Firm-Level and Aggregate Effects of Cheaper Liquidity: Evidence from Factoring *

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Abstract: We show that firms experience large contemporaneous increases in sales and purchases after receiving cheaper liquidity. We focus on factoring, defined as the supplier-initiated sale of receivables. In Brazil, receivables funds (FIDCs) securitize receivables for institutional investors. By assembling a novel transaction-level dataset of factoring with other credit operations for all registered firms and FIDCs, we construct a shift-share instrument for the supply of factoring financing based on FIDC flows. We then use a novel combination of electronic payments, trade credit, and employer-employee matched data to estimate the impacts. A flow-induced increase in receivables demand reduces firms' factoring interest rate. In response, firms demand more permanent labor and less temporary labor. In our model, these effects arise from factoring's purpose of reducing cash inflow volatility, helping firms match inflows to outflows, which firms otherwise achieve at an efficiency cost through substitution across labor types. Using our model, we estimate that an aggregate decrease in the economy-wide factoring spread of 1 percentage point leads to 0.3 to 0.5 percentage point increases in aggregate output and wages.

Keywords: Factoring, Receivables, Trade Credit, Liquidity Shocks, Labor Demand, Corporate Finance, Working Capital

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 the working capital financing that firms use to bridge the gap in cash flows between paying upfront for labor and waiting for future payments from customers? How responsive are firms' production decisions to working capital financing terms? These questions are relevant to central banks and most firms around the world, especially firms in sectors with long production timelines or payment clearing cycles. Small and medium enterprises (SMEs) tend to rely more on working capital financing, due to limited cash and access to corporate treasury operations, but also tend to face challenges acquiring financing due to limited collateral and credit history (BIS, 2023). This paper studies how a change in the price of a specific type of working capital financing affects firms' outcomes across the entire distribution of firms.

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, where the supplier receives a receivable note in return for the good or service, and a payment clearing transaction, where the buyer gives the supplier the promised payment in return for retiring the receivable. Suppliers who want cash before payment clearing can sell the receivable to a financial intermediary called a factor and this type of sale is known as factoring. The worldwide factoring share of receivables has increased from 7% in 1997 to 24% in 2017 (Boissay et al., 2020). In Brazil, the empirical setting for this paper, factoring is the highest volume form of working capital financing. Few papers have estimated the impact of working capital financing terms on firms' outcomes, and none use a dataset encompassing all firms in an economy.

This paper studies the impact of a shift in the factoring interest rate –ȯr equivalently the price of receivables –ȯn firms' financing, labor demand, supply chain relationship terms, and sales. An important feature of the Brazilian setting is the presence of specialized mutual funds called FIDCs, which purchase and securitize firms' receivables, selling debt tranches to institutional investors similarly to a mortgage-backed security. FIDCs' regulatory structure mandates them to primarily purchase receivables, along with short-term Brazilian Treasury notes for liquidity management. 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. FIDCs' share of all factoring in Brazil has grown from 7% in 2015 to 32% in 2023, following trends of greater use of financial technology in factoring and greater asset demand from investors, and FIDCs' share is likely to continue to increase as ongoing reforms broaden the investor base and reduce the informational advantage of banks over FIDCs in factoring. We use FIDCs' past receivables purchases and current flows to instrument for firms' factoring interest rate, and we are the first to show causal estimates 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 FIDC's current demand for receivables must respond to flows to FIDCs due to FIDCs' capital allocation constraints.

We construct a new dataset using several restricted-access databases at the Central Bank of Brazil (BCB). The dataset contains factoring transactions from banks and FIDCs for all 1.03 million formally registered firms in Brazil that have ever sold their receivables. We merge the factoring data, at the firm by month level, to the employer-employee matched dataset (RAIS), the universe of electronic payments, and boleto contracts that specify trade credit payment terms. There are three main takeaways from our summary statistics: firms have greater cash inflow volatility than cash outflow volatility, firms that are smaller and riskier tend to factor a larger share of receivables, and FIDCs tend to purchase receivables from riskier firms. Our interpretations are that the differences in cash flow volatility generates firms' demand for short-term liquidity through working capital financing, and 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.

In light of these facts, the results from our regressions, of a wide range of outcomes on the factoring interest rate, can be interpreted as a contemporaneous local average treatment effect for firms that factor as their marginal source of liquidity. The estimates are large: a one percentage point decrease in the factoring interest rate causes a 16.2% increase in factoring, a 6.1% increase in revenues, and a 3.6% increase in intermediate input expenditure. While total payments to labor increase by 0.6%, permanent labor demand increases by 1.1% and temporary labor demand decreases by 2.1%. Given that the regressions feature firm and month fixed effects, we interpret the large magnitudes of the revenue and input expenditure results as a combination of a temporal substitution component and a cash flow volatility component.

We build a model of factoring to explain how the cash flow volatility affects firms' outcomes, how cheaper factoring can increase aggregate output, and how the general equilibrium estimates differ from partial 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 general equilibrium, a reduction of the factoring interest rate for all firms with adjustment of aggregate prices and allocations, motivated by three broad trends: the increased use of financial technology 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 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.

This paper relates to several strands of literature in finance and macroeconomics. The importance of FIDCs as a marginal source of factoring supply relates to the literature on non-bank credit supply, specifically on 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 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.

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., 2022; 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 his sample of publicly traded firms, and focuses on the moral hazard motivation of trade credit. 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 a explain using a 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 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.

Finally, the literature on the real effects of working capital financing costs primarily focuses on credit lines and working capital loans for large firms, yet understanding the impact of working capital financing terms is arguably more important for the many small firms that have limited cash holdings and financing options. Chodorow-Reich (2014) studies the impact of credit supply on employment, using co-syndication exposure to Lehman Brothers' failure as the shock, and a large share of the credit supply was working capital loans. Chodorow-Reich (2014) finds that a relative decrease in bank health caused an increase in the interest rate spread of 18 basis points, a decrease in lending of 2.3 percentage points, and a decrease in employment of 2.4 percentage points. By comparison, we can directly estimate the impact of the main component of working capital financing costs on employment and other outcomes, both real and financial. If we interpret the Chodorow-Reich (2014) results as solely operating through the cost of financing, so that the financing elasticity is 12.9 and the employment elasticity is 13.2, then we find a similar financing elasticity of 16.1 but smaller employment elasticities of 1 to 2, perhaps due to greater hiring frictions and lower labor mobility in the formal labor market of Brazil compared to the US. Lian and Ma (2021) show that one channel for real effects of working capital financing terms are borrowing constraints based on cash flows. Several papers have shown that the financing conditions of small and medium enterprises (SMEs), and their 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.

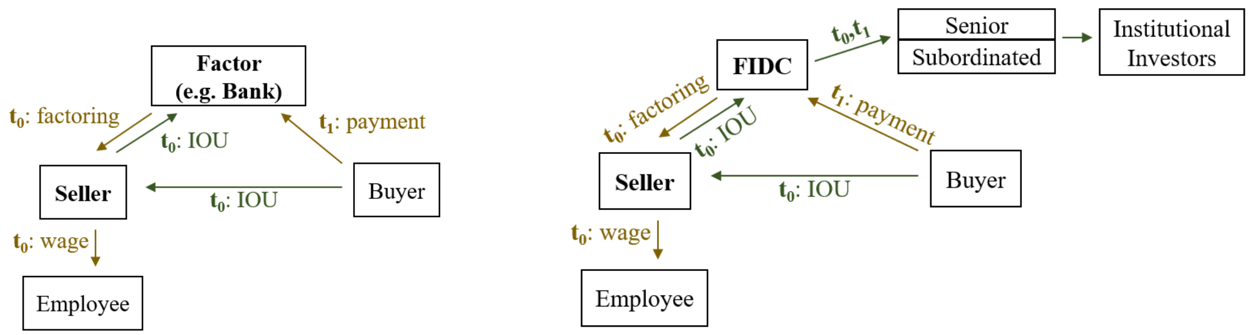
We organize the remainder of the paper as follows. Section 2 describes the institutional setting of factoring and FIDCs. Section 3 describes the data and the key facts. Section 4 introduces the methodology and discusses the regression results. Section 5 interprets the results in the lens of a model of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

2 Factoring and FIDCs

When firms transact, they choose payment terms along 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, serves as proof of accounts receivable, which is an asset on the seller's balance sheet whose 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.

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

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 to a financial intermediary for a discount to its face value. Factoring 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 a subset of 600 FIDCs that primarily purchase firms' receivables, specifically recourse factoring. These FIDCs have combined NAV of 17.7 billion USD, and purchase 4.1 billion USD of firms'

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

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.[7] 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.

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.

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. 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).

The final component of our dataset are the credit operations (SCR). SCR includes all bank loans 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 it for the full set of firms available 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 lines of credit and loans backed by accounts receivable as the main

[7] 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.

alternative forms of working capital financing.

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, comprises \$4.7 billion USD per month.

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 a majority of intermediated capital financing in Brazil.

