Trade credit in a developing country: the role of large suppliers in the production network*

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Abstract

Trade credit can be a substitute for bank credit when firms have limited access to financial institutions. This is particularly relevant in developing countries where bank interest rates are highly dispersed and smaller firms face a prohibitive cost of bank credit. This paper builds a production network model where each pair of sellers and buyers choose intermediate inputs' quantities, prices, and levels of trade credit in a decentralized fashion, given heterogeneous bank interest rates. The dispersion in interest rates is explained by both heterogeneous risk of firms' default and additional heterogeneous costs, labeled as 'frictions.' In equilibrium, suppliers paying low bank interest rates are net providers of trade credit to clients paying high interest rates when this spread is due to frictions. We calibrate the model using balance sheet data, firm-to-firm transaction data, and bank-to-firm credit data for the Brazilian economy. We decompose the observed interest rates between the risk and the frictional components. Trade credit attenuates shocks to financial frictions hitting downstream firms, while it amplifies these shocks when they hit upstream companies. Trade credit also amplifies interest rate shocks due to a higher risk of default. We also use our model to evaluate the importance of trade credit for aggregate output, given the evolution of firm-level interest rates over the last four years. The endogenous adjustment in trade credit levels had a positive impact on output from 2022 when the dispersion of interest rates increased.

Keywords: Trade Credit, Input-Output Network, Financial Shocks.

Jel Classification: E23, E44, L13, L14, O41

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1. Introduction

Credit markets can charge different interest rates for similar loan transactions (Banerjee (2001), Banerjee & Duflo (2005), Gilchrist et al. (2013)). This dispersion is particularly extreme in developing countries where smaller firms usually have very limited access to finance.[1] For these firms, trade credit could be a substitute for bank credit (Petersen & Rajan (1997)). However, if bank interest rate spreads are motivated by high default risks, trade credit may be similarly expensive. This paper presents a model of input-output network of firms endogenously choosing the level of trade credit in decentralized markets. The firms face different bank interest rates due to heterogeneous default risks and heterogeneous financial frictions. We calibrate the model using micro-data for the Brazilian economy on firm-to-firm transactions and bank-to-firm credit relations, and analyze the role of endogenous trade credit in relation to interest rate dispersion.

Our theory is motivated by two main facts regarding the Brazilian economy. The first one is the striking dispersion of credit costs between small and large firms. The average annual interest rate faced by a small Brazilian firm was around 45% over the last five years, well above the central bank interest rate, which oscillated between 2% and 13%.[2] A large interest rate spread is also evident if we compare the interest rates paid by listed firms with the ones paid by their clients. The blue line in figure 1 shows the distribution of short-term bank interest rates paid by the Brazilian listed companies in 2019. The red line plots the distribution of bank interest rates paid by their clients. The average gap is larger than 10 percentage points.

The second fact is that this dispersion in financing costs is reflected in the structure of the trade credit network, as large firms are usually net providers to smaller firms. This polarization in the trade credit market is substantially wider if compared to advanced economies. Figure 2 shows that the median net trade credit (Accounts Receivable minus Accounts Payable over the total current assets) as a share of total current assets of large companies is higher in Brazil if compared to Europe and the US for most sectors (the data refer to 2019).[3]

[1]See Cavalcanti et al. (2021) for the case of Brazil.

[2]A small firm is one with annual revenues below 920.000 USD. The average interest rate for small firms is calculated by the Serviço Brasileiro de Apoio às Micro e Pequenas Empresas. See https://datasebrae.com.br/paineltaxasdejuros.

[3]Large firms are those with yearly revenues over 300 million BRL or 76 million USD (using an average exchange

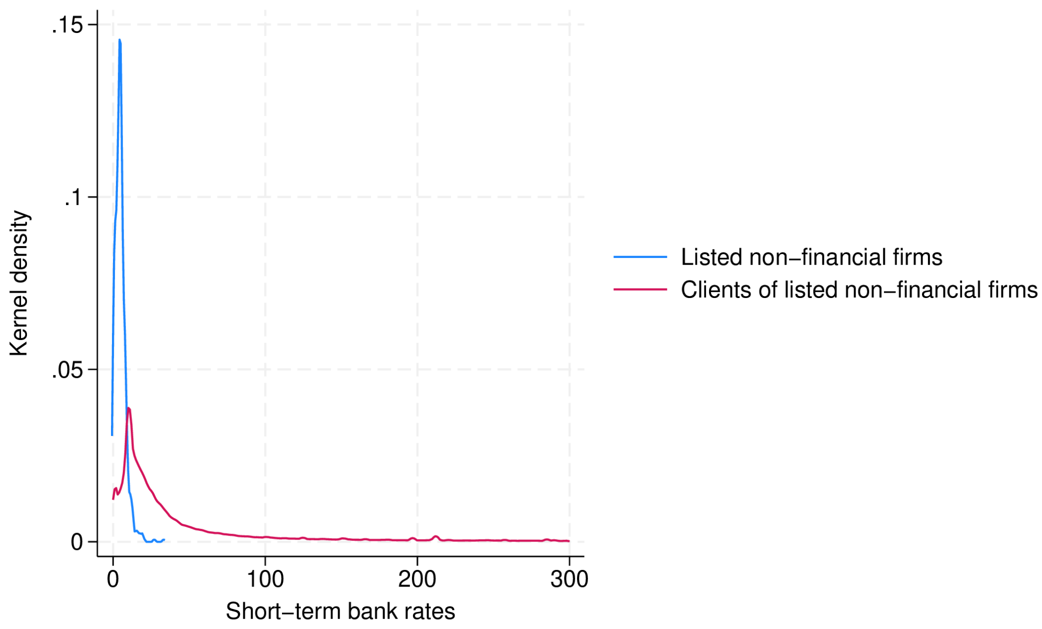


Figure 1: Distribution of interest rates: listed companies VS their clients (2019). Data are from the credit registry and the payment registry of the Central Bank of Brazil.

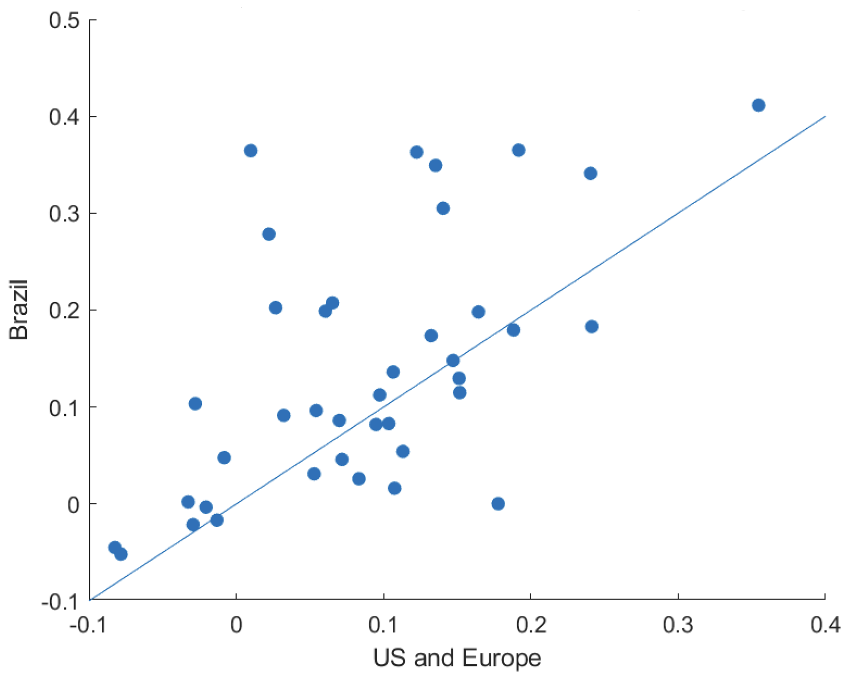


Figure 2: Median share of net trade credit of large firms by sector (2019). Data are from SP Global.

In Section 2, we provide further empirical evidence to motivate our theory. We analyze the effect of a change in the interest rate of a firm and a change in the interest

rate of 3.94 BRL/USD in 2019).

rate of its clients on the supply of trade credit (Accounts Receivables). In order to identify exogenous changes in interest rates, we build a Shift-Share IV based on the heterogeneous exposure of firms from the credit supply by different banks. To run this analysis, we use both detailed firm-to-firm transaction information to identify the clients of a firm and bank-to-firm loan data to build the instrument. We find that firms reduce their supply of trade credit when their interest rate increases. On the contrary, they increase the supply of trade credit when the interest rate of their clients increases.

Based on this evidence, we develop a theory of trade credit in production networks in which firms meet in decentralized markets and bargain over quantities, prices, and levels of trade credit. The framework builds on existing static models of trade credit in economies with sectoral input-output linkages, such as Luo (2020) and Altinoglu (2021). Firms purchase from and provide inputs to other firms, but they all face a working capital constraint limiting their operations. In order to overcome this constraint, they can obtain a loan from the financial sector or delay a fraction of payments to their suppliers. An essential modification with respect to the existing literature is that we model the endogenous choice of trade credit supplied by a seller. We assume that each seller-buyer pair chooses the optimal quantity, price, and level of trade credit through Nash bargaining, taking as given all other intermediate good transactions.

In order to recover a delayed payment, a firm must also incur a monitoring cost. This cost increases with the size of sales and the share of trade credit offered to the buyers.

Another important feature of the model is that firms face heterogeneous costs of bank credit. These divergent interest rates are motivated by both heterogeneous risks of default and heterogeneous financial frictions. The optimal level of trade credit chosen by a seller-buyer pair decreases with the bank interest rate of the seller and increases with the interest rates of the buyer if the differences are driven by frictions.

Given the solutions for sales and trade credit, the aggregate output can be expressed as a function of firm-to-firm specific distortions. Trade credit mitigates the negative effect of higher interest rates for a buyer due to rising frictions while it amplifies the same shock to a seller. Trade credit amplifies shocks to the risk of default.

We calibrate the model using firm-level balance sheet data, firm-to-firm transactions data, and bank-to-firm credit data for the Brazilian economy. One main goal of our calibration is to identify the risk and the frictional components explaining the observed dispersion of bank interest rates. In a preliminary calibration for 2019, we consider an economy made of the 50 largest listed Brazilian companies plus six small representative companies for each macro-sector.

We first use our calibration to analyze the effect of financial shocks at the firm-level. We find that trade credit mitigates negative financial shocks for most firms. Shocks are amplified if hitting large suppliers of trade credit.

Finally, we use our calibration to analyze the role of trade credit in the years after 2019. We show that the endogenous adjustment of trade credit in the network of firms raised output growth, especially in the very last years when the dispersion of interest rates increased.

Related Literature. The paper belongs to the literature on production networks started with Long Jr & Plosser (1983) and recently developed by Acemoglu et al. (2012), Baqaee & Farhi (2018, 2019), and Bigio & La'o (2020).[4] In particular, we contribute to the study of the role of financial frictions on sectoral misallocation.[5].

