# Aggregate Fluctuations and the Role of Trade Credit*

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October, 2024

**Abstract**

This paper studies the aggregate implications of trade credit in a dynamic, general equilibrium model where heterogeneous entrepreneurs choose their lending and borrowing of trade credit in the presence of financial frictions. Motivated by empirical evidence, the model shows how trade credit flows from less constrained firms to more constrained ones, both in the cross-sectional distribution and in firms' response to heterogeneous financial shocks. In the face of an aggregate financial shock, entrepreneurs reduce their trade credit lending, further tightening their customers' borrowing constraints, resulting in an amplification of the initial shock. In contrast, when the financial shock only affects some, but not all, entrepreneurs, trade credit facilitates the flow of financing to entrepreneurs in financial distress, thereby mitigating its negative impacts. This mechanism, however, is only effective when the shock affects a sufficiently small number of entrepreneurs.

**JEL codes**: E23, E44, G32.
**Keywords**: Trade credit, firm heterogeneity, financial crisis, financial frictions.

*I thank Simon Alder, Jan Auerbach, Costas Azariadis, Brian Bergfeld, Filippo Brutti, Julieta Caunedo, V. V. Chari, Kaiji Chen, Yuko Imura, Ivan Jaccard (discussant), Nobu Kiyotaki, Oleksiy Kryvtsov, Mina Lee, Rody Manuelli, Bruce Petersen, B. Ravikumar, Yongseok Shin, Faisal Sohail, Zheng Song, Michael Sposi, David Wiczer, Steve Williamson, Emircan Yurdagul, Zhuoyao Zhang, and audiences at the Bank of Canada, University of Surrey, University of Exeter, 7th BoC-ECB research conference, WashU Grad Student Conference, and Econometric Society meetings for comments. Errors are my own. An earlier version of the paper was titled "Trade Credit in Production Chains." Correspondence: Department of International Economic Analysis, Bank of Canada, 234 Wellington Street, Ottawa, ON K1A 0G9, Canada (e-mail: lin.j.shao@gmail.com).

# 1 Introduction

Trade credit – suppliers' lending of inputs to their customers – is an essential source of financing for U.S. firms. In 2006, for instance, total trade credit liabilities (accounts payable) of the non-financial corporate sector were approximately the same size as its monthly value-added output. Moreover, during financial turmoils, declines in trade credit often contribute significantly to the contraction of total credit. For instance, during the 2007-09 financial crisis, approximately 70% of the decrease in short-term liabilities of non-financial corporate firms was attributable to trade credit. Therefore, understanding how firms' trade credit choices are determined, both during normal times and when facing financial shocks, is crucial for understanding how a shock that originated in the financial sector propagates throughout the economy.

In this paper, I document empirical evidence supporting the existence of a financial motive behind firms' trade credit choices. Trade credit flows, in net terms, from less financially constrained firms to more financially constrained ones. Such a pattern is evident in the cross-sectional distribution and in firms' responses to heterogeneous financial shocks. The willingness of entrepreneurs to provide trade credit is sensitive to disruptions in the financial markets, which acts to amplify an aggregate financial shock. I quantify the size of this amplification effect during the 2007-09 financial crisis and show that the decrease in trade credit during the Great Recession can account for 16% of the decline in output. On the other hand, when the financial shock only hits a fraction of entrepreneurs in the economy, trade credit can mitigate its negative impact, provided that the share of affected entrepreneurs is sufficiently small.

The first part of the paper uses the Compustat dataset to establish a relationship between trade credit and firm-level financial constraints. First, in the cross-section, the net lending of trade credit is higher for larger and older firms. This pattern shows an important reallocative role played by trade credit that channels funds to financially constrained firms. Second, the supply (demand) of trade credit decreases (increases) when firms' access to the financial markets is disrupted. I adopt a similar strategy as Chodorow-Reich (2014) by using firms' relationship banks' exposure to Lehman Brothers as an exogenous variation in firms' access to financing in the aftermath of the Lehman bankruptcy. Firms with higher exposure to Lehman – i.e., whose relationship bank syndicated more loans with Lehman – reduced their lending and increased their borrowing of trade credit more than other firms. In other words, trade credit, in net terms, flows to firms experiencing more significant financial shocks.