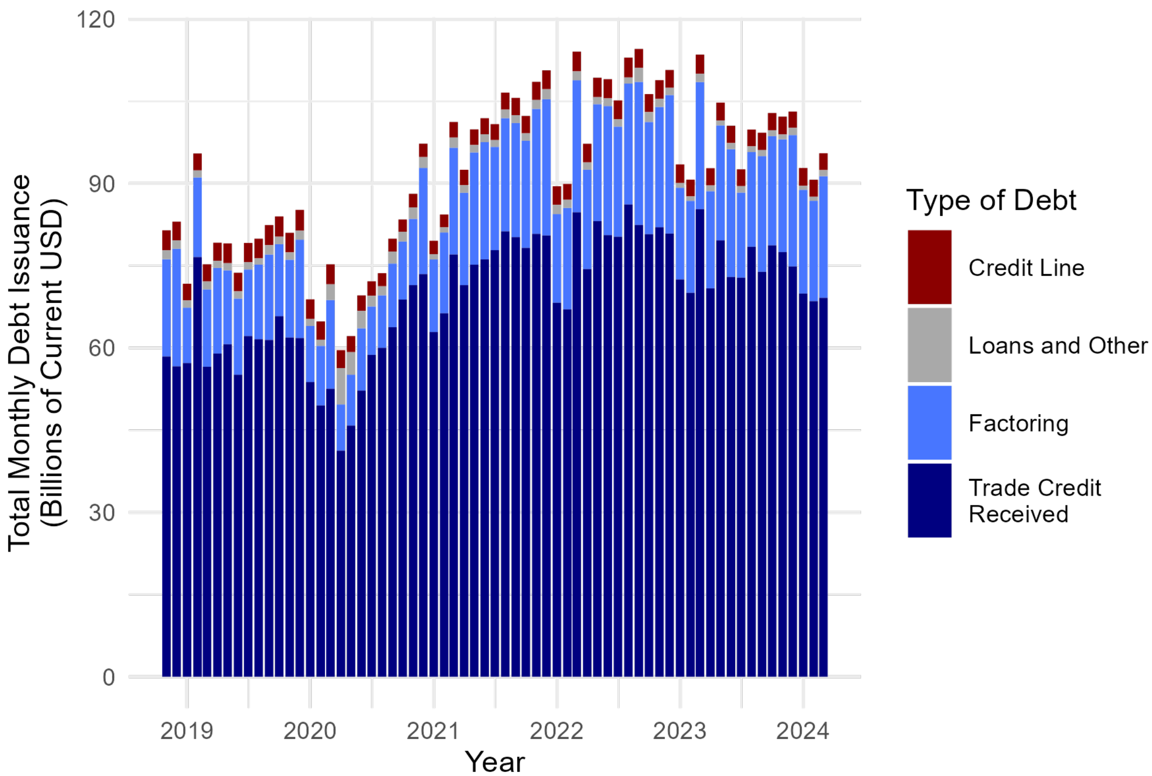
Table 1. Annual Means of Trade Credit, Factoring, and Other Short-Term Debt

	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.

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.[8]

Figure 2. Time Series of Working Capital Financing in Brazil

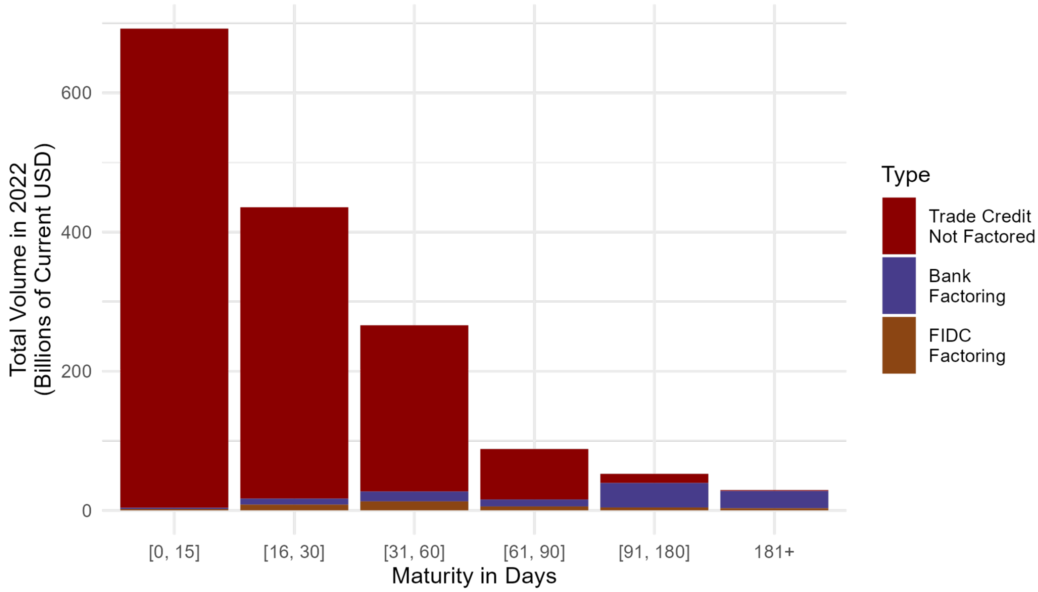


Notes: The data are from the Central Bank of Brazil. This figure shows the composition of firms' short term financing, with maturity under 1 year, among the 1 million firms in our sample. In dark blue is the value of trade credit that a firm receives from its suppliers. In light blue is factoring, the 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.

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. Almost all long maturity receivables are factored.

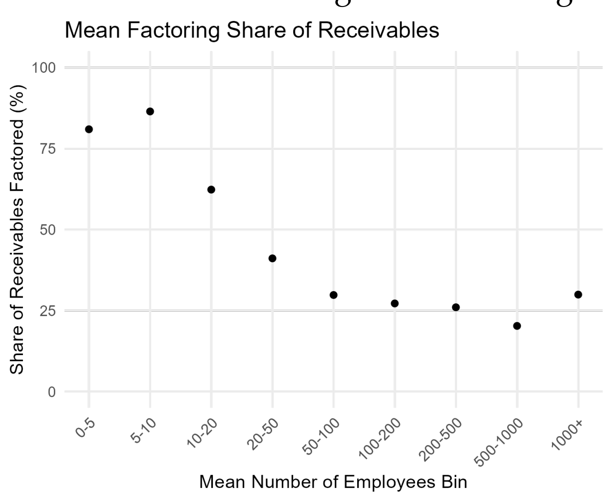
[8] Figure A1 shows that the relative importance of each type of working capital financing is invariant across the distribution of firms' credit score, although the exact magnitudes vary across the distribution.

Figure 3. Distribution of Maturity for Trade Credit and Factoring

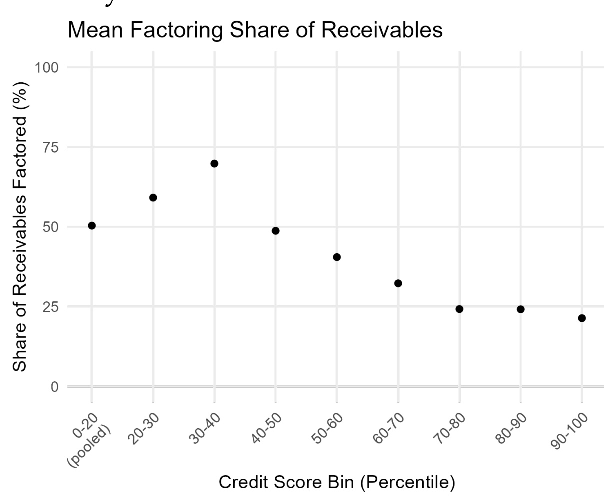


Notes: The data are from the Central Bank of Brazil. This figure partitions factoring and trade credit at the contract level by the maturity bin, then sums the contract value by bin. We measure the maturity of trade credit and receivables by the contract dates and due dates from the boleto transactions. 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 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 A3 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 is driven by flows to funds. FIDC flows have weak autocorrelation of 0.21 from month to month. Table 2 shows summary statistics on FIDCs:

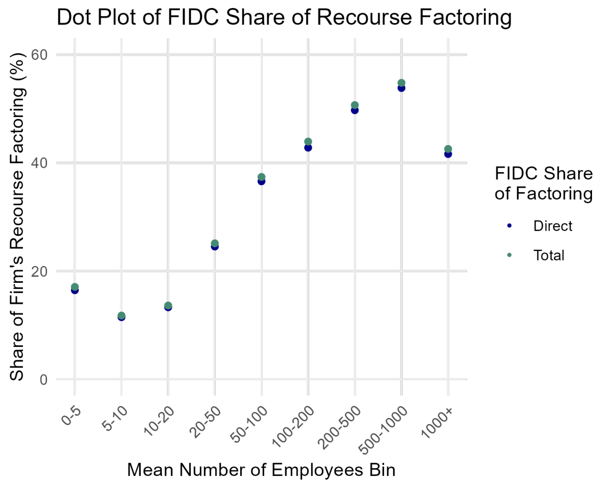
Table 2. Summary Statistics on FIDCs at the FIDC by Month Level