Baqaee & Farhi (2020) build a general theoretical framework for analyzing the effects of distortions on output and TFP in network economies, even when considering nonlinear (that is, non-Cobb-Douglas) production networks. Bigio & La'o (2020) map distortions to financial frictions and conduct a quantitative exercise using data from the US economy to measure how frictions are able to amplify shocks in a network economy. Liu (2019) presents the concept of distortion centrality, which serves as a summary statistics for the aggregate effects of shocks to frictions. In our model, distortions arise from the presence of working capital constraints. Trade credit between suppliers and buyers of inputs is a way to bypass this constraint.

Our model is related to the ones in Altinoglu (2021) and Luo (2020). Similar to these papers, we assume that firms are subject to a working capital constraint, so trade credit acts as a substitute for bank credit. Different from these papers, in our

[4] Carvalho (2014) and Carvalho & Tahbaz-Salehi (2019) provide an extensive review on this literature.

[5] See Hsieh & Klenow (2009), Restuccia & Rogerson (2008), Jones (2011)

model, the level of trade credit is endogenously determined. Specifically, firms choose their production, price, and share of trade credit given bank credit conditions. The endogenous level of trade credit is then a function of the interest rates of the seller and buyer.

Reischer (2019) also considers endogenous trade credit and its interplay with bank credit. However, in our model, the optimal levels of trade credit are determined in a decentralized way through the match of each seller with each buyer. This allows us to calibrate the model using micro-data of firm-to-firm transactions and bank-to-firm credit relations. In addition, our estimation strategy allows us to identify the role of risk and bank frictions in the dispersion of observed bank interest rates.

Bocola & Bornstein (2023) build a dynamic model where oligopolistic suppliers sell intermediary goods to perfectly competitive final goods producers. There is a lag between production and payments, which creates the need for credit contracts. Here, trade credit depends on the reputation of the final goods producer since the firm can default on payments, and the authors study the impacts of changes in credit intermediation costs and borrowing constraints. Bryan Hardy & Simonovska (2023) consider a stylized model with two firms, a large supplier that can borrow in foreign currency while the small firm can only borrow at higher rates, studying how trade credit can also serve as a risk-sharing mechanism for exchange rates. Unlike these two papers, our paper focuses on the interplay between bank credit and trade credit.

Most models of production network consider sector-representative firms and are calibrated with sectoral input-output matrices. In our model, each pair of buyers and sellers choose the quantity, price, and level of trade credit through Nash bargaining. This is similar to the framework by Acemoglu & Tahbaz-Salehi (2024). We calibrate the model using firm-level data and detailed firm-to-firm transaction data for listed companies (while the rest of the economy is represented by small sector-representative firms). Our focus on large companies is justified by the role these companies can have in affecting aggregate output (see Carvalho & Grassi (2019)).

Finally, the paper is also related to the empirical literature on trade credit. Petersen & Rajan (1997) and Demirguc-Kunt & Maksimovic (2001) show how firms can act as credit providers when financial constraints limit the provision of bank credit. In particular, Petersen and Rajan use data from US firms to show that trade credit use varies according to firm size, with large firms being relevant suppliers of trade credit. In the short run, trade credit can also mitigate the costs of financial crises, as shown by Garcia-Appendini & Montoriol-Garriga (2013). Jacobson & Von Schedvin (2015) show how corporate failures propagate upstream through trade credit linkages. Garcia-Marin et al. (2019) proposes a model of trade credit in which firms learn about their trading partners and rationalize the relationship between trade credit and markups in the case of Chile.

The paper is organized as follows. Section 2 presents the empirical evidence motivating the model. Section 3 describes the model and derives the analytical results regarding the impact of bank interest rates on trade credit levels and aggregate output. Section 4 describes the calibration of the model. Section 5 discusses how the trade credit channel works in the economy. Section 6 goes over our numerical exercise. Section 7 concludes.

2. Motivating evidence

2.1. Data description

We describe here the main data used in this section and for the calibration of the model in Section 4. We use data from three different sources. First, we use publicly available balance sheet data for Brazilian listed non-financial companies (almost 300 companies) from Economatica. These companies include the largest firms in the country in terms of both total assets and sales. In particular, the largest 50 companies in our database represent around 8% of total GDP. From these balance sheet data, we are particularly interested in the amount of Accounts Receivable over Total Current Assets.

Second, we identify the network of firm-to-firm transactions using the restricted access payment registry of the Central Bank of Brazil. The data covers all transfers between accounts in different banks and the universe of *boletos*. The *boleto* is a type of payment bill that is particularly popular for transactions among firms in Brazil. *Boletos* are generally used for relatively smaller transactions. Therefore, the number of transactions through *boletos* is considerably larger. For both types of transactions, we can observe the value and identify the seller and the buyer. We build our network of firm-to-firm transactions using the information from both the bank transactions and the *boletos*' database. Since the data on *boletos* are available only from 2019, our empirical analysis focuses on the years from 2019 onward. In particular, we build a picture of the network structure aggregating the total value of transactions for each seller-buyer pair over the entire 2019. We restrict our analysis to the linkages of the listed companies (for which we have balance sheet information about trade credit). Bank transfers accounted for 70% of the volume of total transactions involving listed companies in 2019. Summing *boletos* and bank transfers, we find that the median number of clients for these companies during 2019 is 1031; the average number is higher than 16000. The median value of transactions (over the entire 2019) between a listed company and a client is 3.4 thousand BRL (around 650 USD, as of May 2024), while the average is 512.5 thousand BRL (around 97.4 thousand USD)

Third, we retrieve data on bank interest rates and credit quantities for all listed companies and their clients from the restricted access credit registry of the Central Bank of Brazil.[6] The database covers information on bank loans for all borrowers with credit exposure with a bank above 200 BRL (around 59 USD, as of May 2024). Since our focus is on the substitution between trade credit and bank credit, we only focus on short-term contracts with a maximum duration of one year. These contracts mostly include financing for working capital.

2.2. Bank interest rates and trade credit

Providing trade credit is costly. However, this cost should be lower if a firm has better access to bank finance. On the other side, receiving trade credit should be more beneficial if a firm has restricted access to bank finance. In this section, we explore how the amount of trade credit provided by a firm depends on the cost of bank credit faced by the firm itself and its clients.

Table 1 reports the mean and standard deviation of the variables used in our analysis.

[6] These data have been widely used in other research papers, for example, Ponticelli & Alencar (2016) and Bustos et al. (2020).

Table 1: Summary statistics

	Mean	Standard Deviation	Observations
Accounts Receivable over CA	0.29	0.15	2,545
Average interest rate	5.03	7.4	2,545
Average interest rate of clients	12.73	5.05	2,545
Shares of bank-to-firm loans	0.52	0.43	3,341,646
Average interest rate of banks	18.97	39.08	14,121

Note: Observations for the first three variables refer to a company in a quarter (from 2020 to 2023). Each observation for the shares of bank-to-firm loans refers to one bank-to-firm link in 2019. The average interest rate of banks is the weighted average interest rate that each bank offered in a quarter from 2020 to 2023.

The frequency of our data is quarterly. The average interest rate $r_{n,t}$ of a firm is a weighted average referring to the existing stock of contracts that the company has with banks. The weights are equal to the shares of the size of a contract. The average interest rate of the clients is defined as

$$\bar{r}^c_{n,t} = \sum_{m \in N_n} s^m_{n,2019} r_{m,t},$$

where $s^m_{n,2019}$ is the share of sales of firm n purchased by firm m. These shares are computed considering the network of aggregate transactions in 2019. N_n is the set of clients of firm n during the entire year.

We start considering the following OLS regressions, looking at the effect of quarterly variations in interest rates on variations in Accounts Receivable over Current Assets :

$$\Delta AR_{n,t} = \phi \Delta r_{n,t} + \rho D_n + \sigma D_t + \epsilon_{n,t}, \tag{1}$$

and

$$\Delta AR_{n,t} = \varphi \Delta \bar{r}^c_{n,t} + \varrho D_n + \varsigma D_t + \varepsilon_{n,t}. \tag{2}$$

We include firm-dummies and year-dummies to control for firm-specific effects and aggregate trends related to the business cycle. However, this would not be enough to identify the exogenous effect of a change in the cost of credit on the change in the supply of trade credit. Therefore, we build a Shift-Share IV based on the heterogeneous exposure of firms across different banks. Specifically, the instrument is a weighted average of common interest rate shocks:

$$\Delta f_{n,t} = \sum_b z_{n,b,2019} \Delta R_{b,t}. \tag{3}$$

$R_{b,t}$ is the average interest rate (weighted by the size of each loan) that a bank offers to all companies in a quarter t. We found more than 80 banks in the database. $z_{n,b,2019}$ is the aggregate stock of credit that a firm n obtained from a bank b relative to the firm's total stock of credit in 2019. We use $\Delta f_{n,t}$ as an instrument for $\Delta r_{n,t}$ and $\Delta \bar{f}^c_{n,t} = \Delta \sum_{m \in N_i} s^m_n f_{m,t}$ as an instrument for $\Delta \bar{r}^c_{n,t}$.

The results are presented in Table 2.[7] In line with our predictions, a firm provides less trade credit when the cost to raise liquidity increases. In particular, this result appears only when we use our instrument. Interestingly, the opposite occurs when the interest rate of the clients increases. An increase in the cost of credit is typically associated with a deterioration of the creditworthiness of a firm. This could also decrease the supply of trade credit from suppliers. However, the goal of our SSIV is to identify a shock to the interest rate coming from a reduction in the banks' credit supply. We find that such a shock raises instead the supply of trade credit from the sellers of intermediate inputs.

According to the estimated coefficients, one standard deviation increase in the interest rate variation of the firm reduces the AR variation by 3 percentage points. One standard deviation increase in the interest rate variation of the clients increases the AR variation by approximately 1 percentage point.

In the next section, we provide a theory of trade credit that explains this evidence. A supplier may find it profitable to offer more trade credit as an alternative to bank credit when a client is paying higher interest rates.

[7] For all variables, we excluded top and bottom 5% outliers from the analysis.

Table 2: Effect of bank interest rates on Accounts Receivables

	Δ Accounts Receivables					
	OLS	1st Stage	2nd Stage	OLS	1st Stage	2nd Stage
$\Delta f^c_{n,t}$		0.055***				
		(0.016)				
$\Delta r_{n,t}$	0.009**		-0.166**			
	(0.005)		(0.078)			
$\Delta \bar{f}^c_{n,t}$					0.529***	
					(0.095)	
$\Delta \bar{r}^c_{n,t}$				0.000		0.002**
				(0.001)		(0.001)
firm FE	Y	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y	Y
Observations	2545	2545	2545	3333	3333	3333

Notes: Quarterly data for 2019-2023. Standard errors are clustered at the firm level.

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

3. Model

The economy is static, made of a set N of firms indexed by n. N is partitioned between a set M of large firms and a set I of sector-representative small firms.[8] The total number of firms is $|N|= |I|+|M|$, where $|I|$ is the total number of sectors. Since our balance sheet data on trade credit are only available for listed companies, the small firms should be seen as a representation of the rest of the economy. Intermediate goods are used as inputs for the production of other intermediate goods and for the production of a final consumption good. A representative final firm aggregates the sectoral goods into the final one according to:

$$Q = \prod_{n \in N} (q_n)^{\psi_n}, \quad \text{with} \quad \sum_{n \in N} \psi_n = 1. \tag{4}$$

Below, we describe in detail the problem of an intermediate firm.

