.0064)
Num. Obs.	2,668,026	4,076,721	2,543,940	2,545,958	607,036
Num. Firms	217,956	476,418	287,108	287,201	93,156
Num. Months	65	65	50	50	50

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Notes: All regressions use data from the Central Bank of Brazil. All regressions use firm and month fixed effects, with standard errors clustered at the firm level in parentheses. The predictor variable is the firm-level interest rate on factoring in percentage points, instrumented by the expected change in receivables purchases driven by fund flows. The response variables are the log revenue proxied by payment inflows, log intermediate input expenditure proxied by payment outflows to firms, log wage bill, log labor demand for permanent workers, and log labor demand for temporary workers. There are only 50 months of data for labor variables because the labor data has only been published through December 2022.

Table 5: IV Regressions of Trade Credit Outcomes on the Factoring Interest Rate

	(1)	(2)	(4)	(5)
	Maturity Offer (Days)	Percentage Offer (%)	Maturity Receive (Days)	Percentage Receive (%)
$r^{Fac}_{j,t}$	-0.0354	-0.3885^{**}	0.6737^{***}	0.0272
	(0.0996)	(0.1274)	(0.1358)	(0.0379)
Num. Obs.	4,146,540	4,146,540	4,146,540	4,146,540
Num. Firms	511,896	511,896	511,896	511,896
Num. Months	65	65	65	65

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Notes: All regressions use data from the Central Bank of Brazil. All regressions use firm and month fixed effects, with standard errors clustered at the firm level. The predictor variable is the firm-level interest rate on factoring in percentage points. The instrumental variable is the expected change in receivables purchases driven by fund flows. The response variables are the firm by month level mean maturity of trade credit, offered and received, as well as the share of receivables with at least 15 days maturity, the effective lower bound for factoring.

Table 5 shows that there are small spillovers through the firm-to-firm trade credit network from the change in the factoring interest rate, which we later show is the shadow cost of trade credit, to trade credit terms that firms offer and receive. Column 1 shows that firms that face a one percentage point higher factoring interest rate do not change the maturity of the trade credit that they extend, but column 2 shows that affected firms are -0.39

percentage points less likely to offer any trade credit on the extensive margin.[13] Column 3 shows that affected firms receive slightly longer trade credit terms by 0.67 days, compared to the baseline mean of 22.8 days. Column 4 shows that the proportion that receive trade credit is a precisely estimated zero.[14]

4.2.1 Labor Outcomes

Now we decompose the wage bill coefficient of 0.56% from Table 4 into the hourly wage and hours worked in Table 6. Column 1 of Table 6 shows that the hourly wage rises slightly, which we interpret as firms choosing a higher marginal revenue product of labor in response to the higher marginal revenue product of capital (which equals the composite interest rate in an efficient equilibrium). Columns 2 and 3 show the total reduction in hours worked by each type of employee, with a larger decrease of 1.4% for new hires in Column 2 than the 0.6% decrease for existing employees in Column 3. Table 10 in Section A.2 shows that the results from Table 4 and Table 6 are similar when using the number of employees rather than the total number of hours worked.

Table 6: IV Regressions of Hours Employed Outcomes on Factoring Interest Rate

	(1)	(2)	(3)
	Log Wage (Hourly)	Log Employment (Hours Worked by New Hires)	Log Employment (Hours Worked by Existing Employees)
$r^{Fac}_{j,t}$	$0.0037^{\cdot}$	-0.0135^{**}	-0.0057^{**}
	(0.0020)	(0.0045)	(0.0020)
Num. Obs.	2,543,608	1,124,594	2,526,986
Num. Firms	287,082	183,930	284,845
Num. Months	50	50	50

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Notes: All regressions use data from the Central Bank of Brazil. All regressions use firm and month fixed effects, with standard errors clustered at the firm level. The predictor variable is the firm-level interest rate on factoring in percentage points. The instrumental variable is the expected change in receivables purchases driven by fund flows. The response variables come from restricted access month-level RAIS data. An employee is defined as new if the employee began working at the firm that month.

Altogether, we explain the labor impacts of the factoring interest rate using a cash flow mismatch story. Firms' sales are volatile month to month, and most firms have limited pricing power, so revenue is both volatile and not perfectly forecasted. Factoring allows firms to smooth their cash inflows; in months where firms have less than typical revenue,

[13] This leads affected firms to offer 5.7% less contemporaneous trade credit, compared to their 6.0% decrease in revenue from Table 4.

[14] The reduction in trade credit receipt of 3.1% is similar to the 3.6% reduction in expenditure.

they factor more. On the other hand, labor laws impose constraints on cash outflows. For the majority of firms, labor is the largest expense, and firms must commit in advance to pay permanent employees each month an amount that varies little from month to month. However, firms can adjust total labor expenditure on the margin through hiring more temporary employees and fewer permanent employees. When the factoring interest rate is high, meaning that it is expensive to smooth cash inflows, firms use the labor margin of adjustment to match cash outflows to cash inflows. We codify this explanation in the model in Section 5

4.2.2 Financial Outcomes

Table 7 shows that factoring volume is highly responsive to the factoring interest rate, with little substitution to quantities of other types of financing. Note that the response variable in column 3, the logarithm of actual factoring issuance at the firm level, differs conceptually from the instrumental variable, the expected change in firm-level factoring relative to a baseline of zero FIDC-level flows, based on FIDC-level flows and past factoring. Table 11 in the appendix shows that the interest rate on unsecured credit lines responds to the change in the factoring price, primarily through banks' factoring rates. Unsecured credit lines have a high baseline mean interest rate of 333% and high variance across firms, with standard deviation of 85%. See Tables 11 and 12 in the appendix for additional results on financial outcomes.

Table 7: IV Regressions of Debt Issuance Outcomes on Factoring Interest Rate

	(1)	(2)	(3)	(4)	(5)
	Log Debt Issuance (Debt Under 1 Year)	Log Debt Issuance (Debt Over 1 Year)	Log Debt Issuance Factoring All Issuance	Log Debt Issuance Credit Line (Unsecured)	Log Debt Issuance Credit Line (Secured)
$r^{Fac}_{j,t}$	-0.1627^{***}	0.0163	-0.1692^{***}	0.0167	-0.0319
	(0.0174)	(0.0259)	(0.0180)	(0.0170)	(0.0654)
Num. Obs.	4,146,540	508,179	4,146,540	829,816	410,208
Num. Firms	511,896	130,522	511,896	123,370	57,997
Num. Months	65	65	65	65	65

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Notes: All regressions use data from the Central Bank of Brazil. All regressions use firm and month fixed effects, with standard errors clustered at the firm level. The predictor variable is the firm-level interest rate on factoring in percentage points. The instrumental variable is the expected change in receivables purchases driven by fund flows. The response variables are log debt issuance by category of debt. Column 1 is the subset with maturity of up to 365 days. Column 5 is the subset with maturity of over 365 days. Column 3 is factoring. Column 4 and 5 are unsecured and secured credit lines, respectively, where issuance is defined as any drawdown of the credit line, not a change in the credit limit. Across all firms in Brazil, loans are the highest issuance form of long-term debt, and bonds are second highest.

4.3 Dynamic Effects

In this section, we use local projections, following Jordà (2005) and Plagborg-Møller and Wolf (2021), to estimate the dynamic effects of FIDC flows on the factoring interest rate and firms' outcomes.

4.3.1 Local Projection First Stage

Funds ought to allocate the majority of their asset holdings to receivables. Given the short maturity of receivables, we believe that funds quickly purchase receivables, with short–term transmission to the interest rate that decays over time. The following local projection generalizes the first stage regression (1) over horizons $h \geqslant 0$:

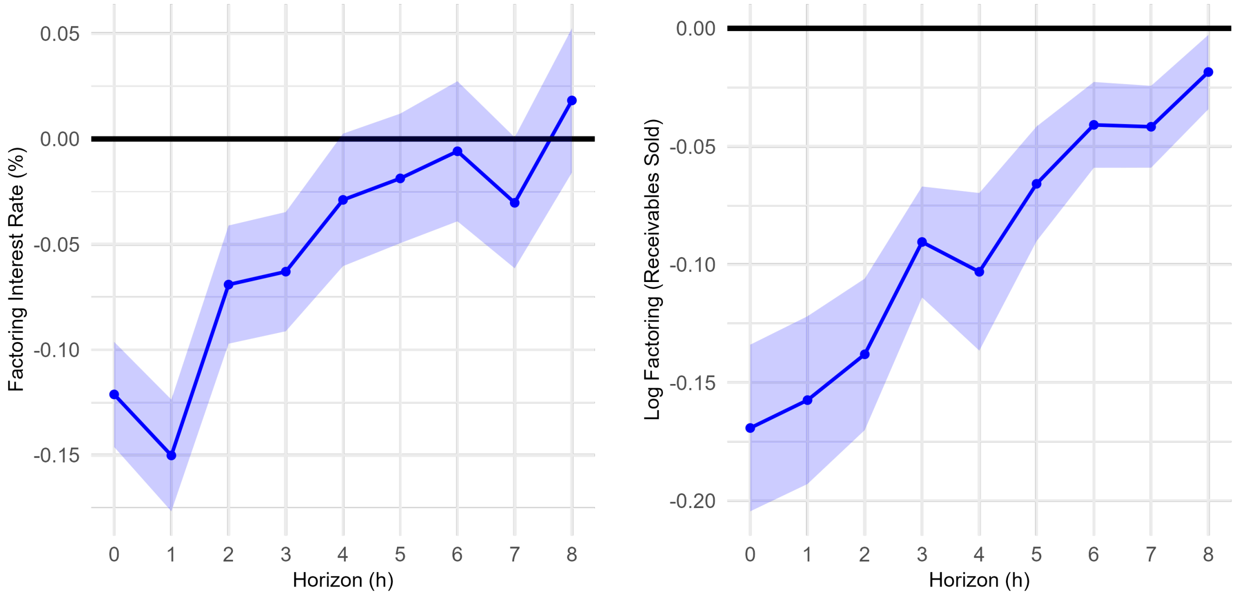
$$r^{Fac}_{j,t+h} = \alpha_{j,h} + \alpha_{t,h} + \beta_h e_{j,t} + \varepsilon_{j,t+h}. \tag{3}$$

Similarly, to see how the timing of firms' outcomes y change with respect to fund flows, we run the panel data IV local projection (IV-LP):

$$y_{j,t+h} = \alpha_{j,h} + \alpha_{t,h} + \beta_h r^{Fac}_{j,t} + \varepsilon_{j,t+h}, \tag{4}$$

Figure 6 shows the coefficients β_h over the horizons from 0 to 8 months, with the first stage (3) on the left in Figure 6a, and the factoring volume outcome from the IV-LP (4) on the right in Figure 6b. The interpretation of Figure 6a is that one standard deviation exposure to funds' net inflows results in a decrease in the interest rate of 12 basis points in the current month, corresponding to column 1 of Table 3, 15 basis points in the next month, seven basis points in the subsequent month, and then decays to zero by the fourth month after the shock. The interpretation of Figure 6b is that a fund flow causing a one percentage point contemporaneous increase in the interest rate, which would be an eight standard deviation exposure to funds' net outflows, causes a 17 log point decrease in current factoring volume, corresponding to column 3 of Table 7, and only gradually decays to 10 log points by the fourth month and 2 log points by the eighth month after the shock.

Figure 6: Local Projection of Factoring Interest Rate and IV-LP of Factoring Volume

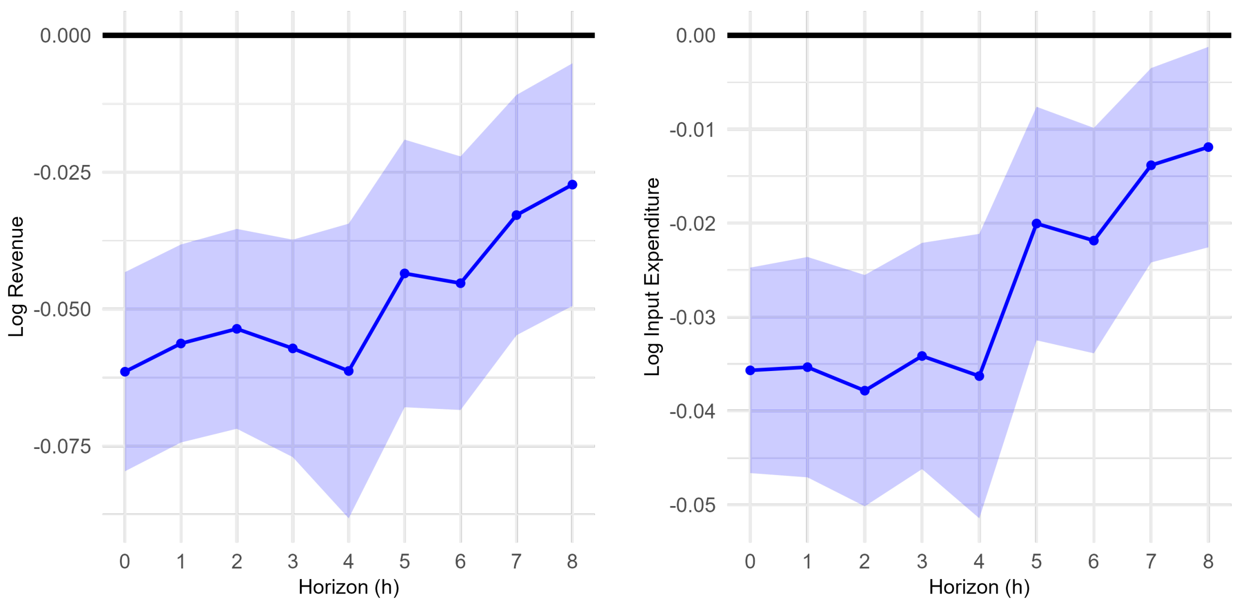


(a) Factoring Interest Rate

(b) Factoring Volume

Notes: The data are from the Central Bank of Brazil. Figure 6a on the left corresponds to the local projection in equation (3) with the factoring interest rate as the outcome variable. Figure 6a on the left corresponds to the panel IV local projection in equation (4) with log factoring issuance volume as the outcome variable.

Figure 7: IV-LP of Revenue and Input Expenditure



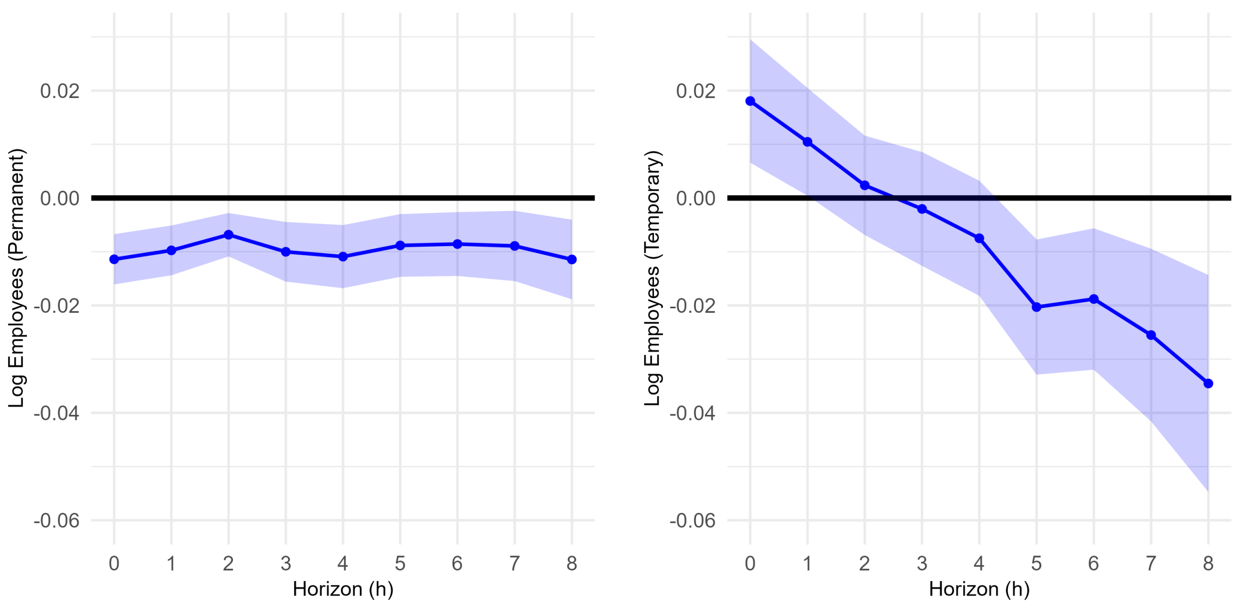
(a) Log Revenue

(b) Log Input Expenditure

Notes: The data are from the Central Bank of Brazil. Both plots correspond to the panel IV local projection in equation (4); on the left is log revenue as measured through boleto transactions (seller), and on the right is log input expenditure as measured through boleto transactions (buyer).

Figure 7 shows that the impacts on revenue and input expenditure persist with only gradual decay. Our explanation for the long lasting effects on revenue and expenditure is in Figure 8a, which shows that the change in permanent labor demand, relative to baseline, persists at the same level as the contemporaneous effect. Our explanation is that the adjustment is on the dimension of hiring; once a firm adjusts its hiring decision, the firm must commit to it because of the high cost of firing a permanent employee. The benefit is that permanent contract employees gain more job-specific human capital, and we find that wage growth is faster for permanent employees than temporary employees, demeaned on firm and employee fixed effects. Also of interest is the reversal of temporary labor demand in Figure 8b. In the short run, temporary labor demand moves in the opposite direction of permanent labor demand because of the cash flow volatility mechanism, where labor flexibility is an imperfect substitute for factoring in matching cash outflows to cash inflows. In the long run, the firm does not need the liquidity from labor flexibility, and instead chooses a level of temporary employment to match the marginal revenue productivity to that of other inputs. See Section A.2.2 for additional IV-LP results, including Figure A10, which shows that the change in the wage bill persists and increases in magnitude over time.

Figure 8: IV-LP of Permanent and Temporary Contract Labor Demand



(a) Log Permanent Labor Demand (b) Log Temporary Labor Demand

Notes: The data are from the Central Bank of Brazil. Both plots correspond to the panel IV local projection in equation (4); on the left is log permanent labor demand, and on the right is log temporary labor demand, both measured in log number of employees.

4.4 Heterogeneity

In this section, we show two categories of regressions that illustrate the heterogeneity across firms in the impacts of the cost of factoring. The first category is an interaction of firm type with the factoring interest rate. The second category is quantile regression.