	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

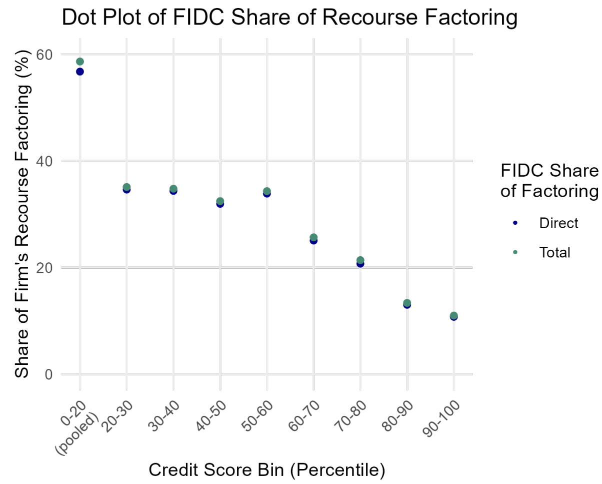
Notes: The data are from the Securities and Exchange Commission of Brazil (CVM). The net asset value, monthly recourse factoring, and flow variables are expressed in billions of USD. The interest rate (IR) is an issuance volume weighted average. The net flow is defined to be the difference between current 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. This would allow us to trace out the financing demand curve of factoring, and then between each two points on 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 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 $r^{Fac}_{j,t}$ on the left hand side and firm-level expected flow-driven "exposure" (net purchases of receivables) on the right hand side, constructed as follows: $x^{Fac}_{j\to f,t}$ 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: $F^{NAV}_{f,t} := \frac{NAV_{f,t} - NAV_{f,t-1}R_{f,t}}{NAV_{f,t-1}}$. We then define fund by factoring type by month exposure $e^{Fac}_{j,t}$ to funds' flows is the firm's share of 3-month lagged fund receivables purchases, scaled by the flow to the fund

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

We normalize e so it is in the unit of standard deviations from the mean. Then the first stage regression is

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

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 fund flows, 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.	3,956,731	1,734,458	2,424,888
Num. Firms	322,087	251,391	123,581
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.

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; only 1.04% of the face value is re-sold 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, so we believe that FIDC flows are not large enough to affect monetary policy. We argue that reverse causality, flows chasing firms with high expected returns, is not a concern because most FIDCs hold receivables of hundreds or thousands of firms, we believe that FIDC flows are largely driven by institutional investors' portfolio allocation constraints, and flows are only weakly autocorrelated across time.

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:

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

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 $6.0\% = e^{-0.0614} - 1$ from column 1, a moderate decrease in intermediate input expenditure of $3.5\% = e^{-0.0357} - 1$ from column 2, and small decrease in expenditure on labor of 0.56% from column 3.[9] 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%, while column 5 shows that the number of hours worked by temporary employees increases by 2.1%. The average number of permanent employees per firm is 46.6, while the average number of temporary employees is 4.3. The mean number

[9]We proxy for revenue and intermediate input expenditure using boleto and other electronic payments between firms.

of weekly working hours for permanent employees is 41.8 and for temporary employees is 37.4, including overtime work. See Table 6 and Table 9 for the decomposition of the impact on labor market variables.

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

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.[10] 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.[11]

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 9 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

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

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

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, 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.

4.2.2 Financial Outcomes

Table 7 shows that factoring volume is highly responsive to the factoring interest rate, with no substitution to quantities of other types of financing.

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.

Note that the response variable in column 3, actual factoring issuance at the firm level, differs 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 10 in the appendix 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 a high baseline mean interest rate of 333% and high variance across firms, with standard deviation of 85%.

Table 8 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 8. 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 that was not paid on its due date; note that 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%.

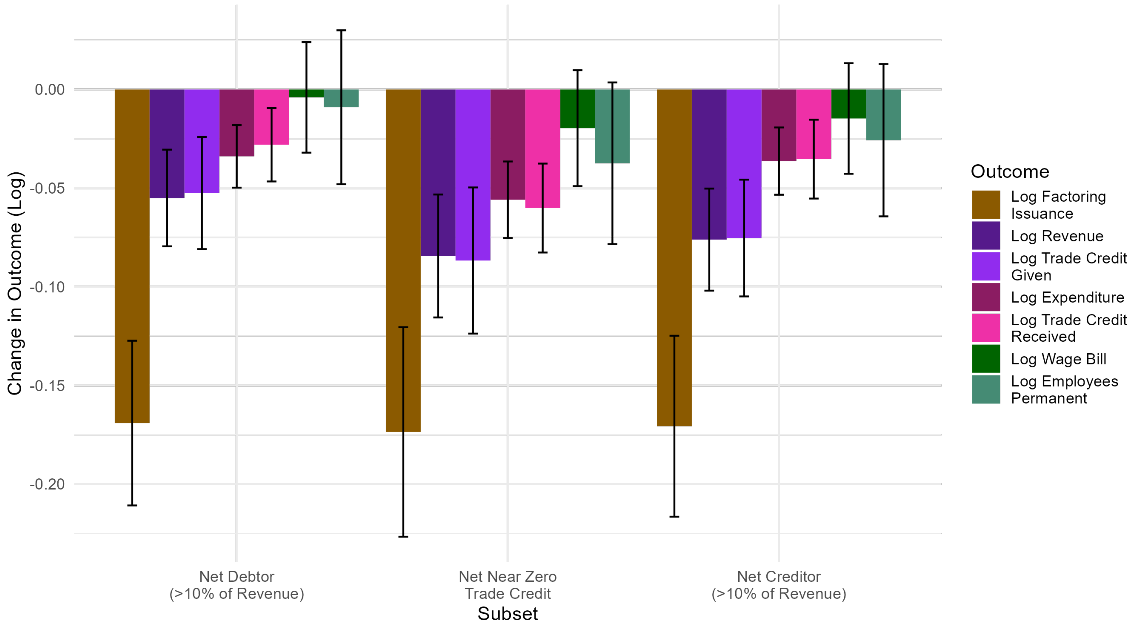
4.2.3 Heterogeneity by Firm Type

Now consider regressions with interactions by bins of firm heterogeneity γ_j:

$$y_{j,t} = \alpha_j + \alpha_t + \beta_1 r^{Fac}_{j,t} \gamma_j + \varepsilon_{j,t} \tag{3}$$

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 6 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.

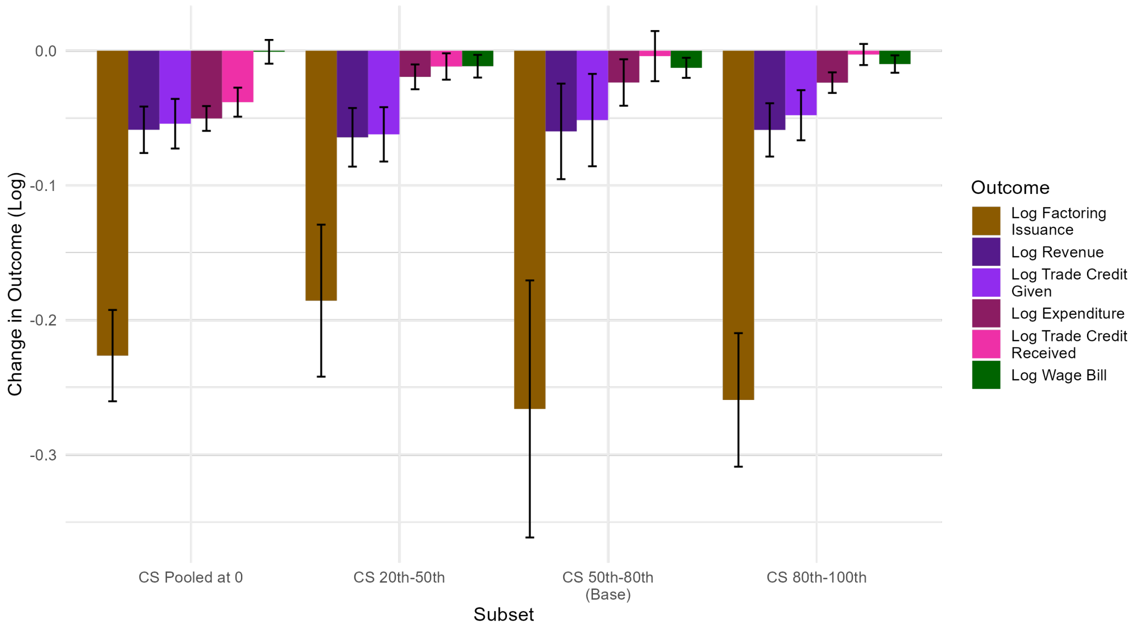
Figure 6. Heterogeneous Effects of the Factoring Interest Rate by Trade Creditor



Notes: The data are from the Central Bank of Brazil. Each color corresponds to regression (3) 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.