[8]This is only going to be relevant in our calibration.

3.1. The problem of an intermediate firm

Each firm n is identified by a specific production technology and a position in the production network. We assume the structure of the input-output network is exogenous. A firm n sells to a subset of firms $N_n \in N$ of firms and purchases from a subset of firms $N^n \in N$. This firm produces according to the following Cobb-Douglas production function:

$$y_n = a_n (h_n)^{\alpha_n} \prod_{m \in N^n} (x_m^n)^{\sigma_m^n}, \tag{5}$$

where h_n is the labor hired by the firm n and x_m^n is the amount of intermediate goods that firm n purchases from firm m. In terms of notation, subscripts refer to sellers, while superscripts refer to buyers. The parameter σ_m^n is the share of intermediate inputs that firm n purchases from firm m.

In order to introduce a role for credit, we assume that there exists a timing friction between the payment of the inputs and the payment received from sales. Specifically, firms face a working capital constraint:

$$\sum_{m \in N^n} (1 - \theta_m^n) p_m^n x_m^n + w_n h_n \leq \sum_{m \in N_n} \kappa_n (1 - \theta_n^m) p_n^m x_n^m + \kappa_n p_n^F q_n + D_n. \tag{6}$$

On the left-hand side, we have the total advanced payment of inputs. θ_m^n, with $0 \leq \theta_m^n \leq 1$, is the share of goods sold by firm m to firm n on which firm m allows for a delayed payment. On the right-hand side, there is the total payment that the firm n obtains in advance from sales plus the amount of bank credit. Notice that the firm can discriminate its price across each intermediate client, p_n^m, and final buyers, p_n^F. θ_n^m is the share of trade credit offered by firm n to firm m. These shares are endogenously chosen by the firms. κ_n, with $0 \leq \kappa_n \leq 1$, is a parameter representing the looseness of the working capital constraint. This parameter should be interpreted as a technological restriction on the ability of the firm to readily obtain payments from sales to finance the purchase of inputs.[9] D_n is the amount of bank credit obtained by firm n.

When offering trade credit, a firm must pay a monitoring cost:

$$c_n (\theta_n^m)^\gamma \left(\theta_n^m p_n^m x_n^m\right) = c_n (\theta_n^m)^{1+\gamma} p_n^m x_n^m. \tag{7}$$

This cost increases in the total amount of trade credit offered by the firm n, $\theta_n^m p_n^m x_n^m$.

[9] In our calibration, we assume the κ are sector-specific.

Moreover, it also depends on the share of trade credit out of total sales through the term $(\theta_n^m)^\gamma$, with $\gamma > 1$. This second term implies that it is costlier to get full repayment for the same value of trade credit if it represents a higher share of the total sales. This convexity in the cost of trade credit also guarantees an interior optimal solution for θ_n^m. Finally, the cost proportionally depends on a parameter c_n, with $0 < c_n < 1$, which captures how the good is physically suited for recollection.

Each firm n is also identified by a specific bank interest rate, r_n. We treat the financial sector as exogenous to the model. Consider that banks have large pockets, are risk-neutral, and can invest in an alternative technology paying return r. The dispersion in interest rates is explained by two factors. Each firm has an exogenous probability of default. With probability $(1 - \pi_n)$, a firm has the chance not to repay its obligations to the banks and its suppliers at no cost. In addition, firms may have to pay different interest rates for reasons unrelated to risk. Banks may have to pay a cost ζ_n for each unit of credit when lending to a firm n. We associate these additional costs with the presence of frictions between firms and banks. Both the risk and the frictional cost are priced in the interest rate. In equilibrium, it must be:

$$R_n \equiv \pi_n r_n = r + \zeta_n. \tag{8}$$

We define R_n as the expected interest rate paid by firm n. If all firms had the same risk of default, the dispersion in interest rate r_n is completely determined by frictions ζ_n and can be represented by the dispersion of R_n. If the costs ζ_n were identical across firms, so would be the R_n, and the dispersion in interest rates r_n would only depend on the π_n. One main goal of our calibration will be identifying both the π_n and the ζ_n for each firm.

A firm n wants to maximize its expected profits

$$\begin{aligned}\sum_{m \in N_n} \left[(1 - \theta_n^m) + \pi_m \theta_n^m\right] p_n^m x_n^m + p_n^F q_n - w_n h_n - \sum_{m \in N^n} \left[(1 - \theta_m^n) + \pi_n \theta_m^n\right] p_m^n x_m^n \\ - R_n D_n - c_n \sum_{m \in N_n} (\theta_n^m)^{1+\gamma} p_n^m x_n^m, \end{aligned} \tag{9}$$

subject to working capital constraint (6) and technology restriction

$$y_n = \sum_{m \in N_n} x_n^m + q_n. \tag{10}$$

The first line in (9) represents the total sales minus the cost of inputs. A firm m has the chance of defaulting at no cost on both trade credit and bank credit with probability $(1-\pi_n)$. Therefore, a firm n gets upfront payment $(1-\theta_n^m)p_n^m x_n^m$ from a firm m, while the remaining portion $\theta_n^m p_n^m x_n^m$ is only paid with probability π_m. In the second line, we have the cost of bank credit and the monitoring cost of trade credit. Notice that the firm obtains D_n pays r_n with probability π_n. Given $r_n > 0$, the working capital constraint must be binding if $D_n > 0$. Since all the firms in our data have positive short-term debt, we will focus on equilibria in which the working capital constraints are binding for all n.[10]

The intermediate firm chooses h_n, q_n, and D_n as a price-taker. Differently, the markets of inputs for other intermediate goods are decentralized. We assume that each pair of buyer and seller meet and bargain the quantity x_n^m, the price p_n^m, and the level of trade credit θ_n^m specific to that transaction. In the next subsection, we describe the details of this bargaining process.

3.2. Firm-to-firm transactions

Each intermediate seller and intermediate buyer meet in a decentralized fashion. The quantity, the price, and the level of trade credit are determined by Nash bargaining. We assume that at the moment of the bargaining process, the prices, quantities, and levels of trade credit relative to all other intermediate inputs are taken as given. The pair only internalizes that by increasing the amount of goods sold or inputs purchased, they will have to reduce or increase the amount of goods sold to the final good firm and adjust the size of the bank loan. Specifically, the pair maximizes:

$$\left\{ \left[1 + R_n\kappa_n(1-\theta_n^m) - (1-\pi_m)\theta_n^m - c_n\left(\theta_n^m\right)^{1+\gamma}\right] p_n^m x_n^m - (1+R_n\kappa_n)p_n^F x_n^m \right\}^{\beta}$$
$$\left\{ (1+R_m\kappa_m)p_m^F \left(y_m - \sum_{k\in N_m} x_m^k \right) - \left[1 + R_m(1-\theta_n^m) - (1-\pi_m)\theta_n^m\right] p_n^m x_n^m \right\}^{1-\beta}. \tag{11}$$

The quantities inside the curly brackets are, respectively, the surplus of the seller and buyer. These are the differences in expected profits if the transaction occurs or not. β is the bargaining share of the seller.

[10] In order to keep the solution of the model as simple as possible, we are not imposing limited liability constraints. A few firms in our calibration ended up with negative profits, which means they would need some additional exogenous resources to cover the losses. Since the model is intended to capture the role of trade credit in the short-run transmission of financial shocks, we consider this a reasonable simplification.

The optimal x_n^m, θ_n^m, and p_n^m are obtained by taking the first order conditions. The optimal quantity is

$$p_n^F x_n^m = \frac{1 + R_m \kappa_m}{1 + R_m(1-\theta_n^m) - (1-\pi_m)\theta_n^m} \frac{1 + R_n\kappa_n(1-\theta_n^m) - (1-\pi_m)\theta_n^m - c_n\left(\theta_n^m\right)^{1+\gamma}}{1 + R_n\kappa_n} \sigma_n^m p_m^F y_m. \quad (12)$$

The optimal level of trade credit solves the following equation:

$$\frac{R_n\kappa_n + (1-\pi_m) + c_n(1+\gamma)\left(\theta_n^m\right)^{\gamma}}{1 + R_n\kappa_n(1-\theta_n^m) - (1-\pi_m)\theta_n^m - c_n\left(\theta_n^m\right)^{1+\gamma}} = \frac{R_m + (1-\pi_m)}{1 + R_m(1-\theta_n^m) - (1-\pi_m)\theta_n^m}. \quad (13)$$

The following Proposition characterizes the solutions for the optimal θ_n^m.

Proposition 1 *The optimal* θ_n^m

- *is equal to 0 if* $R_m < \kappa_n R_n$*;*
- *is equal to 1 if* $R_m > \kappa_n R_n + \left(\gamma + \frac{1+R_m}{\pi_m}\right) c_n$*;*
- $\in (0,1)$ *in any other case.*

If $\theta_n^m \in (0,1)$*, it always decreases in* R_n*, increases in* R_m*, and increases in* π_m*.*
Proof. *See Appendix A.1.* ■

The left-hand side in equation (13) represents the cost elasticity of trade credit. This depends on the cost of tightening the working capital constraint, the risk of losing a larger portion of sales in case of buyer's default, and the monitoring cost. The marginal cost increases in the expected bank interest rate of the supplier R_n. Intuitively, a higher bank interest rate due to higher frictions makes the supply of trade credit more costly. The right-hand side represents the benefit elasticity of trade credit. Trade credit is beneficial for the buyer because it relaxes its working capital constraint and reduces the expected repayment. This benefit increases with a higher expected bank interest rate, R_m. If a client is more financially restricted, its demand is more sensitive to the supply of trade credit. The condition in equation (13) implies that the optimal θ_n^m decreases in R_n and increases in R_m, in line with the results we showed in the empirical section.

The only solution that depends on the bargaining shares and surpluses is the one for the optimal price:

$$p_n^m = \left[\beta\frac{y_m - \sum_{k\in N_m} x_m^k}{\sigma_n^m y_m} + (1-\beta)\right]\frac{1+R_n\kappa_n}{1+R_n\kappa_n(1-\theta_n^m)-(1-\pi_m)\theta_n^m - c_n\left(\theta_n^m\right)^{1+\gamma}}p_n^F. \tag{14}$$

However, these intermediate prices only determine how the profits are distributed across the firms and do not affect the aggregate output. From the formula, it is clear that a seller is willing to offer trade credit since the implicit interest rate is embedded in the price of the good.

3.3. Market clearing

All intermediate good markets clear so that the total production equals the demand from all firms and sectors plus the demand from the final producers:

$$y_n = q_n + \sum_{m\in N_n} x_n^m. \tag{15}$$

The total number of workers is fixed for each sector i and equal to H_i. However, a worker can choose to work in one of the firms inside the sector:

$$H_i = \sum_{n\in S_i} h_n,$$

where S_i is the set of firms in a sector i. In equilibrium, wages inside each sector must be equalized.