Motivated by the empirical evidence, I build a quantitative model incorporating two key features: (i) firm heterogeneity in financial constraints and (ii) interaction between trade credit and firms' access to the financial market.

The model features a roundabout production process where the final good can be used as consumption, investment, or intermediate input. There is a continuum of entrepreneurs who differ by wealth and productivity, creating heterogeneity in firms' financial constraints. Trade credit and bank credit coexist, and trade credit flows – together with intermediate input goods – from relatively unconstrained to relatively constrained entrepreneurs. The process also creates collateral (accounts receivable), which the lenders of trade credit can use to obtain bank loans. Hence, trade credit redistributes credit across entrepreneurs with different degrees of financial friction and increases the overall level of credit in the economy.

Despite its minimal structure, the model can replicate both motivating facts. Specifically, it generates a cross-sectional distribution of trade credit across firm sizes consistent with empirical evidence. In addition, the model predicts trade credit flows from entrepreneurs experiencing less severe financial shocks to those experiencing more severe shocks, consistent with the pattern observed following the bankruptcy of Lehman Brothers.

I use a calibrated version of the model to evaluate the aggregate implications of trade credit quantitatively. First, I show that the presence of trade credit in the model economy significantly improves the allocative efficiency across entrepreneurs. In the steady state, aggregate productivity is 10.9% higher in the benchmark economy relative to a counterfactual economy without trade credit, as credit facilitates the redistribution of credit from less financially constrained to those with tighter financial conditions. In addition, even if I increase bank credit in the counterfactual economy so that the aggregate debt-to-capital ratio is equal across the two models, aggregate productivity is 3.3% lower in the counterfactual economy than in the benchmark model. This suggests that trade credit performs better than bank credit in financing the most constrained entrepreneurs. Indeed, in the benchmark economy, high-productivity entrepreneurs produce a larger share of aggregate output, despite having a lower wealth share than in the counterfactual economy.

Next, I use the model to quantify the role of trade credit in a financial crisis. To generate a financial crisis of plausible magnitude, I introduce a shock process to the collateral constraints of *all* entrepreneurs, such that the model delivers the same magnitude decrease in aggregate credit market liabilities and accounts receivable upon impact as observed in the 2007–09 financial crisis. I find an amplification effect by endogenous changes in trade credit as a response to the tightening credit constraint. In particular, the fall in output following the financial shock is 16 percent larger in my benchmark economy relative to the counterfactual model without trade credit. Following the shock, there is a shift in entrepreneurs' willingness to borrow and lend trade credit, leading to an increase in the trade credit interest rate and a decrease in aggregate trade credit relative to output. The contraction in trade credit disproportionately restricts the borrowing of the most constrained entrepreneurs, who rely on trade credit for financing, while unconstrained entrepreneurs (net trade-credit lenders) gain from the rising trade credit interest rate. Both effects cause more severe misallocation and greater losses in aggregate productivity. Although the higher value of liquidity in the presence of trade credit incentivizes entrepreneurs to save more and hence leads to a faster accumulation of capital, the misallocation channel dominates quantitatively. Therefore, while the reallocative effect of trade credit increases the economy's steady-state output, the misallocation channel amplifies the aggregate consequences during the 2007-09 financial crisis.

While trade credit amplifies aggregate financial shocks, it can mitigate financial shocks that affect only *some*, but not all, entrepreneurs, as it allows financing to flow to entrepreneurs in idiosyncratic financial distress. The mitigation effect, however, is strongest when only a small fraction of entrepreneurs experience a tightening in their collateral constraints. As the shock becomes more widespread, fewer entrepreneurs are in a position financially to lend trade credit, diminishing trade credit's ability to mitigate the shock. According to the model analysis, when less than 0.3% of entrepreneurs are affected by the financial shock, the benchmark economy suffers a smaller output loss than the counterfactual economy. Conversely, when the share of affected entrepreneurs exceeds 0.3%, trade credit's mitigation effect is dominated by its amplification effect, leading to greater output loss in the benchmark than in the counterfactual economy. In other words, as the financial shock spreads, affecting more and more entrepreneurs, trade credit plays an increasingly similar role as it does during an aggregate financial shock.