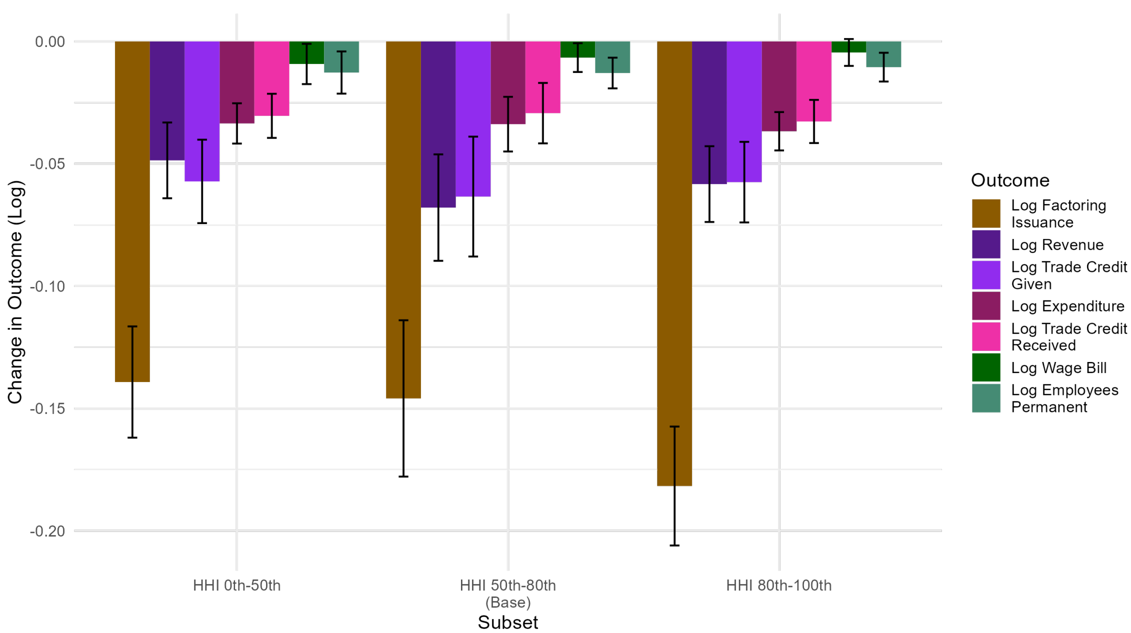
Figure 7 shows that the main results in Table 4 are true across the distribution of firms, not specific to firms with low credit scores that are more financially constrained. The base category is firms with credit scores between the 50th and 80th percentiles. Firms with the lowest credit scores, pooled 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 7. Heterogeneous Effects of the Factoring Interest Rate by Credit Score



Notes: The data are from the Central Bank of Brazil. Each color corresponds to a regression of (3) 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 8. Heterogeneous Effects of the Factoring Interest Rate by HHI



Notes: The data are from the Central Bank of Brazil. Each color corresponds to a regression of (3) 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 8 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.

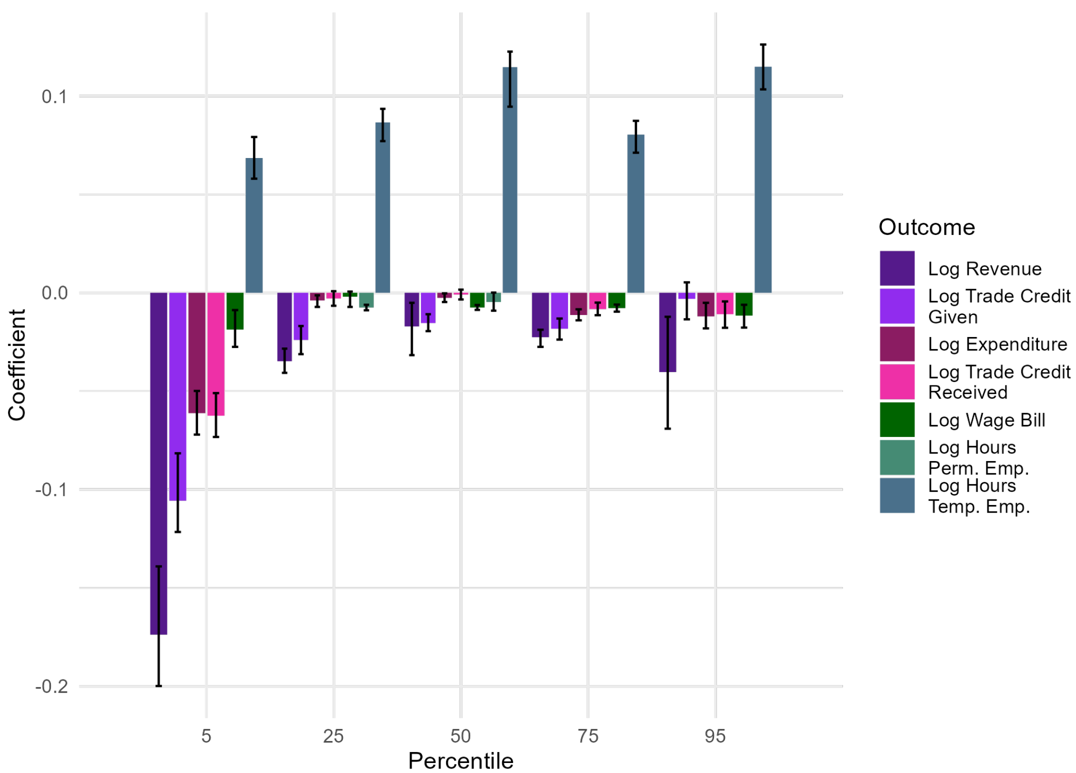
4.2.4 Heterogeneity by Quantile

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):

$$Q_{\tilde{y}_{j,t}}(\tau \mid \widetilde{\hat{r}}^{Fac}_{j,t}) = \beta(\tau)\widetilde{\hat{r}}^{Fac}_{j,t} + \varepsilon_{j,t}(\tau), \tag{4}$$

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 9. 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 (4). 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 calcuated using rank inversion.

The interpretation of each coefficient in Figure 9 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, mainly for small firms that factor a lot; intermediate input purchases are responsive but not as much as revenue; labor demand decreases, with a moderate increase in temporary workers and a small 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 mainly reflecting substitution of economic activity and payments across short periods of time.

The purpose of the model is to rationalize the micro-elasticities in the empirical results, and also estimate the "macro-elasticities" of how aggregate output and factoring volume respond to the factoring spread, which has implications for the trade credit multiplier. The only other empirical factoring papers, Bottazzi et al (2023) and Amberg et al (2023), estimate the impact of introducing factoring to firms. However, factoring already exists in many countries, and the main challenge 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 sell 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.[12] 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:

$$\ell_{jt} = \left(\omega \left(\psi_t \ell_j^P \right)^{\frac{\sigma-1}{\sigma}} + (1-\omega) \left(\ell_{j1}^T \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}. \tag{5}$$

Firm j chooses ℓ_j^P at the beginning of period 0 and choose 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

[12] 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.

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 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 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.

$$\max_{\{y_{jt}, x_{jt}, \ell_j^P, \ell_{jt}^T, B_j^F\}} \pi_j := \beta \mathbb{E}_0 \left[\pi_{j1} + \eta \pi_{j1} \mathbb{1}\{\pi_{j1} < 0\}\right] + m_{j0}, \tag{6}$$

$$\text{s.t. } B_j^F \leqslant \frac{p_j y_{j0}}{R_j^F}, \tag{7}$$

$$0 \leqslant m_{j0} \equiv B_j^F - \ell_j^P w^P - \ell_{j0}^T w_0^T, \tag{8}$$

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

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

The key feature of factoring is that the upper bound $\frac{p_j y_{j0}}{R_j^F}$ in (7) is inherently endogenous to the firm's output choice y_{j0}. In this setup, the lower bound $\ell_j^P w^P + \ell_{j0}^T w_0^T$ in (8) 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:

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

The aggregator firm's objective in each period is standard: choose purchases y_{jt} to minimize expenditure $\int_0^1 p_j y_{jt} di$ 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

$$
\frac{p_j}{P} = \left(\frac{y_{jt}}{Y_t} \right)^{-\frac{1}{s}}. \tag{9}
$$

There is a representative household. The household's utility is logarithmic over consumption.[13] 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.[14] In each period, the household has exponential labor supply disutility $\xi > 1$.

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

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

[13] 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.

[14] 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.

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.

$$\max_{\{c_0, c_1, \ell^P, \ell_0^T, \ell_1^T\}} \log(c_0) + \beta \log(c_1) - \sum_{t=0}^{1} \left[\left(\ell^P + \ell_t^T \right)^{\xi} + \nu \left(\ell^P - \ell_t^T \right) \right], \tag{10}$$
$$\text{s.t. } c_0 + c_1 = 2\ell^P w^P + \sum_t \ell_t^T w_t^T.$$

5.2.1 Equilibrium

Given model parameters, firms optimize (15), households optimize (14), and markets clear in each period:

$$Y_t = \left(\int_{j=0}^{1} y_{jt}^{\frac{s-1}{s}} \right)^{\frac{s}{s-1}} = c_t + \int_{j=0}^{1} x_{jt} \, di, \tag{11}$$

$$\int_{j=0}^{1} \ell_j^P \, di = \ell^P, \tag{12}$$

$$\int_{j=0}^{1} \ell_{jt}^T \, di = \ell_t^T. \tag{13}$$

See Section B in the appendix for the method that we use to solve the model.