3.4. Aggregate output and effect of shocks

Let the Domar weight of a firm n be the total value of the firm's sales as a fraction of aggregate GDP:

$$\lambda_n \equiv \frac{p_n^F y_n}{Q}. \tag{16}$$

We also define the following firm-to-firm distortions affecting the input-output relations among firms:

$$\phi_n^m = \frac{1+R_m\kappa_m}{1+R_m(1-\theta_n^m)-(1-\pi_m)\theta_n^m}\frac{1+R_n\kappa_n(1-\theta_n^m)-(1-\pi_m)\theta_n^m - c_n\left(\theta_n^m\right)^{1+\gamma}}{1+R_n\kappa_n}. \tag{17}$$

Each distortion is composed of two terms. The first one, $\frac{1+R_m\kappa_m}{1+R_m(1-\theta_n^m)-(1-\pi_m)\theta_n^m}$, represents how financial frictions affect the purchasing from the buyer. This term increases in θ_n^m. Moreover, it decreases in r_m (implying higher distortions) if $\theta_n^m < \frac{1-\kappa_m}{1-(1-\pi_m)\kappa_m}$. The second term, $\frac{1+R_n\kappa_n(1-\theta_n^m)-(1-\pi_m)\theta_n^m-c_n(\theta_n^m)^{1+\gamma}}{1+R_n\kappa_n}$, decreases in θ_n^m: it represents the cost of trade credit that the seller is paying. This cost depends on both the interest rate of the seller and the monitoring cost. In particular, the term decreases in r_n (implying higher distortion) if $\theta_n^m < \left(\frac{\pi_m}{c_n}\right)^{\frac{1}{\gamma}}$.[11]

The demand for intermediate inputs from one firm to another can be expressed as a function of distortions and total sales. Specifically, the demand from firm m to firm n can be written as:

$$p_n^F x_n^m = \sigma_n^m \phi_n^m p_m^F y_m. \tag{18}$$

The term ϕ_n^m distorts the value transacted between the seller and the buyer. The optimal θ_n^m solving equation (13) maximizes ϕ_n^m (or minimizes the distortion). Intuitively, the buyer and the seller choose the level of trade credit that maximizes the value of the transaction.

Given the equilibrium distortions, and using (15) and (18), we can find a solution for the Domar weights as a function of distortions and model primitives:

$$\Lambda = \left(\mathbb{I}_{|N|} - \Sigma' \circ \Phi'\right)^{-1}(\psi). \tag{19}$$

Σ is the $|N| \times |N|$ matrix of input-output technological parameters σ_n^m. Φ is the matrix of distortions ϕ_n^m. Finally, ψ is the $|N|$-sized vector of technological shares from the final good production function.

Proposition 2 *The aggregate output is given by*

$$\log Q = \sum_{m\in N} \psi_m \log \psi_m + \underbrace{\sum_{m\in N} \lambda(1)_m \log A_m}_{\text{productivity \& labor allocation}} + \underbrace{\sum_{m\in N} \lambda(1)_m \sum_{n\in N^m} \sigma_n^m \log\left(\sigma_n^m \phi_n^m\right)}_{\text{input}-\text{output distortions}} \tag{20}$$

with

$$A_m = a_m \left(\frac{\frac{1+\kappa_m R_m}{1+R_m}}{\sum_{k\in S_i} \frac{1+\kappa_k R_k}{1+R_k}\lambda_k} \right)^{\alpha_m}, \tag{21}$$

[11]If $\theta_n^m > \frac{1-\kappa_m}{1-(1-\pi_m)\kappa_m}$ ($\theta_n^m > \left(\frac{\pi_m}{c_n}\right)^{\frac{1}{\gamma}}$), a higher interest rate may induce the buyer (seller) to increase the demand (supply) to relax a tighter working capital constraint. In this case, a higher cost of bank credit will increase output. However, the firms' profits will still be lower.

$$\Lambda = \left(\mathbb{I}_{|N|} - \Sigma' \circ \Phi'\right)^{-1} \psi, \tag{22}$$

and

$$\Lambda(1) = \left(\mathbb{I}_{|N|} - \Sigma'\right)^{-1} \psi. \tag{23}$$

The aggregation in equation (20) is quite standard in the production network literature. An important feature of our model is that the distortions ϕ_m^n are endogenous. The term $\sum_{m \in N} \lambda(1)_m \sum_{n \in N^m} \sigma_n^m \log \phi_n^m$ describes the direct negative effect of each seller-buyer distortion on aggregate output. If the α_n were small enough (small labor shares), this term would summarize the role of distortions on aggregate output. In the next Proposition we compare the effect of bank interest rates on aggregate output in our baseline model with respect to a scenario in which trade credit is exogenously shut down ($\theta_n^m = 0$).

Proposition 3 *Consider an equilibrium with* $\theta_n^m < \min\left[\frac{1-\kappa_m}{1-(1-\pi_m)\kappa_m}, \left(\frac{\pi_m}{c_n}\right)^{\frac{1}{\gamma}}\right]$ *(higher interest rates reduce production) and small labor shares* ($\alpha_n \to 0$)*. The presence of trade credit:*

- *smoothes shocks to buyer's expected rate* R_m*;*
- *amplifies shocks to seller's expected rate* R_n*;*
- *amplifies shocks to buyer's risk* π_m*.*

Proof. *See Appendix A.2* ■

The last Proposition says that a negative financial shock to a buyer (higher R_m) can be mitigated if the firm is receiving trade credit. On the contrary, the same shock is amplified when hitting the seller. Since a firm can be a buyer and a seller at the same time, the overall effect of a shock to a firm depends on its position in both the production network and the trade credit network.

The next Proposition describes the benefit of endogenous trade credit with respect to a scenario with fixed levels of θ_n^m.

Proposition 4 *Consider an equilibrium with* $\theta_n^m < \min\left[\frac{1-\kappa_m}{1-(1-\pi_m)\kappa_m}, \left(\frac{\pi_m}{c_n}\right)^{\frac{1}{\gamma}}\right]$ *(higher interest rates reduce production) and small labor shares* ($\alpha_n \to 0$)*. The first-order effects of a change in the expected interest rates* R *are identical if trade credit levels* *can endogenously change or not. Considering second-order effects, output is larger in the endogenous change scenario if*

$$\sum_{m \in N} \lambda(1)_m \sum_{n \in N^m} \sigma_n^m \frac{\pi_m}{[1 + R_m - (1 + R_m - \pi_m)\theta_n^m]^2} \underbrace{\left(-\frac{\partial \theta_n^m}{\partial R_n}\right)}_{\geq 0} R_n \left[(\hat{R}_m)(\hat{R}_n)\right] < 0. \tag{24}$$

Proof. *See Appendix A.3* ■

Proposition 4 shows that the channel of endogenous trade credit adjustment is more relevant when the spread between the interest rates of buyers with respect to their suppliers gets larger.

4. Calibration

The model is calibrated using data for 2019. In addition to the micro-data described in Section 2, we also use data from the Brazilian Statistical Office (IBGE) for 2019. We collapse a 66 sector matrix into 6 sectors, according to Table 3.

Table 3: 6-Sector Structure of the Model

Sector	ISIC 2-Digit Codes	Num. of Firms
Commodities	01 - 09	3
Manufacturing	10 - 33	15
Utilities	35 - 40	12
Construction	41 - 44	4
Trade	45 - 48	9
Services	49 - 96	7

Note: Sectors are defined following the 2-digit International Standard Industrial Classification of All Economic Activities (ISIC).

We simulate our model with the 50 largest Brazilian publicly traded firms. The distribution of firms by sector is shown in Table 3. We include one representative small firm per sector, bringing the total number of firms to 56. We assume that the level of trade credit offered by a representative firm is exogenous.

We use the aggregate data from IBGE to estimate the technology parameters of the small sector-representative firms. Labor shares α, sector expense shares σ, and final demand shares ψ are computed from the input-output matrix provided by

IBGE. Labor shares are computed by dividing total labor cost (wages and payments) by the sector's total cost.

We use the transaction data from the Central Bank of Brazil (described in Section 2.1) to estimate the final demand shares ψ_n and the technology parameters of the 50 large firms.

To obtain the firm shares σ_m^n, we first divide firm m's purchases from each firm n by their total purchases. Let s_m^n denote this share. For small firms, we assume they use the same share for all firms in a sector, such that the sum of shares in one sector equals the sectoral share in the IO matrix. We then calculate σ_m^n such that they satisfy the following equations:

$$s_m^n = \frac{\phi_m^n \sigma_m^n}{\sum_m \phi_m^n \sigma_m^n}$$
$$\sum_m \sigma_m^n = 1 - \alpha_n$$

The interest rates r_n are obtained from the credit registry of the Central Bank of Brazil. For each company, we compute the weighted average of the interest rates referring to all short-term credit contracts. For each sector-representative firm, we compute the weighted average interest rates of all firms in the sector (excluding the 50 large companies).

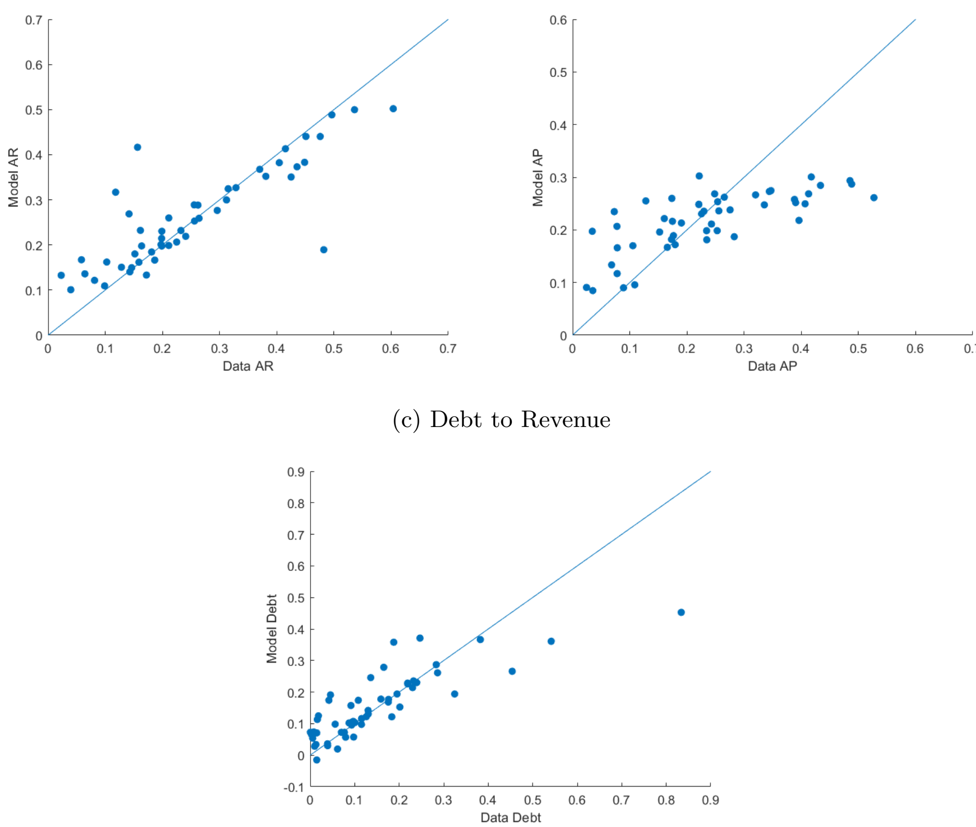
Parameters κ_n, c_n, γ, π_n, and the (exogenous) θ^S offered by the representative small firms are estimated such that trade credit levels in the model match the data. The moments we use to measure trade credit are the shares of accounts receivable and accounts payable over total current assets. These data are available from public firms' balance sheet data (Economatica) for the 50 listed companies. We also match the debt-to-revenue shares of the firms. These values are computed using the data from the credit registry and the firms' income statements. We use the mean shares from 2019Q1 to 2019Q4. In the model, AR shares are calculated as

$$AR_n = \frac{\sum_m \theta_n^m p_n^m x_n^m}{p_n^F y_n}$$

While AP shares are given by

$$AP_n = \frac{\sum_m \theta_m^n p_m^n x_m^n}{p_n^F y_n}$$

Debt-to-revenue is $D_n/(p_n^F y_n)$.