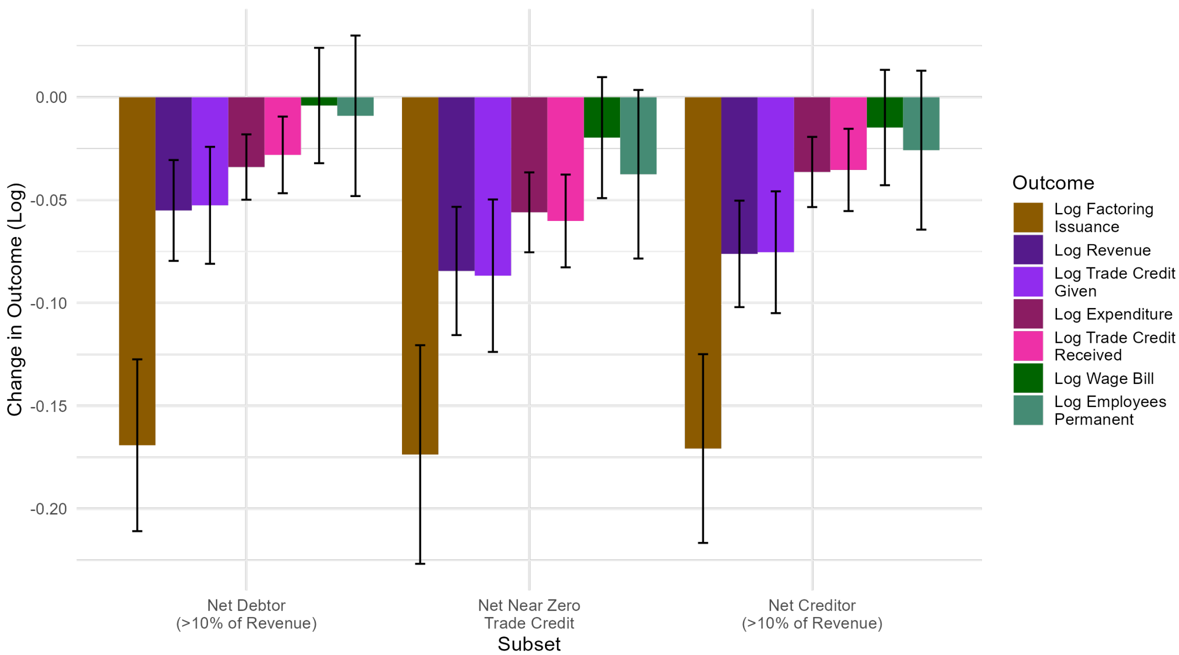
4.4.1 Heterogeneity by Firm Type

Consider regressions with interactions of the factoring interest rate $r_{j,t}^{\text{Fac}}$ with bins of firm heterogeneity γ_j:

$$y_{j,t} = \alpha_j + \alpha_t + \beta_1 r_{j,t}^{\text{Fac}} \gamma_j + \varepsilon_{j,t} \tag{5}$$

We classify each firm as a net creditor, net debtor, or neither for trade credit by taking the difference of total trade credit extended and total trade credit received over the sample period, and dividing by the firm's total revenue. If the ratio is greater than 0.1, then we consider firm to be a net creditor. If the ratio is less than -0.1, then we consider the firm a net debtor. We expect net creditors to have larger responses to the factoring price because they factor more receivables, so they receive more cash on hand for inframarginal factoring, and they may be more sensitive to factoring the marginal receivable, akin to the shadow price of trade credit.

Figure 9: Heterogeneous Effects of the Factoring Interest Rate by Net Trade Credit

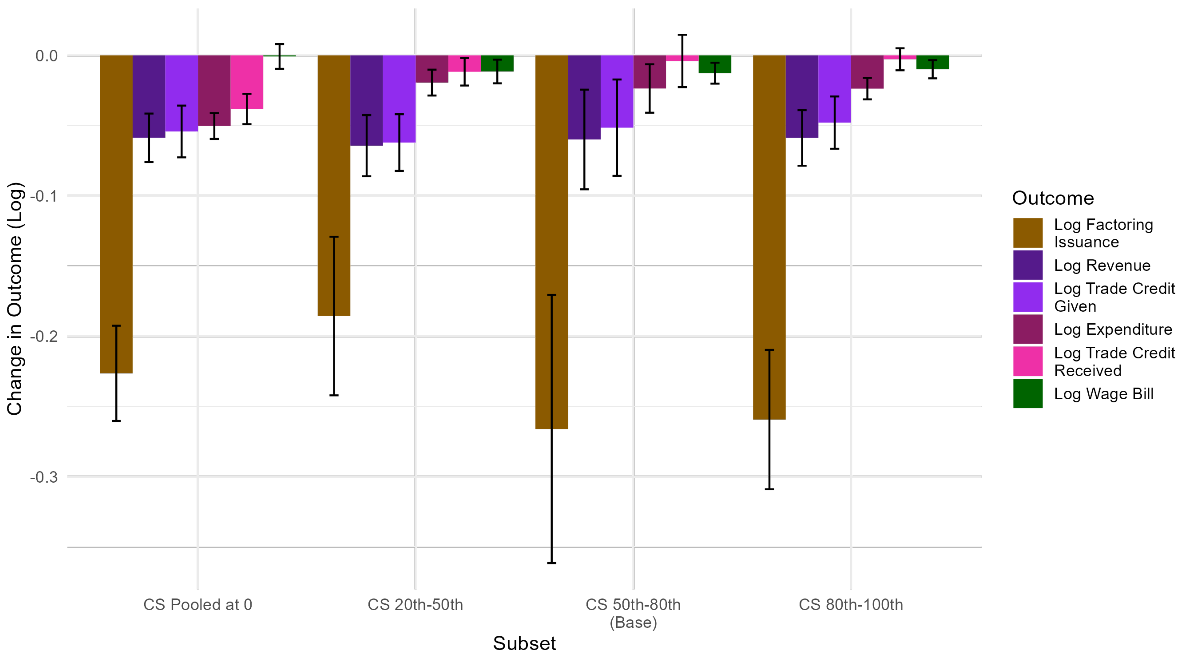


Notes: The data are from the Central Bank of Brazil. Each color corresponds to the heterogeneity interaction regression (5) with a different outcome variable, with bins defined by whether the firm is a net trade creditor with average net lending exceeding 10% of revenue, a net trade debtor with average net borrowing exceeding 10% of revenue, or neither. The error bars show 95% confidence intervals.

Figure 9 shows that net debtors indeed have smaller responses to the factoring price, with statistically significant differences for revenue, input expenditure, trade credit received, and trade credit extended, but not for labor outcomes. While the error bars overlap, the t-stats on the differences range from 2 to 3.

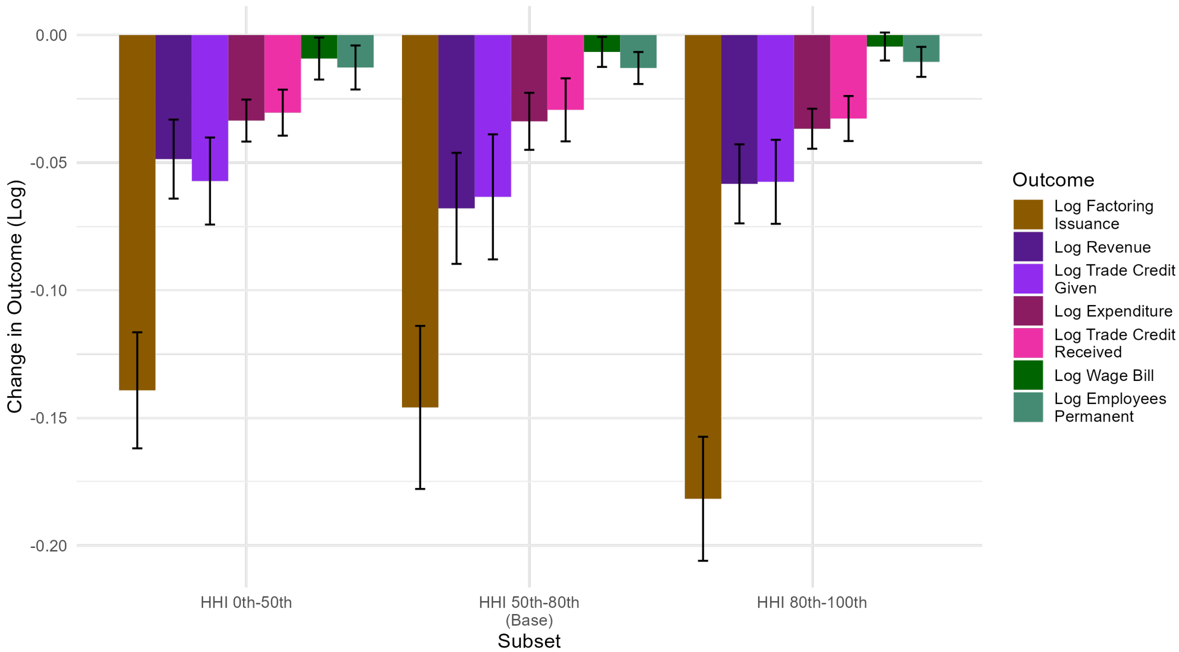
Figure 10 shows that the main results in Table 4 are true across the distribution of firms, not specific to firms with low credit scores that are more financially constrained. The base category is firms with credit scores between the 50th and 80th percentiles. Firms with the lowest credit scores, pooled at the minimum score, decrease intermediate input expenditure more and do not reduce expenditure on labor. Otherwise, the interactions of credit score bins with the factoring interest rate are similar across bins, despite the greater financial constraints faced by low credit score firms.

Figure 10: Heterogeneous Effects of the Factoring Interest Rate by Credit Score



Notes: The data are from the Central Bank of Brazil. Each color corresponds to the heterogeneity interaction regression (5) with a different outcome variable, with bins defined by the quantile of the firm's credit score in June 2023 from the main corporate credit bureau in Brazil. The error bars show 95% confidence intervals.

Figure 11: Heterogeneous Effects of the Factoring Interest Rate by HHI



Notes: The data are from the Central Bank of Brazil. Each color corresponds to the heterogeneity interaction regression (5) with a different outcome variable, with bins defined by the tercile of the firm's HHI. The error bars show 95% confidence intervals.

Likewise, Figure 11 shows that there is minimal heterogeneity by the Herfindahl-Hirschman Index (HHI) of the firm's sector defined at the 7-digit CNAE level, which roughly corresponds to 6-digit HS code. HHI proxies for market concentration, and Dass et al. (2015); Fabbri and Klapper (2016); Giannetti et al. (2021) suggest that trade credit varies with firms' bargaining power and market power, but this does not pass through to factoring.

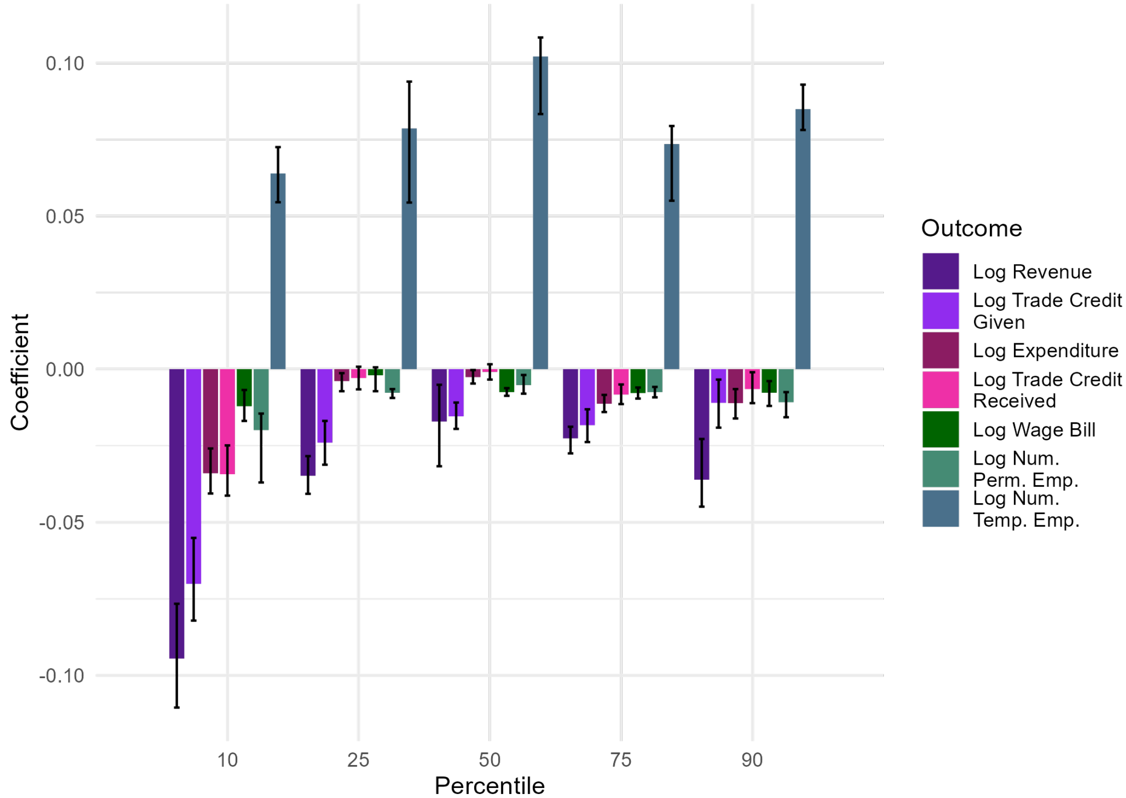
4.4.2 Heterogeneity by Quantile

We also estimate quantile regressions for each of the main outcomes, to assess how firms at different points in the outcome distribution respond to the factoring interest rate. For each quantile τ and outcome y, we run the IV quantile regression based on Canay (2011):

$$Q_{\tilde{y}_{j,t}}(\tau \mid \widetilde{\hat{r}}^{\text{Fac}}_{j,t}) = \beta(\tau)\widetilde{\hat{r}}^{\text{Fac}}_{j,t} + \varepsilon_{j,t}(\tau), \tag{6}$$

where the outcome $\tilde{y}$ and the factoring interest rate $\widetilde{\hat{r}}$ are de-meaned on firm and month fixed effects, and the factoring interest rate $\widetilde{\hat{r}}$ is fitted from the first stage (1).

Figure 12: Quantile Treatment Effects of the Factoring Interest Rate



Notes: The data are from the Central Bank of Brazil. Each bar represents a quantile regression using the fund flow instrument corresponding to equation (6). Each color represents a different outcome variable, while each set of bars is a given quantile: the 5th, 25th, 50th, 75th, and 95th percentiles. Standard errors are calculated using rank inversion.

The interpretation of each coefficient in Figure 12 is the IV treatment effect at the given quantile of the distribution of the outcome. Note that the simple average of the quantile treatment effects does not reconstruct the average treatment effect in the earlier tables due to differences in methodology with fixed effects. Rather, the quantile regression coefficients are useful for comparison across quantiles. The dark purple bar represents log revenue. The impact of factoring interest rate on revenue is largest for the firms with least revenue. The same pattern holds for trade credit offered, in light purple, as well as expenditure, in maroon, and trade credit received, in pink. The impact on wage bill is a bit larger for the smallest firms, and otherwise close to zero. This is a weighted average of a decrease in permanent employees across the entire distribution, and an increase in temporary employees.

In conclusion, the heterogeneity results by revenue, trade credit, and expenditure suggest that credit constraints may amplify the effects for the smallest firms, while the labor results suggest that the cash flow volatility motivation of factoring is important for firms across the distribution of size and creditworthiness.

5 Model and Counterfactual

5.1 Conceptual Overview

Our regression results show that factoring volume is the most responsive to the interest rate; revenue is highly responsive, more so for small firms that factor a lot; intermediate input purchases are responsive but not as much as revenue; labor demand decreases, with a short-run increase in temporary workers and a persistent decrease in permanent workers, mainly through reduced hiring. We interpret the results as micro-elasticities: micro both in the sense of at the firm level, with firm and month fixed effects, and in the sense of temporary changes, idiosyncratic at the firm level.

The purpose of the model is to rationalize the micro-elasticities in the empirical results, and also estimate "macro-elasticities:" how do aggregate output and factoring volume respond to the factoring spread. The only other empirical factoring papers, Bottazzi et al (2023) and Amberg et al (2023), estimate the total impact of introducing factoring to firms, rather than elasticities using fine variation in interest rates. However, factoring already exists in many countries, and the main challenge for policymakers is reducing the underlying frictions that keep factoring expensive. These frictions include verification costs that a receivable has not been double-pledged, screening costs of the creditworthiness of the buyer (in addition to the seller as typical with financing), and search costs for a firm to find the factor offering the best price.

5.2 Model Setup

There is a unit continuum of producer firms with identical baseline productivity who produce differentiated goods. There are two time periods, morning (period 0) and afternoon (period 1). Firms produce in both the morning and afternoon. Firm j produces its good with a Cobb-Douglas production function over labor ℓ and intermediate inputs x with constant labor share α:

$$y_{jt} = \ell_{jt}^{\alpha} x_{jt}^{1-\alpha}.$$

Firms sell to a representative aggregator firm who bundles the differentiated goods into a final good with elasticity of substitution $s > 1$:

$$Y_t = \left(\int_{j=0}^{1} y_{jt}^{\frac{s-1}{s}} \right)^{\frac{s}{s-1}}, \quad P = \left(\int_{j=0}^{1} p_j^{-(s-1)} \right)^{-\frac{1}{s-1}} \equiv 1.$$

The aggregator firm sells the final good to producer firms and to households. In the morning, producer firms offer trade credit on all sales, meaning that producer firms pay in the afternoon for intermediate inputs used in the morning.[15] All afternoon sales are paid upfront. Firms must pay their employees at the end of each period.

Firms can hire two types of labor: permanent labor ℓ^P, whose wage and quantity must be the same in the morning and afternoon, and temporary labor ℓ_t^T, which the firm can freely adjust. In the morning, permanent labor has the same relative productivity $\psi_0 = 1$ as temporary labor, while in the afternoon, permanent labor is more productive: $\psi_1 = \psi > 1$. Normalize the price of the final good to 1 in each period, so the real wages are w^P for permanent and w_t^T for temporary labor. There is constant elasticity of substitution $\sigma > 1$ between permanent and temporary labor, with share ω on permanent labor:

$$\ell_{jt} = \left(\omega \left(\psi_t \ell_j^P \right)^{\frac{\sigma-1}{\sigma}} + (1-\omega) \left(\ell_{j1}^T \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}. \tag{7}$$

Firm j chooses ℓ_j^P at the beginning of period 0 and chooses ℓ_{jt}^T at the beginning of period t.