5.3 Model Calibration

We calibrate the model primarily using moments in the data that are implied by the model structure. See Section B.2 in the appendix for more details.

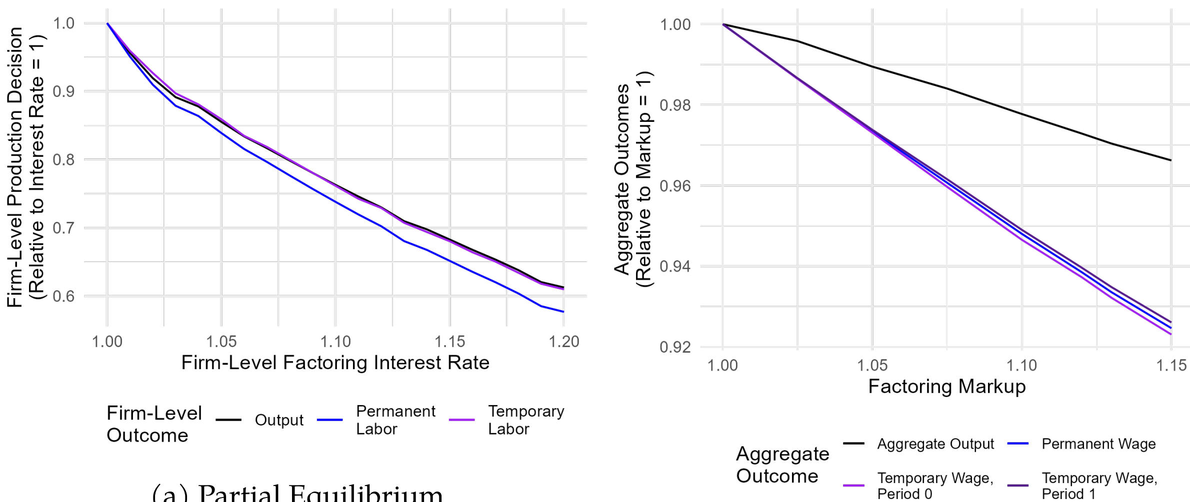
Parameter	Value	Description	Method
α	0.43	Cobb-Douglas labor	Data: Expenditure share
ψ	1.31	Gain to experience	Data: Ratio of existing to new hire wage for permanent vs temporary
μ^F	1.13	Factoring spread	Data: IR minus (default rate + 3-month T-bill)
σ	1.80	EoS permanent vs temporary labor	Data: Regression
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 description or method for any parameter, see Section B.2 in the appendix

5.4 Counterfactuals

There are two main counterfactuals that we consider. Figure 10a shows the partial equilibrium equivalent of the regressions, 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. Figure 10b shows 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 10. 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 10 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 due to the change in wage and due to the inelasticity of labor supply when firms collectively reallocate labor demand from permanent to temporary contracts.

6 Conclusion

This paper contributes new evidence that explain why factoring is the main form of working capital financing in Brazil and increasingly important worldwide, especially for small firms with low creditworthiness. We are the first to estimate the causal impact of factoring interest rate on firms' production decisions, trade credit, and firm outcomes, using a novel dataset that covers trade credit terms, factoring, other lending, payments, and employment for almost all formally registered firms in Brazil. 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. These results highlight the dual function of factoring in mitigating cash flow volatility and enabling firms to offer trade credit in the face of other financial constraints.

Our findings underscore the importance of factoring as a financial tool, particularly for small and credit-constrained firms.

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 forms of financing, factoring directly decreases cash inflow volatility through shifting the non-payment risk to a financial intermediary. Factoring also differs from other financing because its borrowing constraint features bounds that are directly endogenous to firms' output decision, 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.

Future research will examine how specific policy reforms to receivables registries, tokenization in the supply chain, expanded access to FIDCs, and fintech market approval affect the factoring interest rate through reducing transaction costs and increasing competition between banks and FIDCs in the supply of factoring.

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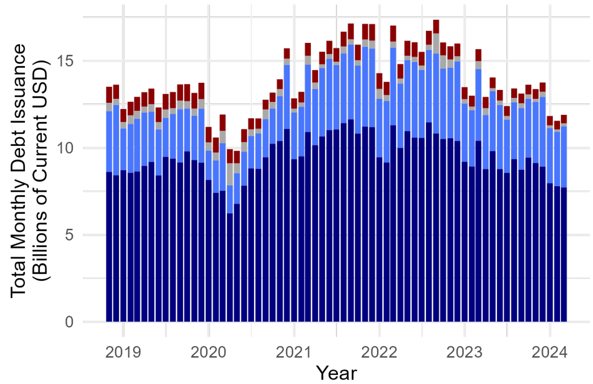
A Empirical Appendix

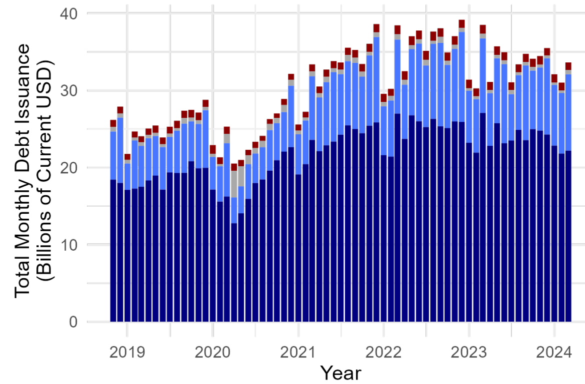
A.1 Additional Summary Statistics for Factoring

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

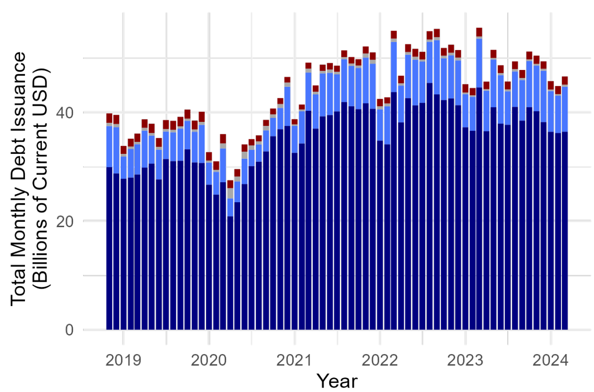
Figure A1. Working Capital Financing Composition by Firms' Credit Score (Right)



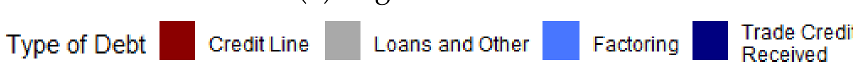
(a) Low Credit Score



(b) Medium Credit Score



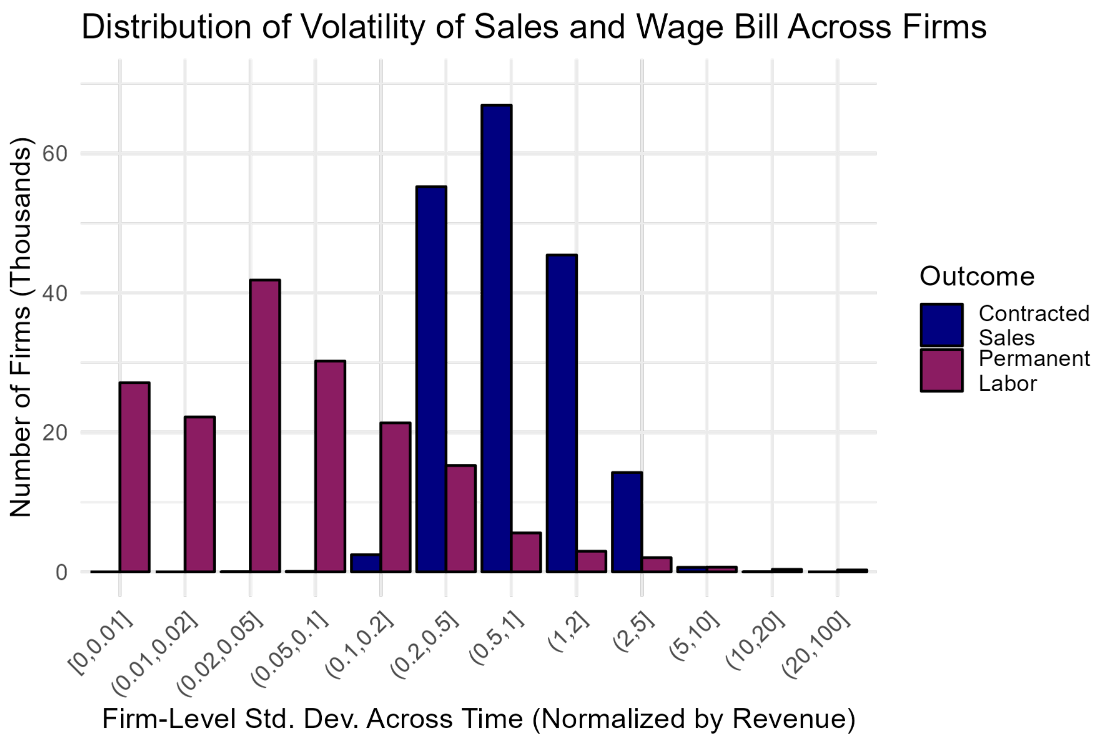
(c) High Credit Score



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.

