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

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Overview of Factoring

- Firms rely on **short-term financing instruments** to manage **inflexible payment obligations** vs. **volatile payment inflows**

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  - Example: wage bill and debt repayments vs. sales volatility and trade credit
  - Working capital requirements can constrain **production**
- One type of short-term financing is **factoring**, where "supplier" firms sell their accounts receivable from customers upfront to financial intermediaries at a discount
  - BIS: Global growth in factoring by non-financial firms
  - Increasing share of non-bank financial intermediaries vs banks in Brazil
- **High-Level Question:** How and why do changes in factoring supply affect real outcomes?

Research Question: **How does cheaper factoring affect firms' liquidity, financing, production, and input demand?**

Research Question, Empirical Strategy, and Main Results

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Empirical strategy on firm $\times$ month panel $\approx$ all active formally-registered firms in Brazil:

- Shift-share IV: institutional investor flows to receivables funds (FIDCs) shift firms' *factoring interest rate* and quantity through changes in FIDCs' receivables demand

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- Large contemporaneous increases in revenue (6.1 bp) and input expenditure (3.6 bp)
- Substitution toward input expenditure flexibility: fewer temporary workers (2.1 bp) and more permanent workers (1.1 bp)
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Model: Cash-flow volatility $\rightarrow$ factoring as liquidity for constrained firms

Data FIDCs IV IV-LP Model Setup Model Results

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Lesson: Factoring prices short-term liquidity, and firms substitute financing for operational flexibility

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Contribution: First Causal Estimate of the Impacts of Factoring Supply

This paper studies impacts of small changes in price of short-term liquidity, rather than quantities of bank credit or trade credit contracts or extensive margins

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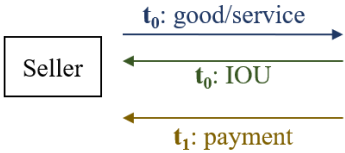
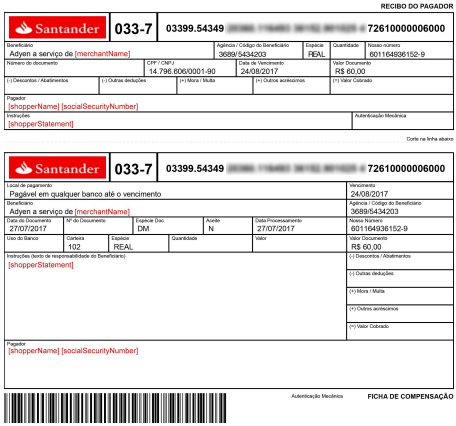
Nonbank credit and fund flows: Fleckenstein et al. (2021); Gopal, Schnabl (2022); Chernenko, Erel, Prilmeier (2022); de Fiore, Gambacorta, Manea (2023)

- **Receivables fund flows shift factoring prices and liquidity provision**

Background on Trade Credit in Brazil

In Brazil, most firm-to-firm transactions use boletos, the invoice payment rail, specifying the amount, the *contract* date, and the *due* date of payment from the buyer to the seller





Contract date

Due date

Amount due

Trade Credit, Payments, Factoring, and Bank Credit Data

We construct a comprehensive transaction-level dataset of boletos from the Central Bank of Brazil (BCB), from November 2018 to March 2024

- 21.4 billion transactions, 204 thousand sellers to firms, 470 thousand buyers

Small & less creditworthy firms factor more | Trade credit across the firm size distribution | Long-maturity receivables tend to be factored
Summary table | Return to Overview

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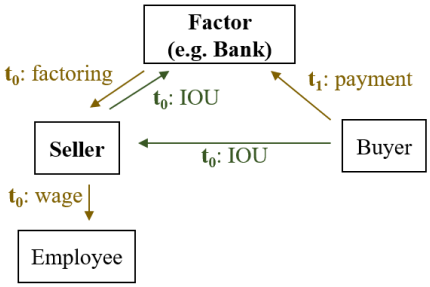
Along with comprehensive transaction-level data for bank transfers (TED), instant payments (PIX), and credit operations (SCR), also from the BCB

- We are the first to correctly use the factoring data from the BCB; data structure varies by factoring operation type in the BCB's relational databases
- **We are the first to use comprehensive data on factoring for all firms in an economy**



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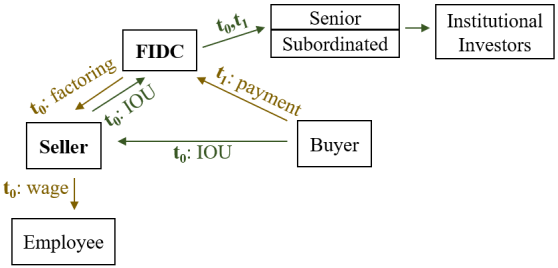
Why Brazil? Receivables Funds (FIDCs)

FIDCs are mutual funds whose primary assets are receivables purchased directly from firms (suppliers)

- 73% of assets are receivables, most of the remainder are Brazilian T-bills
- 762 FIDCs, mostly multi-sector; 251k suppliers sell receivables to FIDCs



FIDC tend to purchase high-risk receivables
FIDC spreads have decreased over time
FIDC vs banks summary table
FIDC size
FIDC diversification
FIDC IV construction
Monetary policy response
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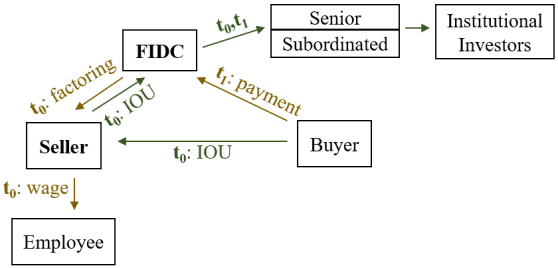
FIDCs securitize shares to institutional investors

- Similar to mortgage-backed CDOs in the US



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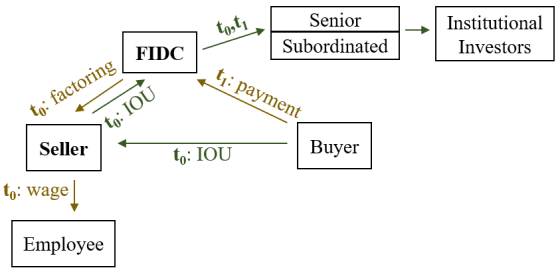

We construct flows to FIDCs, and firms' exposure, using:

- Fund by share class by month data on returns and NAV from CVM
- Transaction-level fund operations from BCB

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Estimation: IV Regression on the Firm-Month Panel

How does a supply shock of factoring financing affect firms' decisions and outcomes?

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Causal equation: β_1 is the effect of a 1 pct pt increase in factoring interest rate $r_{j,t}^{\text{Fac}}$ on firm j's outcomes $y_{j,t}$ in month t:

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

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Shift-share IV: institutional investors' flows to FIDCs drive expected purchases $e_{j,t}$ of firm j's receivables

- Quasi-exogenous flows (e.g. from liquidity-driven asset reallocation by institutional investors)
- Endogenous exposure, sticky across time

Return to Overview

Constructing the Shift-Share IV: Flow-Induced Purchases

Since FIDCs' assets have short maturity, we use flow-induced purchases and "issuance" rather than trading (literature uses bond or equity funds)

- $x_{j \to f,t}$ is fund f's purchases of firm j's receivables
- $X_{f,t}$ is fund f's total purchases of assets
- $F_{f,t}$ is the net inflow to fund f: $F_{f,t} := \frac{\text{NAV}_{f,t} - \text{NAV}_{f,t-1} R_{f,t}}{\text{NAV}_{f,t-1}}$

Fund by factoring type by month exposure $e_{j,t}$ to funds' flows is

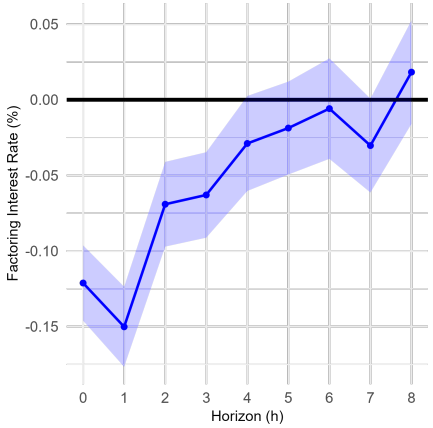
$$e_{j,t} := \sum_f \underbrace{\frac{x_{j \to f,\underline{t}}}{X_{f,\underline{t}}}}_{\text{Shares}} \underbrace{F_{f,t}}_{\text{Shifts}}$$

where $\underline{t}$ denotes the cumulative mean until time t (also tested n-month rolling windows; similar magnitudes with less precision)

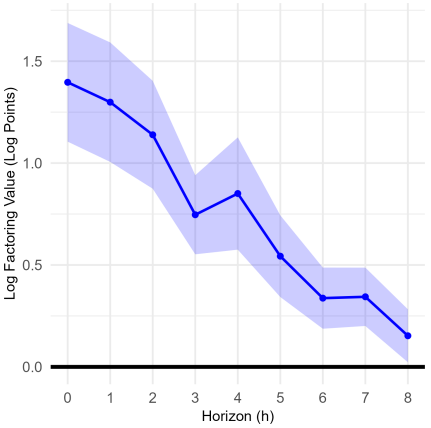
Return to Overview | Return to FIDC Diagram | Pre-Trend Test

Dynamic Effects: Local Projection First Stage

Dynamic first stage: how does the receivable demand shock $e_{j,t}$ pass through to the factoring interest rate and quantity (volume of receivables sold)? $r^{\text{Fac}}_{j,t+h} = \alpha_{j,h} + \alpha_{t,h} + \beta_h e_{j,t} + \varepsilon_{j,t+h}$



(a) Factoring Interest Rate

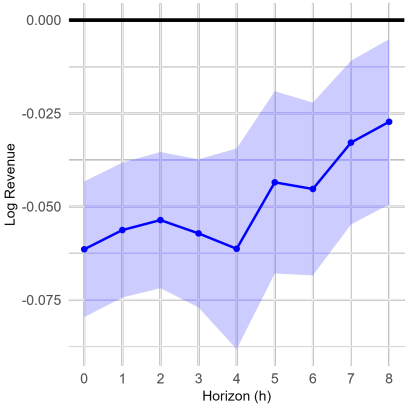


(b) Factoring Quantity

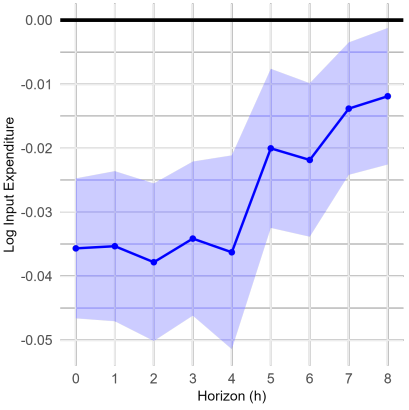
Return to Overview
First Stage Table
Revenue Outcomes
Outcomes Table