(a) Acc Receivable (b) Acc Payable (c) Debt to Revenue

Figure 3: Model fit of TC shares and debt

We assume that the c and π are firm-specific, while the κ are sector-specific. θ^S are specific to the sector-sector link, such that there is a SxS matrix of θ^S. Figure 3 shows the fit between the model shares and the data shares, Table 4 presents the estimated κ parameters for each sector, and Figure 4 shows the distribution of the estimated c and π. We restrict κ to be between 0 and 0.8, π between 0 and 1, and θ between 0 and 0.7 for small firms. The estimated γ is 2.56.

One main goal of our calibration is identifying what drives the dispersion in observed interest rates r_n. In our model, we distinguish between two possible forces (recall equation (8)): risk and frictions. Our identification strategy relies on the fact that the default risk of a firm is priced by both banks and intermediate good suppliers offering trade credit. When an observed higher bank interest rate is associated with low Accounts Payable and low Accounts Receivable on the suppliers' side, our estimation procedure assigns a higher role to risk. If, instead, a higher bank interest rate is associated with higher shares of trade credit from the suppliers, we attribute

Table 4: Estimated Parameters

Sector	κ
Commodities	0.8
Manufacturing	0.77
Utilities	0.79
Construction	0.58
Trade	0.75
Services	0.68

(a) c (b) π

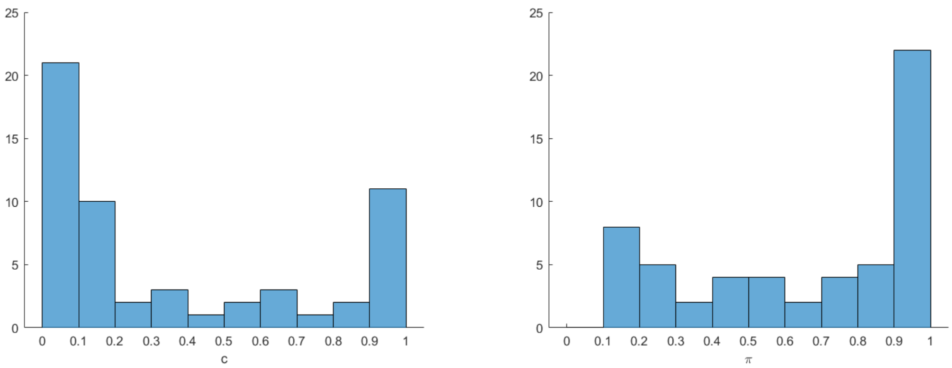


Figure 4: Estimated Parameter Distribution

a higher value to frictions. Figure 5 shows the difference between the distribution of observed interest rates r_n and estimated R_n (financial frictions) for the 50 large companies. If risk was the only driver, all R_n would be identical.

Figure 13, in the Appendix, shows how the optimal θ_n^m of a firm negatively depends on its interest rate and positively depends on the interest rate of a client. The figure reports this relation for a selected pair of firms (specifically, the seller is a large firm from Manufacturing while the buyer is a small representative firm from Service). Results are qualitatively similar for any other pair.

5. Illustrating the role of trade credit in shock transmission

In this section, we graphically analyze how trade credit can mitigate or amplify the effect of negative financial shocks.

Recall Equation (17), which shows the expression for the distortion in a link

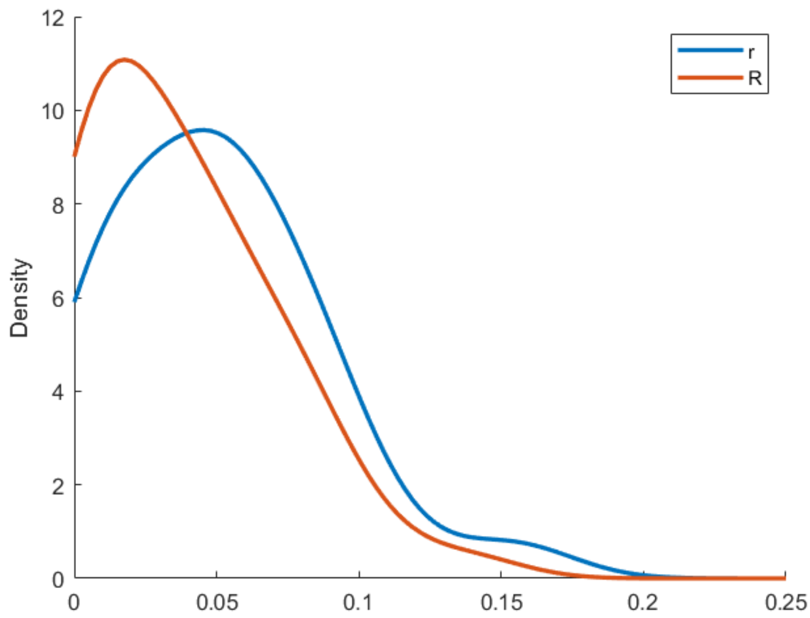


Figure 5: Kernel density of observed r_n and estimated R_n.

between two firms. The first term, $\frac{1+R_m\kappa_m}{1+R_m(1-\theta_n^m)-(1-\pi_m)\theta_n^m}$, is the buyer-side distortion, which arises from the working capital constraint. Here, trade credit presents an upside to the firm by relaxing its financial constraint and allowing it to purchase more. In contrast, $\frac{1+R_n\kappa_n(1-\theta_n^m)-(1-\pi_m)\theta_n^m-c_n(\theta_n^m)^{1+\gamma}}{1+R_n\kappa_n}$ is the seller-side distortion. It represents the cost of trade credit to the supplier, which is then passed to the client in the form of a markup. Thus, the downside of trade credit for a buyer is facing higher prices from the supplier.

Figure 6 plots the value of the distortion for different values of θ_n^m, along with the values of the buyer and seller-side components. Starting from a low level of trade credit, for a marginal increase in θ_n^m, the demand (buyer-side) effect dominates. However, for large values of trade credit, higher costs outweigh the benefits, and the curve slopes downward. The first-order condition in Equation (13) means that the supplier chooses the amount of trade credit that maximizes the value of ϕ_n^m, thus maximizing sales.

Now, we consider how trade credit affects the transmission of interest rate shocks. Consider an increase to the interest rate of the buyer for a given level of risk π_m (pictured in Figure 7a). This causes the buyer-side term of the distortion to shift down. Without trade credit, this represents a shift from point A to A'. With trade

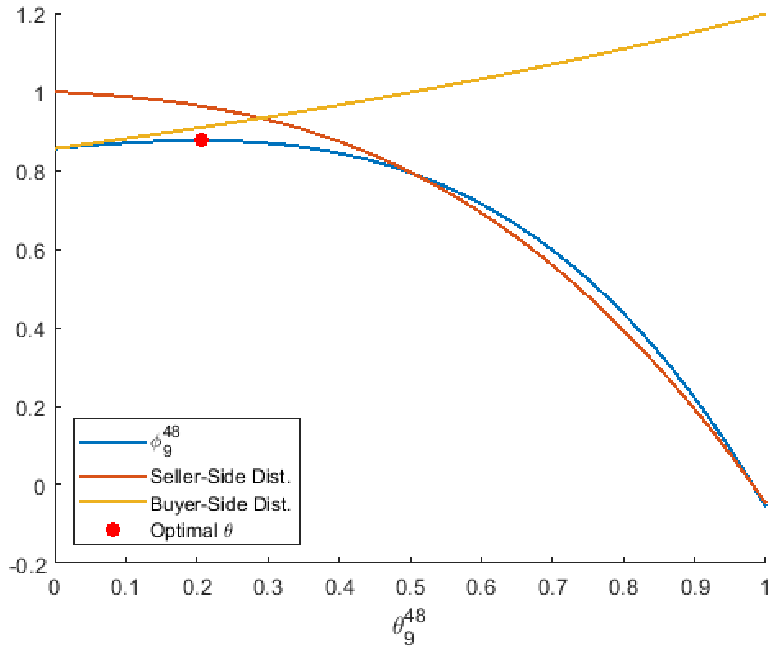


Figure 6: Plot of ϕ_9^{48} against θ_9^{48}

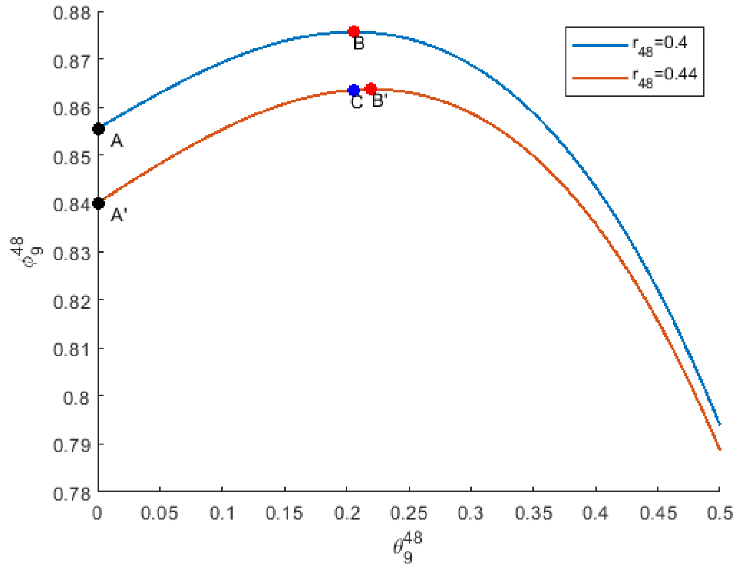
credit, however, the shift is from B to B'. The change in the distortion is lower than with $\theta_n^m = 0$, which means trade credit mitigates the effects of financial shocks, in line with Proposition 3. If trade credit was kept fixed, then the shift would be from B to C, which represents a larger loss than from B to B'. There is an additional mitigation effect stemming from the endogenous movement of trade credit.