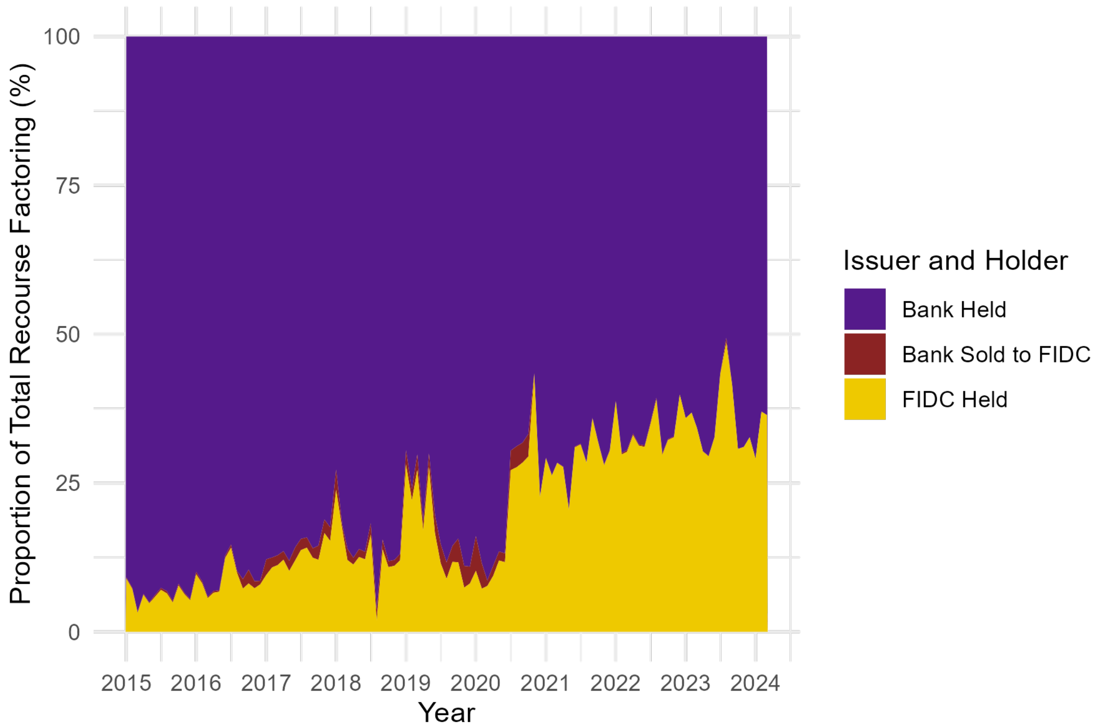
Figure A2. Firms' Cash Inflow Volatility Is an Order of Magnitude Higher than Cash Outflow Volatility



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 FIDC share of factoring has increased from 7% in 2015 to 32% in 2023.

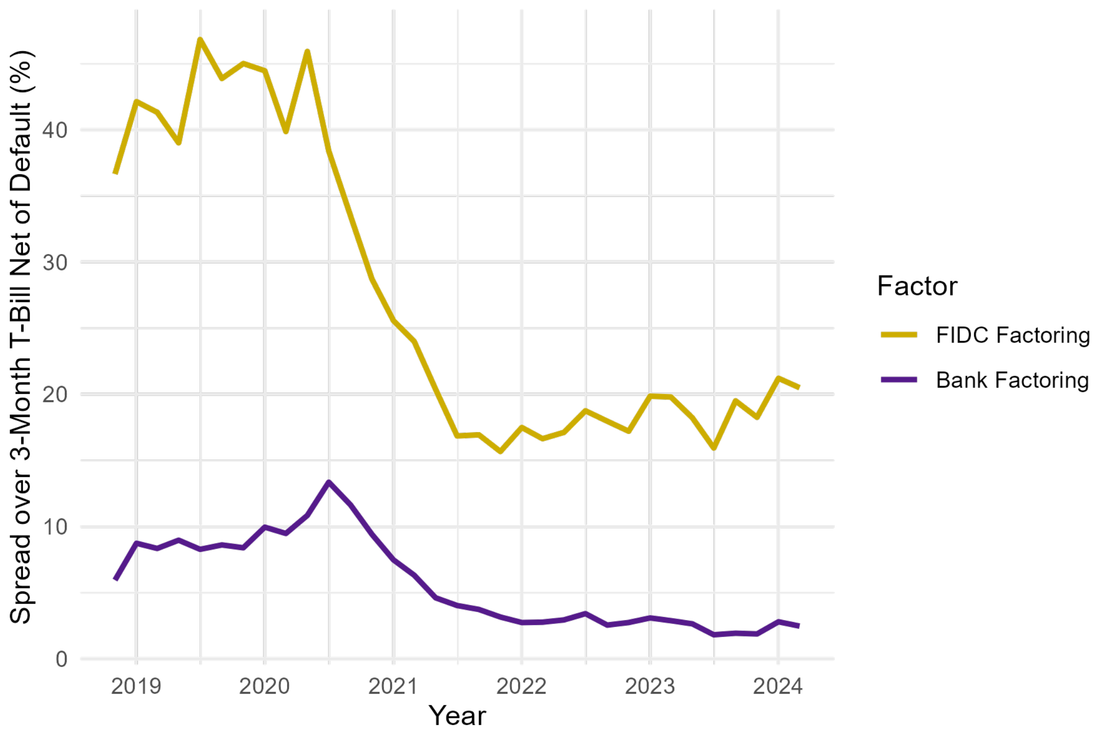
Figure A3. Time Series of FIDC Share of Factoring



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 A4 shows that a decrease in spread of factoring has coincided with the growth in FIDC share of factoring shown in Figure A3. 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 A6, FIDCs purchase receivables from riskier firms compared to banks.

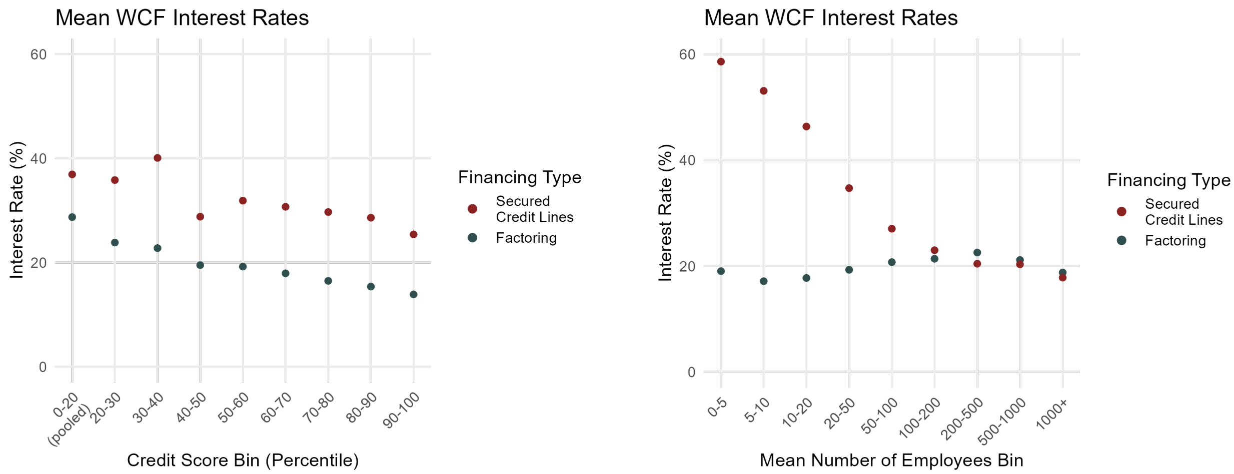
Figure A4. Interest Rate Spreads by Type and Source of Financing



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.

Figure A5 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.