Dynamic Effects: IV Local Projection for Revenue and Expenditure Outcomes

Dynamic IV regressions: how do firms' revenue and input expenditure at horizon $h \geq 0$ respond to the receivable demand shock, scaled by the time t impulse? $y_{j,t+h} = \alpha_{j,h} + \alpha_{t,h} + \beta_h r^{\text{Fac}}_{j,t} + \varepsilon_{j,t+h}$



(a) Log Revenue (IV)

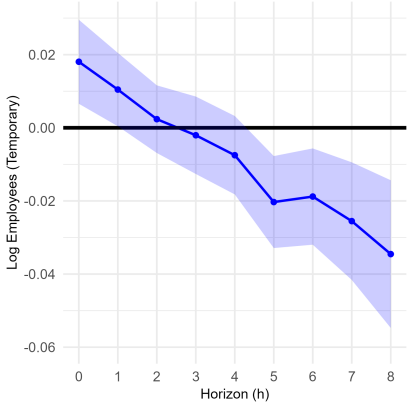


(b) Log Input Expenditure (IV)

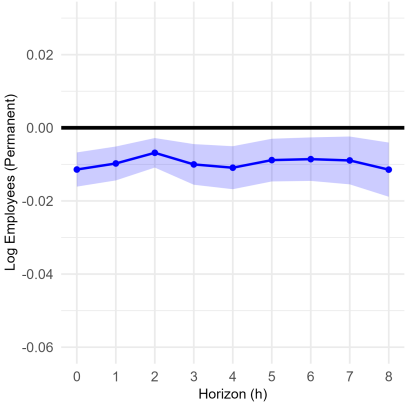
Return to Overview
Trade Credit Outcomes
Labor Outcomes
Outcomes Table

Dynamic Effects: IV Local Projection for Labor Demand Outcomes

Dynamic IV regressions: how do firms' labor demand at horizon $h \geq 0$ respond to the receivable demand shock, scaled by the time t impulse? $y_{j,t+h} = \alpha_{j,h} + \alpha_{t,h} + \beta_h r_{j,t}^{\text{Fac}} + \varepsilon_{j,t+h}$



(a) Log Temporary Labor (IV)



(b) Log Permanent Labor (IV)

Return to Overview
Trade Credit Outcomes
Revenue Outcomes
Outcomes Table

Heterogeneity Overview

We test two dimensions of firm heterogeneity:

- IV regressions with interactions of firm type θ_k (size, credit score, HHI) : By Trade Credit Position

$$y_{j,t} = \alpha_j + \alpha_t + \sum_k \beta_k \hat{r}^{\text{Fac}}_{j,t} \theta_{j,k} + \varepsilon_{j,t}.$$

- IV quantile regressions: how do firms at different points in the outcome distribution respond to the factoring interest rate? Quantile

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

  where $\tilde{y}$ and $\widetilde{\hat{r}}$ are de-meaned on firm and month FE

No significant heterogeneity in interaction regressions; in the quantile regressions for revenue and input purchase, the bottom quantiles had larger effects

Summary of Empirical Results and Overview of Model

One bp decrease in factoring interest rate causes

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- Wage bill rises by 0.56 bp, decomposed into differential changes across labor contracts: permanent labor increases by 1.1 bp, and temporary labor decreases by 2.1 bp
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The purpose of the model is to

1. Rationalize the micro-level empirical estimates through endogenous trade credit and factoring
2. Simulate responses of aggregate outcomes to a change in the aggregate factoring spread
   - Innovation in digital technology (e.g. receivables tokenization), central bank policy (e.g. registries), and rising investor demand for receivables portend a continued decrease in factoring spreads

Intuition: Cash Flow Volatility | Fact: Spreads Decreased | Model Setup | Firm's Problem | Return to Overview | Skip to Conclusion

Next Steps

Goals before submission: address (i) "static model vs dynamic IRFs", (ii) "fund flows are fundamental", and (iii) "just another credit supply shock"

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- For each confounder or shock (risk-free rate, risk premia) $\Rightarrow$ differential flows and/or differential exposure?
  - Placebo timing / pre-trends (first pass done)
  - "Shouldn't-move" outcomes: instrument predicts no effects where it shouldn't
  - Regress proxies for aggregate shocks (e.g., monetary policy exposure bins) on the shift-share instrument
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4) Balance sheet digitization to answer repeated questions about investment, assets, and expenditure shares

Classification of Next Steps

Feasible and seemingly high-payoff for submission beyond the previous slide:

- *Re-frame "temporary vs permanent" as broader expenditure flexibility*
  - CNAE-based classification: spot vs contract, seasonality, lumpiness, investment vs materials
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Unsure whether to do before submission:

- Microfound reduction in factoring spreads via competition / information acquisition / adverse selection
- Richer decomposition in the model: direct liquidity injection vs substitution (labor vs other flexibility), input/output market channels

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  - CNAE-based classification: spot vs contract, seasonality, lumpiness, investment vs materials
  - Decision: NLP approach to classification vs simple data-driven taxonomy
- *Contribution is not "another credit supply shock"* due to corporate liquidity perspective on factoring (model) connected to empirical mechanism regressions (flexibility margins)

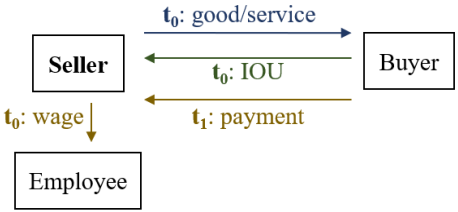
Unsure whether to do before submission:

- Microfound reduction in factoring spreads via competition / information acquisition / adverse selection
- Richer decomposition in the model: direct liquidity injection vs substitution (labor vs other flexibility), input/output market channels

Likely will only do for referee feedback:

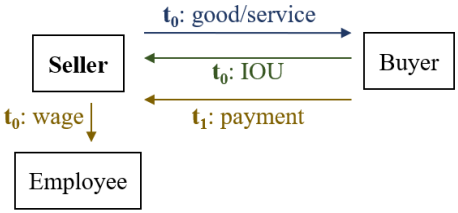
- "Spare borrowing capacity" horse race, connecting to long literature on capital structure
- FIDC-to-supplier micro-level contracting facts (survival of relationships, histograms of partners)
- Large redesigns of instrument (granular IV variants) beyond using predicted flows

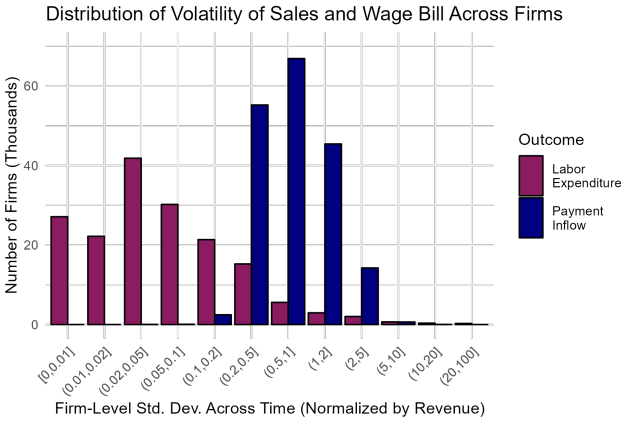
Firms' Demand for Liquidity Arises from Cash Flow Volatility Mismatch



Firms' Demand for Liquidity Arises from Cash Flow Volatility Mismatch

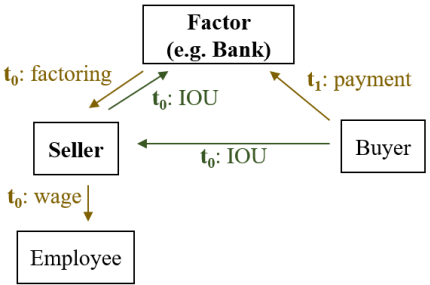
Volatile inflows vs rigid payroll create liquidity risk that distorts production and labor choice



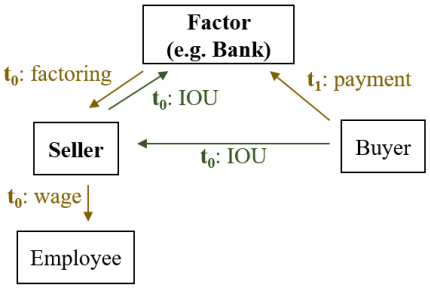


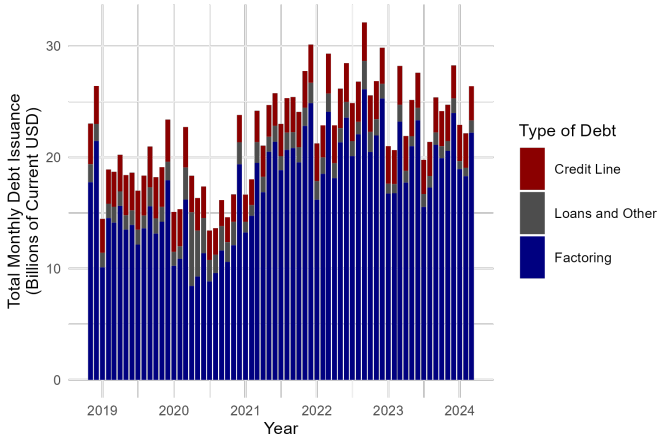
Firms use working capital financing (WCF) to resolve this demand for liquidity

Factoring Provides Liquidity by Advancing Cash on Receivables



Factoring Provides Liquidity by Advancing Cash on Receivables





Factoring is the main tool firms use to stabilize cash flow

By credit score | With trade credit | Worldwide | Trade finance

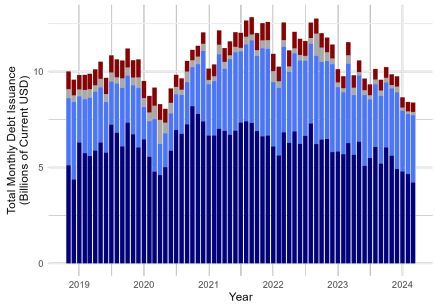
Factoring and Trade Finance

- Factoring differs from **letters of credit** (LoC), a guarantee from the buyer's bank without upfront payment
- Receivables-backed loans and reverse factoring (buyer-initiated) are less common
- Factoring is well-suited to tokenization and programmable payments
- In international trade, trade insurance and LoC (intermediated through ex-im banks) are more popular than factoring, although this could change with cross-border payment interoperability and standardization of contract enforcement

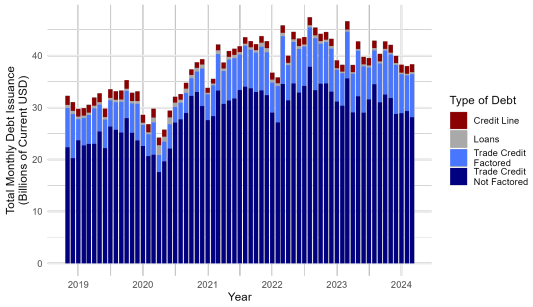
Return to Factoring Definition

Working Capital Financing Trend by Firm Credit Score

Firms with low credit score (left) factor a larger share of trade credit than firms with high credit score (right)