The only dimensions of firm heterogeneity are the realization and distribution of the liquidity shock. Let $\epsilon_j \in [0,1]$ be the share of receivables y_{j0} promised in the morning that fail to materialize in the afternoon. Let $\zeta_j = \mathbb{E}_0 \epsilon_j$ be its mean. Let G_ζ denote the CDF of ζ_j and let $G_\epsilon(\epsilon \mid \zeta_j)$ denote the conditional CDF of ϵ. Heterogeneity in ζ_j represents the ex ante differences across firms in their buyers' creditworthiness, due to differences in sectoral volatility and firm-to-firm matching, without the complication of explicitly modeling the firm network. Firms observe the shock before choosing temporary labor and inputs in the afternoon, but must continue to pay permanent employees the contracted wage. The proceeds of the liquidity shock are rebated lump sum to consumers in the second period. Due to the timing of the liquidity shock, firms behave as if they were choosing their morning and afternoon production allocations in the morning, together with their financing decisions.

In the baseline model, the only type of financing available to the firm is factoring. The firm borrows at the beginning of the morning and repays at the end of the afternoon. Firm j borrows B_j^F, up to the face value of the morning accounts receivable $p_j y_{j0}$ discounted by gross interest rate R_j^F. Because firms begin with zero cash on hand, firms must factor at least the morning wage bill $w^P \ell_j^P + w_0^T \ell_{j0}^T$. Factoring services are imperfectly competitive with constant spread (markup) $\mu^F \geqslant 1$. The main counterfactual for the model is how outcomes change when the factoring spread μ^F decreases. Then the factoring interest rate

[15] We observe a high trade credit share across the firm distribution. To micro-found always offering trade credit, assume that there are two quality levels of the final good. Low quality is worthless. Firms incur a small cost to produce high quality with certainty. Quality is verifiable by the customer and any third party in the afternoon, and the customer can refuse to pay if she discovers the quality to be low.

is based on the share of inflows ζ_j that are shocked:

$$R_j^F = \frac{\beta^{-1}\mu^F}{1-\zeta_j}.$$

Firms begin with zero cash on hand. Firms do not earn a return on cash, but firms can retain cash between the morning and afternoon. Firms cannot default to suppliers in the afternoon, nor to labor in either period, because payments are made upfront.

The producer firm's objective in the morning is to maximize expected profits at the end of the afternoon, by choosing intermediate inputs x_{jt}, permanent labor ℓ_j^P, temporary labor ℓ_{jt}^T, and factoring B_j^F, taking as given wages $\{w^P, w_t^T\}$, factoring interest rate R_j^F, shock e_j, and model parameters. The firm faces a cost of default η, applied to negative profits, which occur when the firm does not have enough cash in the afternoon to repay suppliers with whom it contracted in the morning.

$$\max_{\{y_{jt}, x_{jt}, \ell_j^P, \ell_{jt}^T, B_j^F\}} \pi_j := \beta \mathbb{E}_0 \left[\pi_{j1} + \eta \pi_{j1} \mathbb{1}\{\pi_{j1} < 0\}\right] + m_{j0}, \tag{8}$$

$$\text{s.t. } B_j^F \leqslant \frac{p_j y_{j0}}{R_j^F}, \tag{9}$$

$$0 \leqslant m_{j0} \equiv B_j^F - \ell_j^P w^P - \ell_{j0}^T w_0^T, \tag{10}$$

$$\pi_{j1} := p_j y_{j1} - \ell_j^P w^P - \ell_{j1}^T w_1^T - P x_{j1} + \tilde{m}_{j1},$$

$$\tilde{m}_{j1} = (1-\epsilon_j)\left(p_j y_{j0} - R_j^F B_j^F\right) - P x_{j0}.$$

The key feature of factoring is that the upper bound $\frac{p_j y_{j0}}{R_j^F}$ in (9) is inherently endogenous to the firm's output choice y_{j0}. The lower bound $\ell_j^P w^P + \ell_{j0}^T w_0^T$ in (10) is also endogenous to the firm's decision.

The producer firm's objective in the afternoon is to maximize marginal profits, taking as given the choices made in the morning: $\{y_{j0}, x_{j0}, \ell_j^P, \ell_{j0}^T, p_j, B_j^F\}$ and the realization of the shock ϵ_j. Since there is no residual uncertainty, the firm's objective is deterministic:

$$\max_{\{x_{j1}, \ell_{j1}^T\}} \pi_{j1} := p_j y_{j1} - \ell_j^P w^P - \ell_{j1}^T w_1^T - P x_{j1} + \tilde{m}_{j1},$$

$$\text{s.t. } y_{j1} = \tilde{\ell}_{j1}^{\alpha} x_{j1}^{1-\alpha},$$

$$\tilde{\ell}_{j1} = \left(\omega\left(\psi \ell_j^P\right)^{\frac{\sigma-1}{\sigma}} + (1-\omega)\left(\ell_{j1}^T\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}},$$

$$\ell_{j1}^T, x_{j1} \geqslant 0.$$

The aggregator firm's objective in each period is standard: choose purchases y_{jt} to minimize expenditure $\int_0^1 p_j y_{jt} dj$ subject to $Y_t = \left(\int_{j=0}^1 y_{jt}^{\frac{s-1}{s}}\right)^{\frac{s}{s-1}}$. The first-order condition implies

$$\frac{p_j}{P} = \left(\frac{y_{jt}}{Y_t}\right)^{-\frac{1}{s}}. \tag{11}$$

There is a representative household. The household's utility is logarithmic over consumption.[16] The household has exponential disutility $\xi > 1$ from labor in each period, i.e. the household prefers to supply similar labor in the morning and afternoon. The household has relative preference ν for permanent versus temporary labor.[17]

$$u_t(c_t, \ell_t^T) = \log(c_t) - \sum_{t=0}^{1} \left[\frac{1}{\xi}\left(\ell^P + \ell_t^T\right)^{\xi} - \nu(\ell^P - \ell_t^T)\right].$$

The household receives its pay in each period, owns the financiers who lend to the firms, and pays for its consumption in the afternoon. Because of the timing of its income and expenditure, the household never demands to borrow. The household begins with zero cash. The household's optimization problem is to choose ℓ^P and ℓ_t^T to maximize discounted utility, given real wages w^P for permanent and w_t^T for temporary labor, subject to its budget constraint.

$$\max_{\{c_0, c_1, \ell^P, \ell_0^T, \ell_1^T\}} \log(c_0) + \beta \log(c_1) - \sum_{t=0}^{1} \left[\left(\ell^P + \ell_t^T\right)^{\xi} + \nu\left(\ell^P - \ell_t^T\right)\right], \tag{12}$$
$$\text{s.t. } c_0 + c_1 = 2\ell^P w^P + \sum_t \ell_t^T w_t^T.$$

[16]In this model, the shape of household utility over consumption is unimportant because there is only effectively one period, the afternoon, when the household pays for its consumption, and because there is no heterogeneity among households. With linear or CARA or CRRA utility, the results are qualitatively unchanged.

[17]In an extension, we generalize this to heterogeneous worker types, and we use the mix as a reduced form way to aggregate over this heterogeneity. e.g. older workers who prefer permanent, vs young inexperienced workers who prefer temporary because the search costs are too high for them to receive permanent offers.

5.2.1 Equilibrium

Given model parameters, firms optimize (20), households optimize (19), and markets clear in each period:

$$Y_t = \left(\int_{j=0}^{1} y_{jt}^{\frac{s-1}{s}}\right)^{\frac{s}{s-1}} = c_t + \int_{j=0}^{1} x_{jt}\, dj, \tag{13}$$

$$\int_{j=0}^{1} \ell_j^P\, dj = \ell^P, \tag{14}$$

$$\int_{j=0}^{1} \ell_{jt}^T\, dj = \ell_t^T. \tag{15}$$

See Section B in the appendix for the method that we use to solve the model. See Section C for the dynamic generalization that also introduces the collateralized credit line as an alternative source of financing.

5.3 Model Calibration

We calibrate the model primarily using moments in the data that are implied by the model structure, summarized in Table 8. The parameters α, β, ψ, and μ^F are calculated using aggregate moments. The Cobb-Douglas parameter α is expenditure share on labor. The discount rate β scales the overnight interst rate by the mean maturity of factored receivables; the value is almost exactly the same when using 3-month T-bills instead. The relative slope of the hourly wage to experience curve for permanent contract versus temporary contract employees is the gain to experience ψ for the afternoon versus the morning. The difference between FIDC factoring interest rates and the total cost of capital, as a weighted average across all factoring transactions, is the aggregate factoring spread μ^F. For the labor type elasticity of substitution σ, we regress $\log \ell_{j1}^T$ on $\log w_1^T$, net of firm and month fixed effects, then we use σ and equation (29) to calibrate ω. We calibrate ν at the indifference point in household FOCs between supplying an additional unit of permanent versus temporary labor. For the Frisch elasticity $\frac{1}{\xi-1}$ and the goods elasticity of substitution, we use the values in the BCB's calibration of its DSGE model. Finally, because we cannot observe the cost of default, we use the value 25% from Glover (2016). See Section B.2 in the appendix for more details.

Table 8: Summary of Model Calibration

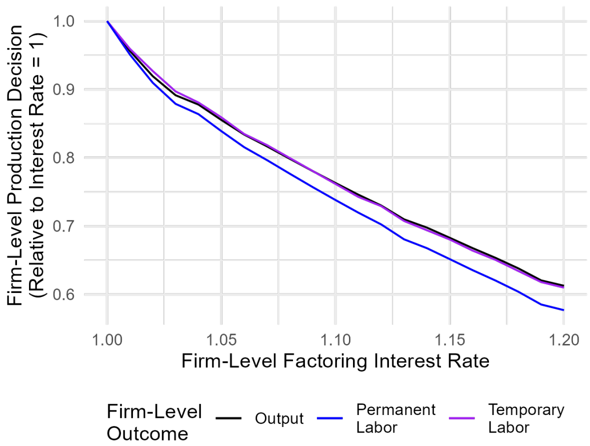
Parameter	Value	Description	Method
α	0.43	Cobb-Douglas labor	Data: Expenditure share
ψ	1.31	Gain to experience	Data: Ratio of existing to new hire wage for permanent vs temporary
μ^F	1.13	Factoring spread	Data: IR minus (default rate + 3-month T-bill)
σ	1.80	EoS permanent vs temporary labor	Data: Regression
ω	0.89	CES share parameter on permanent employees	Data: σ and model-derived moment
ν	0.009	Relative labor preference term	Data: model-derived moment
ξ	5.48	Exponential disutility of labor supply, equiv. to a Frisch elasticity of 0.22	BCB SAMBA DSGE
s	11	EoS across differentiated goods	BCB SAMBA DSGE
β	0.979	Discount rate between morning and afternoon	Data: 3-month T bill
η	0.25	Cost of default	Glover (JFE 2016).

Notes: This table shows the calibration of each parameter in the model. For more details on the calibration methods, see Section B.2 in the appendix.

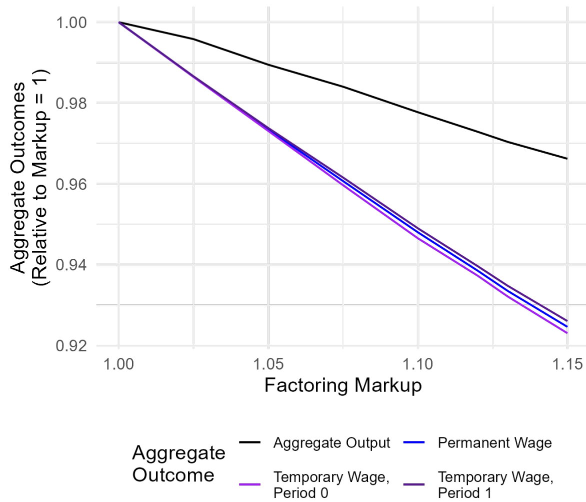
5.4 Counterfactuals

There are two main counterfactuals that we consider. The first counterfactual is the partial equilibrium equivalent of the regressions, shown in Figure 13a, where we decrease the interest rate R_j^F for a specific firm, holding fixed the equilibrium values $\{Y_j, w_{jt}^T, w^P\}$. As the firm's factoring risk ζ_j increases, permanent labor demand decreases faster than temporary labor demand and output. The second counterfactual, shown in Figure 13b, is the general equilibrium hypothetical, where we decrease the factoring spread μ^F, which decreases R_j^F for all firms. Across equilibria, as the factoring spread decreases, there is a larger increase in wage than in output due to the inelasticity of labor supply. See Section B.3 in the appendix for additional model results.

Figure 13: Model-Implied Counterfactuals



(a) Partial Equilibrium



(b) General Equilibrium

Notes: These figures show two counterfactuals from solving the model under different conditions. On the left, for the partial equilibrium counterfactual, we decrease the interest rate R_j^F for a specific firm, holding fixed the equilibrium values $\{Y_j, w_{jt}^T, w^P\}$, as well as all parameters. On the right, for the general equilibrium counterfactual, we decrease the factoring spread μ^F, which decreases R_j^F for all firms, holding all other parameters fixed.

The main takeaway from Figure 13 is that the partial equilibrium elasticities with respect to the factoring interest rate, which are around -3.1, are similar in magnitude to the regression results from Section 4.2, while the general equilibrium elasticities are -0.3 for output and -0.5 for the wage bill, an order of magnitude smaller than the partial equilibrium effects. The general equilibrium dampening is due to the change in wage and the inelasticity of labor supply when firms collectively reallocate labor demand from permanent to temporary contracts.

6 Conclusion

This paper contributes new evidence on why factoring is the dominant form of working capital financing in Brazil and increasingly important worldwide, especially for small firms with limited credit access. Using a large novel dataset covering trade credit terms, factoring, other lending, payments, and employment for nearly all formally registered firms in Brazil, we are the first to estimate the causal impact of the factoring interest rate on firms' production decisions, trade credit, and outcomes. We show that a decrease in the factoring interest rate leads to a large contemporaneous increase in firms' sales and input purchases, with an increase in permanent employment and a decrease in temporary employment. While the sales and input purchase effects mostly dissipate after several months, the increase in permanent employment is persistent, and temporary employment also increases in the long run as the firm grows and the short–term liquidity motive for labor substitution is no longer pertinent. These results highlight the dual role of factoring in mitigating cash flow volatility and enabling firms to extend trade credit under financial constraints.

Our model provides a framework to understand how firms' demand for factoring is driven by cash flow volatility and non-payment risk from customers. Unlike other financing instruments, factoring directly decreases cash inflow volatility through shifting the non-payment risk to a financial intermediary. The factoring borrowing limit is endogenously linked to firms' output, which amplifies the partial equilibrium response of factoring volume and output to the factoring interest rate. These effects are dampened in general equilibrium due to adjustments in wages and in firms' responses to changes in aggregate output.

More broadly, the findings reveal how non-bank intermediaries, specifically FIDCs, serve as a major source of corporate liquidity supply and transmit shocks to asset demand and portfolio reallocation to the real economy. By quantifying the magnitude and duration of these effects, the paper connects the literature on credit-supply shocks to the growing importance of non-bank intermediation in corporate finance. Future research will examine how policy reforms to receivables registries, tokenization in the supply chain, expanded access to FIDCs, and fintech market entry affect the factoring interest rate by reducing transaction costs and increasing competition between banks and FIDCs in the supply of factoring.

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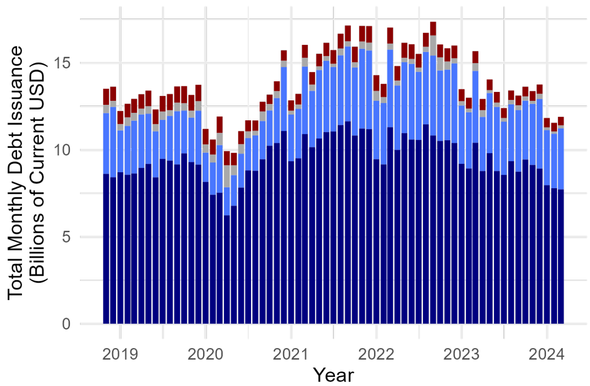
A Empirical Appendix

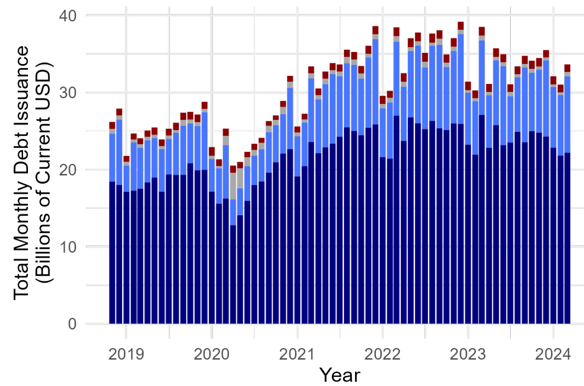
A.1 Additional Summary Statistics for Factoring

Figure A1 shows that low credit score firms use factoring as a greater share of working capital financing than high credit score firms.

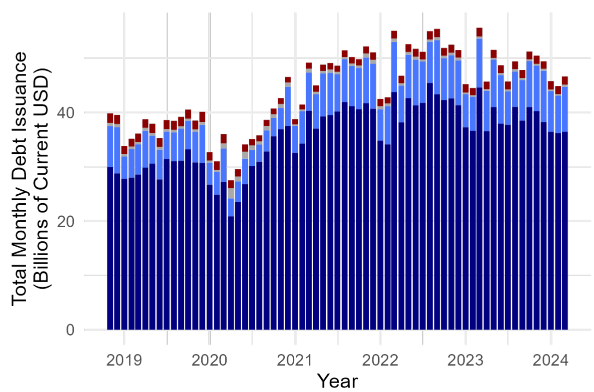
Figure A1: Working Capital Financing Composition by Firms' Credit Score (Right)



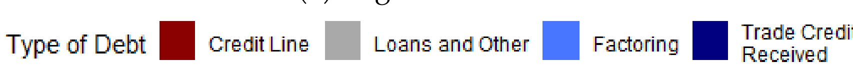
(a) Low Credit Score



(b) Medium Credit Score



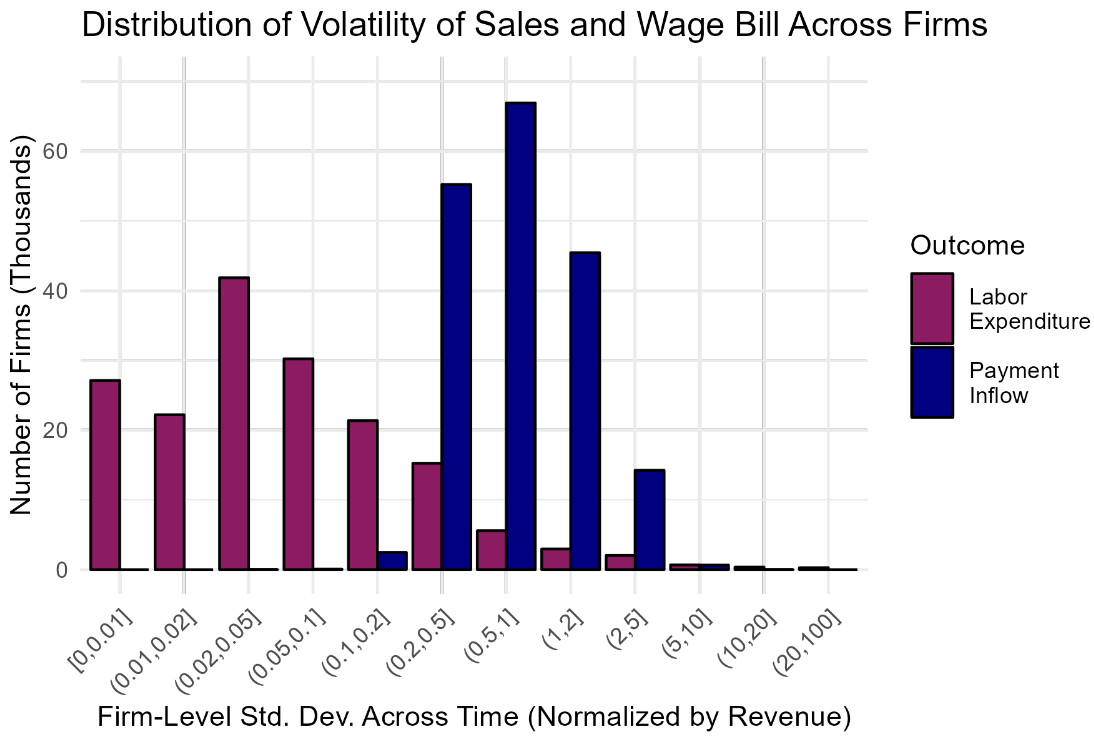
(c) High Credit Score



Notes: This figure uses data from the Central Bank of Brazil to show the time series of working capital financing, partitioned by the tercile of the credit score of the firms as of June 2023, the only month with available data. In dark blue is the value of trade credit that a firm receives from its suppliers. In light blue is factoring, the sale of receivables from the trade credit that a firm offers its customers. In red are credit lines, which generally require firms to post collateral. In gray are working capital loans and bonds.