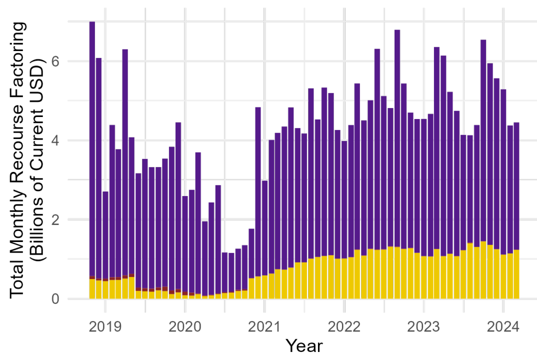
Figure A5. Mean Interest Rates of Factoring and Credit Lines across the Firm Distribution



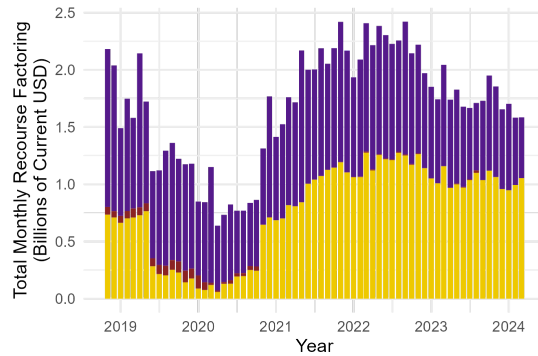
Notes: Each subfigure partitions firms into bins along the horizontal axis and computes the issuance volume weighted mean interest rate within each bin for each type of working capital financing (WCF). On the left, we classify each firm by its mean number of employees across time. On the right, we classify 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.

FIDCs tend to purchase receivables from *larger* firms with *low credit score*. Figure A6 shows that the time series of FIDC purchase patterns across the distribution of firms, partitioned by number of employees (left) and credit score (right).

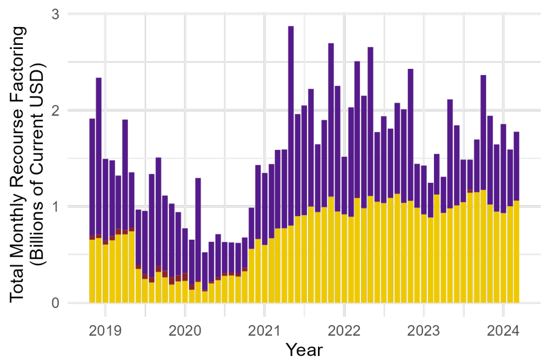
Figure A6. FIDC Share of Factoring by Firm Size (Left) and Credit Score (Right)



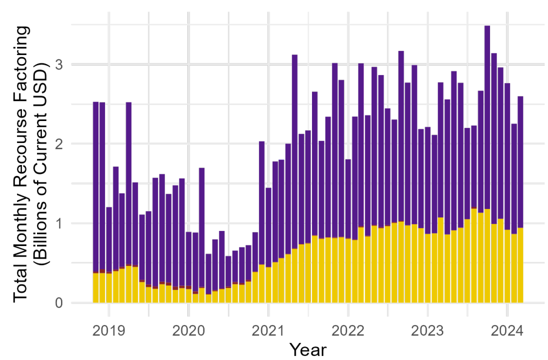
(a) 0 up to 100 Employees



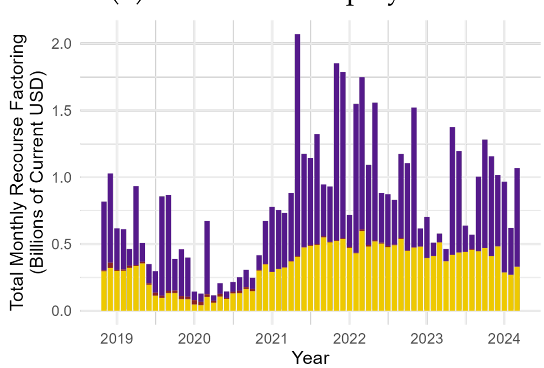
(b) Low Credit Score



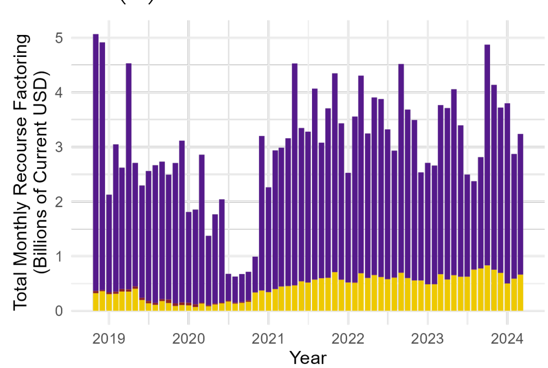
(c) 100 to 1000 Employees



(d) Medium Credit Score



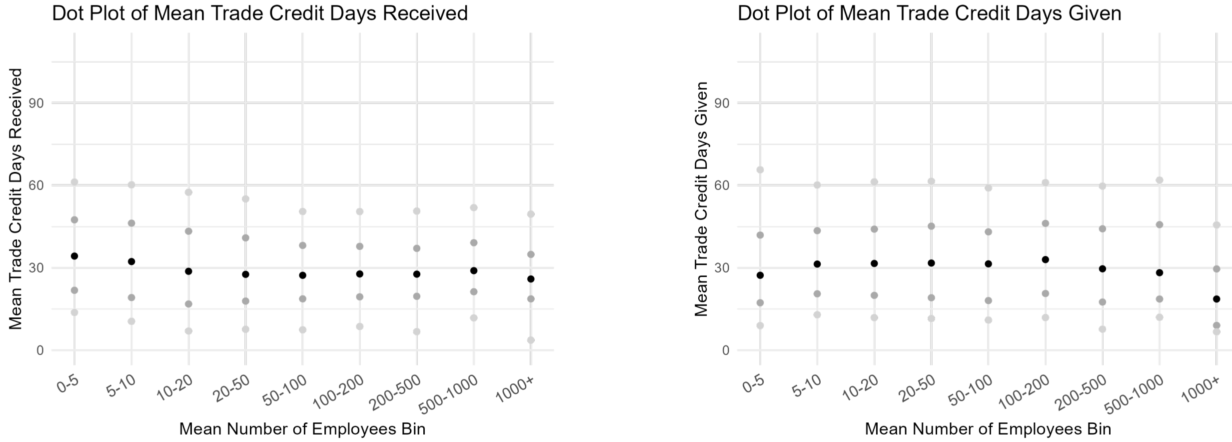
(e) Above 1000 Employees



(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 A7. 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 A7 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.

A.2 Additional Regression Results

Column 1 of Table 9 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 9 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 9 correspond to a decrease of 0.61 permanent employees and an increase of 0.08 temporary employees, respectively.

Table 9. 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 10 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 a high baseline mean interest rate of 333% and high variance across firms, with standard deviation of 85%.

Table 10. 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.

B Model Appendix

B.1 Solving the Model

In this section, we describe how we solve the model, beginning with the firms' objective in (6) and the household's objective in (10).

B.1.1 Household Block

We solve the labor supply block by taking the FOCs of the Lagrangian in (14)

$$\begin{aligned}\max_{\{c_0,c_1,\ell^P,\ell_0^T,\ell_1^T\}} \mathcal{L}^{HH} = \log(c_0) + \beta\log(c_1) - \sum_{t=0}^{1}\left[\frac{1}{\xi}\left(\ell^P + \nu\ell_t^T\right)^{\xi} - \nu(\ell^P - \ell_t^T)\right] \\ - \lambda^H \cdot \left(c_0 + c_1 - 2\ell^P w^P - \sum_t \ell_t^T w_t^T\right), \qquad (14) \\ \text{s.t. } c_0 + c_1 = 2\ell^P w^P + \sum_t \ell_t^T w_t^T.\end{aligned}$$

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

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

$$\frac{\partial\mathcal{L}^{HH}}{\partial\ell_t^T} = -\left(\ell^P + \ell_t^T\right)^{\xi-1} - \nu + \lambda_1 - \lambda^H w_t^T = 0.$$

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 (8), 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. See appendix for the derivation:

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

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 $\ell_{j1}^{T}, x_{j1}, \pi_{j1}$ in the afternoon, and given wages w^{P}, w_{0}^{T} and parameters:

$$\max_{\{y_{j0}, x_{j0}, \ell_j^P, \ell_{j0}^T, B_j^F\}} \beta \mathbb{E}\left[\pi_{j1} + \eta \mathbb{1}\{\pi_{j1} < 0\}\right] + B_j^F - \left(\ell_j^P w^P + \ell_{j0}^T w_0^T\right), \tag{15}$$

$$\text{s.t. } B_j^F \leqslant \frac{p_j y_{j0}}{R_j^F}, \tag{16}$$

$$0 \leqslant B_j^F - \ell_j^P w^P - \ell_{j0}^T w_0^T, \tag{17}$$

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

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

B_j^F is endogenous subject to the lower bound (17) and upper bound (16). 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 $\{B_j^F, \ell_j^P\}$. Conditional on B_j^F and ℓ_j^P, the morning objective function $\mathbb{E}_0 \pi_j$ has no residual uncertainty over $\{\ell_{j0}^T, x_{j0}\}$, and the afternoon objective function π_{j1} has no uncertainty over $\{\ell_{j1}^T, x_{j1}\}$. We calculate the argmax of $\mathbb{E}_0 \pi_j$ over $\{B_j^F, \ell_j^P\}$.