(a) Low Credit Score



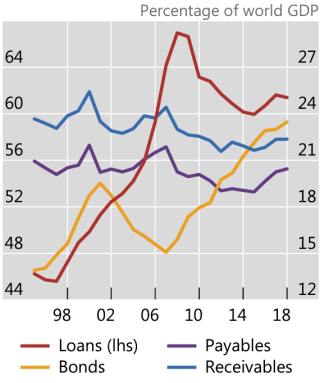
(b) High Credit Score

But all firms heavily rely on trade credit and factoring the receivables from trade credit

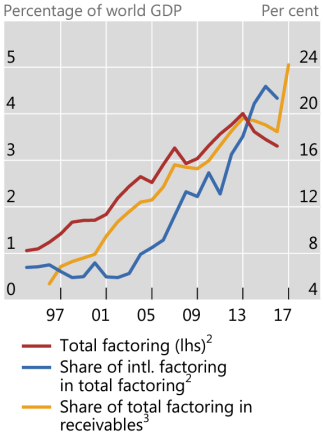
Return to Overall Factoring Trend

Trade Credit is Widely Used Worldwide, with Increasing Factoring Share

Trade credit, corporate loans and bonds[1]

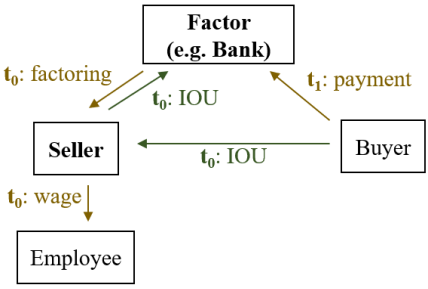


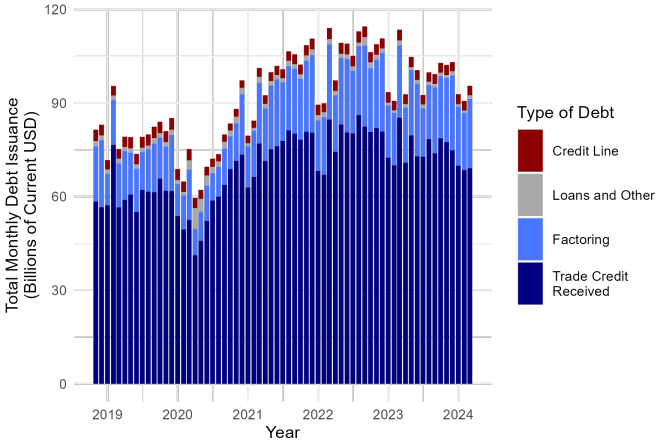
Evolution of factoring over time



Return to Overall Factoring Trend

Factoring is the Sale of Accounts Receivable Arising from **Trade Credit**

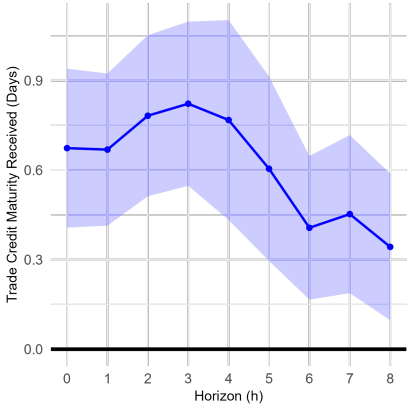




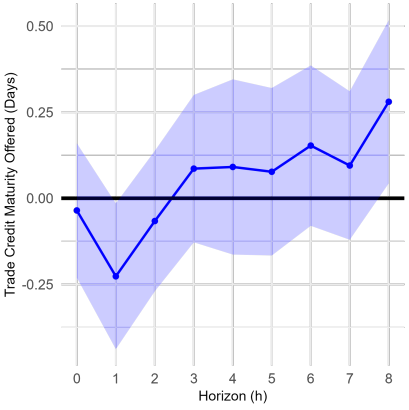
Return

Dynamic Effects: IV Local Projection for Trade Credit Outcomes

Dynamic IV regressions: how do firms' trade credit terms at horizon $h \geq 0$ respond to the receivable demand shock, scaled by the time t impulse? $y_{j,t+h} = \alpha_{j,h} + \alpha_{t,h} + \beta_h r^{\text{Fac}}_{j,t} + \varepsilon_{j,t+h}$



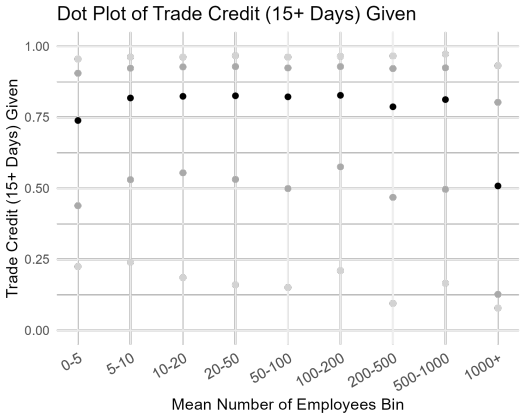
(a) Log Trade Credit Received (IV)



(b) Log Trade Credit Offered (IV)

Return to Overview
Labor Outcomes
Revenue Outcomes

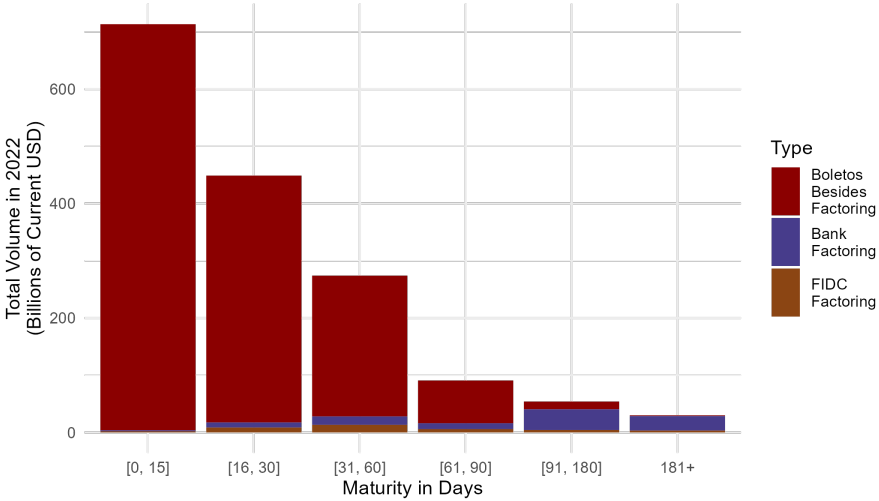
Most Firms Across the Size Distribution Give and Receive Trade Credit



Notes: These figures show the median (black), 25th and 75th percentiles (dark gray), and 10th and 90th percentiles (light gray) of the firm-level proportion of payments with maturity of 15+ days, aggregated by bin of firm-level employment.

Return to Data Overview

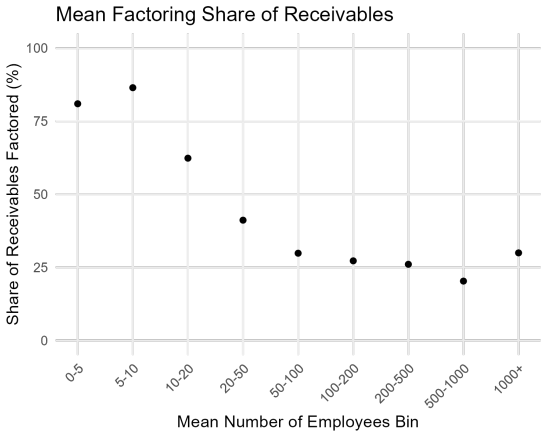
Longer Maturity Receivables are More Likely to be Factored



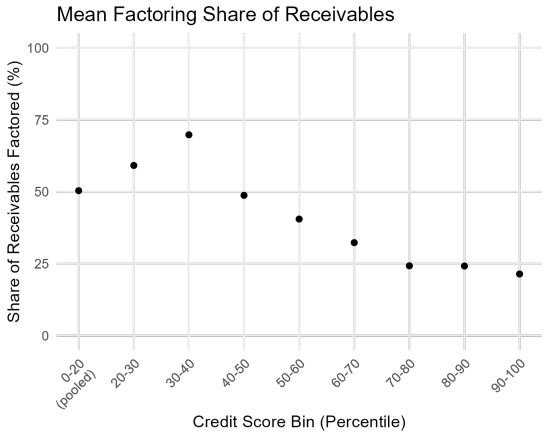
Return to Data Overview

Small and Low Creditworthiness Firms Factor the Most

Factoring shares by firm size (left) and credit score (right)



(a) by decile of firm size proxied by wage bill

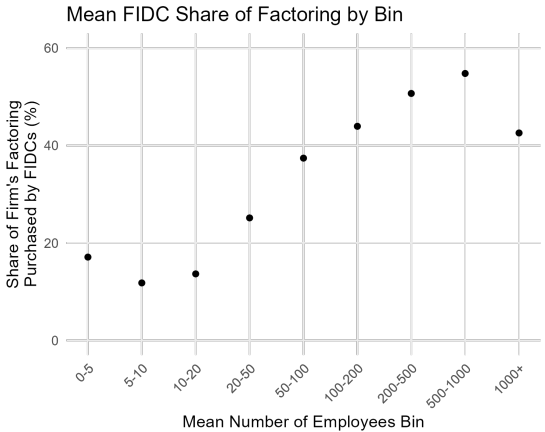


(b) by decile of firm credit score

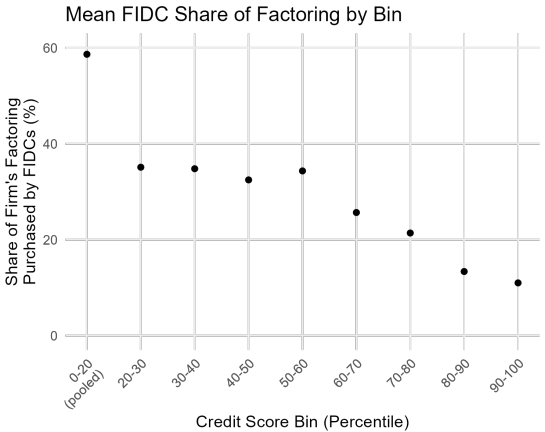
Interest rates for factoring vs secured credit lines | Return to Data Overview

FIDCs' Receivables Acquisition

FIDCs tend to purchase receivables from *larger* firms (left) with *low credit score* (right)



(a) FIDC Share by Number of Employees



(b) FIDC Share by Credit Score

FIDC and IR Spread Trends | FIDC vs bank summary table

Annual means of trade credit and factoring:

	Mean Overall	Mean Small Firms	Mean Medium Firms	Mean Large Firms
Panel A: Trade Credit Received				
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				
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				
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