In Figure 7b, we consider an interest rate increase for the seller. In the scenario where $\theta_n^m = 0$, there is no change in the distortion. With trade credit, however, higher financing costs for the supplier are passed on to the clients. In this case, the distortion shifts from B to B', and shocks are amplified compared to the economy without trade credit, in line with Proposition 3. However, the endogenous adjustment does mitigate some of this effect, as the loss in distortion from B to B' is lower than from B to C.

6. Numerical Exercises

In this section, we use our calibrated model to run a few numerical exercises. We start analyzing the effect of increasing the expected interest rate R_n of a firm one by one , which is an increase in the financial friction, on the aggregate output. We

(a) Int. Rate Shock to Buyer



(b) Int. Rate Shock to Seller

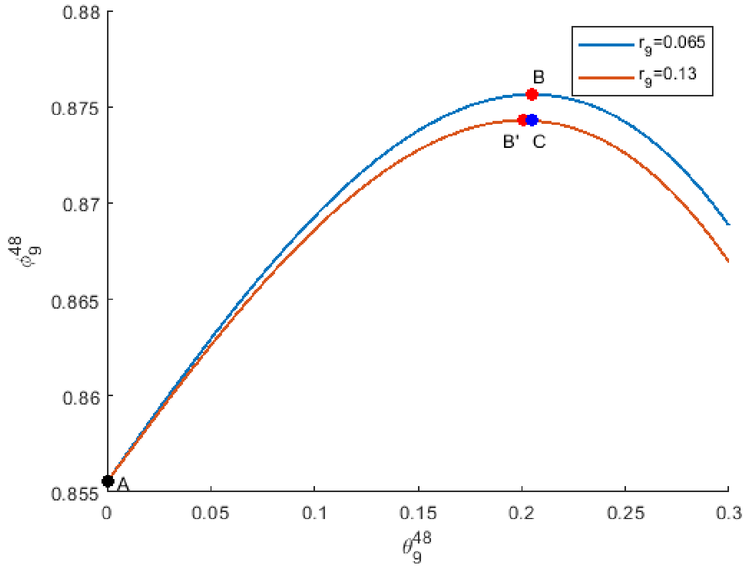


Figure 7: Effects of interest rate increases on ϕ_9^{48}

increase each firm-level interest rate by a factor $\frac{0.001}{\lambda_n}$. Figure 8 compares the effect on the total output of the same shock in our baseline model against the scenario in which the levels of trade credit are exogenously set at 0. In almost all cases, trade credit smoothes the negative effect of the shock. In some cases the effect with endogenous trade credit is actually positive. As discussed in Section 3.4, these are the cases in which a higher cost of bank credit pushes the firm to produce or demand more in order to counterbalance a tighter working capital constraint. In a few cases, the negative effect of the shock is larger in the scenario with trade credit. These are firms that are upstream in the supply chain and are large suppliers of trade credit. An increase in the expected interest rate of these firms reduces their supply of trade credit. The resulting amplification is not offset by the increase in trade credit supply by the suppliers of these firms.

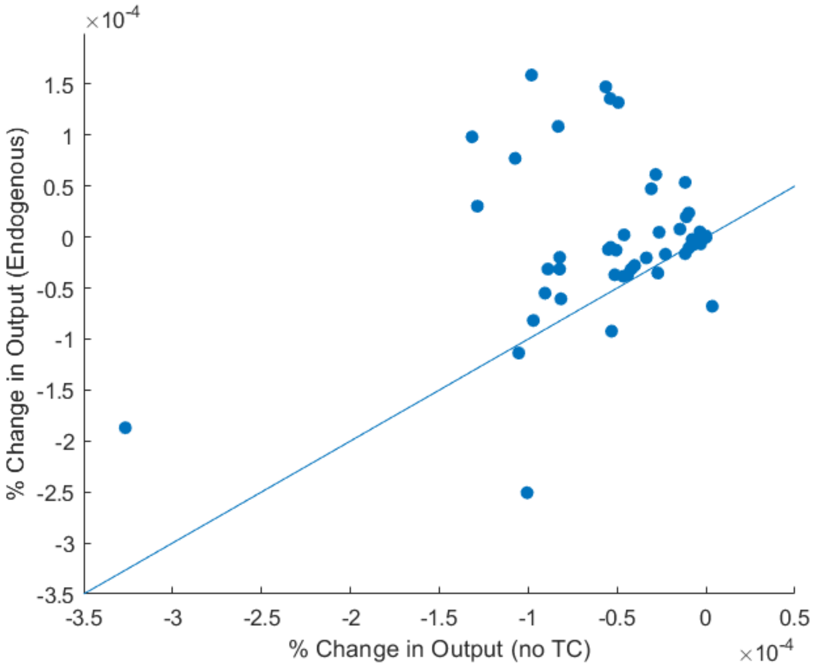


Figure 8: Output change after an increase to firm-specific R_n: endogenous trade credit VS no trade credit.

In Figure 9, we replicate the same exercise, this time computing the effect on the aggregate welfare of firms and workers. This is the aggregate output minus the sum of all expected credit repayment and the sum of all monitoring costs. Now, there are no positive effects after an increase in interest rates. The welfare loss is still lower without trade credit in the few cases of large suppliers of trade credit.

Next, we will use our 2019 calibration to investigate the role of trade credit in the following years. Specifically, we feed the model with the observed cross-section of interest rates $r_{n,t}$ in 2020, 2021, 2022, and 2023.[12] The goal is re-estimating the

[12]We also calibrate aggregate productivity for each year such that yearly output growth matches Brazil's GDP

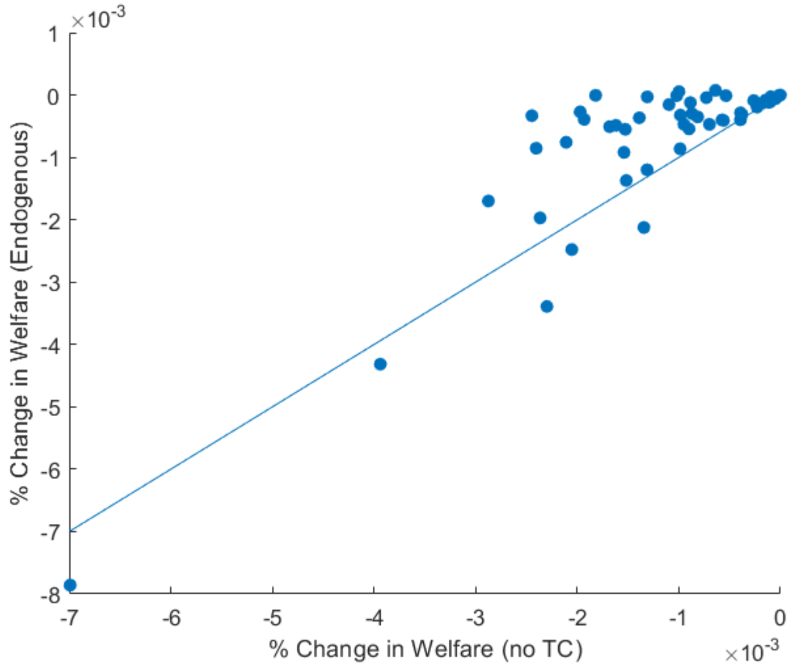


Figure 9: Welfare change after an increase to firm-specific R_n: endogenous trade credit VS no trade credit.

$\pi_{n,t}$ and the $R_{n,t}$ for each year, keeping all other parameters constant at 2019 levels. In order to obtain new cross-sections of $\pi_{n,t}$ (and then compute $R_{n,t} = \pi_{n,t} r_{n,t}$), we re-calibrate the model using the AR and AP shares as targeted moments in each year.

In Appendix B, we report the evolution of output (figure 14) and welfare (figure 15) in the baseline case with endogenous trade credit, the case in which trade credit is constant 2019 levels, and the case with no trade credit. In Figure 16, we compute the additional growth due to the presence of trade credit. Without trade credit, GDP growth from 2020 to 2023 would have been 2% lower.

In figure 10, the blue line reports the relative evolution of accumulated output growth in the baseline scenario with endogenous adjustment of trade credit with respect to the case in which all the θ_n^m are kept constant at 2019 levels. Endogenous trade credit was beneficial for the economy after 2021, while output growth from 2020 to 2021 was higher in the scenario with constant trade credit. To explore the reasons for this result, in the same figure, we report the results of two additional exercises. The orange line shows the relative output growth in the case in which we fix all the

growth in the baseline scenario with endogenous trade credit.

π_n at the 2019 levels, while expected interest rates are $R_{n,t} = \pi_n r_{n,t}$, with $r_{n,t}$ being the observed year-specific firm-level interest rates. In this exercise, we attribute all the changes in the interest rates to changes in financial frictions. The yellow line shows instead the relative output growth if we fixed the R_n at 2019 levels and set $\pi_{n,t} = \frac{R_n}{r_{n,t}}$. Here, we attribute all the changes in observed interest rates to changes in risk. Considering these two extreme cases helps us understand what drives the changing importance of trade credit endogenous adjustments. Changes in the blue line are closer to those of the orange one, suggesting that the relevance of endogenous trade credit is mostly related to changes in the dispersion of expected interest rates R_n (or financial frictions).

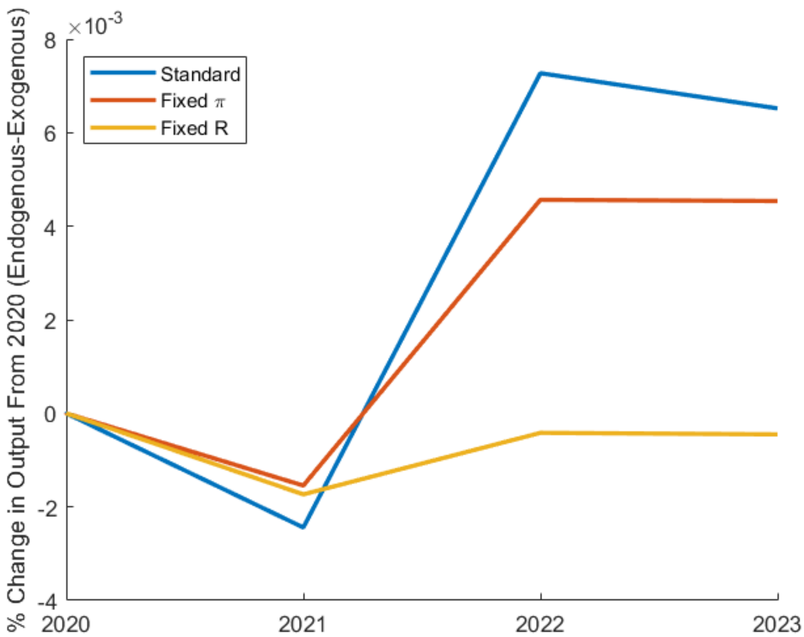


Figure 10: Relative evolution of accumulated output growth (2020-2023): endogenous trade credit scenario relative to constant trade credit scenario. The π_n and R_n are re-calibrated for the baseline endogenous case using data on interest rates and trade credit for each year. All remaining parameters are kept constant at 2019 levels.