Figure A2 shows that almost all firms have normalized monthly cash inflow volatility between 0.2 and 5, where the denominator is the magnitude of cash inflows. By comparison, when we compute the normalized monthly volatility of the main component of cash outflows, permanent labor expenditure, we find that 70% of firms have values below 0.1. Even when we control for the share of permanent labor expenditure in all expenditure, around 40%, we find that many firms have cash outflow volatility equal to an order of magnitude higher than cash inflow volatility. This cash flow mismatch generates firms' demand for working capital financing, and factoring in particular.

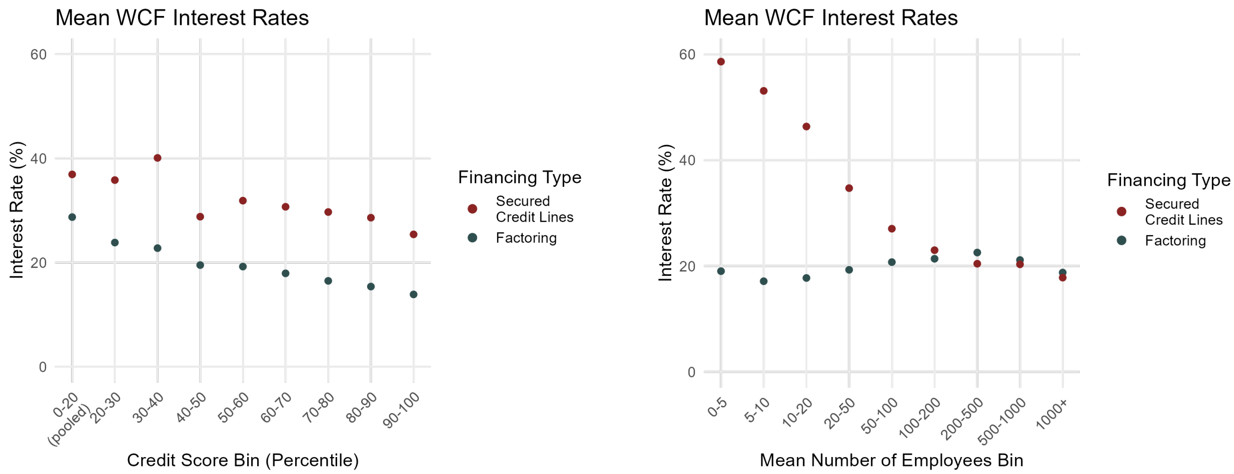
Figure A2: Firms' Cash Inflow Volatility Is an Order of Magnitude Higher than Cash Outflow Volatility



Notes: This figure uses data from the Central Bank of Brazil to show the distribution of firm-level standard deviations of contracted sales, as proxied by boleto contracts, and permanent labor expenditure, measured via the employer-employee matched dataset (RAIS). For each firm, we compute the monthly standard deviation of contracted sales and permanent labor, and normalize each by the mean monthly contracted sales. We then count the number of firms in each bin of normalized standard deviations.

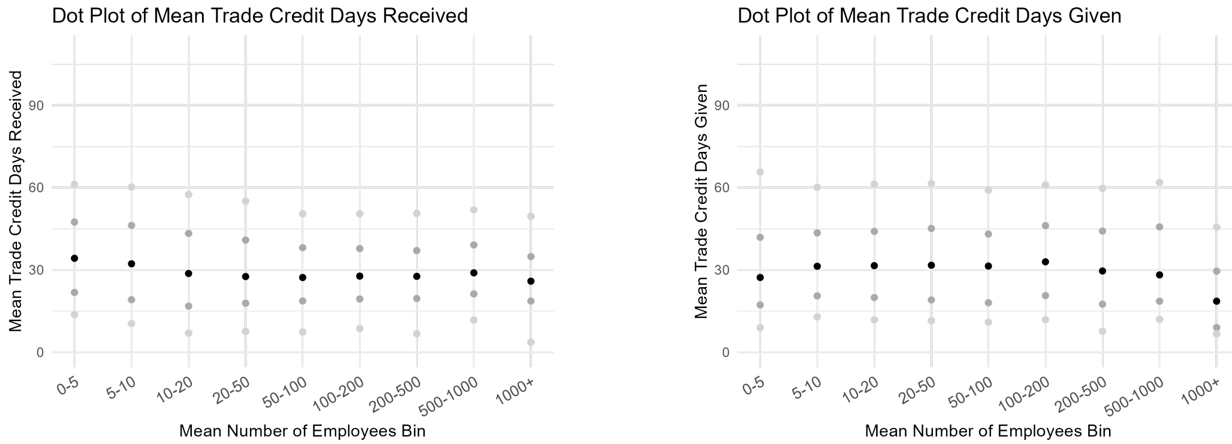
Figure A3 shows that the interest rates of secured credit lines and recourse factoring are both increasing in the risk of the debtor (decreasing in its credit score), but there is a stronger relationship for credit lines than factoring over the distribution of firm size, due to the factoring risk depending in part on the risk profile of the customers. This is one explanation for why small firms factor receivables at a higher rate than large firms.

Figure A3: Mean Interest Rates of Factoring and Credit Lines across the Firm Distribution



Notes: This figure uses data from the Central Bank of Brazil. Each subfigure partitions firms into bins along the horizontal axis and computes the issuance volume weighted mean interest rate within each bin for each type of working capital financing (WCF). On the left, we classify each firm by its mean number of employees across time. On the right, we classify firms by deciles of credit score in June 2023, the only month with available data. The bottom 19% of firms have a credit score of 0, generally signaling a lack of any credit history, so we pool together the bottom two deciles.

Figure A4: Trade Credit Maturity Distribution across the Distribution of Firms' Number of Employees

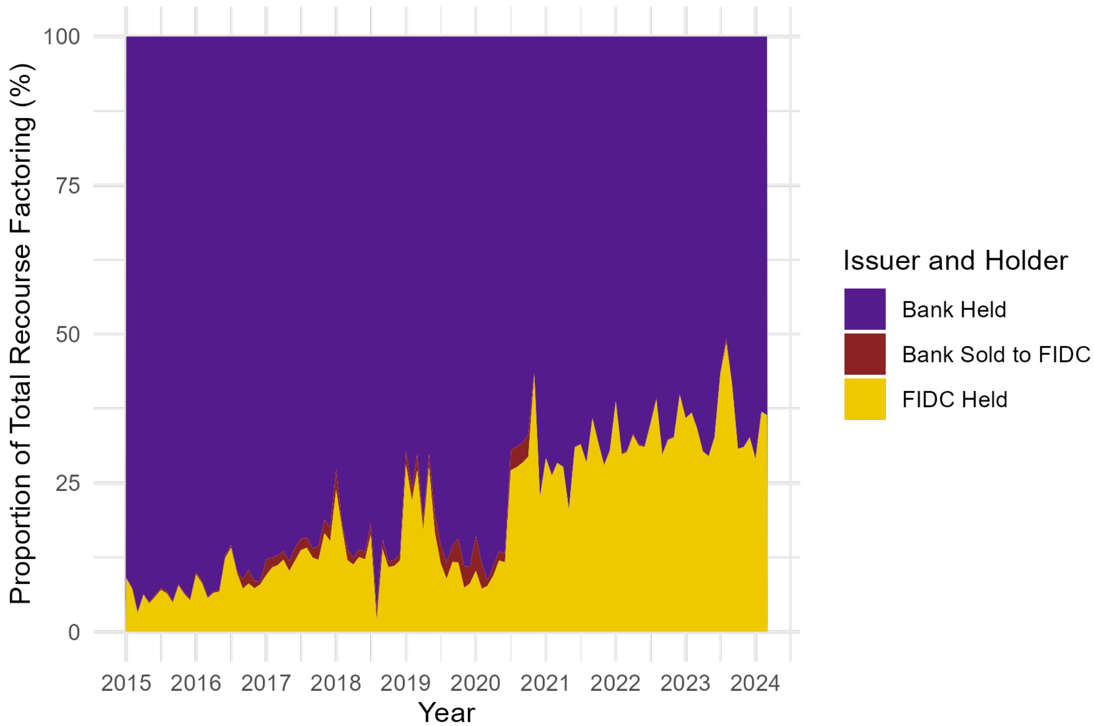


Notes: This figure uses data from the Central Bank of Brazil. Each subfigure partitions firms into bins of credit score as of June 2023, the only month with available data. The bottom 19% of firms have a credit score pooled near 0, generally signaling a lack of any credit history, so we pool together the bottom two deciles. The figure on the left shows the maturity distribution of trade credit received from suppliers, while the figure on the right shows the maturity distribution of trade credit given to customers. The black dots show the mean maturity, the inner medium gray dots show the 25th and 75th percentile, and the outer light gray dots show the 10th and 90th percentile, among the set of firms within each bin.

Figure A4 shows that there is also no strong relationship between a firm's credit score and the maturity of the trade credit that it gives or receives. However, the very largest firms, with over 2,000 employees and/or annual revenue of $1 billion USD, roughly corresponding to the set of publicly traded firms in Brazil, tend to pay upfront for their purchases from suppliers, and offer fewer days of trade credit to customers as well.

Figure A5 shows that the FIDC share of factoring has increased from 7% in 2015 to 32% in 2023.

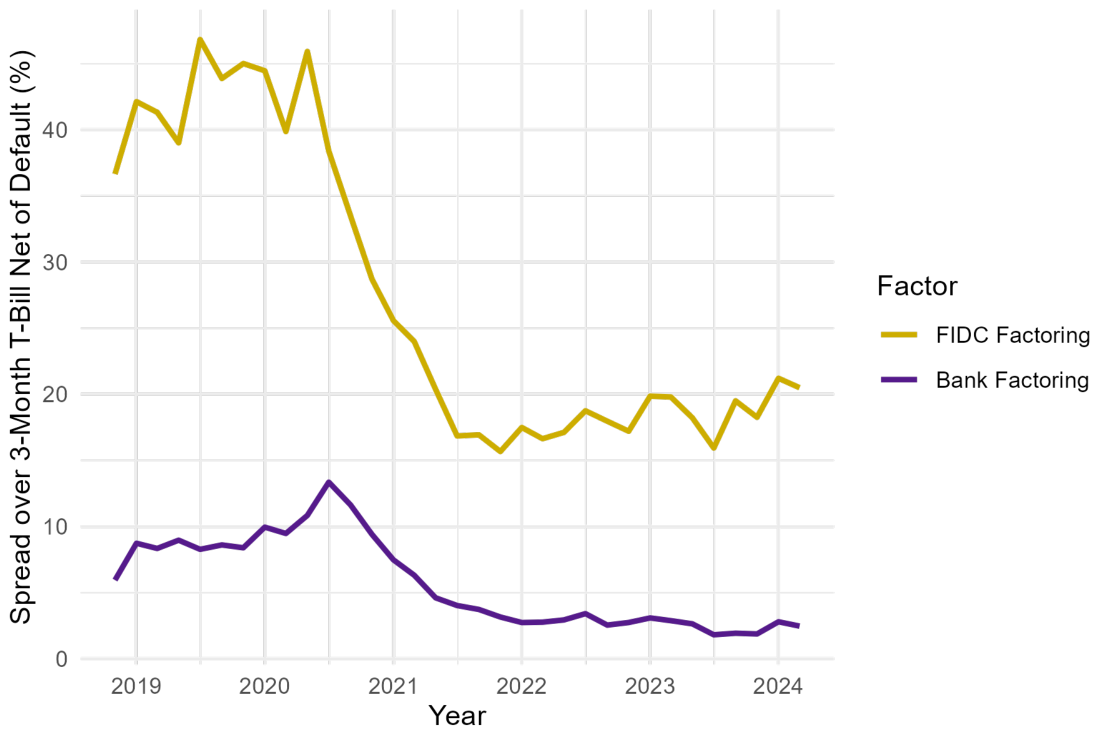
Figure A5: Time Series of FIDC Share of Factoring



Notes: This figure uses data from the Central Bank of Brazil to show the time series of the share of all receivables that are purchased by FIDCs, shown in gold, versus banks, shown in purple. A small proportion of receivables are purchased by banks and then resold to FIDCs; this is shown separately in red.

Figure A6 shows that a decrease in spread of factoring has coincided with the growth in FIDC share of factoring shown in Figure A5. FIDC factoring spreads are higher than bank factoring spreads because of the risk premium corresponding to the different composition of borrowers. As we show in Figure 5 and Figure A7, FIDCs purchase receivables from riskier firms compared to banks.

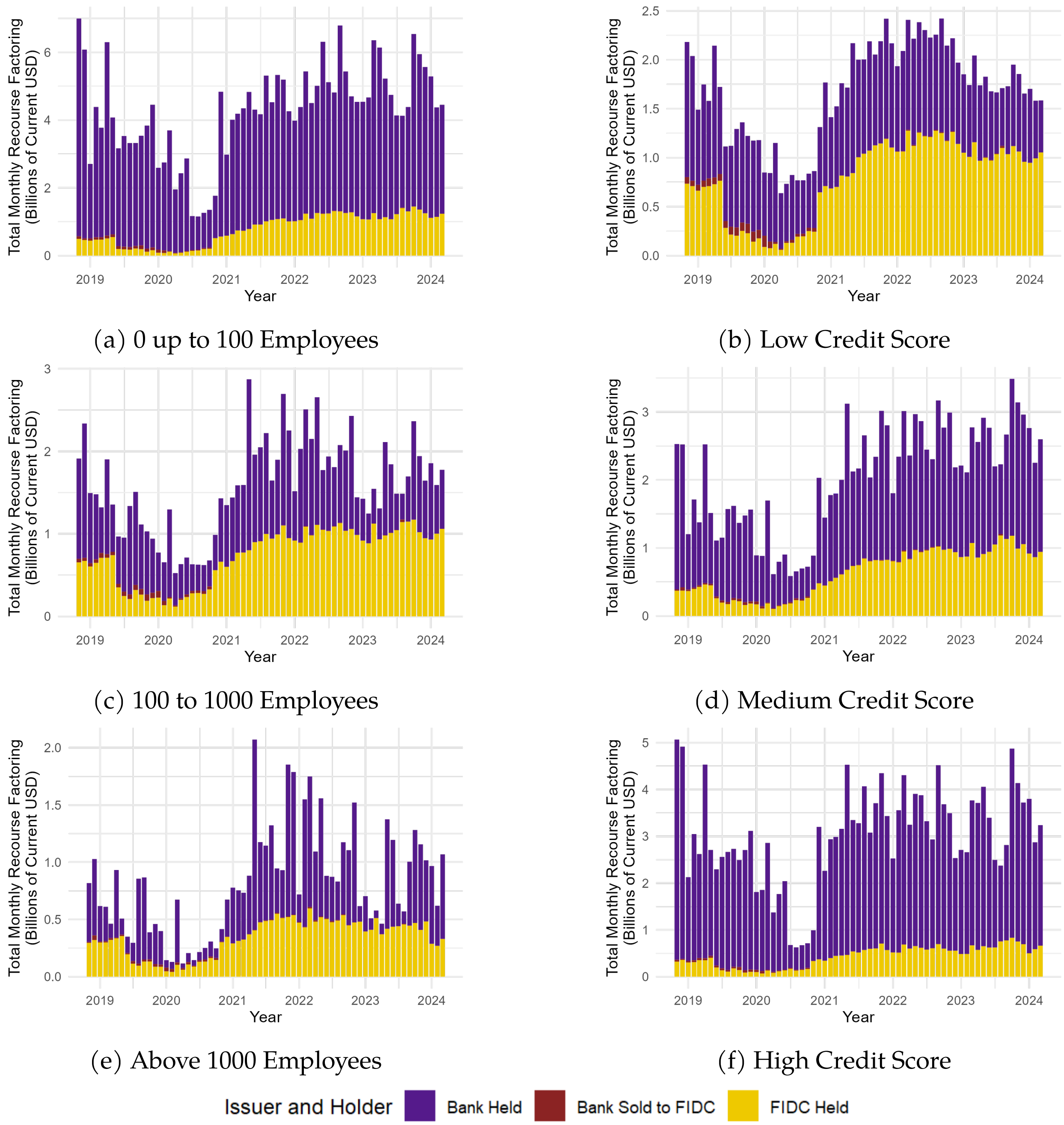
Figure A6: Interest Rate Spreads by Type and Source of Financing



Notes: This figure uses data from the Central Bank of Brazil to show the time series of the factoring interest rate spreads relative to the 3-month Brazilian Treasury bill rate. The spread is defined as the difference between the interest rate and the sum of the default rate and the baseline financing rate. We use the 3-month Brazilian Treasury bill rate as the baseline interest rate because the mean maturity for factoring, 62 days to FIDCs and 121 days to banks, is closest to the 3 month maturity mark.