For the 627k firms with labor data, we observe an annual average of 1.7 billion trade credit contracts and 56.6 million factoring contracts

Return to Data Overview

Annual means of other working capital financing:

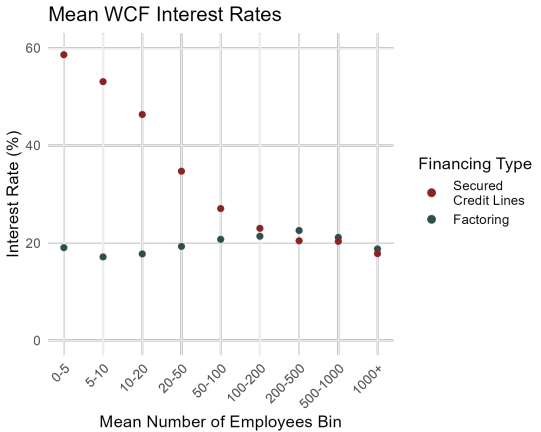
	Mean Overall	Mean Small Firms	Mean Medium Firms	Mean Large Firms
Panel D: Secured Credit Lines				
Volume (Million USD)	0.04	0.02	0.26	0.72
Interest Rate (%)	30.63	45.13	23.24	18.67
Maturity (Days)	66.10	57.22	72.86	69.14
Panel E: Unsecured Credit Lines				
Volume (Million USD)	0.02	0.01	0.07	0.17
Interest 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

For the 627k firms with labor data, we observe an annual average of 1.72 million uses of secured credit line, 7.64 million uses of unsecured credit line, and 3.57 million contracts of other short-term debt

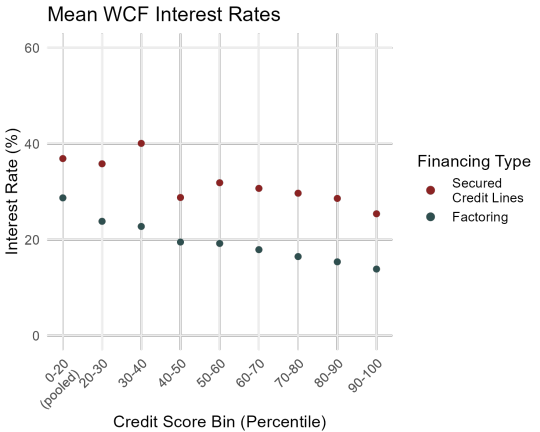
Return to Data Overview

Interest Rates for Factoring vs Secured Credit Lines

Interest rates over the distribution of firm size (left) and credit score (right)



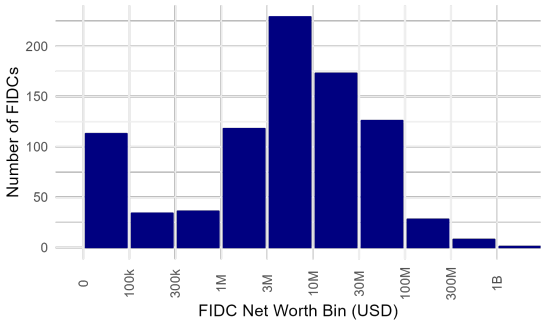
(a) by decile of firm size proxied by wage bill



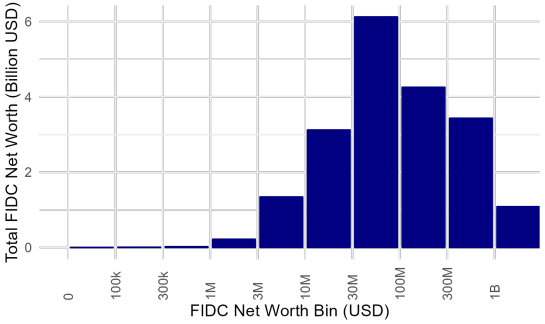
(b) by decile of firm credit score

Return

Distribution of FIDC Net Asset Value (NAV)



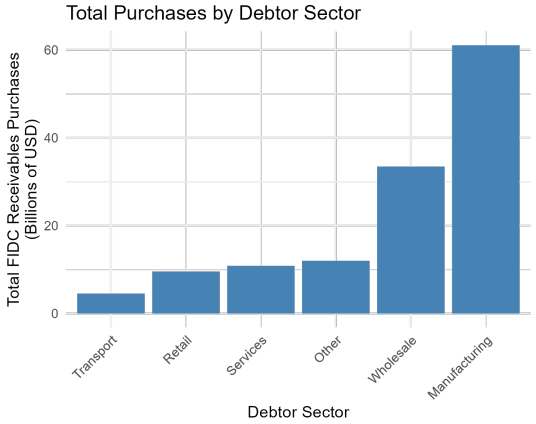
(a) Number of FIDCs by NAV Bin

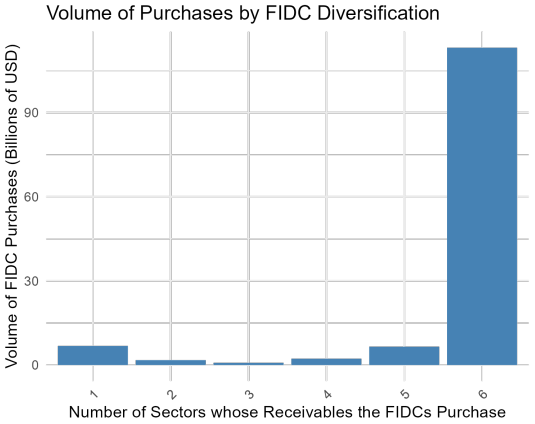


(b) Total FIDC NAV by NAV Bin

Return to FIDC figures | Return to FIDC overview | Return to model overview

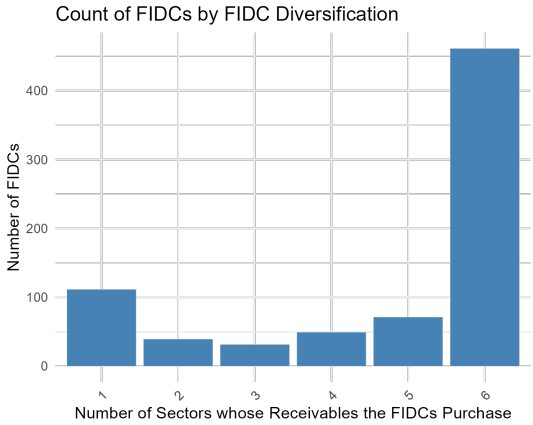
FIDC Portfolio Diversification

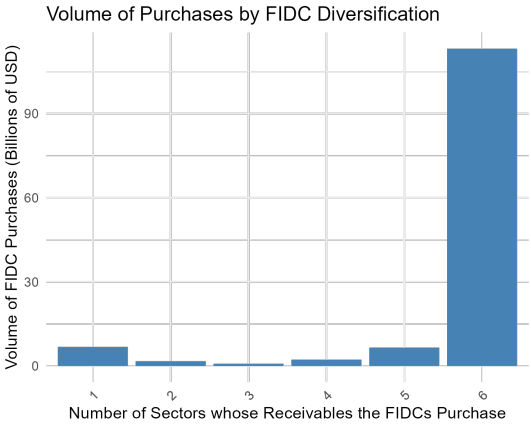




Return to FIDC overview

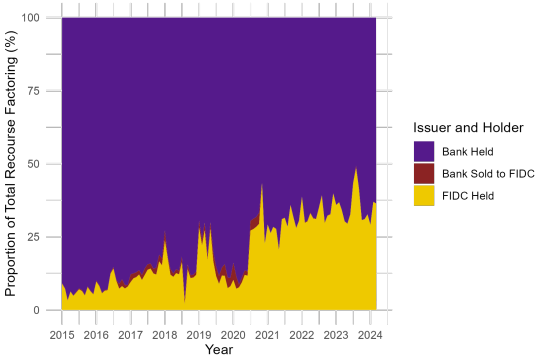
FIDC Portfolio Diversification



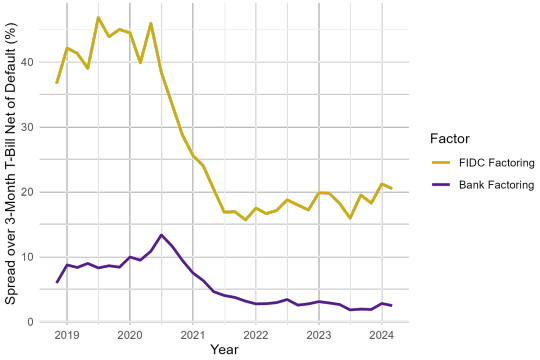


Return to FIDC overview

FIDC Share of Factoring Increased as Spreads Decreased



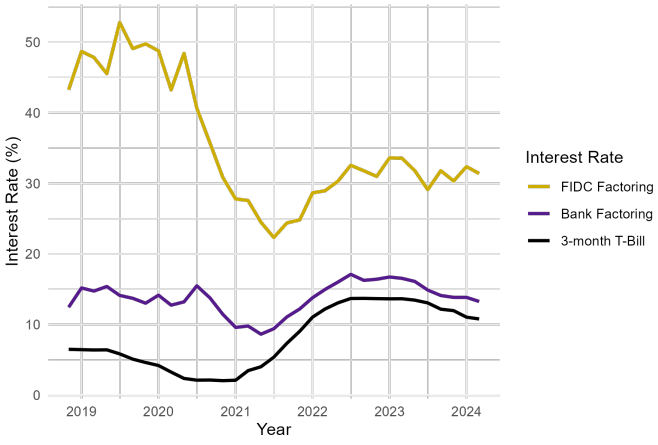
(a) FIDC Share of Factoring



(b) Spreads

Return to FIDC figures | Return to FIDC overview | Return to model overview | Interest rates

Comparison of Interest Rates



Return to FIDC figures
Return to FIDC overview

FIDC vs Bank Factoring Summary Statistics

	Banks			FIDCs		
	Mean Small Firms	**Mean Medium Firms**	**Mean Large Firms**	**Mean Small Firms**	**Mean Medium Firms**	**Mean Large Firms**
	1	2	3	4	5	6
Mean Issuance (Million USD / Year)	0.07	0.32	1.07	0.01	0.24	0.89
Mean Interest Rate (%)	15.09	13.73	11.11	34.68	31.91	29.59
Mean Maturity (Days)	155.22	121.25	134.27	54.64	62.20	70.05

Return to FIDC figures Return to FIDC overview

First Stage: Seller firm's factoring interest rate $r_{j,t}^{\text{Fac}}$ on normalized exposure $e_{j,t}$ to fund flows

$$r_{j,t}^{\text{Fac}} = \alpha_j + \alpha_t + \gamma_1 e_{j,t} + \varepsilon_{j,t}$$

	First Stage	Decomposition	
	IR Factoring Issuance (All)	IR Factoring Issuance (Funds)	IR Factoring Issuance (Banks)
	(1)	(2)	(3)
$e_{j,t}$	$\mathbf{-0.1212}^{***}$	-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.