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

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. Note that if the problem were convex, we could directly solve for ℓ_j^P as shown in the appendix:

$$\begin{aligned} 0 = {} & \tilde{C}_0^P Y_1^{\frac{1}{1+(s-1)\alpha}} \tilde{\ell}_{j1}^{\frac{1}{\sigma} - \frac{1}{1+(s-1)\alpha}} \left(\ell_j^P\right)^{-\frac{1}{\sigma}} - w^P \\ & + \left(1-\zeta_j\right)\left[\tilde{C}_1^P Y_0^{\frac{1}{1+(s-1)\alpha}} \tilde{\ell}_{j0}^{\frac{1}{\sigma} - \frac{1}{1+(s-1)\alpha}} \left(\ell_j^P\right)^{-\frac{1}{\sigma}} - R_j^F w^P\right], \end{aligned} \tag{18}$$

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 $\tilde{C}_1^P \equiv \omega \frac{(s-1)\alpha}{s}\left(\left(1-\zeta_j\right)\frac{(s-1)(1-\alpha)}{s}\right)^{\frac{s}{1+(s-1)\alpha}}$ 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

$$
\begin{aligned}
\frac{\partial \pi_{j1}}{\partial x_{j1}} &= \frac{(s-1)(1-\alpha)}{s} P Y_1^{\frac{1}{s}} \tilde{\ell}_{j1}^{\frac{(s-1)\alpha}{s}} x_{j1}^{-\frac{1+(s-1)\alpha}{s}} - P = 0, \\
x_{j1} &= \left(\frac{(s-1)(1-\alpha)}{s} \right)^{\frac{s}{1+(s-1)\alpha}} Y_1^{\frac{1}{1+(s-1)\alpha}} \tilde{\ell}_{j1}^{\frac{(s-1)\alpha}{1+(s-1)\alpha}}, \qquad (19)
\end{aligned}
$$

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 (19):

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

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

$$w_1^T = \tilde{C}_1^T Y_1^{\frac{1}{1+(s-1)\alpha}} \tilde{\ell}_{j1}^{\frac{1}{\sigma}-\frac{1}{1+(s-1)\alpha}} \left(\ell_{j1}^T\right)^{-\frac{1}{\sigma}}. \tag{20}$$

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:

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

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 (17) as long as $\mu^F > 0$, and otherwise are indifferent between factoring any amount.[15] 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

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

We proceed with a similar derivation to (20) 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:

$$\begin{aligned}\frac{\partial \mathbb{E}_0\pi_j}{\partial x_{j0}} &= \left(1-\zeta_j\right)\frac{(s-1)(1-\alpha)}{s} P Y_0^{\frac{1}{s}} \tilde{\ell}_{j0}^{\alpha\frac{s-1}{s}} x_{j0}^{-\frac{1+(s-1)\alpha}{s}} - P = 0, \\ x_{j0} &= \left(\left(1-\zeta_j\right)\frac{(s-1)(1-\alpha)}{s}\right)^{\frac{s}{1+(s-1)\alpha}} Y_0^{\frac{1}{1+(s-1)\alpha}} \tilde{\ell}_{j0}^{\frac{(s-1)\alpha}{1+(s-1)\alpha}}, \end{aligned} \tag{21}$$

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

$$R_j^F w_0^T = \tilde{C}_0^T Y_0^{\frac{1}{1+(s-1)\alpha}} \tilde{\ell}_{j0}^{\frac{1}{\sigma}-\frac{1}{1+(s-1)\alpha}} \left(\ell_{j0}^T\right)^{-\frac{1}{\sigma}}, \tag{22}$$

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.

[15] 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 (21) and (19) to obtain

$$0 = \tilde{C}_0^P Y_1^{\frac{1}{1+(s-1)\alpha}} \tilde{\ell}_{j1}^{\frac{1}{\sigma}-\frac{1}{1+(s-1)\alpha}} \left(\ell_j^P\right)^{-\frac{1}{\sigma}} - w^P$$
$$+ (1-\zeta_j)\left[\tilde{C}_1^P Y_0^{\frac{1}{1+(s-1)\alpha}} \tilde{\ell}_{j0}^{\frac{1}{\sigma}-\frac{1}{1+(s-1)\alpha}} \left(\ell_j^P\right)^{-\frac{1}{\sigma}} - R_j^F w^P\right], \tag{23}$$

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 (22) and (20), 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 (18)
- Inner loop: given the guess of ℓ_j^P, use bisection with (22) to obtain ℓ_{j0}^T, and bisection with (20) 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 (12); 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 (13); 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 (11) 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 FE.

- $\omega = 0.89$. CES share parameter on permanent employees. Aggregate equation (5) 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 $\bar{w}$. Since

- $\xi = 5.48$ 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%.

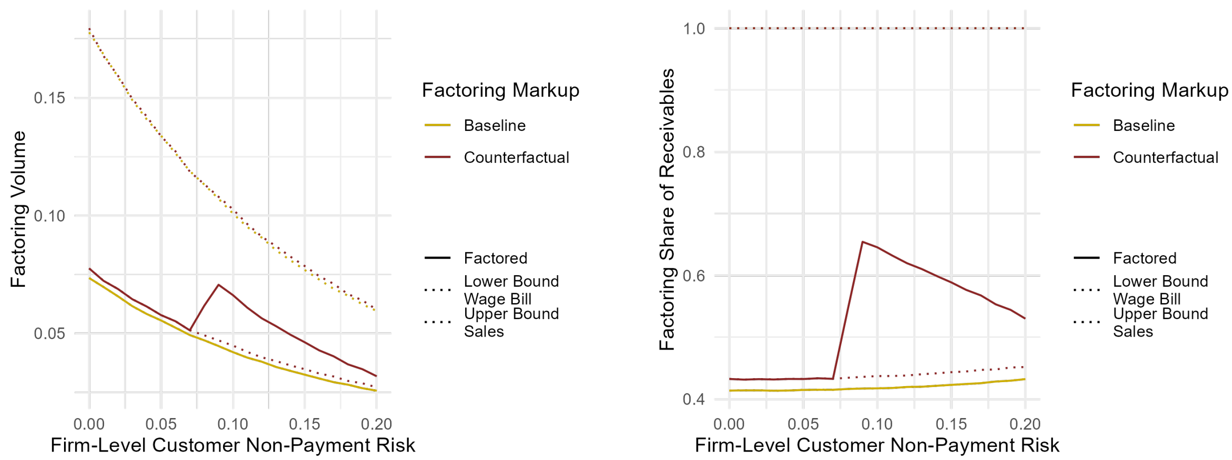
- $\eta = 0.25$ is the cost of default, following Glover (2016).

B.3 Additional Model Results

Figure A8 and Figure A9 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 A8 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 A8a shows the absolute amount factored, as well as the lower bound in equation (8) and the upper bound in equation (7) across the distribution of factoring risk ζ_j on the horizontal axis. On the right, Figure A8b shows the same outcomes normalized by the upper bound of morning receivables $p_j y_{j0}$.

Figure A8. Factoring Demand over the Factoring Risk Distribution



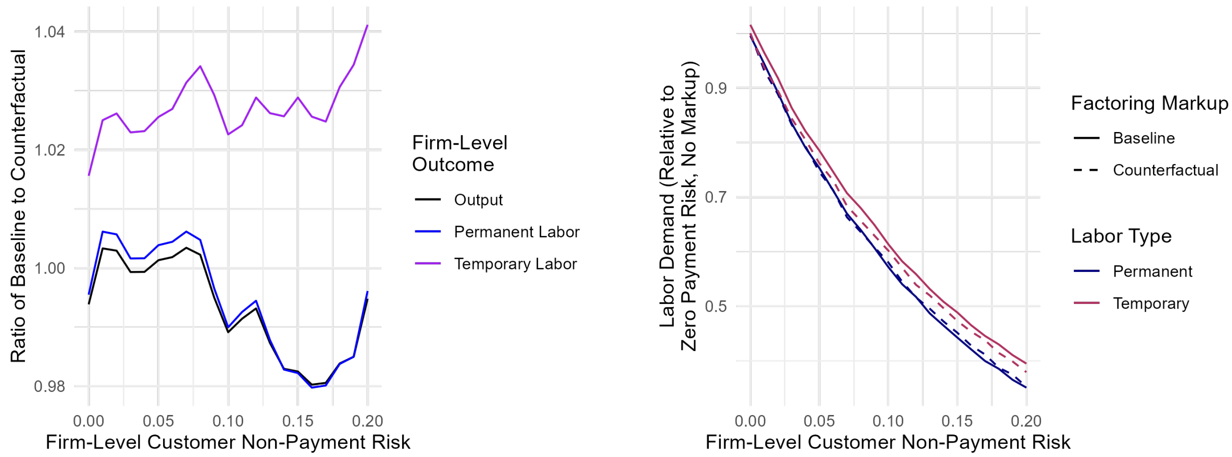
(a) Absolute Factoring

(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 A9 compare outcomes between the baseline and counterfactual equilibria, across the distribution of factoring risk ζ_j on the horizontal axis. In Figure A9a, a value of 1 means that a given firm has the same outcome between the two equilibria, while a value above 1 means that the outcome has higher value in the baseline equilibrium, where factoring spreads are higher. Figure A9a 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 A9b 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 A9. 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 means that a given firm has the same outcome between the two equilibria, while a value above 1 means that 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.