FIDCs tend to purchase receivables from *larger* firms with *low credit score*. Figure A7 shows the time series of FIDC purchase patterns across the distribution of firms, partitioned by number of employees (left) and credit score (right).

Figure A7: FIDC Share of Factoring by Firm Size (Left) and Credit Score (Right)



(a) 0 up to 100 Employees

(b) Low Credit Score

(c) 100 to 1000 Employees

(d) Medium Credit Score

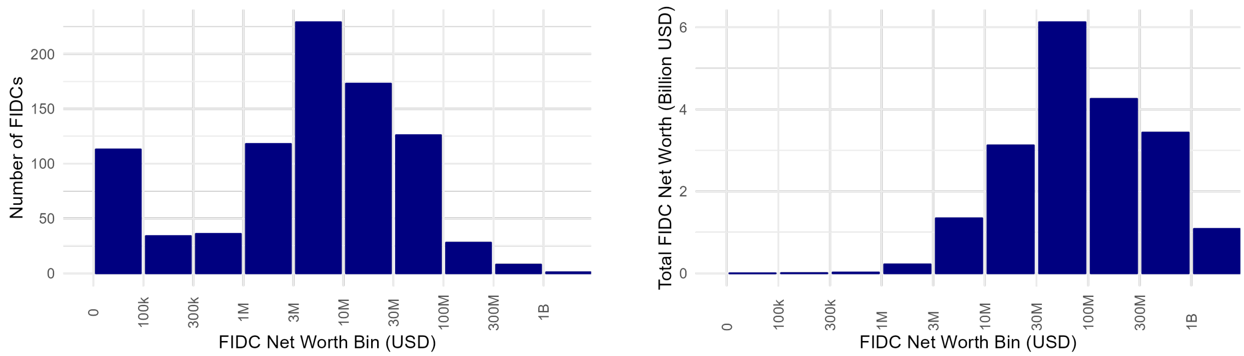
(e) Above 1000 Employees

(f) High Credit Score

Notes: This figure uses data from the Central Bank of Brazil to show the factoring volume from banks and FIDCs in each month, partitioned on the left by the number of employees, and partitioned on the right by the tercile of the credit score of the firms as of June 2023, the only month with available data. All factoring in Brazil is either to FIDCs (in yellow) or to banks (in purple). A small proportion is originally factored to banks and then sold to FIDCs (in red).

Figure A8 shows the distribution of FIDC size (left) and the distribution of FIDC net asset value (NAV) across bins of FIDC size (right) at the end of the sample period, March 2024. FIDCs are small compared to other asset classes of mutual funds. Many FIDCs have net asset value between \$1 million USD and \$100 million USD.

Figure A8: Distribution of FIDC Size



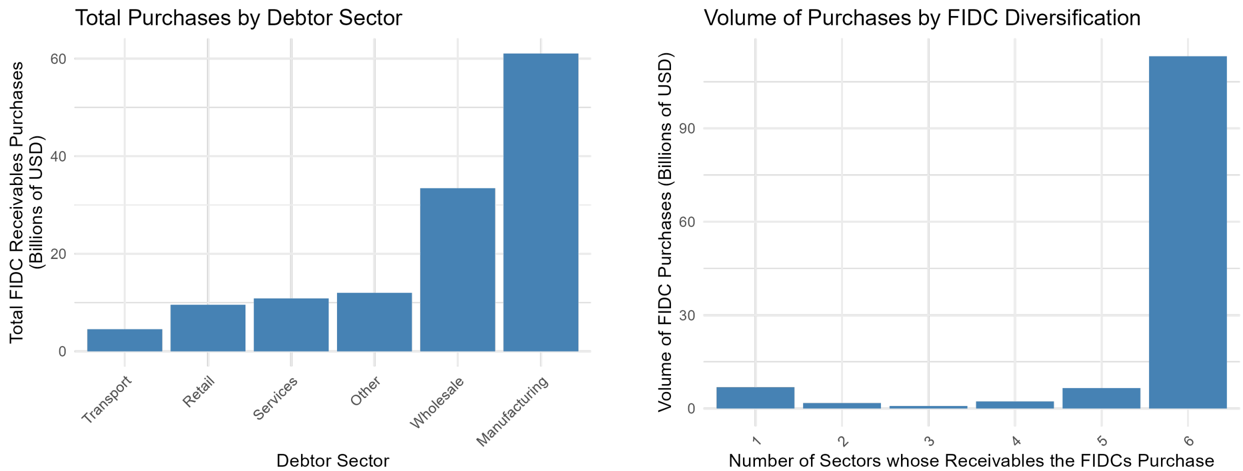
(a) Count of FIDCs by NAV Bin

(b) Total FIDC NAV by NAV Bin

Notes: This figure uses monthly fund report data from the CVM to show the distribution of FIDC size, by the count of the number of FIDCs in each size bin (left), and by the total NAV among FIDCs in each size bin (right). The count of FIDCs includes FIDCs that were inactive at the time of the snapshot in March 2024, but not formally registered as shut down.

Figure A9 shows the diversification of FIDCs across major sectors, as measured by the firm-level CNAE code. The CNAE codes are aggregated into sector labels, and we compute FIDC purchases of receivables across debtors during the 65 months in the sample from November 2018 to March 2024. On the right, most receivables purchases by FIDCs are specifically by FIDCs that purchase receivables from all major sectors.

Figure A9: FIDC Diversification across Major Sectors



(a) FIDCs' Total Receivables Purchases by Major Sector

(b) FIDCs' Total Receivables Purchases by the Number of Major Sectors

Notes: This figure uses data on FIDCs' receivables purchases from the Central Bank of Brazil, merged to seller firms' CNAE code. On the left is the total receivables purchases by FIDCs by major sector, using the first two digits of the CNAE code. On the right, each FIDC is classified by the number of major sectors from which the FIDC purchases receivables, and then computes the sum of receivables purchase volume. The "6" bar shows that most FIDCs' receivables purchases are by FIDCs that purchase from all five major sectors, as well as other sectors like agriculture.

Table 9 shows that firm-month characteristics are similar across positive and negative flows.

Table 9: Average Firm Characteristics by Magnitude of Flow

	Negative Flow	Near Zero Flow	Positive Flow
Credit Score (0 to 1000)	517	501	500
Factoring Interest Rate (%)	30.6	30.7	30.3
Monthly Factoring (Thousand USD)	112.6	120.4	98.1
Monthly Other Debt (Thousand USD)	24.6	23.8	14.6
Trade Credit Maturity Offered (Days)	21.6	21.9	27.8
Trade Credit Maturity Received (Days)	37.1	36.9	41.0

Notes: We construct the flows from data from the Securities and Exchange Commission of Brazil (CVM), and firms' characteristics are from the Central Bank of Brazil. We define a flow to be "near zero" if it is between -0.1 and 0.1 standard deviations of zero, where the standard deviation is defined over nonzero values. 26% of firm-month observations have zero flow, mostly because the FIDCs that purchase the given firm's receivables did not receive any inflow nor outflow in the given month. The third and fourth rows refer to the amount of financing issuance.

A.2 Additional Regression Results

A.2.1 Additional Outcome Variables

Column 1 of Table 10 shows that a 1 percentage point increase in the factoring interest rate causes a 0.47% decrease in the number of employees, which is slightly smaller in magnitude than the 0.56% decrease in wage bill from Table 4. This can be further decomposed into a 1.1% decrease in the number of permanent employees in column 3, and a 1.8% increase in the number of temporary employees in column 4, which are comparable in magnitude to the labor demand results in terms of hours of work from Table 4. The mean number of permanent employees is 46.6, and the mean number of temporary employees is 4.3, so columns 3 and 4 of Table 10 correspond to a decrease of 0.61 permanent employees and an increase of 0.08 temporary employees, respectively. The mean number of permanent employees is 46.6, and the mean number of temporary employees is 4.3, so columns 3 and 4 of Table 10 correspond to a decrease of 0.61 permanent employees and an increase of 0.08 temporary employees, respectively.

Table 10: IV Regressions of Number of Employee Outcomes on Factoring Interest Rate

	(1)	(2)	(3)	(4)
	Log Number of Employees (Total)	Log Number of Employees (New Hire)	Log Number of Employees (Permanent)	Log Number of Employees (Temporary)
$r^{Fac}_{j,t}$	-0.0047^{*}	-0.0141^{**}	-0.0114^{***}	0.0181^{**}
	(0.0021)	(0.0045)	(0.0024)	(0.0059)
Num. Obs.	2,556,738	1,126,587	2,548,410	608,088
Num. Firms	288,507	184,070	287,381	93,219
Num. Months	50	50	50	50

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Notes: All regressions use data from the Central Bank of Brazil. All regressions use firm and month fixed effects, with standard errors clustered at the firm level. The predictor variable is the firm-level interest rate on factoring in percentage points. The instrumental variable is the expected change in receivables purchases driven by fund flows. The response variables come from restricted access month-level RAIS data. An employee is defined as new if the employee began working at the firm that month.

Table 11 shows that the interest rate on unsecured credit lines highly responds to the change in the factoring price, primarily through banks' factoring rates. Unsecured credit lines have a high baseline mean interest rate of 333% and high variance across firms, with standard deviation of 85%.

Table 11: IV Regressions of Interest Rate Outcomes on Factoring Interest Rate

	(1)	(2)	(3)	(4)	(5)
	IR (Debt Under 1 Year)	IR (Debt Over 1 Year)	IR Credit Line (Unsecured)	IR Credit Line (Secured)	IR (Loans Over 1 Year)
$r^{Fac}_{j,t}$	1.5021^{***}	-2.0535^{*}	6.9139^{**}	-3.5990	-0.0787
	(0.2217)	(0.9247)	(2.2363)	(3.9875)	(0.1800)
Num. Obs.	4,146,540	508,179	829,816	410,208	438,844
Num. Firms	511,896	130,522	123,370	57,997	123,553
Num. Months	65	65	65	65	65

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Notes: All regressions use data from the Central Bank of Brazil. All regressions use firm and month fixed effects, with standard errors clustered at the firm level. The predictor variable is the firm-level interest rate on factoring in percentage points. The instrumental variable is the expected change in receivables purchases driven by fund flows. The response variables are the interest rates by category of debt. Column 1 is the subset with maturity of up to 365 days. Columns 2 and 3 are unsecured and secured credit lines, where issuance is defined as any drawdown of the credit line, not a change in the credit limit. Column 4 is loans with maturity of over 365 days.

Table 12 shows that default rates on factoring increase substantially with the factoring interest rate, but the default rate on other debt is unchanged. A one percentage point higher factoring interest rate causes a 0.27 percentage point higher default rate to banks, from a baseline of 0.40%, and a 1.68 percentage point higher default rate to FIDCs, from a baseline of 10.3%. We believe that the much higher default rate to FIDCs corresponds to a weaker threat of exclusion in response to default. While FIDCs only provide factoring services to firms, banks provide a wide range of financial services, and there is far more concentration among banks in most financial services compared to concentration in factoring.

Table 12: IV Regressions of Default Rate Outcomes on Factoring Interest Rate

	(1)	(2)	(3)	(4)
	Default Rate Rec. Factoring (to Banks, %)	Default Rate Other (to Banks, %)	Default Rate Rec. Factoring (to FIDCs, %)	Default Rate Other (to FIDCs, %)
$r^{Fac}_{j,t}$	0.2772*	−0.1945	1.6804**	0.0098
	(0.1174)	(0.2567)	(0.5329)	(0.0558)
Num. Obs.	2,739,575	2,739,575	1,435,934	1,435,934
Num. Firms	234,524	234,524	243,683	243,683
Num. Months	65	65	64	64

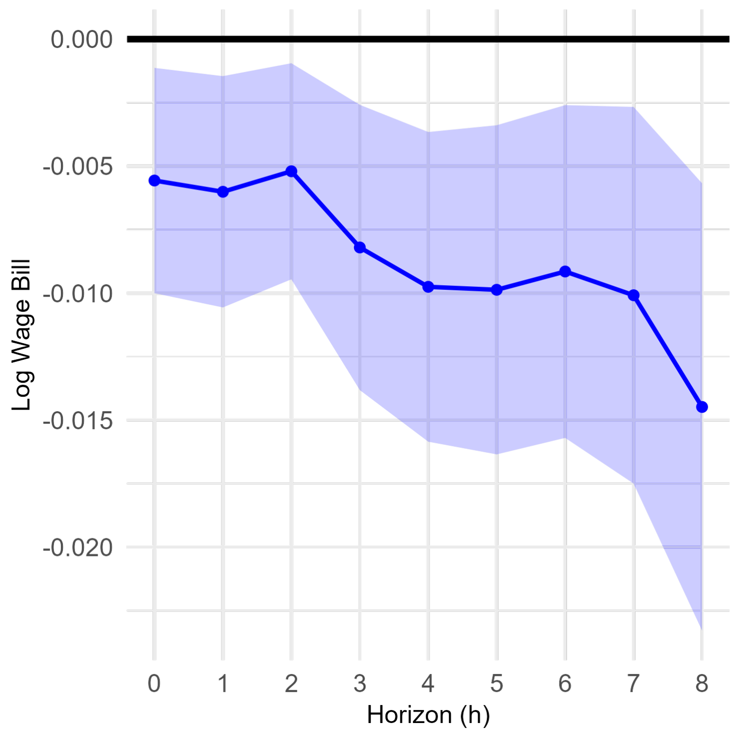
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Notes: All regressions use data from the Central Bank of Brazil. All regressions use firm and month fixed effects, with standard errors clustered at the firm level. The predictor variable is the firm-level interest rate on factoring in percentage points. The instrumental variable is the expected change in receivables purchases driven by fund flows. The response variables are the default rates on recourse factoring and other debt issued by banks and FIDCs. The default rate is defined to be the percentage of debt not paid on its due date. This is lower than the percentage of debt that the creditor eventually collects. The issuance-weighted default rate for recourse factoring to banks is 0.40% and the issuance-weighted default rate for recourse factoring to FIDCs is 10.3%.

A.2.2 Additional IV-LP Results

The subsequent figures show panel IV local projection results for additional outcome variables. Figure A10 shows that the wage bill decreases further over time in response to the temporary increase in the factoring interest rate in Figure 6a. Refer to Figure 8 for the impacts on temporary and permanent labor demand.

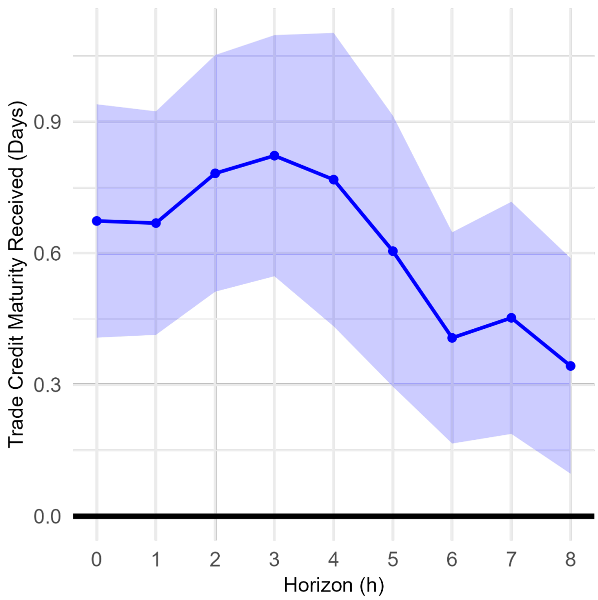
Figure A10: IV-LP of Wage Bill



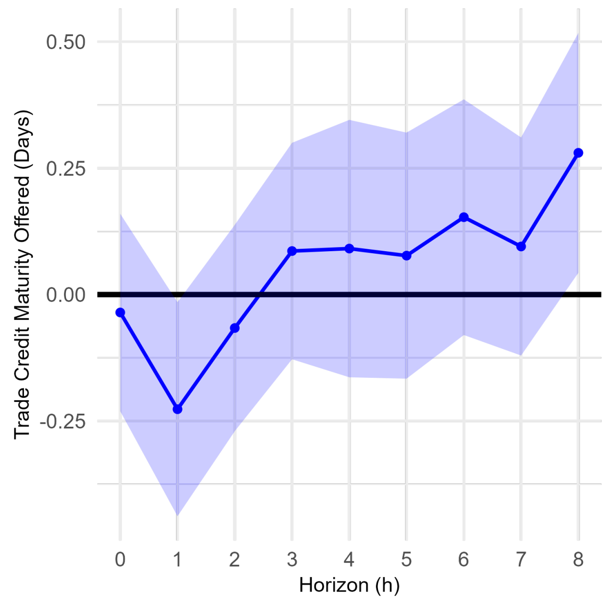
Notes: The data are from the Central Bank of Brazil. Both plots correspond to the panel IV local projection in equation (4); on the left is , trade credit received (as the buyer) and on the right is trade credit offered (as the seller).

Figure A11a shows that firms that face a higher interest rate, due to fund outflows, receive longer trade credit maturity, and it persists in the medium run, with magnitude 0.6 to 0.8 days upon a baseline average of 59.4 days. Figure A11b shows that there is no change in the maturity of trade credit that the shocked firm offers to its customers.

Figure A11: IV-LP of Trade Credit Maturity



(a) Buyer (Received)



(b) Seller (Offered)

Notes: The data are from the Central Bank of Brazil. Both plots correspond to the panel IV local projection in equation (4); on the left is , trade credit received (as the buyer) and on the right is trade credit offered (as the seller).

A.3 Robustness: Fixed Effects

In this section, we show that the results in Table 4 are robust to alternative specifications of fixed effects in (16) that interact aggregated firm characteristics k with month t to capture time-varying shocks.

$$r^{Fac}_{j,k,t} = \alpha_j + \alpha_{k,t} + \gamma_1 e^{Fac}_{j,k,t} + \varepsilon_{j,k,t}. \tag{16}$$

The base regression (column 1) uses firm and month fixed effects. Column 2 uses firm and state-by-month fixed effects, for the 26 states and one federal district in Brazil. Column 3 uses firm and sector-by-month fixed effects, for the 285 three-digit CNAE codes. Column 4 uses firm, state-by-month, and sector-by-month fixed effects. This controls for any time-varying shocks across locations and sectors, and the residual variation uses individual firm exposure to FIDC flows demeaned on any shocks in those dimensions. Table 13 compares the first stage regression in equation (1), of the factoring interest rate $r^{Fac}_{j,t}$ on exposure $e^{Fac}_{j,t}$ to fund flows, across the aforementioned fixed effects:

Table 13: First Stage Regressions Across Fixed Effect Specifications

	(1)	(2)	(3)	(4)
$e^{Fac}_{j,t}$	-0.1212^{***}	-0.1137^{***}	-0.1256^{***}	-0.1188^{***}
	(0.0127)	(0.0135)	(0.0128)	(0.0136)
Fixed Effects:				
Firm	X	X	X	X
Month	X	X	X	X
State-Month			X	X
Sector-Month		X		X

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Notes: These regressions use data from the Central Bank of Brazil. The dataset is at the firm by month level. Standard errors are clustered at the firm level and shown in parentheses. If a firm does not factor in a given month, then the interest rate is undefined, and the observation is dropped from the regression.