LP First Stage | Return to Main First Stage

First Stage: Seller firm's factoring interest rate $r_{j,t}^{\text{Fac}}$ on normalized exposure $e_{j,t}$ to fund flows

$$r_{j,t}^{\text{Fac}} = \alpha_j + \alpha_t + \gamma_1 e_{j,t} + \varepsilon_{j,t}$$

	First Stage
	IR Factoring Issuance (All)
	(1)
$e_{j,t}$	$-\mathbf{0.1212}^{***}$
	(0.0127)
Num. Obs.	3,956,731
Num. Firms	322,087
Num. Months	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 clustered at the firm level are in parentheses**. If a firm does not factor in a given month, then there is no interest rate, and the observation is dropped from the regression.

LP First Stage | Decomposition into Bank vs FIDC

IV Regression, Main Outcomes

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

	(1)	(2)	(3)	(4)	(5)
	Log Revenue	Log Expenditure	Log Wage Bill	Log Hours (Permanent)	Log Hours (Temporary)
$r^{\text{Fac}}_{j,t}$	-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

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

IV-LP | Hourly Wage | Hours Worked | Other Labor Outcomes | Trade Credit | Default Rate | Debt | Debt Detail | Interest Rates | Pre-Trend Test

IV Regression, Weekly Wage and Log Hours Worked

	Log Wage (Hourly)	Log Employment (Hours Worked)	Log Employment (Hours Worked by New Hires)	Log Employment (Hours Worked by Existing Emp.)
$r_{j,t}^{\text{Fac}}$	$0.0037^{\cdot}$	-0.0045^{*}	-0.0135^{**}	-0.0057^{**}
	(0.0020)	(0.0020)	(0.0045)	(0.0020)
Num. Obs.	2,543,608	2,554,459	1,124,594	2,526,986
Num. Firms	287,082	288,331	183,930	284,845
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 first began working at the firm in the given month.

Return to Main Regressions

IV Regression, Hours Worked Decomposition

	Hours Worked (New Hire, Perm.)	Hours Worked (Existing, Perm.)	Hours Worked (New Hire, Temp.)	Hours Worked (Existing, Temp.)
$r_{j,t}^{\text{Fac}}$	-436.3^{***}	-41.8^{**}	157.3^{***}	48.3597^{***}
	(96.4)	(15.2)	(32.2)	(11.2)
Num. Obs.	2,479,680	2,479,680	2,479,680	2,479,680
Num. Firms	288,112	288,112	288,112	288,112
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 are **total labor hours per month per firm**, from restricted access month-level RAIS data. An employee is defined as new if the employee first began working at the firm in the given month.

Return to Main Regressions

IV Regression, Employment Outcomes

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

	(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)
$r^{\text{Fac}}_{j,t}$	−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 this month and not in the previous year.

Return to Main Regressions

IV Regression, Default Outcomes

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

	Default Rate Rec. Factoring (to Banks, %)	Default Rate Other (to Banks, %)	Default Rate Rec. Factoring (to FIDCs, %)	Default Rate Other (to FIDCs, %)
$r_{j,t}^{\text{Fac}}$	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%.

IV Regression, Trade Credit Outcomes

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

	Maturity Offer (Days)	Percentage Offer (%)	Log Value Offer	Maturity Receive (Days)	Percentage Receive (%)	Log Value Receive
$r^{\text{Fac}}_{j,t}$	−0.0354	−0.3885**	−0.0591***	0.6737***	0.0272	−0.0316***
	(0.0996)	(0.1274)	(0.0102)	(0.1358)	(0.0379)	(0.0061)
Num. Obs.	4,146,540	4,146,540	2,538,086	4,146,540	4,146,540	4,015,309
Num. Firms	511,896	511,896	203,995	511,896	511,896	469,959
Num. Months	65	65	65	65	65	65

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; ·$p < 0.1$

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.

Return to Main

IV Regression, Summary of Debt Outcomes

	Log Debt Issuance All Debt	Log Debt Issuance Factoring	Log Debt Issuance Besides Factoring
$r_{j,t}^{\text{Fac}}$	-0.1548^{***}	-0.1617^{***}	-0.0241
	(0.0161)	(0.0167)	(0.0204)
Num. Obs.	3,094,560	3,094,560	788,450
Num. Firms	420,586	420,586	124,513
Num. Months	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. Note that 72.5% of all debt issuance has maturity under 1 year, and 49.9% of all debt issuance is factoring.

Return to Main Regressions

IV Regression, Debt Outcomes

	(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)
$r_{j,t}^{\text{Fac}}$	-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

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.

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

Return to Main Regressions

IV Regression, Interest Rate Outcomes

	IR (Debt Under 1 Year)	IR (Debt Over 1 Year)	IR Credit Line (Unsecured)	IR Credit Line (Secured)	IR (Loans Over 1 Year)
$r_{j,t}^{\text{Fac}}$	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.

Return to Main Regressions

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

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

	(1) Factoring Interest Rate	(2) Log Revenue	(3) Log Expenditure	(4) Log Temporary Labor	(5) Log Permanent Labor
$e_{j,t}^{\text{Fac}}$	-0.501	0.074	0.052	-0.056	0.033
	(1.287)	(0.089)	(0.061)	(0.095)	(0.040)

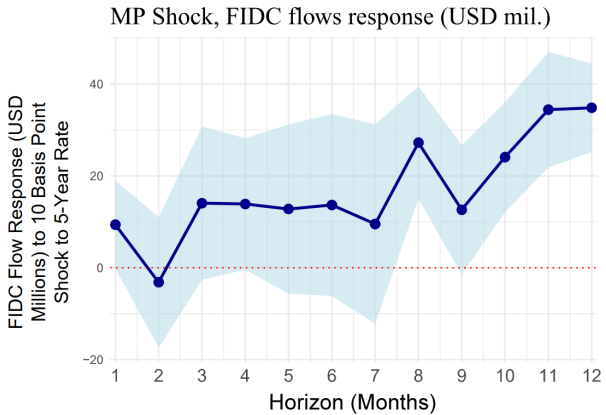
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

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

Return to IV Construction | Return to Main Regressions

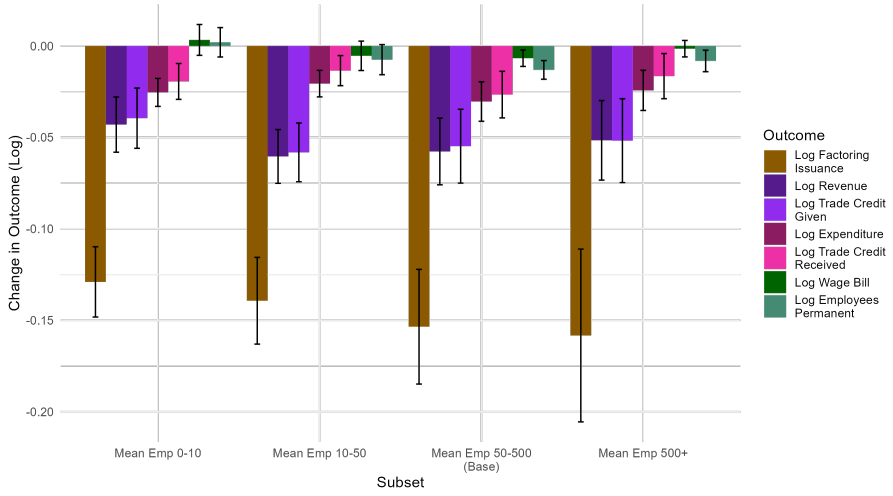
FIDCs' monetary policy exposure is similar to money market funds, dissimilar to most other funds

Monetary tightening is associated with increased inflows into FIDCs, whose assets' short maturities allows for immediate pass-through