Our conjecture is confirmed once we look at the evolution of the estimated $R_{n,t}$ in our baseline case. Figure 11 shows the positive correlation between the relative output growth and the standard deviation of estimated $R_{n,t}$ in every year. [13]

Interest rates in Brazil started to increase in 2021. Our estimated dispersion of R_n

[13]Figures 17 and 18 in the Appendix report the averages and standard deviations of both the $R_{n,t}$ and the $\pi_{n,t}$.

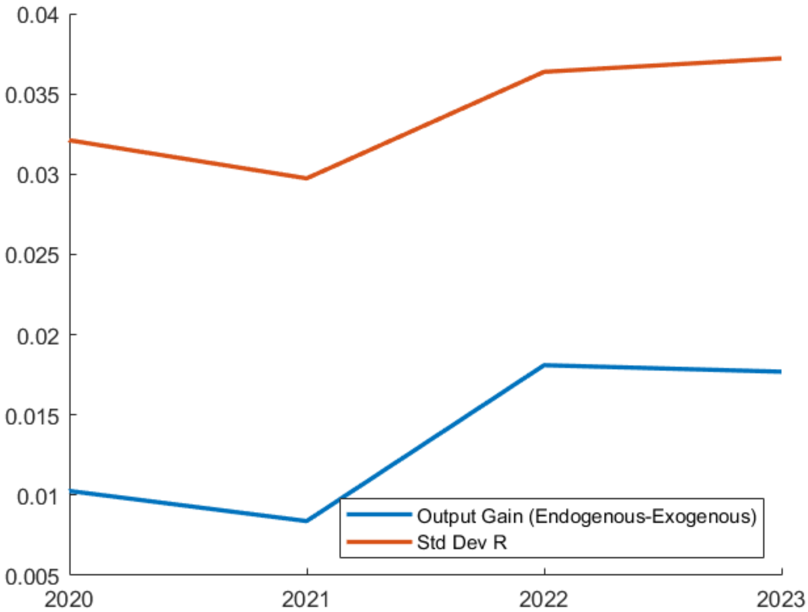


Figure 11: Relative evolution of accumulated output growth (endogenous VS constant) and standard deviation of estimated R_n in the baseline scenario. The π_n and R_n are re-calibrated for the baseline endogenous case using data on interest rates and trade credit for each year. All remaining parameters are kept constant at 2019 levels.

also increased from 2021 to 2023. In line with Proposition 4, endogenous adjustments in the network of trade credit are more important when financial frictions are more dispersed so that large suppliers pay relatively lower interest rates. Figure 12 shows that the buyer-seller spread in R_n increased after 2021 for most of the large firms in our calibration.

7. Conclusion

This paper developed a model of endogenous trade credit in a multi-firm network environment with interest rate dispersion and input-output linkages. Firms choose prices, quantities, and optimal levels of trade credit via Nash bargaining in decentralized markets. Bank interest rates are heterogeneous for two reasons: default risk and financial frictions. Those firms facing lower frictions provide trade credit to firms facing higher frictions. This is in line with empirical evidence showing that, in Brazil, large firms that receive bank credit at a lower cost are net providers of trade credit.

We calibrated the model using Brazilian firm-to-firm transaction data and firm-

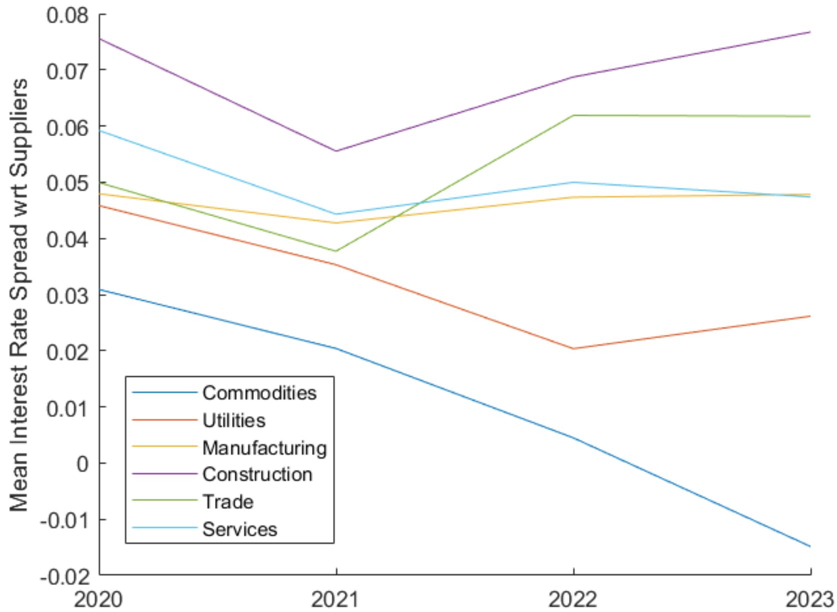


Figure 12: Weighted average spread of R_n between buyers and sellers by sector of sellers (2020-2023). The π_n and R_n are re-calibrated for the baseline endogenous case using data on interest rates and trade credit for each year. All remaining parameters are kept constant at 2019 levels.

level credit data and identified the risk and the friction component of bank interest rates across different firms. Trade credit usually mitigates the effect of negative financial shocks but can amplify shocks to upstream firms that are large suppliers of trade credit. We find that the endogenous adjustment of trade credit in the network of firms has been beneficial for the economy during the last few years, given the increasing role of financial frictions in interest rate dispersion. In particular, trade credit explains 2% of the output growth between 2020 and 2023.

Our findings also open up questions for future research. In the model, bank interest rates are exogenous. However, both the risk and the friction components can be endogenized after explicitly modeling a banking sector. In such an environment, banks' loan decisions may interact with firms' trade credit decisions. An important question is if, and to which extent, this interaction could also affect the pass-through of monetary policy.

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A. Proofs

A.1. Proof of Proposition 1

Equation (13) can be simplified as:

$$c_n \left[(1+R_m)(1+\gamma)\left(\theta_n^m\right)^\gamma - (1+R_m-\pi_m)\gamma\left(\theta_n^m\right)^{1+\gamma}\right] = (R_m - R_n\kappa_n)\pi_m. \quad (25)$$

The left-hand side increases in θ_n^m. The minimum value is 0 for $\theta_n^m = 0$. Therefore, the optimal θ_n^m must be 0 if the right-hand side is negative. This occurs if $R_m < R_n\kappa_n$. The maximum value of the left-hand side is $(1+R_m+\gamma\pi_m)c_n$ at $\theta_n^m = 1$. The optimal θ_n^m is 1 if $R_m > \kappa_n R_n + \left(\gamma + \frac{1+R_m}{\pi_m}\right) c_n$. For $0 < \theta_n^m < 1$ it is:

- $\frac{\partial\theta_n^m}{\partial R_n} = -\frac{\kappa_n\pi_m}{c_n\gamma(1+\gamma)(\theta_n^m)^{\gamma-1}[(1+R_m)-(1+R_m-\pi_m)\theta_n^m]} < 0;$
- $\frac{\partial\theta_n^m}{\partial R_m} = \frac{1+R_n\kappa_n-\pi_m+c_n(1+\gamma)(\theta_n^m)^\gamma}{1+R_m-\pi_m}\left(-\frac{1}{\kappa_n}\frac{\partial\theta_n^m}{\partial R_n}\right) > 0;$
- $\frac{\partial\theta_n^m}{\partial\pi_m} = \frac{R_m-R_n\kappa_n-c_n\gamma(\theta_n^m)^{1+\gamma}}{c_n\gamma(1+\gamma)(\theta_n^m)^{\gamma-1}[(1+R_m)-(1+R_m-\pi_m)\theta_n^m]} > 0.$

A.2. Proof of Proposition 3

The first-order approximation of the term $\sum_{n\in N}\lambda(1)_n\sum_{m\in N^n}\sigma_m^n\log\left(\sigma_m^n\phi_m^n\right)$ from the aggregate output in equation (20) is

$$\sum_{m\in N}\lambda(1)_m\sum_{n\in N^m}\sigma_n^m\left[\underbrace{\left(\frac{\partial\phi_n^m}{\partial R_m}\frac{R_m}{\phi_n^m}\right)}_{\equiv\epsilon(\theta_n^m)_{R_m}}\hat{R}_m + \underbrace{\left(\frac{\partial\phi_n^m}{\partial R_n}\frac{R_n}{\phi_n^m}\right)}_{\equiv\epsilon(\theta_n^m)_{R_n}}\hat{R}_n + \underbrace{\left(\frac{\partial\phi_n^m}{\partial\pi_m}\frac{\pi_m}{\phi_n^m}\right)}_{\equiv\epsilon(\theta_n^m)_{\pi_m}}\hat{\pi}_m\right], \quad (26)$$

with

- $\epsilon(\theta_n^m)_{R_m} = \frac{\kappa_m[1-(1-\pi_m)\theta_n^m]-(1-\theta_n^m)}{1+R_m-(1+R_m-\pi_m)\theta_n^m}\frac{1}{1+\kappa_m R_m};$
- $\epsilon(\theta_n^m)_{R_n} = \frac{\kappa_n\left[c_n(\theta_n^m)^{1+\gamma}-\pi_m\theta_n^m\right]}{1+\kappa_n R_n-(1+R_n\kappa_n-\pi_n)\theta_n^m-c_n(\theta_n^m)^{1+\gamma}}\frac{1}{1+\kappa_n R_n};$
- $\epsilon(\theta_n^m)_{\pi_m} = \left(\frac{1}{1+\kappa_n R_n-(1+R_n\kappa_n-\pi_n)\theta_n^m-c_n(\theta_n^m)^{1+\gamma}} - \frac{1}{1+R_m-(1+R_m-\pi_m)\theta_n^m}\right)\theta_n^m.$

Given $\theta_n^m < \min\left[\frac{1-\kappa_m}{1-(1-\pi_m)\kappa_m}, \left(\frac{\pi_m}{c_n}\right)^{\frac{1}{\gamma}}\right]$, it is $\epsilon(0)_{R_m} < \epsilon(\theta_n^m)_{R_m} < 0$, $\epsilon(\theta_n^m)_{R_n} < \epsilon(0)_{R_n} = 0$, and $\epsilon(\theta_n^m)_{\pi_m} > \epsilon(0)_{\pi_m} = 0$.

A.3. Proof of Proposition 4

Since the chosen θ_n^m maximizes ϕ_n^m, the first-order effects of a change in R_n or R_m on ϕ_n^m must be identical if the θ_n^m are allowed to adjust or not (by the implicit function theorem).