Table 14 compares the reduced form regression in (17) across the following fixed effect interactions of firms' aggregated characteristics k with month t. The base regression (column 1) uses firm and month fixed effects. Column 2 uses firm and state-by-month fixed effects, for the 26 states and one federal district in Brazil. Column 3 uses firm and sector-by-month fixed effects, for the 285 three-digit CNAE codes. Column 4 uses firm, state-by-month, and sector-by-month fixed effects.

$$y_{j,k,t} = \alpha_j + \alpha_{k,t} + \beta_1 r^{Fac}_{j,k,t} + \varepsilon_{j,k,t} \tag{17}$$

Table 14: IV Regressions of Main Outcomes Across Fixed Effect Specifications

	(1)	(2)	(3)	(4)
Panel A: Log Revenue				
$r^{Fac}_{j,t}$	-0.0614^{***}	-0.0678^{***}	-0.0584^{***}	-0.0648^{***}
	(0.0093)	(0.0112)	(0.0092)	(0.0110)
Panel B: Log Input Expenditure				
$r^{Fac}_{j,t}$	-0.0357^{***}	-0.0520^{***}	-0.0355^{***}	-0.0501^{***}
	(0.0056)	(0.0076)	(0.0054)	(0.0071)
Panel C: Log Wage Bill				
$r^{Fac}_{j,t}$	-0.0056^{*}	$-0.0051^{\cdot}$	-0.0060^{**}	-0.0056^{*}
	(0.0023)	(0.0027)	(0.0023)	(0.0028)
Panel D: Log Permanent Labor Demand				
$r^{Fac}_{j,t}$	-0.0114^{***}	-0.0112^{***}	-0.0124^{***}	-0.0121^{***}
	(0.0024)	(0.0028)	(0.0025)	(0.0030)
Panel E: Log Temporary Labor Demand				
$r^{Fac}_{j,t}$	0.0181^{**}	0.0160^{*}	0.0166^{**}	$0.0139^{\cdot}$
	(0.0059)	(0.0075)	(0.0056)	(0.0071)
Fixed Effects:				
Firm	X	X	X	X
Month	X	X	X	X
State-Month			X	X
Sector-Month		X		X

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Notes: All regressions use data from the Central Bank of Brazil. All regressions use firm and month fixed effects, with standard errors clustered at the firm level in parentheses. The predictor variable is the firm-level interest rate on factoring in percentage points, instrumented by the expected change in receivables purchases driven by fund flows. The response variables are the log revenue proxied by payment inflows, log intermediate input expenditure proxied by payment outflows to firms, log wage bill, log labor demand for permanent workers, and log labor demand for temporary workers.

A.4 Robustness: Falsification

In Table 15, we run the regression (18) of lagged outcomes on the shift-share IV $e_{j,t}$:

$$y_{j,t-1} = \alpha_j + \alpha_t + \beta_{pre} e_{j,t} + \varepsilon_{j,t}, \tag{18}$$

The main concern that (18) addresses is anticipation, whether firms respond to expectations of the upcoming shock. Note that the shock $e_{j,t}$ has an autoregressive structure with coefficient 0.21, so the expectation is not that the estimate $\hat{\beta}_{pre}$ is zero, but rather that it is much smaller than the coefficient in the corresponding reduced form regression of current outcome on the current IV. Table 15 shows the results in log points for easier readability.

Table 15: Pre-Trend Falsification Test: Regressions of Lagged Outcomes on Current Flows

	(1) Factoring Interest Rate	(2) Log Revenue	(3) Log Expenditure	(4) Log Temporary Labor	(5) Log Permanent Labor
$e^{Fac}_{j,t}$	-0.501	0.074	0.052	-0.056	0.033
	(1.287)	(0.089)	(0.061)	(0.095)	(0.040)
Fixed Effects:					
Firm	X	X	X	X	X
Month	X	X	X	X	X

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Notes: These regressions use data from the Central Bank of Brazil. The dataset is at the firm by month level. Standard errors are clustered at the firm level and shown in parentheses. Each column is a separate regression with a different outcome variable. Column (1) corresponds to the first stage, while columns (2) through (5) correspond to the reduced form. All results are shown in log points for readability.

B Model Appendix

B.1 Solving the Model

In this section, we describe how we solve the model, beginning with the firms' objective in (8) and the household's objective in (31).

B.1.1 Household Block

We solve the labor supply block by taking the FOCs of the Lagrangian in (19)

$$\begin{aligned}\max_{\{c_0,c_1,\ell^P,\ell_0^T,\ell_1^T\}} \mathcal{L}^{HH} &= \log(c_0) + \beta\log(c_1) - \sum_{t=0}^{1}\left[\frac{1}{\xi}\left(\ell^P + \nu\ell_t^T\right)^{\xi} - \nu(\ell^P - \ell_t^T)\right] \\ &\quad - \lambda^H \cdot \left(c_0 + c_1 - 2\ell^P w^P - \sum_t \ell_t^T w_t^T\right), \qquad (19)\\ \text{s.t. } c_0 + c_1 &= 2\ell^P w^P + \sum_t \ell_t^T w_t^T.\end{aligned}$$

The consumption FOCs give $c_0 = \beta c_1$ and $\lambda^H = \frac{1}{c_0}$. The labor FOCs are

$$\begin{aligned}\frac{\partial\mathcal{L}^{HH}}{\partial\ell^P} &= -\sum_{t=0}^{1}\left(\ell^P + \ell_t^T\right)^{\xi-1} + 2\nu + 2\lambda_1 - 2\lambda^H w^P = 0,\\ \frac{\partial\mathcal{L}^{HH}}{\partial\ell_t^T} &= -\left(\ell^P + \ell_t^T\right)^{\xi-1} - \nu + \lambda_1 - \lambda^H w_t^T = 0.\end{aligned}$$

We solve numerically. There are 6 unknowns $\{c_0, c_1, \ell^P, \ell_0^T, \ell_1^T, \lambda^H\}$ with 6 equations: the 2 consumption FOCs, the 3 labor FOCs, and the two budget constraints. In practice, it is easier to solve a reduced system of 3 unknowns $\{\ell^P, \ell_0^T, \ell_1^T\}$ in 3 equations by substituting out λ^H.

$$\lambda^H(w_t^T - w^P) = \frac{1}{2}\sum_{t'=0}^{1}\left(\ell^P + \ell_{t'}^T\right)^{\xi-1} - \left(\ell^P + \ell_t^T\right)^{\xi-1} - 2\nu.$$

After solving for $\{\ell^P, \ell_0^T, \ell_1^T\}$, we can use the consumption FOC and the budget constraint to solve for $\{c_0, c_1\}$.

B.1.2 Firm Block

Firms must factor at least what is paid to labor in the morning. Firms may decide to factor more to avoid the risk of high ϵ_j, which affects the otherwise risk-neutral firm's objective function through the penalty for ending the afternoon with negative profit. Firms generally do not hit the factoring borrowing constraint in (10), and there is no return on cash nor motive for precautionary (excess) borrowing. Work backwards by first solving for the constrained optimal x_{j1}, ℓ_{j1}^T in the afternoon. The firm takes as given the choices made in the morning: $\{y_{j0}, x_{j0}, \ell_j^P, \ell_{j0}^T, p_j, B_j^F\}$ and the realization of the shock ϵ_j. Since there is no residual uncertainty, the firm's objective is to maximize marginal profits

$$\begin{aligned}
\max_{\{x_{j1}, \ell_{j1}^T\}} \ & \pi_{j1} := p_j y_{j1} - \ell_j^P w^P - \ell_{j1}^T w_1^T - P x_{j1}, \\
\text{s.t. } & y_{j1} = \tilde{\ell}_{j1}^{\alpha} x_{j1}^{1-\alpha}, \\
& \tilde{\ell}_{j1} = \left(\omega \left(\psi \ell_j^P \right)^{\frac{\sigma-1}{\sigma}} + (1-\omega) \left(\ell_{j1}^T \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \\
& \frac{p_j}{P} = \left(\frac{y_{j1}}{Y_1} \right)^{-\frac{1}{s}}, \\
& \ell_{j1}^T, x_{j1} \geqslant 0.
\end{aligned}$$

The unconstrained FOCs are

$$\begin{aligned}
\frac{\partial \pi_{j1}}{\partial x_{j1}} &= \frac{(s-1)(1-\alpha)}{s} P Y_1^{\frac{1}{s}} \tilde{\ell}_{j1}^{\frac{(s-1)\alpha}{s}} x_{j1}^{-\frac{1+(s-1)\alpha}{s}} - P = 0, \\
\frac{\partial \pi_{j1}}{\partial \ell_{j1}^T} &= \frac{(s-1)\alpha}{s} P Y_1^{\frac{1}{s}} \tilde{\ell}_{j1}^{-\frac{\alpha+s(1-\alpha)}{s}} x_{j1}^{\frac{(s-1)(1-\alpha)}{s}} \frac{\partial \tilde{\ell}_{j1}}{\partial \ell_{j1}^T} - w_1^T = 0,
\end{aligned}$$

where $\tilde{C}_1^T \equiv (1-\omega) \frac{(s-1)\alpha}{s} \left(\frac{(s-1)(1-\alpha)}{s} \right)^{\frac{(s-1)(1-\alpha)}{1+(s-1)\alpha}}$ is a constant.

$$\begin{aligned}
x_{j1} &= \left(\frac{(s-1)(1-\alpha)}{s} \right)^{\frac{s}{1+(s-1)\alpha}} Y_1^{\frac{1}{1+(s-1)\alpha}} \tilde{\ell}_{j1}^{\frac{(s-1)\alpha}{1+(s-1)\alpha}}, \\
w_1^T &= \tilde{C}_1 Y_1^{\frac{1}{1+(s-1)\alpha}} \tilde{\ell}_{j1}^{\frac{1}{\sigma} - \frac{1}{1+(s-1)\alpha}} \left(\ell_{j1}^T \right)^{-\frac{1}{\sigma}}.
\end{aligned}$$

In the morning, choose $\{y_{j0}, x_{j0}, \ell_j^P, \ell_{j0}^T, B_j^F\}$ to maximize expected profit, given the choices of $\ell^T_{j1}, x_{j1}, \pi_{j1}$ in the afternoon, and given wages w^P, w^T_0 and parameters:

$$\max_{\{y_{j0}, x_{j0}, \ell^P_j, \ell^T_{j0}, B^F_j\}} \beta\mathbb{E}\left[\pi_{j1} + \eta\mathbb{1}\{\pi_{j1} < 0\}\right] + B^F_j - \left(\ell^P_j w^P + \ell^T_{j0} w^T_0\right), \tag{20}$$

$$\text{s.t. } B^F_j \leqslant \frac{p_j y_{j0}}{R^F_j}, \tag{21}$$

$$0 \leqslant B^F_j - \ell^P_j w^P - \ell^T_{j0} w^T_0, \tag{22}$$

$$\pi_{j1} = p_j y_{j1} - \ell^P_j w^P - \ell^T_{j1} w^T_1 - P x_{j1} + \tilde{m}_{j1},$$

$$\tilde{m}_{j1} = (1 - \epsilon_j)\left(p_j y_{j0} - R^F_j B^F_j\right) - P x_{j0}.$$

B^F_j is endogenous subject to the lower bound (22) and upper bound (21). The penalty for default introduces a non-convexity that requires tedious case work for an analytical solution. For each firm type j, corresponding to a cash flow risk value ζ_j, create a grid of $\{B^F_j, \ell^P_j\}$. Conditional on B^F_j and ℓ^P_j, the morning objective function $\mathbb{E}_0\pi_j$ has no residual uncertainty over $\{\ell^T_{j0}, x_{j0}\}$, and the afternoon objective function π_{j1} has no uncertainty over $\{\ell^T_{j1}, x_{j1}\}$. We calculate the argmax of $\mathbb{E}_0\pi_j$ over $\{B^F_j, \ell^P_j\}$.

$$R^F_j w^T_0 = \tilde{C}^T_0 Y_0^{\frac{1}{1+(s-1)\alpha}} \tilde{\ell}_{j0}^{\frac{1}{\sigma} - \frac{1}{1+(s-1)\alpha}} \left(\ell^T_{j0}\right)^{-\frac{1}{\sigma}},$$

where $\tilde{C}^T_0 \equiv (1-\omega)\frac{(s-1)\alpha}{s}\left(\left(1-\zeta_j\right)\frac{(s-1)(1-\alpha)}{s}\right)^{\frac{(s-1)(1-\alpha)}{1+(s-1)\alpha}}$ is a constant. Note that if the problem were convex, we could directly solve for ℓ^P_j as shown in the appendix:

$$\begin{aligned} 0 = {} & \tilde{C}^P_0 Y_1^{\frac{1}{1+(s-1)\alpha}} \tilde{\ell}_{j1}^{\frac{1}{\sigma} - \frac{1}{1+(s-1)\alpha}} \left(\ell^P_j\right)^{-\frac{1}{\sigma}} - w^P \\ & + \left(1-\zeta_j\right)\left[\tilde{C}^P_1 Y_0^{\frac{1}{1+(s-1)\alpha}} \tilde{\ell}_{j0}^{\frac{1}{\sigma} - \frac{1}{1+(s-1)\alpha}} \left(\ell^P_j\right)^{-\frac{1}{\sigma}} - R^F_j w^P\right], \end{aligned} \tag{23}$$

where $\tilde{C}^P_0 \equiv \omega\psi^{\frac{\sigma-1}{\sigma}}\frac{(s-1)\alpha}{s}\left(\frac{(s-1)(1-\alpha)}{s}\right)^{\frac{(s-1)(1-\alpha)}{1+(s-1)\alpha}}$ and $\tilde{C}^P_1 \equiv \omega\frac{(s-1)\alpha}{s}\left(\left(1-\zeta_j\right)\frac{(s-1)(1-\alpha)}{s}\right)^{\frac{s}{1+(s-1)\alpha}}$ are constants.

In the afternoon,

$$\begin{aligned}
\max_{\{x_{j1},\ell^T_{j1}\}} \; & \pi_{j1} := p_j y_{j1} - \ell^P_j w^P - \ell^T_{j1} w^T_1 - P x_{j1}, \\
\text{s.t. } & y_{j1} = \tilde{\ell}^{\alpha}_{j1} x^{1-\alpha}_{j1}, \\
& \tilde{\ell}_{j1} = \left(\omega \left(\psi \ell^P_j \right)^{\frac{\sigma-1}{\sigma}} + (1-\omega) \left(\ell^T_{j1} \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \\
& \frac{p_j}{P} = \left(\frac{y_{j1}}{Y_1} \right)^{-\frac{1}{s}}, \\
& \ell^T_{j1}, x_{j1} \geqslant 0.
\end{aligned}$$

Substitute out p_j:

$$\max_{\{x_{j1},\ell^T_{j1}\}} \; \pi_{j1} := P Y_1^{\frac{1}{s}} \tilde{\ell}_{j1}^{\frac{(s-1)\alpha}{s}} x_{j1}^{\frac{(s-1)(1-\alpha)}{s}} - \ell^P_j w^P - \ell^T_{j1} w^T_1 - P x_{j1}$$

The unconstrained FOCs are

$$\begin{aligned}
\frac{\partial \pi_{j1}}{\partial x_{j1}} &= \frac{(s-1)(1-\alpha)}{s} P Y_1^{\frac{1}{s}} \tilde{\ell}_{j1}^{\frac{(s-1)\alpha}{s}} x_{j1}^{-\frac{1+(s-1)\alpha}{s}} - P = 0, \\
x_{j1} &= \left(\frac{(s-1)(1-\alpha)}{s} \right)^{\frac{s}{1+(s-1)\alpha}} Y_1^{\frac{1}{1+(s-1)\alpha}} \tilde{\ell}_{j1}^{\frac{(s-1)\alpha}{1+(s-1)\alpha}}, \qquad (24)
\end{aligned}$$

and

$$\frac{\partial \pi_{j1}}{\partial \ell^T_{j1}} = \frac{(s-1)\alpha}{s} P Y_1^{\frac{1}{s}} \tilde{\ell}_{j1}^{-\frac{\alpha+s(1-\alpha)}{s}} x_{j1}^{\frac{(s-1)(1-\alpha)}{s}} \frac{\partial \tilde{\ell}_{j1}}{\partial \ell^T_{j1}} - w^T_1 = 0,$$

where

$$\frac{\partial \tilde{\ell}_{j1}}{\partial \ell^T_{j1}} = (1-\omega) \left(\omega \left(\psi \ell^P_j \right)^{\frac{\sigma-1}{\sigma}} + (1-\omega) \left(\ell^T_{j1} \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{1}{\sigma-1}} \left(\ell^T_{j1} \right)^{-\frac{1}{\sigma}} = (1-\omega) \tilde{\ell}_{j1}^{\frac{1}{\sigma}} \left(\ell^T_{j1} \right)^{-\frac{1}{\sigma}}.$$

Substituting out x_{j1} from (24):

$$x_{j1}^{\frac{(s-1)(1-\alpha)}{s}} = \left(\frac{(s-1)(1-\alpha)}{s} \right)^{\frac{(s-1)(1-\alpha)}{1+(s-1)\alpha}} Y_1^{\frac{(s-1)(1-\alpha)}{s(1+(s-1)\alpha)}} \tilde{\ell}_{j1}^{\frac{(s-1)^2\alpha(1-\alpha)}{s(1+(s-1)\alpha)}}.$$

Then the ℓ^T_{j1} FOC yields ℓ^T_{j1} as a function of ℓ^P_j, taking wages, the price index, and aggregate output as given:

$$w_1^T = \tilde{C}_1^T Y_1^{\frac{(s-1)(1-\alpha)}{s(1+(s-1)\alpha)}+\frac{1}{s}} \tilde{\ell}_{j1}^{\frac{(s-1)^2\alpha(1-\alpha)}{s(1+(s-1)\alpha)}-\frac{\alpha+s(1-\alpha)}{s}+\frac{1}{\sigma}} \left(\ell_{j1}^T\right)^{-\frac{1}{\sigma}}.$$

where $\tilde{C}_1^T \equiv (1-\omega)\frac{(s-1)\alpha}{s}\left(\frac{(s-1)(1-\alpha)}{s}\right)^{\frac{(s-1)(1-\alpha)}{1+(s-1)\alpha}}$ is a constant. Simplify the $\tilde{\ell}_{j1}$ exponent by combining the first and second terms:

$$\frac{(s-1)^2\alpha(1-\alpha)-\big(\alpha+s(1-\alpha)\big)\big(1+(s-1)\alpha\big)}{s\big(1+(s-1)\alpha\big)},$$

The second term is

$$\begin{aligned}\big(s-(s-1)\alpha\big)\big(1+(s-1)\alpha\big) &= s(1+(s-1)\alpha)-(s-1)\alpha(1+(s-1)\alpha), \\ &= s+s(s-1)\alpha-(s-1)\alpha-(s-1)^2\alpha^2.\end{aligned}$$

Expand the numerator:

$$\begin{aligned}&s^2\alpha(1-\alpha)-2s\alpha(1-\alpha)+\alpha(1-\alpha)-\Big(s+s(s-1)\alpha-(s-1)\alpha-(s-1)^2\alpha^2\Big) \\ &\quad = s^2\alpha-s^2\alpha^2-2s\alpha+2s\alpha^2+\alpha-\alpha^2-\Big(s+s^2\alpha-s\alpha+s\alpha-\alpha+s^2\alpha^2-2s\alpha^2+\alpha^2\Big). \\ &\quad = s^2\alpha-s^2\alpha^2-2s\alpha+2s\alpha^2+\alpha-\alpha^2-s-s^2\alpha+2s\alpha-\alpha+s^2\alpha^2-2s\alpha^2+\alpha^2, \\ &\quad = -s,\end{aligned}$$

so the $\tilde{\ell}_{j1}$ exponent is $-\frac{1}{1+(s-1)\alpha}+\frac{1}{\sigma}$. Similarly, the Y_1 exponent simplifies to $\frac{1}{1+(s-1)\alpha}$. Then ℓ_{j1}^T is implicitly a function of ℓ_j^P, the wage w_1^T, and aggregate output Y_1 through the equation

$$w_1^T = \tilde{C}_1^T Y_1^{\frac{1}{1+(s-1)\alpha}} \tilde{\ell}_{j1}^{\frac{1}{\sigma}-\frac{1}{1+(s-1)\alpha}} \left(\ell_{j1}^T\right)^{-\frac{1}{\sigma}}. \tag{25}$$

Taking as given the $\{\ell_j^P\}$ choices from the morning, solve for w_1^T by aggregating across firms using labor market clearing and the household's labor supply equation:

$$\int_{j=0}^{1} \ell_{j1}^T dj = \ell_1^T = 1-2\ell^P-\ell_0^T.$$

Substitute w_1^T back in to obtain ℓ_{j1}^T. Then use the x_{j1} FOC to solve for x_{j1} as a function of ℓ_j^P and ℓ_{j1}^T. These FOCs do not depend on the η term, nor on the shock ϵ_j. These only affect the factoring decision in the morning.