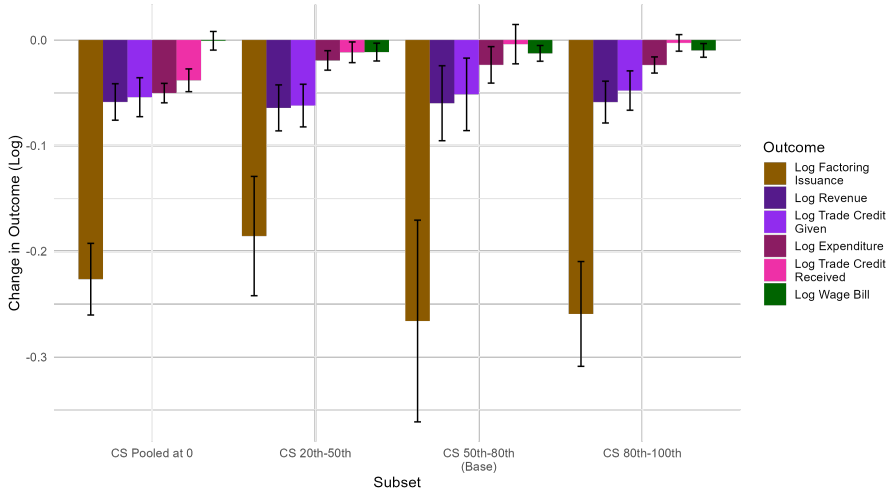


Return

Heterogeneity By Firm Type: Interaction with Firm Size

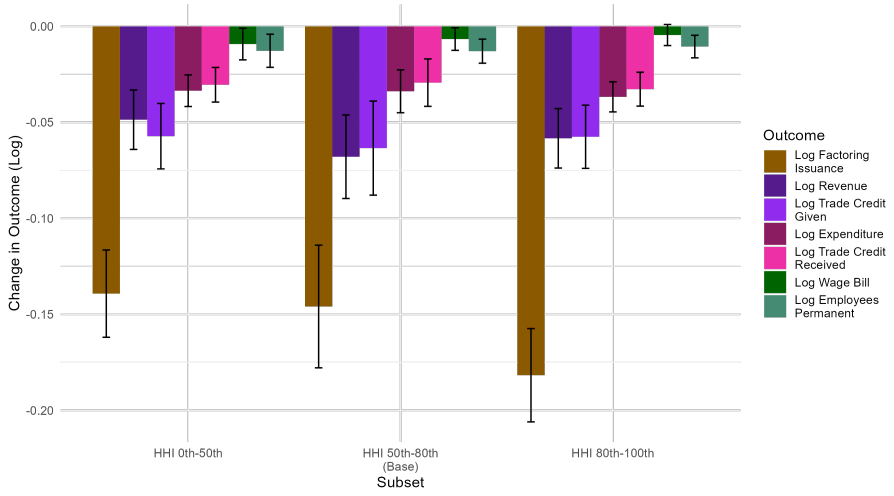


By Firm Type: Interaction with Credit Score



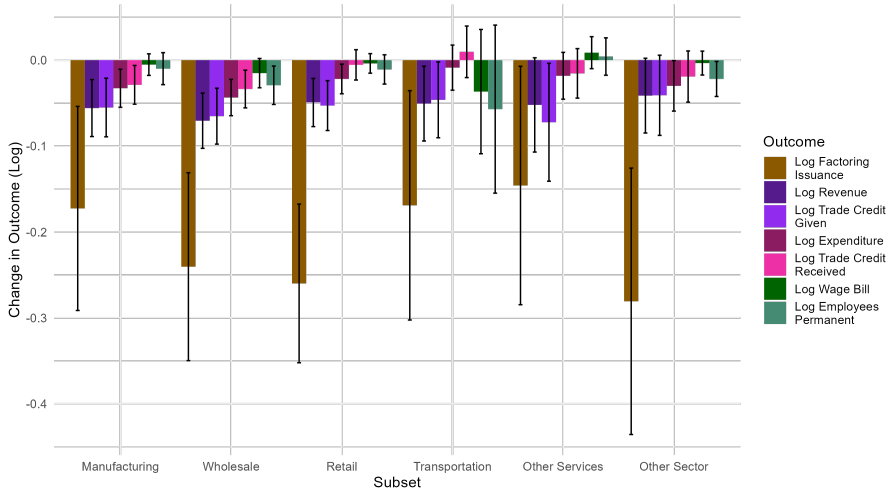
Explanation Maturity Return

By Firm Type: Interaction with HHI

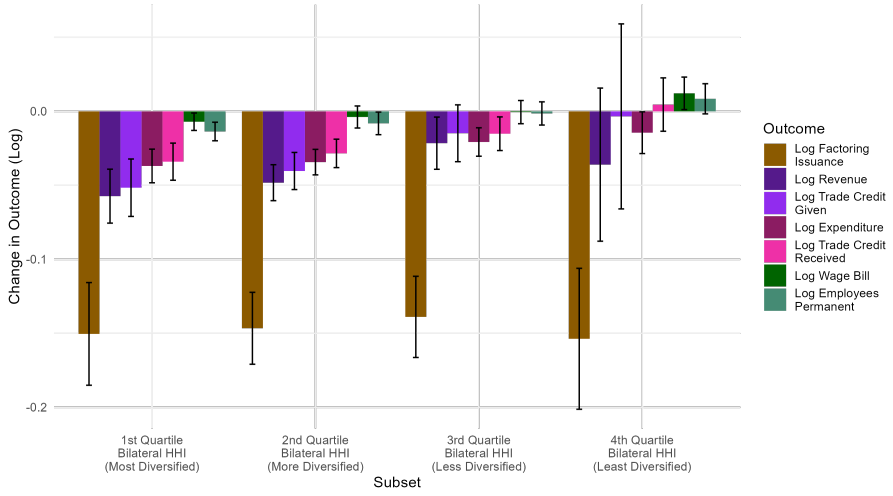


Explanation Maturity Return

By Firm Type: Interaction with Sector

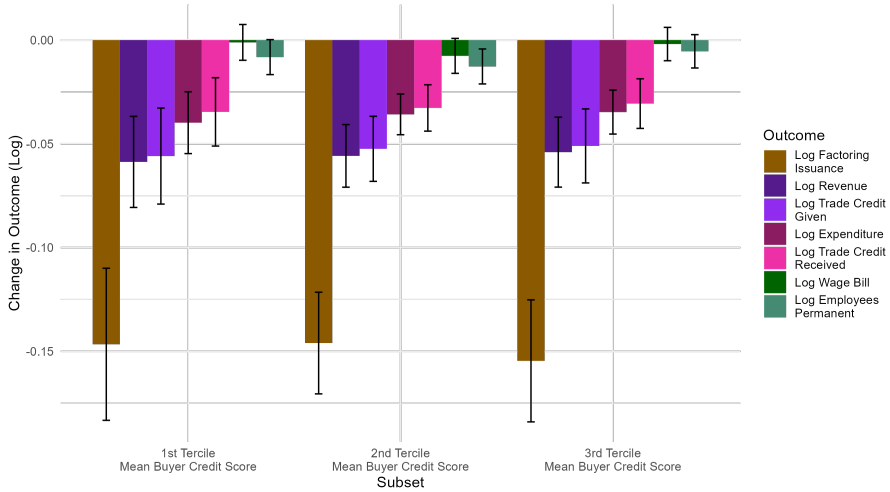


By Firms' Buyer Portfolio: Interaction with Bilateral HHI



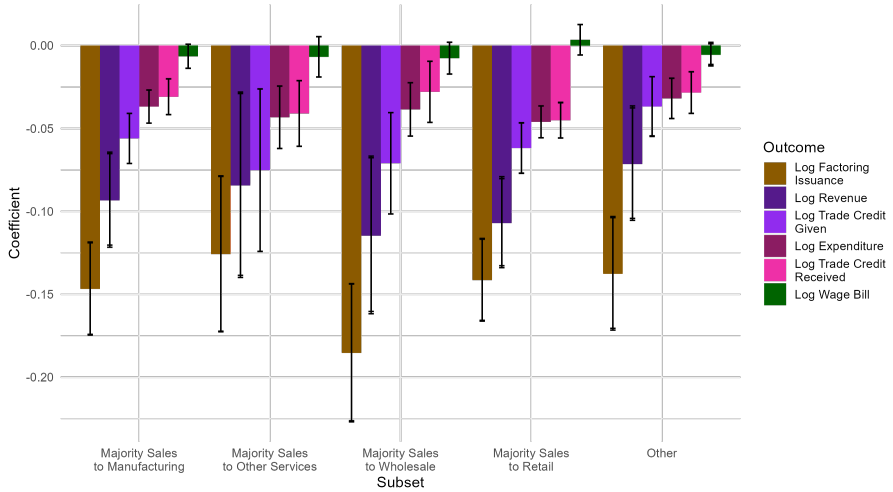
Explanation | Additional Buyer Portfolio | Return

By Firms' Buyer Portfolio: Interaction with Buyer Credit Score



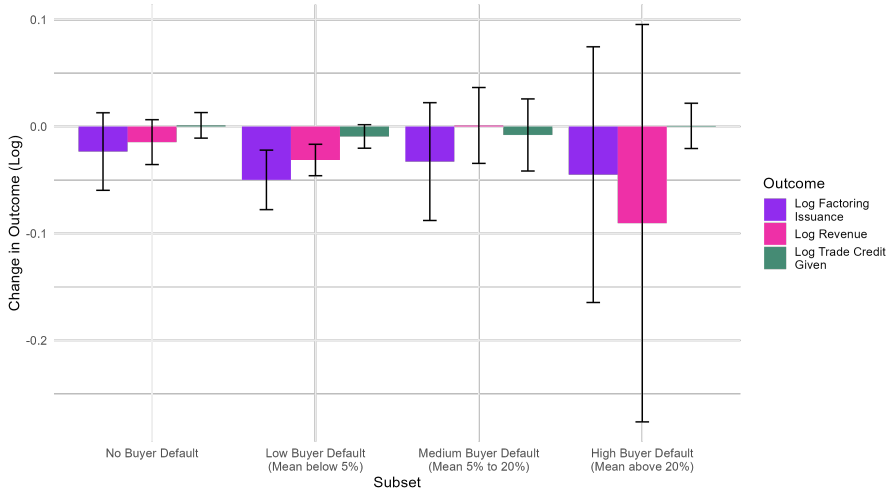
Explanation Return

By Firms' Buyer Portfolio: Interaction with Main Buyer Sector



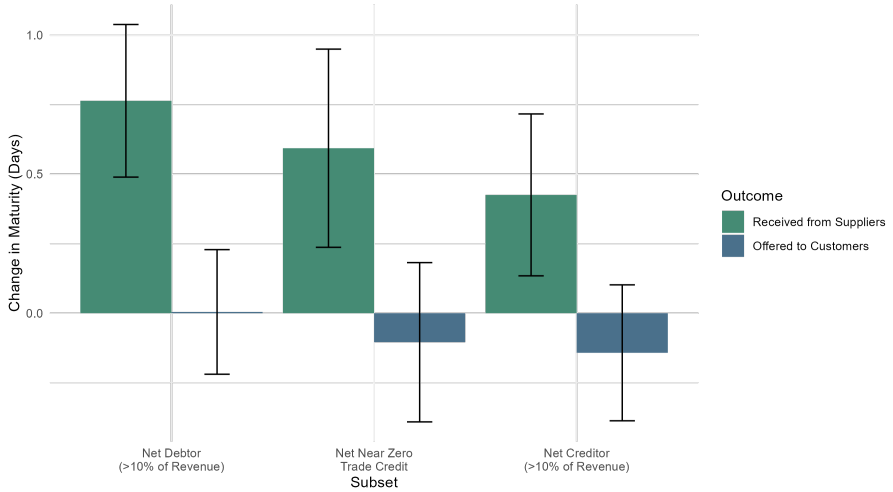
Explanation Return

By Firms' Buyer Portfolio: Interaction with Weighted Mean Buyer Default Rate



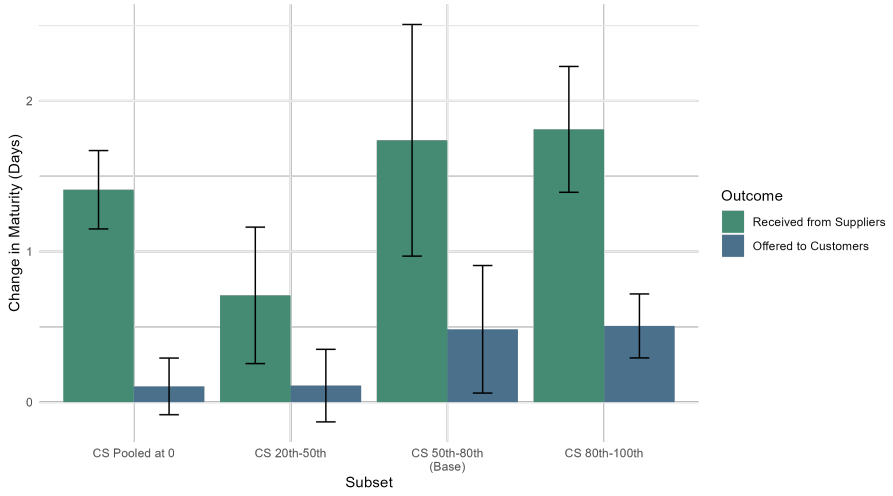
Explanation | Return to Bilateral HHI | Return