The quadratic term of the second-order approximation of

$$\sum_{n\in N}\lambda(1)_n\sum_{m\in N^n}\sigma_m^n\log\left(\sigma_m^n\phi_m^n\right)$$

is augmented in the case with endogenous trade credit by:

$$\begin{aligned}\sum_{m\in N}\lambda(1)_m\sum_{n\in N^m}\sigma_n^m\underbrace{\frac{\epsilon(\theta_n^m)_{R_m}}{\partial\theta_n^m}}_{>0}\underbrace{\frac{\partial\theta_n^m}{\partial R_m}}_{\geq 0}R_m(\hat{R}_m)^2\\
+\sum_{m\in N}\lambda(1)_m\sum_{n\in N^m}\sigma_n^m\underbrace{\frac{\epsilon(\theta_n^m)_{R_n}}{\partial\theta_n^m}}_{<0}\underbrace{\frac{\partial\theta_n^m}{\partial R_n}}_{\leq 0}R_n(\hat{R}_n)^2\\
-\sum_{m\in N}\lambda(1)_m\sum_{n\in N^m}\sigma_n^m\underbrace{\frac{\epsilon(\theta_n^m)_{R_m}}{\partial\theta_n^m}}_{>0}\underbrace{\left(-\frac{\partial\theta_n^m}{\partial R_n}\right)}_{\geq 0}R_n\left[(\hat{R}_m)(\hat{R}_n)\right],\end{aligned}\tag{27}$$

with

$$\frac{\epsilon(\theta_n^m)_{R_m}}{\partial\theta_n^m}=\frac{\pi_m}{[1+R_m-(1+R_m-\pi_m)\theta_n^m]^2}.$$

If the last line in (27) is positive, the entire expression is positive.

B. Additional figures

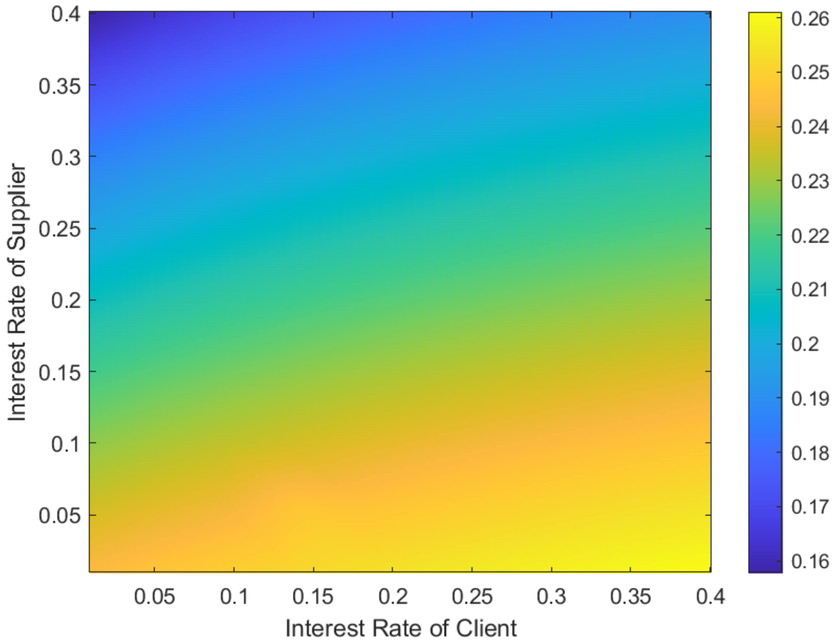

Figure 13: Optimal trade credit given interest rate of supplier and client. Seller is a large firm from Manufacturing, buyer is a representative small firm from Service.

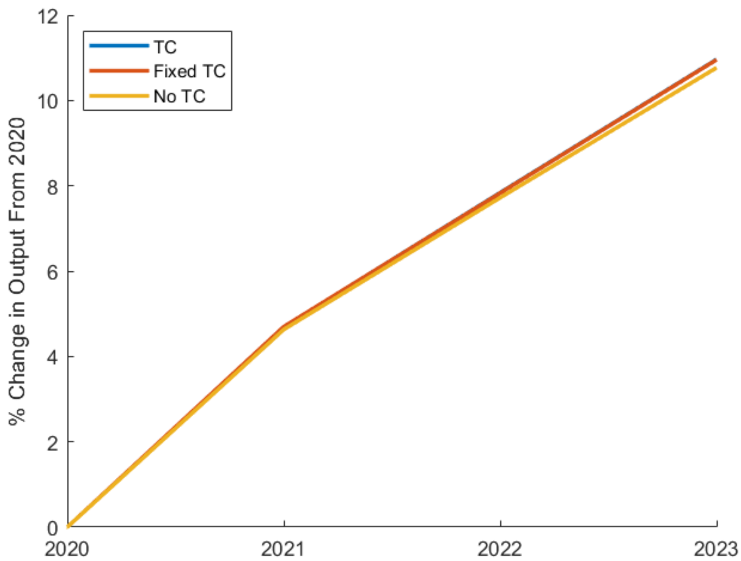

Figure 14: Evolution of accumulated output growth (2020-2023). The π_n and R_n are re-calibrated using data on interest rates and trade credit for each year. All remaining parameters are kept constant at 2019 levels.

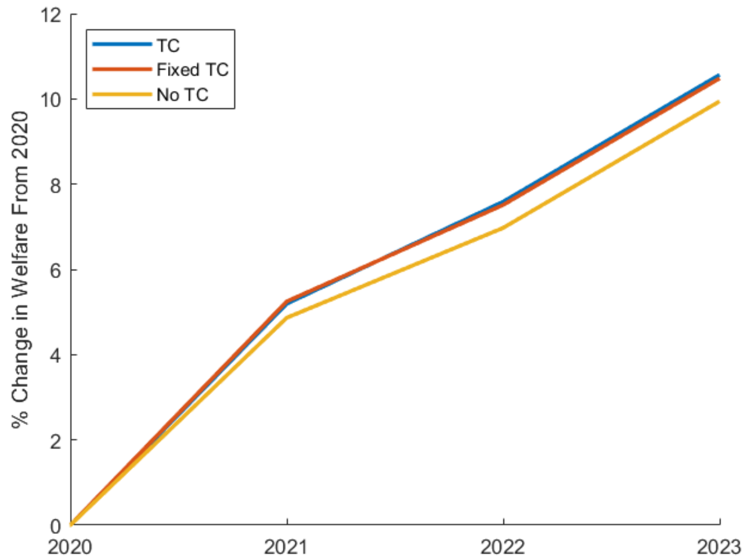

Figure 15: Evolution of accumulated welfare growth (2020-2023). The π_n and R_n are re-calibrated using data on interest rates and trade credit for each year. All remaining parameters are kept constant at 2019 levels.

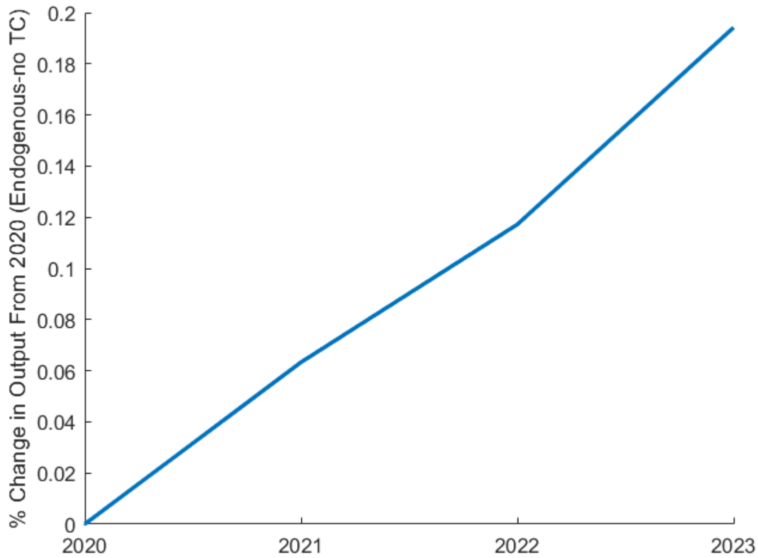

Figure 16: Additional growth in the baseline model with respect to model with no trade credit (2020-2023). The π_n and R_n are re-calibrated using data on interest rates and trade credit for each year. All remaining parameters are kept constant at 2019 levels.

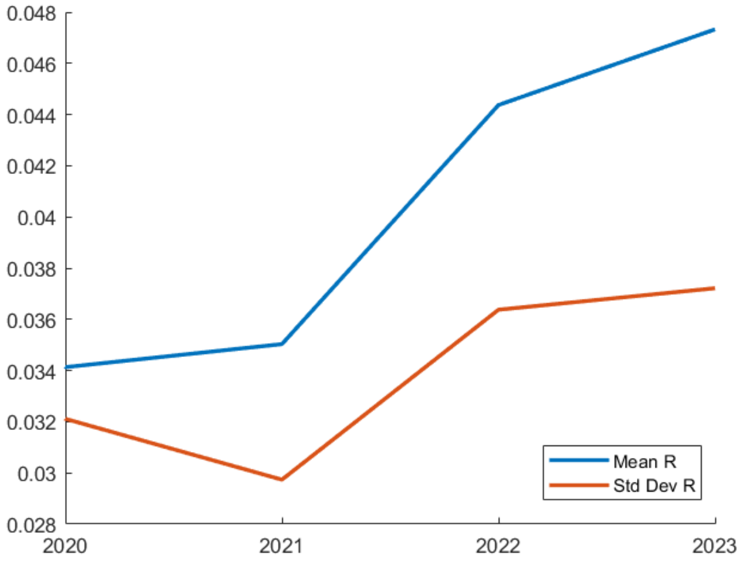

Figure 17: Evolution of average and standard deviation of estimated R_n (2020-2023). The π_n and R_n are re-calibrated using data on interest rates and trade credit for each year. All remaining parameters are kept constant at 2019 levels.

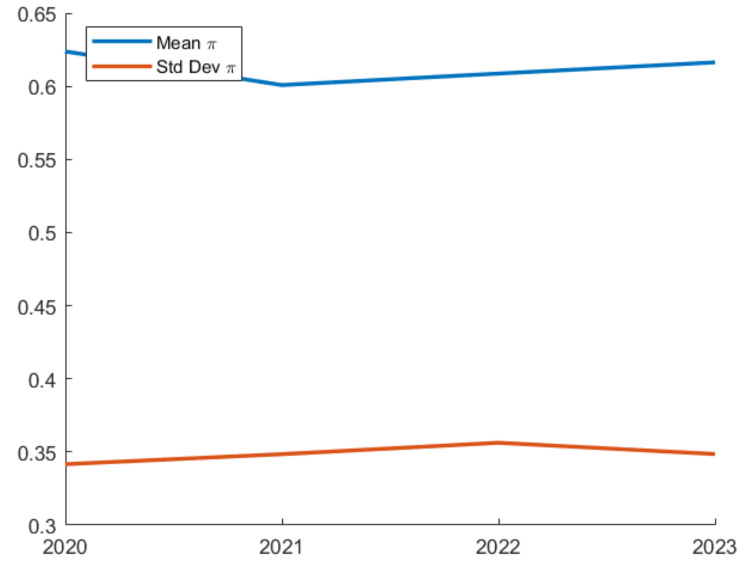

Figure 18: Evolution of average and standard deviation of estimated π_n (2020-2023). The π_n and R_n are re-calibrated using data on interest rates and trade credit for each year. All remaining parameters are kept constant at 2019 levels.