If there were no penalty for default, all firms factor the lower bound from (22) as long as $\mu^F > 0$, and otherwise are indifferent between factoring any amount.[18] Firms still adjust by reducing period 0 production relative to period 1 production (in turn reducing permanent labor demand as R_j^F increases). Without loss of generality, assume that firms factor the bare minimum $B_j^F = \ell_j^P w^P + \ell_{j0}^T w_0^T$, so the factoring spread μ^F is akin to a tax of R_j^F on period 0 labor. All terms in the objective function are scaled by β from the perspective of the morning, so we can drop them because multiplying by β is a uniform transformation. The morning problem is equivalent to

$$\begin{aligned}
\max_{\{y_{jt}, p_j, x_{jt}, \ell_j^P, \ell_{jt}^T\}} \mathbb{E}_0 \pi_j &= \left(1-\zeta_j\right)\left(p_j y_{j0} - R_j^F B_j^F\right) - P x_{j0} + \left(p_j y_{j1} - \ell_j^P w^P - \ell_{j1}^T w_1^T - P x_{j1}\right), \\
\text{s.t. } B_j^F &= \ell_j^P w^P + \ell_{j0}^T w_0^T,
\end{aligned}$$

We proceed with a similar derivation to (25) for ℓ_{j0}^T. First define

$$\tilde{\ell}_{j0} := \left(\omega\left(\ell_j^P\right)^{\frac{\sigma-1}{\sigma}} + (1-\omega)\left(\ell_{j0}^T\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}.$$

Take the FOC with respect to material inputs:

$$\begin{aligned}
\frac{\partial \mathbb{E}_0 \pi_j}{\partial x_{j0}} &= \left(1-\zeta_j\right)\frac{(s-1)(1-\alpha)}{s} P Y_0^{\frac{1}{s}} \tilde{\ell}_{j0}^{\alpha\frac{s-1}{s}} x_{j0}^{-\frac{1+(s-1)\alpha}{s}} - P = 0, \\
x_{j0} &= \left(\left(1-\zeta_j\right)\frac{(s-1)(1-\alpha)}{s}\right)^{\frac{s}{1+(s-1)\alpha}} Y_0^{\frac{1}{1+(s-1)\alpha}} \tilde{\ell}_{j0}^{\frac{(s-1)\alpha}{1+(s-1)\alpha}},
\end{aligned} \tag{26}$$

and

$$\frac{\partial \mathbb{E}_0 \pi_j}{\partial \ell_{j0}^T} = \frac{(s-1)\alpha}{s} P Y_0^{\frac{1}{s}} \tilde{\ell}_{j0}^{-\frac{\alpha+s(1-\alpha)}{s}} x_{j0}^{\frac{(s-1)(1-\alpha)}{s}} \frac{\partial \tilde{\ell}_{j0}}{\partial \ell_{j0}^T} - R_j^F w_0^T = 0.$$

Using the substitution $\frac{\partial \tilde{\ell}_{j0}}{\partial \ell_{j0}^T} = (1-\omega)\tilde{\ell}_{j0}^{\frac{1}{\sigma}}\left(\ell_{j0}^T\right)^{-\frac{1}{\sigma}}$,

$$R_j^F w_0^T = \tilde{C}_0^T Y_0^{\frac{1}{1+(s-1)\alpha}} \tilde{\ell}_{j0}^{\frac{1}{\sigma}-\frac{1}{1+(s-1)\alpha}} \left(\ell_{j0}^T\right)^{-\frac{1}{\sigma}}, \tag{27}$$

where $\tilde{C}_0^T \equiv (1-\omega)\frac{(s-1)\alpha}{s}\left(\left(1-\zeta_j\right)\frac{(s-1)(1-\alpha)}{s}\right)^{\frac{(s-1)(1-\alpha)}{1+(s-1)\alpha}}$ is a constant.

[18]The reasoning is that factoring reduces expected profit. If there is no insurance value to factoring, since firms are risk-neutral, then firms factor as little as needed to satisfy constraints.

Now take the derivative of the objective function $\mathbb{E}_0\pi_j$ with respect to ℓ_j^P:

$$\frac{\partial \mathbb{E}_0\pi_j}{\partial \ell_j^P} = (1-\zeta_j)\left[\frac{(s-1)\alpha}{s} P Y_0^{\frac{1}{s}} \tilde{\ell}_{j0}^{-\frac{\alpha+s(1-\alpha)}{s}} x_{j0}^{\frac{s-1}{s}(1-\alpha)} \frac{\partial \tilde{\ell}_{j0}}{\partial \ell_j^P} - R_j^F w^P\right] + \frac{(s-1)\alpha}{s} P Y_1^{\frac{1}{s}} \tilde{\ell}_{j1}^{-\frac{\alpha+s(1-\alpha)}{s}} x_{j1}^{\frac{s-1}{s}(1-\alpha)} \frac{\partial \tilde{\ell}_{j1}}{\partial \ell_j^P} - w^P = 0.$$

Substitute out

$$\frac{\partial \tilde{\ell}_{j1}}{\partial \ell_j^P} = \omega \psi^{\frac{\sigma-1}{\sigma}} \tilde{\ell}_{j1}^{\frac{1}{\sigma}} \left(\ell_j^P\right)^{-\frac{1}{\sigma}},$$
$$\frac{\partial \tilde{\ell}_{j0}}{\partial \ell_j^P} = \omega \tilde{\ell}_{j1}^{\frac{1}{\sigma}} \left(\ell_j^P\right)^{-\frac{1}{\sigma}},$$

and x_{jt} from (26) and (24) to obtain

$$0 = \tilde{C}_0^P Y_1^{\frac{1}{1+(s-1)\alpha}} \tilde{\ell}_{j1}^{\frac{1}{\sigma}-\frac{1}{1+(s-1)\alpha}} \left(\ell_j^P\right)^{-\frac{1}{\sigma}} - w^P + (1-\zeta_j)\left[\tilde{C}_1^P Y_0^{\frac{1}{1+(s-1)\alpha}} \tilde{\ell}_{j0}^{\frac{1}{\sigma}-\frac{1}{1+(s-1)\alpha}} \left(\ell_j^P\right)^{-\frac{1}{\sigma}} - R_j^F w^P\right], \tag{28}$$

where $\tilde{C}_0^P \equiv \omega \psi^{\frac{\sigma-1}{\sigma}} \frac{(s-1)\alpha}{s} \left(\frac{(s-1)(1-\alpha)}{s}\right)^{\frac{(s-1)(1-\alpha)}{1+(s-1)\alpha}}$ and $\tilde{C}_1^P \equiv \omega \frac{(s-1)\alpha}{s} \left((1-\zeta_j)\frac{(s-1)(1-\alpha)}{s}\right)^{\frac{s}{1+(s-1)\alpha}}$ are constants.

In combination with (27) and (25), this equation pins down ℓ_j^P when taking as given the factoring price R_j^F and aggregate equilibrium outcomes $\{Y_0, Y_1, w^P, w_0^T, w_1^T\}$. Since $\frac{\partial \mathbb{E}_0\pi_j}{\partial \ell_j^P}$ is decreasing in ℓ_j^P, $\frac{\partial \mathbb{E}_0\pi_j}{\partial \ell_{j0}^T}$ is decreasing in ℓ_{j0}^T, and $\frac{\partial \pi_{j1}}{\partial \ell_{j1}^T}$ is decreasing in ℓ_{j1}^T, the following algorithm suffices to obtain labor demand:

- Outer loop: bisection method over ℓ_j^P with (23)
- Inner loop: given the guess of ℓ_j^P, use bisection with (27) to obtain ℓ_{j0}^T, and bisection with (25) to obtain ℓ_{j1}^T.

B.1.3 Solving for the Equilibrium

From outer-most to inner-most loop,

1. Iterate over w^P for (14); if permanent labor demand is greater than supply, then increase w^P, otherwise decrease w^P.
2. Iterate over w_0^T and w_1^T for (15); the ℓ_{j0}^T FOC does not directly depend on w_1^T, and the ℓ_{j1}^T FOC does not directly depend on w_0^T, so given a guess of w^P, temporary labor

demand can be equated to temporary labor supply in the morning and afternoon in parallel.

3. Iterate over guesses of Y_0 and Y_1 so that (13) holds. Because household consumption c_t only depends on the wages and not directly on Y_t, and x_{jt} is increasing in Y_t with first-order elasticity $\frac{1}{1+(s-1)\alpha} < 1$, a quick bisection suffices for Y_t.

4. Solve for the allocations $\{\ell_j^P, \ell_{j0}^T, \ell_{j1}^T\}_{\zeta_j \sim G_\zeta}$ following the algorithm from the previous section.

B.2 Calibration

The following is a list of each parameter and a justification for its calibration.

- $\alpha = 0.43$: Cobb-Douglas share on labor vs intermediate inputs. Payments to labor are 2.997 $\cdot 10^{12}$ USD, vs intermediate input purchases by firms are 4.040 $\cdot 10^{12}$ USD. Excluding firms in the trade & wholesale sector, for which intermediate input purchases are almost as high as revenue.

- $\psi = 1.31$ is the gain to experience for permanent workers vs temporary workers (in the afternoon vs the morning). The average ratio of existing employee hourly wage to new hire hourly wage is 1.77 for permanent and 1.34 for temporary employees. The mean ratio of the permanent to temporary ratio is 1.31. We purposely do not control for tenure because this primarily reflects that permanent employees spend longer at firms.

- $\mu^F = 1.13$ is the factoring spread. The mean federal funds rate (SELIC) was 7.83%. The default rate to FIDCs was 10.30% (conservatively calculated as the amount unpaid at due). The weighted average interest rate from FIDCs is 33.29%. So the spread is 1.3329/1.1813

- $\sigma = 1.80$: Elasticity of substitution between temporary and permanent employees. In a static model, this is the answer to "given a change in the ratio of temporary to permanent hourly wage, how much does a firm's ratio of temporary to permanent employees change?" From month to month, the permanent wage and number of employees barely changes by design, so σ is the coefficient of $\log \ell_{j1}^T$ on $\log w_1^T$, net of firm and month fixed effects.

- $\omega = 0.89$. CES share parameter on permanent employees. Aggregate equation (29) over all firms, and let L^P and L^T denote the total hours supplied of permanent and temporary employees, respectively. Then,

$$\frac{L^P}{L^T} = \left(\frac{\omega}{1-\omega}\right)^{\sigma} \implies \omega = \frac{1}{1+\left(\frac{L^T}{L^P}\right)^{\frac{1}{\sigma}}} = \frac{1}{1+0.0816^{0.56}}.$$

- $\nu = 0.009$ is the relative labor preference term. At the worker by month level, demeaning by worker and month fixed effects, the mean wage for temporary workers is 0.29 BRL per hour higher than for permanent workers, or 1.8% higher. For workers to be indifferent on the margin between permanent and temporary labor, then $\frac{\partial \mathcal{L}^{HH}}{\partial \ell^P} = \frac{\partial \mathcal{L}^{HH}}{\partial \ell^T}$. From the household FOCs,

$$\frac{\partial \mathcal{L}^{HH}}{\partial \ell^P} = \frac{\partial \mathcal{L}^{HH}}{\partial \ell^T} \iff \nu + \frac{w^P}{\bar{w}} = -\nu + \frac{w^T}{\bar{w}} \iff \nu = \frac{w^T - w^P}{2\bar{w}},$$

  where $\lambda_2 = \frac{1}{\bar{w}}$ is the marginal utility of consumption; we assume one total unit of labor supply, so consumption equals the weighted mean wage $\bar{w}$.

- $\xi = 5.48$ is the exponential disutility of labor supply, and $\frac{1}{\xi-1}$ is the Frisch elasticity. We follow the Central Bank of Brazil calibration of its SAMBA DSGE model, see Table 4 of Fasolo et al. (2024), corresponding to a Frisch elasticity of 0.22.

- $s = 11$ is the elasticity of substitution across goods. We follow the Central Bank of Brazil calibration of its SAMBA DSGE model. See Table 4 of Fasolo et al. (2024).

- $\beta = 0.979$ is the discount rate between the morning and afternoon. The mean days outstanding of factored receivables is 121 days, while the average overnight interest rate was 7.62%.

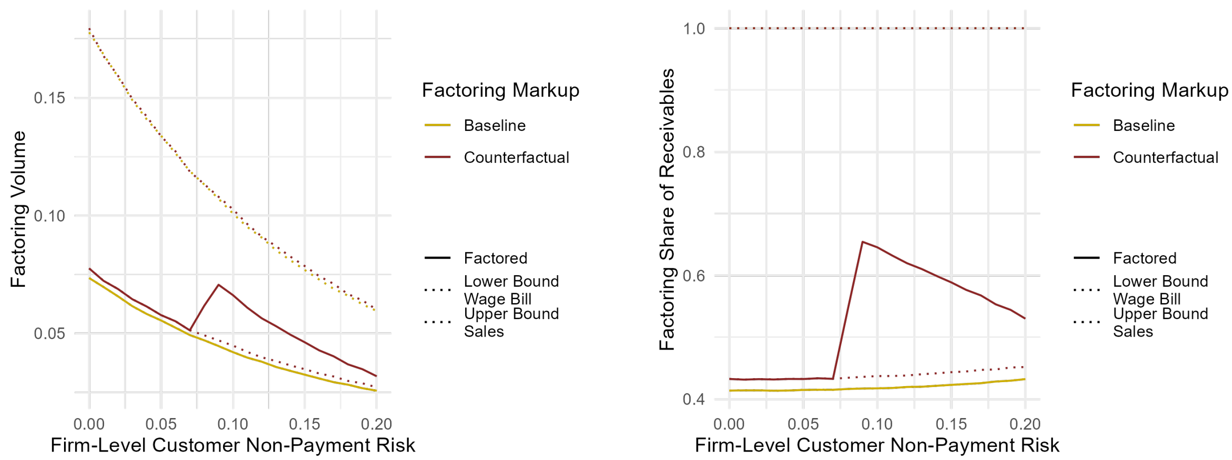
- $\eta = 0.25$ is the cost of default, following Glover (2016).

B.3 Additional Model Results

Figure A12 and Figure A13 compare the distributions of outcomes across the baseline equilibrium, with $\mu^F = 1.13$, and the counterfactual equilibrium, with perfect competition $\mu^F = 1$ between factors.

Figure A12 shows that the model can replicate the empirical factoring summary statistic in Figure 4b, that firms with moderately low credit score factor the largest share of receivables. On the left, Figure A12a shows the absolute amount factored, as well as the lower bound in equation (10) and the upper bound in equation (9) across the distribution of factoring risk ζ_j on the horizontal axis. On the right, Figure A12b shows the same outcomes normalized by the upper bound of morning receivables $p_j y_{j0}$.

Figure A12: Factoring Demand over the Factoring Risk Distribution

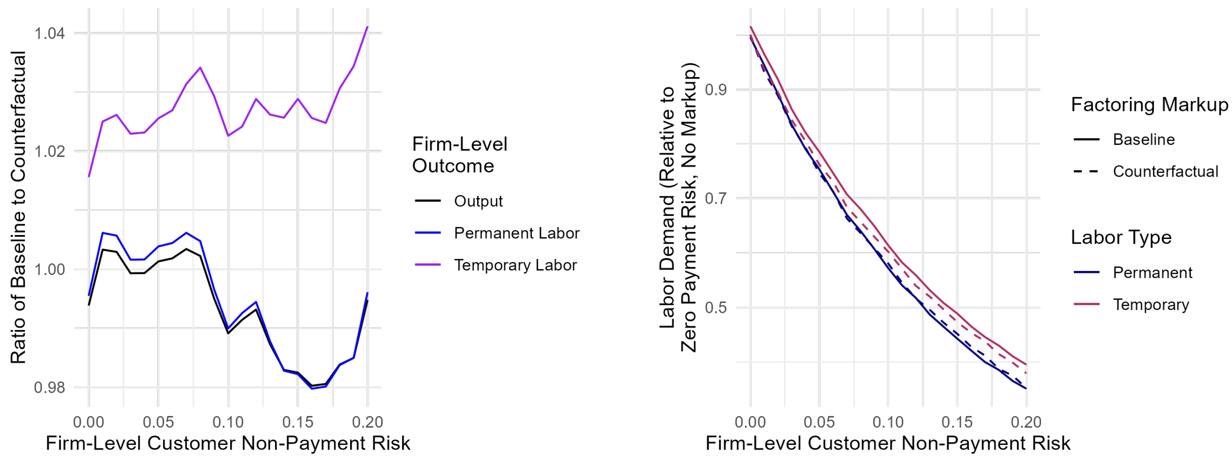


(a) Absolute Factoring (b) Relative Factoring

Notes: These figures show the model-implied factoring demand in absolute terms (left) across the distribution of firm risk ζ_j, as well as in relative terms compared to the morning receivables $p_j y_{j0}$ (right). In gold are the baseline values, with $\mu^F = 1.13$, and in red are the counterfactual outcomes, with $\mu^F = 1$.