By Firm Type: Interaction with Trade Credit Position



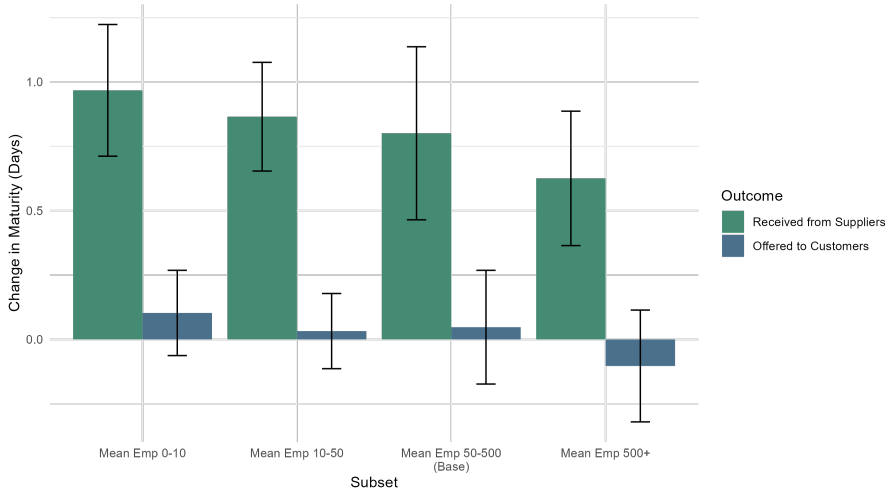
Explanation Main Outcomes Return

By Firm Type: Interaction with Credit Score



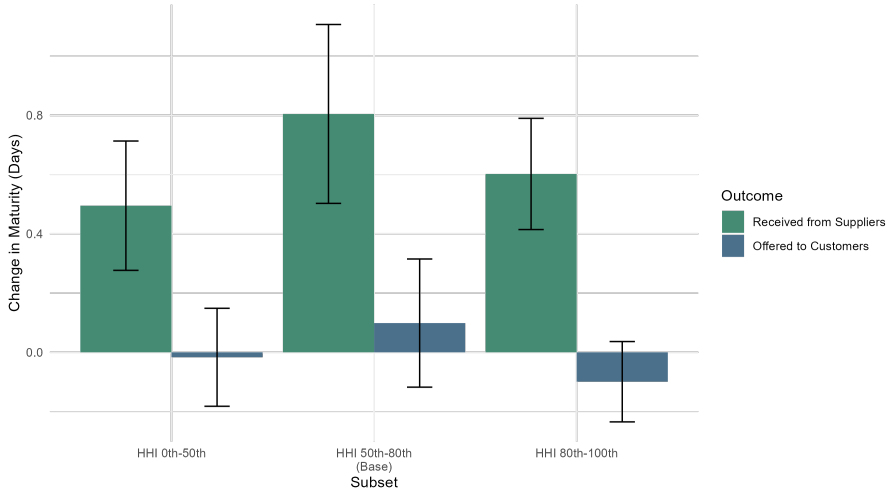
Explanation Main Outcomes Return

By Firm Type: Interaction with Firm Size



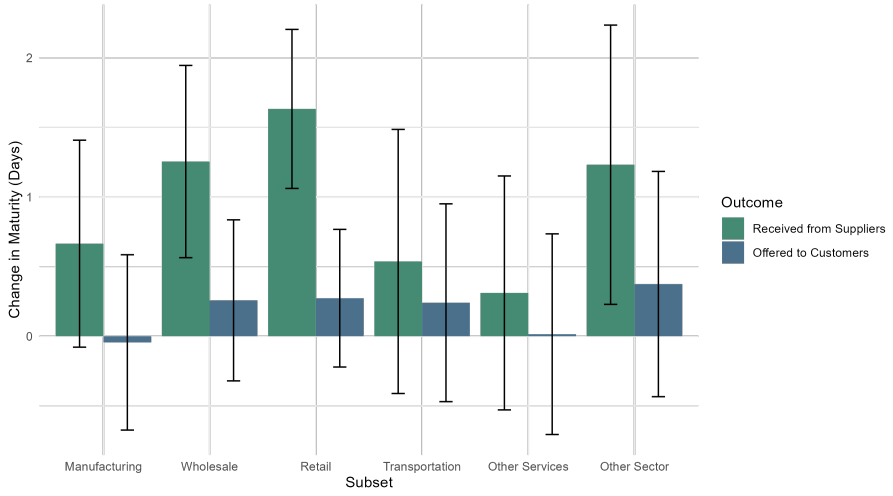
Explanation Return

By Firm Type: Interaction with HHI



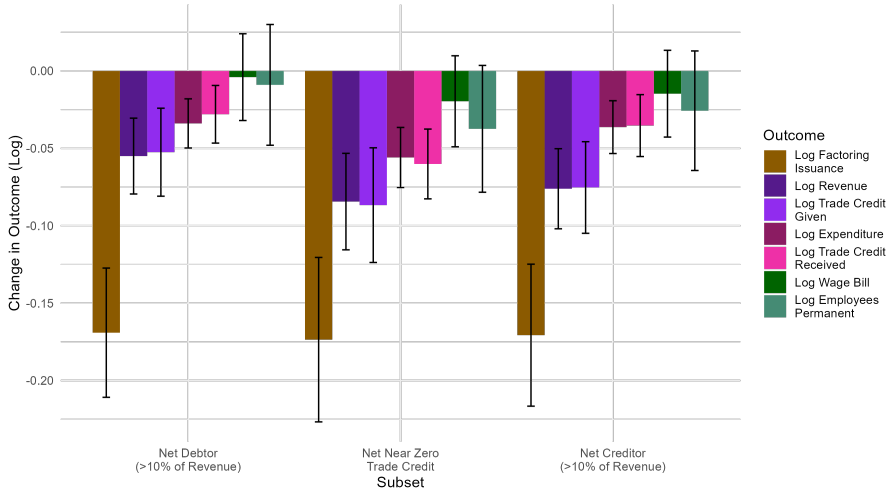
Explanation Main Outcomes Return

By Firm Type: Interaction with Sector



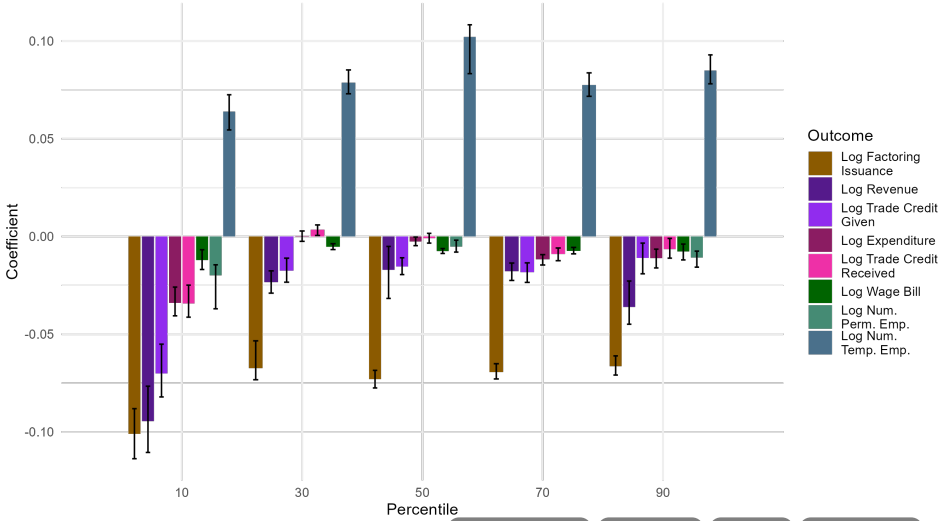
Main Outcomes Return

Heterogeneity By Firm Type: Interaction with Trade Credit Position



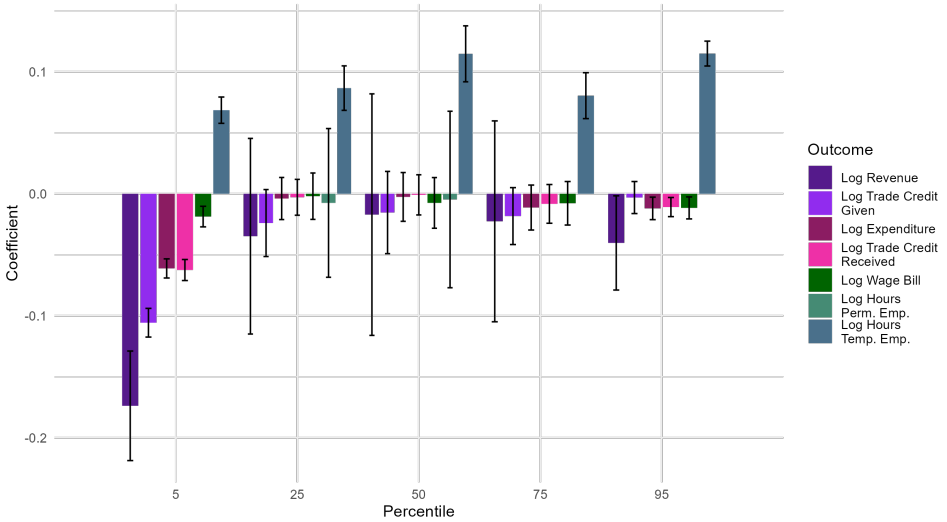
Explanation | Maturity | Size | Sector | Credit Score | Trade Credit | HHI | Bilateral HHI | Buyer Risk

Quantile Regression: Main Outcomes



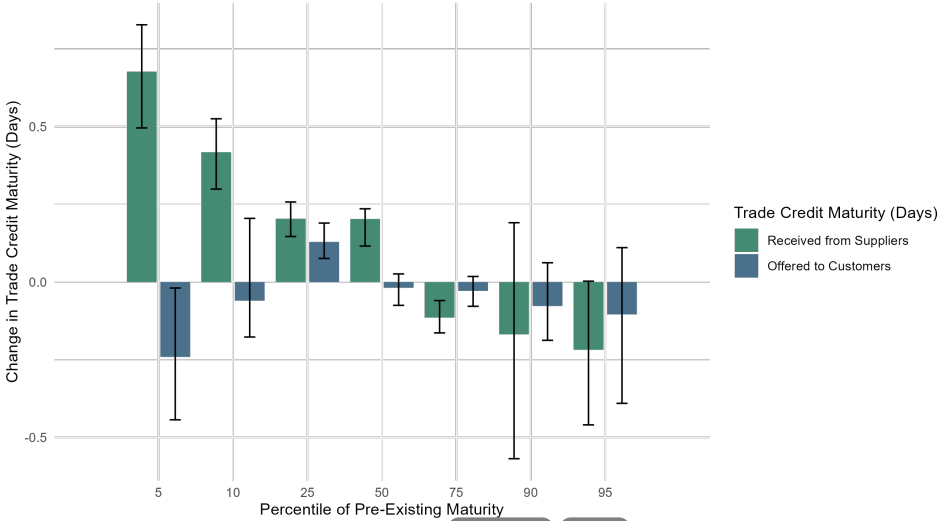
This graph uses Koenker (2005) rank inversion for SEs. Canay (2011) SE | Explanation | Maturity | Hours Worked

Quantile Regression



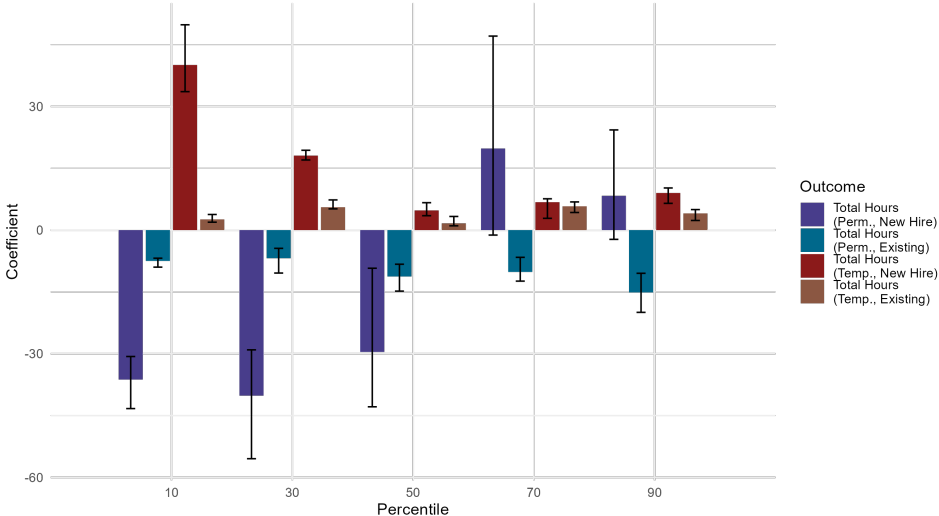
Explanation | Koenker (2005) SE

Quantile Regression: Maturity Outcomes



This graph uses Koenker (2005) rank inversion for SEs. Explanation Return

Quantile Regression: Hours Worked Outcomes



This graph uses Koenker (2005) rank inversion for SEs. Explanation Return

Model Intuition: Cash Flow Volatility

Cash flow volatility mismatch:

- Firms' cash outflows have a rigid component due to labor contracts and labor law
- Firms' cash inflows are more volatile, both due to timing of sales and timing of payment conditional on sales, as well as whether buyers fulfill payment
  - Factoring removes the payment dimension of cash inflow volatility
- Perfectly predictable cash inflows would lead firms to hire exclusively on long-term contracts, due to productivity gain from employee experience
- Volatility in cash inflows drives demand for temporary labor and factoring
- Decreasing factoring costs leads to
  - Less volatility (substitution) of production across time
  - More permanent employment and higher long-run productivity

Return to model overview

Model Setup: Firm Block

- **Firms**: A unit continuum of monopolistically competitive firms producing differentiated goods across two periods, morning (0) and afternoon (1)
- **Production Function**: Firms use a Cobb-Douglas production function over labor ℓ and intermediate inputs x with labor share α

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

- **Payments**: Wages are always upfront, so are afternoon sales
  - Morning sales: Trade credit with payment in afternoon
- **Liquidity Shocks**: ϵ_j share of morning receivables y_{j0} does not arrive, with firm type $\zeta_j = \mathbb{E}_0 \epsilon_j$

Return to Overview Skip to Conclusion

Model Setup: Labor and Financing

- **Labor Types**:
  - Permanent labor ℓ^P: Fixed for both periods, more productive by ψ in afternoon.
  - Temporary labor ℓ_t^T: Adjustable at each period t.
- **Labor Composite**: Constant elasticity of substitution $\sigma > 1$ with share ς on permanent labor:

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

- **Factoring**:
  - Firms factor B_j^F in the morning with credit limit varying with morning receivables y_{j0}
  - Factoring interest rate R_j^F is based on the expected share ζ_j of shocked inflows; ζ_j is close to 0 for most firms

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

Return to Overview Skip to Conclusion

Model Setup: Firm Problem in Morning

Taking as given wages $\{w^P, w_t^T\}$ and factoring interest rate R_j^F, choose ℓ_j^P and B_j^F along with other inputs to maximize expected firm value subject to cost of default η:

$$\max_{\{y_{jt}, x_{jt}, \ell_j^P, \ell_{jt}^T, B_j^F\}} \pi_j := \beta \mathbb{E}_0 \left[\pi_{j1} + \eta \mathbb{1}\{\pi_{j1} < 0\}\right] + B_j^F - \ell_j^P w^P - \ell_{j0}^T w_0^T,$$

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

$$B_j^F \geq \ell_j^P w^P + \ell_{j0}^T w_0^T,$$

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

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

where $\tilde{m}_{j1}$ is a firm's residual cash in the afternoon from the morning, net of factoring and input purchase

Return to Model Overview | Return to Paper Overview | Skip to Conclusion

Model Setup: Firm Problem in Afternoon

Taking as given wages $\{w^P, w_t^T\}$, decisions made in morning $\{y_{j0}, x_{j0}, \ell_j^P, \ell_{j0}^T, p_j, B_j^F\}$, and shock realization ϵ_j, maximize residual profits

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

where the $\frac{p_j}{P}$ equation is the standard CES FOC from the aggregator firm's objective function

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Model Setup: Household

Representative household, disutility $\xi > 1$ from labor, relative preference $\nu \in \mathbb{R}$ for permanent vs temporary labor

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

Household problem:

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

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Model Equilibrium

Given model parameters, firms optimize in morning and afternoon, households optimize, and markets clear in each period:

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

$$\int_{j=0}^{1} \ell_j^P \, \mathrm{d}j = \ell^P,$$

$$\int_{j=0}^{1} \ell_{jt}^T \, \mathrm{d}j = \ell_t^T.$$

Return to Overview Skip to Conclusion

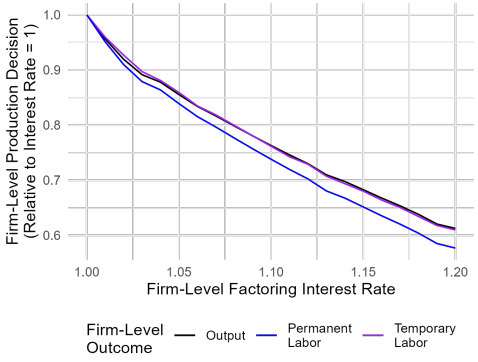
Model Calibration

Parameter	Value	Description	Method
α	0.43	Cobb-Douglas labor	Data: Expenditure share
ψ	1.31	Gain to experience	Data: Ratio of existing to new hire wage for permanent vs temporary
μ^F	1.13	Factoring markup	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).

Return to Overview Skip to Conclusion

Model Results: Firm-Level (PE) vs Aggregate (GE)

On the left is the partial equilibrium, changing R_j^F while holding equilibrium outcomes constant

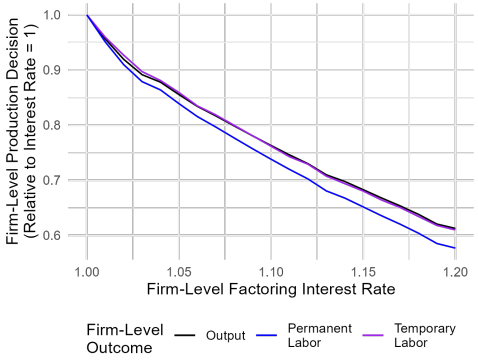


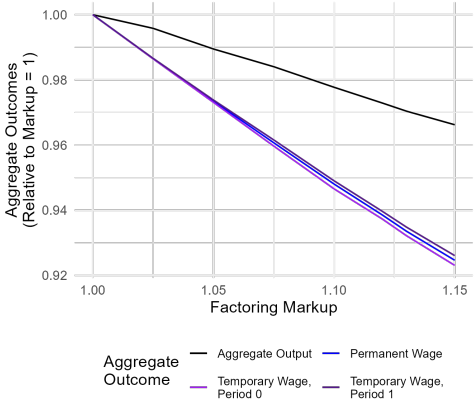
Factoring share | Heterogeneity | Return to Overview

Model Results: Firm-Level (PE) vs Aggregate (GE)

On the left is the partial equilibrium, changing R_j^F while holding equilibrium outcomes constant

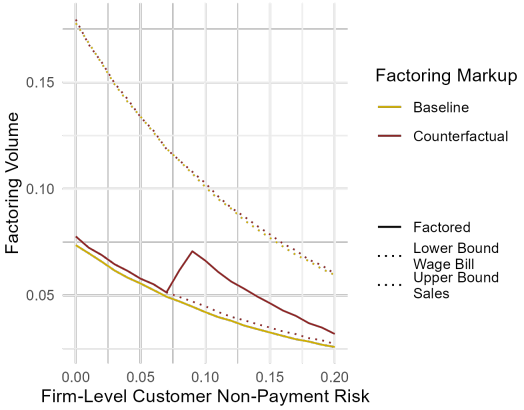
On the right is the general equilibrium, changing the economy-wide factoring markup μ^F

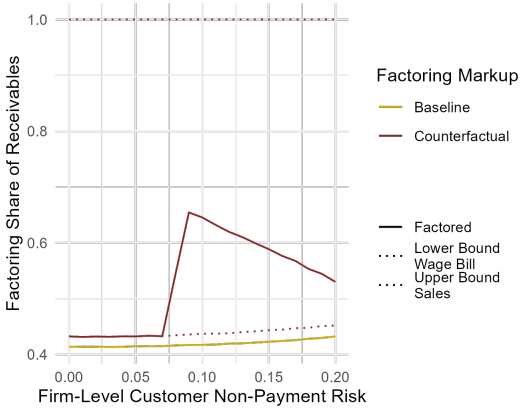




Factoring share | Heterogeneity | Return to Overview

Model Results: Factoring Share

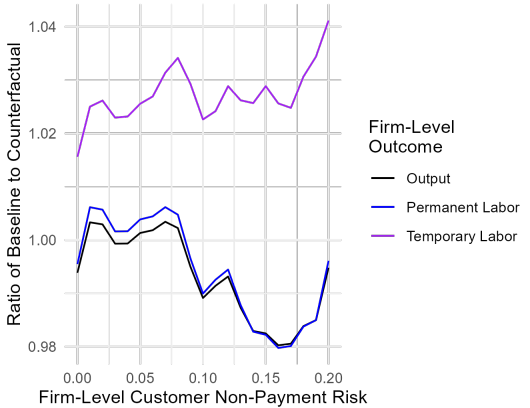


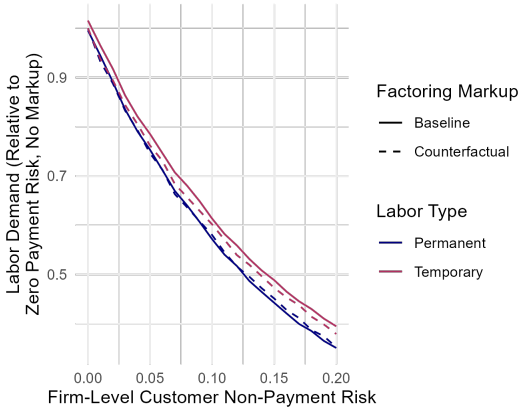


Return to model results

Model Results: Heterogeneity

On the left is the ratio of outcomes between baseline markup $= 1.13$ and counterfactual markup $= 1$
On the right are permanent and temporary labor between baseline and counterfactual





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