Figure A13 compares outcomes between the baseline and counterfactual equilibria, across the distribution of factoring risk ζ_j on the horizontal axis. In Figure A13a, a value of 1 indicates a given firm has the same outcome between the two equilibria, while a value above 1 indicates the outcome has higher value in the baseline equilibrium, where factoring spreads are higher. Figure A13a shows that all firms have greater demand for temporary labor in the baseline versus the counterfactual equilibrium, but the difference across equilibria is greater for the riskier firms. By comparison, output and permanent labor demand are higher in the counterfactual equilibrium for riskier firms but not the less risky firms. Figure A13b shows the normalized value of labor demand between the baseline and counterfactual equilibria, showing that as the factoring spread increases, moving from the dotted to the dashed line, permanent labor demand decreases and temporary labor demand increases. Also, the absolute decrease in labor demand as factoring risk ζ_j increases is greater for permanent labor than for temporary labor under both equilibria.

Figure A13: Distributional Comparison of Outcomes across Equilibria



(a) Ratio of Outcomes in across Equilibria

(b) Labor Demand

Notes: These figures show the model-implied outcomes across the distribution of factoring risk ζ_j. On the left are the ratios of firm-level outcomes between the baseline and counterfactual equilibria. A value of 1 indicates a given firm has the same outcome between the two equilibria, while a value above 1 indicates the outcome has higher value in the baseline equilibrium, where factoring spreads are higher. On the right are the values of permanent and temporary labor demand, where the counterfactual labor demand for both types of labor for the firms with $\zeta_j = 0$ is normalized to 1.

C Dynamic Extension of the Model

The following is a dynamic extension of the model in Section 5 that also introduces an alternative source of short–term financing, the secured credit line.

C.1 Model Setup

There is a unit continuum of monopolistically competitive producer firms with identical fundamental productivity who produce differentiated goods that a competitive aggregator firm bundles into the final good. There are infinite discrete time periods indexed by t. Within each period, there are sub-periods τ: trade credit transactions in the morning, denoted by 0, and spot transactions in the afternoon denoted by 1. Payments clearing only occurs in the afternoon, meaning that firms do receive revenue from their morning sales until the afternoon. Firms' production in each period corresponds to their allocation of sales to trade credit versus spot transactions. Firms receive a non-pecuniary dynamic signaling value $\tilde{S} > 0$ from offering trade credit, for instance competing for sales by demonstrating to customers that the supplier is reliable, motivated by the trade credit literature. Firms must pay labor upfront in each subperiod; this generates demand for short–term financing. Let β denote the discount rate between morning and afternoon, and let $\tilde{\beta}$ denote the discount rate between periods.

C.1.1 Production

Firm j produces its good with a Cobb-Douglas production function over labor ℓ and intermediate inputs x with constant labor share α:

$$y_{jt\tau} = \ell_{jt\tau}^{\alpha} x_{jt\tau}^{1-\alpha}.$$

Firms sell to a representative aggregator firm who bundles the differentiated goods into a final good with elasticity of substitution $s > 1$. The good's price p_{jt} varies across periods but is constant between the morning and afternoon. The final good is the numeraire, so its price is always normalized to be 1.

$$Y_{t\tau} = \left(\int_{j=0}^{1} y_{jt\tau}^{\frac{s-1}{s}} \right)^{\frac{s}{s-1}}, \quad P_t = \left(\int_{j=0}^{1} p_{jt}^{-(s-1)} \right)^{-\frac{1}{s-1}} \equiv 1.$$

The aggregator firm sells the final good to households and to producer firms, who use the final good as an intermediate input.

Firms can hire two types of labor: permanent contract labor $\ell_{t\tau}^{P}$ and temporary contract labor $\ell_{t\tau}^{T}$. The firm can freely allocate labor to the morning or afternoon within each period. Let $\ell_t^P = \ell_{t0}^P + \ell_{t1}^P$ and $\ell_t^T = \ell_{t0}^T + \ell_{t1}^T$ denote the total labor demand in period t. The firm faces a cost c_f to reduce its permanent labor count, while the firm can freely adjust its temporary labor count and freely increase its permanent labor count. Permanent workers are more productive by fraction $\psi > 1$, both due to selection of workers into permanent versus temporary contracts, and learning on the job for permanent workers but not temporary workers. Labor enters the production function through the bundle $\ell_{jt\tau}$:

$$\ell_{jt\tau} = \left(\omega \left(\psi \ell_{jt\tau}^{P} \right)^{\frac{\sigma-1}{\sigma}} + (1-\omega) \left(\ell_{jt\tau}^{T} \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}. \tag{29}$$

The only fundamental dimension of firm heterogeneity is the distribution of the liquidity shock. Let $\epsilon_{jt} \in [0, 1]$ be the share of receivables y_{jt0} promised in the morning that fail to materialize in the afternoon. Let $\zeta_j = \mathbb{E}_0 \epsilon_{jt}$ be its mean, where $\mathbb{E}_0$ denotes the expectation in the morning. Let G_ζ denote the cumulative distribution function (CDF) of ζ_j and let $G_\epsilon(\epsilon \mid \zeta_j)$ denote the conditional CDF of ϵ. Heterogeneity in ζ_j

represents the ex ante differences across firms in their buyers' creditworthiness, due to differences in sectoral volatility and firm-to-firm matching. This is a reduced form way to capture the heterogeneity that generates differential demand for factoring, without the complication of explicitly modeling the firm network. Firms observe the shock before choosing temporary labor and inputs in the afternoon, but must continue to pay permanent employees the contracted wage. The proceeds of the liquidity shock are rebated lump sum to consumers in the second period. Due to the timing of the liquidity shock, firms behave as if they were choosing their morning and afternoon production allocations in the morning, together with their financing decisions.

There are two types of financing, a collateralized credit line and factoring. For both types of financing, the firm borrows at the beginning of the morning and repays at the end of the afternoon. Firm j borrows B_j^C amount from the credit line, secured by a fixed value of a non-productive asset A, with gross interest rate R_j^C. Firm j borrows B_j^F, up to the face value of the morning accounts receivable $p_j y_{jt0}$ discounted by gross interest rate R_j^F. Firms take interest rates as given. Firms must finance the difference between their cash on hand and the morning wage bill $w_t^P \ell_{jt}^P + w_{t0}^T \ell_{jt0}^T$. Firms initially begin with zero cash on hand. Firms do not earn a return on cash, but firms can retain cash between the morning and afternoon, as well as between periods. Firms cannot default to suppliers in the afternoon, nor to labor in either period, because payments are made upfront. The producer firm's objective in the morning is to maximize expected profits at the end of the afternoon, by choosing intermediate inputs $x_{jt\tau}$, permanent labor demand ℓ_{jt}^P, temporary labor demand $\ell_{jt\tau}^T$, factoring B_{jt}^F, and credit line usage B_{jt}^C, taking as given wages $\{w_t^P, w_{t\tau}^T\}$, the factoring interest rate R_{jt}^F, the liquidity shock e_{jt}, and model parameters. The firm faces a cost of default η, applied to negative profits, which occur when the firm does not have enough cash in the afternoon to repay suppliers with whom it contracted in the morning. Without loss of generality, the firm's optimization problem at time $t = 0$ is

$$
\begin{aligned}
&\max_{\{y_{jt\tau}, x_{jt\tau}, \ell_{jt}^P, \ell_{jt\tau}^T, B_{jt}^F\}_{t \geqslant 0, \tau \in \{0,1\}}} \sum_{t=0}^{\infty} \tilde{\beta}^t \left(\pi_{jt} + \tilde{S} y_{it0} \right), \\
\text{s.t. } \pi_{jt} &\equiv \beta \mathbb{E}_0 \left[\pi_{jt1} + \eta \pi_{jt1} \mathbb{1}\{\pi_{jt1} < 0\} \right] + m_{jt0}, \\
B_{jt}^C &\leqslant \frac{A}{R_{jt}^C}, \\
B_{jt}^F &\leqslant \frac{p_{jt} y_{jt0}}{R_{jt}^F}, \\
0 &\leqslant m_{jt0} \equiv B_j^F - \ell_{jt}^P w^P - \ell_{j0}^T w_0^T, \\
\pi_{jt1} &:= p_{jt} y_{jt1} - \ell_{jt}^P w_t^P - \ell_{jt1}^T w_{t1}^T - P x_{jt1} - B_{jt}^C (R_{jt}^C - 1) + \tilde{m}_{jt1}, \\
\tilde{m}_{jt1} &= (1 - \epsilon_{jt}) \left(p_{jt} y_{jt0} - R_{jt}^F B_{jt}^F \right) - P x_{jt0}.
\end{aligned}
$$

The aggregator firm's objective in each period is standard: choose purchases $y_{jt\tau}$ to minimize expenditure $\int_0^1 p_{jt} y_{jt\tau} dj$ subject to $Y_{t\tau} = \left(\int_{j=0}^1 y_{jt\tau}^{\frac{s-1}{s}}\right)^{\frac{s}{s-1}}$. The first-order condition implies

$$\frac{p_{jt}}{P} = \left(\frac{y_{jt\tau}}{Y_{t\tau}}\right)^{-\frac{1}{s}}. \tag{30}$$

C.1.2 Financing

Credit lines are offered by a competitive set of financiers. There is no default risk for the secured credit line because the financier can repossess and sell the asset by incurring fractional cost ξ, for $\xi \in [0,1)$, so $R_j^C = \beta^{-1}\xi$.

The factoring market is imperfectly competitive due to information asymmetries across lenders. We model this in reduced form by assuming that the markup for a given firm is inversely proportional to the relative asset demand D_j^F for the firm's receivables, and the factoring interest rate is the cost of capital (inclusive of receivables risk ζ_j) scaled up by the markup:

$$R_{jt}^F = \frac{\beta^{-1}\left(\mu\left(D_{jt}^F\right)^{-\vartheta} + 1\right)}{1-\zeta_j}.$$

The partial equilibrium counterfactual is a shift in asset demand D_j^F for a specific firm j, while the general equilibrium counterfactual is a shift in D_j^F for all firms.

C.1.3 Household

There is a continuum of identical households, i.e. a representative household. The household's utility is logarithmic over consumption.[19] The household has exponential disutility $\xi > 1$ from labor supply, and is indifferent between supplying labor in the morning versus afternoon because the household gets paid upfront either way. The

[19]In this model, the shape of household utility over consumption is unimportant because there is only effectively one period, the afternoon, when the household pays for its consumption, and because there is no heterogeneity among households. With linear or CARA or CRRA utility, the results are qualitatively unchanged.

household has relative preference ν for permanent versus temporary labor.[20]

$$u_t(c_t, \ell^T_{t\tau}) = \log(c_t) - \sum_{t=0}^{1} \left[\frac{1}{\xi} \left(\ell^P_t + \ell^T_{t\tau} \right)^{\xi} - \nu(\ell^P - \ell^T_t) \right].$$

The household receives its pay in each period, owns the financiers who lend to the firms, and pays for its consumption in the afternoon. Because of the timing of its income and expenditure, the household never demands to borrow. The household begins with zero cash. The household's optimization problem is to choose ℓ^P_t and $\ell^T_{t\tau}$ to maximize discounted utility, given real wages w^P_t for permanent and $w^T_{t\tau}$ for temporary labor, subject to its budget constraint. The household's problem is static because the household takes as given both the price and the hours offered by employers.

$$\max_{\{c_0, c_1, \ell^P, \ell^T_0, \ell^T_1\}} \log(c_t) - \sum_{t=0}^{1} \left[\left(\ell^P_t + \ell^T_{t\tau} \right)^{\xi} + \nu \left(\ell^P_t - \ell^T_{t\tau} \right) \right], \tag{31}$$
$$\text{s.t. } c_t = \ell^P_{t\tau} w^P_t + \sum_t \ell^T_{t\tau} w^T_{t\tau}.$$

C.1.4 Equilibrium

We define a Markov perfect equilibrium in which firms solve a dynamic optimization problem subject to their liquidity shocks and production technology, households solve their static labor-supply problem, and markets clear. Let $s_t \in \mathcal{S}$ denote the aggregate state of the economy at time t, including

- Aggregate information about firms' labor demand: $\int \ell^P_{jt}\, dj$,
- Distribution of firms' cash-on-hand m_{jt}, use of credit lines $\{B^C_{jt}\}$ and factoring $\{B^F_{jt}\}$.

Each firm j has an individual state $x_{jt} \in \mathcal{X}$, includes its permanent labor from the previous period, $\ell^P_{j,t-1}$, its current cash holdings m_{jt}, and its receivables risk type ζ_j. We write the full state as (s_t, x_{jt}). In each period t, firm j chooses:

$$\left\{ \ell^P_{jt},\ \ell^T_{jt0},\ \ell^T_{jt1},\ x_{jt0},\ x_{jt1},\ B^F_{jt},\ B^C_{jt},\ m_{j,t+1} \right\}$$

to maximize its expected discounted sum of profits plus the non-pecuniary trade-credit value $\tilde{S} y_{jt0}$. Let R^C_{jt}, R^F_{jt}, $w^P_t, w^T_{t0}, w^T_{t1}$, and p_{jt} be taken as given. The firm's continuation

[20] In an extension, we generalize this to heterogeneous worker types, and we use the mix as a reduced form way to aggregate over this heterogeneity. e.g. older workers who prefer permanent, vs young inexperienced workers who prefer temporary because the search costs are too high for them to receive permanent offers.

value is captured by a time-invariant Bellman equation:

$$V(x_{jt}; s_t) \;=\; \max_{\substack{\ell^P_{jt},\, \ell^T_{jt\tau},\, x_{jt\tau},\\ B^F_{jt},\, B^C_{jt},\, m_{j,t+1}}} \Big\{ \pi_{jt} + \tilde{S}\, y_{jt0} \;+\; \tilde{\beta}\, \mathbb{E}\big[V\big(x_{j,t+1};\, s_{t+1}\big)\big] \Big\},$$

subject to the production and financing constraints listed earlier. A competitive equilibrium is a sequence of allocations and prices such that:

- Each firm solves its Bellman equation given $(w^P_t, w^T_{t\tau}, R^C_{jt}, R^F_{jt}, p_{jt})$ and the law of motion for s_t.
- Each household solves its static labor-supply problem and supply labor $\ell^P_t, \ell^T_{t\tau}$ that clears the labor market:

$$\int_0^1 \ell^P_{jt}\, dj \;=\; \ell^P_t, \quad \int_0^1 \ell^T_{jt\tau}\, dj \;=\; \ell^T_{t\tau}.$$

- The goods market clears in each sub-period ($\tau = 0, 1$):

$$Y_{t\tau} \;=\; c_{t\tau} \;+\; \int_0^1 x_{jt\tau}\, dj,$$

  with $c_{t0} + c_{t1} = c_t$ representing total consumption in period t.
- The aggregate state s_t evolves according to $s_{t+1} = \Gamma(s_t)$, where Γ is induced by firms' optimal decisions and exogenous shocks.

C.2 Method of Simulated Moments (MSM)

We estimate the dynamic model using the method of simulated moments, fit to the impulse-response functions (IRFs) from the local projection empirical results. First, we collect the empirical IRFs: From the local-projection regressions, we store the estimated sequences

$$\{\widehat{\beta}^{\text{data}}_{\text{FS},h}\}_{h=\{0,1,\ldots,H\}} \quad \text{and} \quad \{\widehat{\beta}^{\text{data}}_{\text{RF},h}\}_{h=\{0,1,\ldots,H\}},$$

where $\widehat{\beta}^{\text{data}}_{\text{FS},h}$ is the estimated IRF of the first stage $R^F_{j,t+h}$ with respect to D^F_{jt}, and $\widehat{\beta}^{\text{data}}_{\text{RF},h}$ is the estimated IV IRF of the outcome $y_{j,t+h}$ with respect to R^F_{jt} instrumented by D^F_{jt}. These two sets of IRFs together form our empirical moments vector $\widehat{m}^{\text{data}}$.

Let $\theta \in \Theta \subset \mathbb{R}^d$ denote the vector of structural parameters to estimate. For a given guess θ, we simulate the model by numerically solving the dynamic equilibrium given θ, generate a panel of simulated firms $\big\{(i,t)\big\}_{i=1,\ldots,N;\, t=1,\ldots,T}$. In each period t, we draw the exogenous shock D^F_{it} that shifts factoring asset demand, feed it into the model's pricing equation for R^F_{it}, and record the endogenous outcomes $\{y_{it}, x_{it}, \ell^T_{it}, \ell^P_{it}, y_{it0}/y_{it1}\}$, etc. Next, we estimate the model-based IRFs. In the simulated data, we run an analogous local projection of $R^{F}_{i,t+h}$ on the shock $D^{F}_{i,t+h}$:

$$R^{F}_{i,t+h}(\theta) \;=\; \alpha_{i,h} + \gamma_{t,h} + \beta^{\text{model}}_{\text{FS},h}(\theta)\, D^{F}_{i,t+h} \;+\; \varepsilon^{\text{sim}}_{i,t+h}.$$

We collect $\{\beta^{\text{model}}_{\text{FS},h}(\theta)\}^{H}_{h=0}$. We proceed similarly for outcomes y_{it}, x_{it}, etc. This gives us the model-implied vector of IRFs $\widehat{m}^{\text{model}}(\theta)$ replicating the structure of the empirical IRFs. Now we define the MSM objective function. Let W be the $(2K+2) \times (2K+2)$ weighting matrix. Define

$$Q(\theta) \;=\; \Big[\widehat{m}^{\text{data}} - \widehat{m}^{\text{model}}(\theta)\Big]' W \Big[\widehat{m}^{\text{data}} - \widehat{m}^{\text{model}}(\theta)\Big].$$

Here, $\widehat{m}^{\text{data}}$ and $\widehat{m}^{\text{model}}(\theta)$ each contain $(K+1)$ elements for $\theta_{0:K}$ and $(K+1)$ elements for $\beta_{0:K}$. We minimize the distance between model-implied and data by solving for

$$\theta^{*} \;=\; \arg\min_{\theta \in \Theta} Q(\theta).$$