The findings from my quantitative analysis reconcile two empirical facts in the trade credit literature. First, the existing literature documents that trade credit plays a "redistributive" role during periods of tight credit, passing funds from more liquid firms to less liquid firms (Meltzer, 1960 and Nilsen, 2002). These papers suggest trade credit could help mitigate the impacts of financial shocks. Second, however, on the aggregate level, trade credit does not appear to increase during monetary and credit contractions (Gertler and Gilchrist, 1993). Indeed, during the Asian financial crisis and the 2007–09 global financial crisis, aggregate trade credit declined in absolute terms and relative to output (Love et al., 2007). Through the lenses of my model, these facts are consistent with how the two aspects of trade credit – its aggregate quantity and its distribution across firms – can be affected by a financial crisis. First, in a financial crisis, shocks might be distributed unevenly across firms, in which case, trade credit would flow to those facing a more severe shock. Second, the decline in aggregate trade credit reflects a contraction in overall trade credit lending activity as an endogenous response to financial market disruptions. Therefore, trade credit could impact economic outcomes through both channels, with the ultimate effect depending on the shock's aggregate and distributional properties.

There exists a long theoretical and empirical literature on trade credit (see Cuñat and Garcia-Appendini, 2012 for a review). Theoretically, the model in this paper builds on the insight that trade credit exists because suppliers have a certain comparative advantage in lending to their customers relative to financial intermediaries (Biais and Gollier, 1997, Fabbri and Menichini, 2010, Burkart and Ellingsen, 2004 and Cuñat, 2007). Empirically, evidence documented in this paper lends support to the existence of the financial motive behind trade credit (Schwartz, 1974 and Petersen and Rajan, 1997).

This paper also contributes to the literature on trade credit's role in propagating financial shocks (see Kiyotaki and Moore, 1997). Recent developments in this literature consider the economy's input-output structure, including the aggregate impact of trade credit in an input-output economy (Altinoglu, 2018, Luo, 2020 and Reischer, 2019) and trade credit's impact on the cross-sector correlation in economic activity (Raddatz, 2010 and Miranda-Pinto and Zhang, 2022). My paper complements this strand of the literature by exploring the role played by trade credit in the presence of firm heterogeneity. Importantly, it illustrates the importance of incorporating the underlying heterogeneity in firms' credit constraints and trade credit positions to evaluate the role of trade credit in the aggregate economy.

Lastly, I introduce trade credit into a quantitative dynamic general equilibrium model with firm heterogeneity and financial frictions, building on the existing research such as Buera and Moll (2015), Buera et al. (2015), Khan and Thomas (2013), and Zetlin-Jones and Shourideh (2017). The model extends the working capital constraint in Jermann and Quadrini (2012) by incorporating a trade credit component. Previous papers such as Zetlin-Jones and Shourideh (2017) examine how shocks originating in the financial sector affect the real economy, with calibration to match firms' net liability, a part of which is trade credit. I model trade credit separately from other liabilities (i.e., bank credit in my model). By incorporating trade credit, the model captures the endogenous response of trade credit to the exogenous shocks in the financial market, which I show is quantitatively significant. Relatedly, a recent paper by Hardy et al. (2022) incorporates trade credit in a more general model of firm-to-firm lending to study its impact on economic fluctuations in emerging market economies.

# 2 Empirical Motivation

This section establishes the empirical facts that motivate and discipline the model. First, I use the US Compustat data to study firms' choice of trade credit in the cross-section, focusing on the relationship between trade credit and the degree of financial constraints firms face. Following this, I study how firms' trade credit choices change following a negative financial shock by examining the events around the bankruptcy of the Lehman Brothers.

## 2.1 Trade credit in the cross section

**Data.** I construct a sample of firms using the Compustat North America database for 2000-2007, excluding firms in the financial sector (SIC 60-69).[1] While I focus on the 2000-2007 period, the patterns I observe are also present in more extended time series. The Compustat data used in this section are at the quarterly frequency.

Trade credit shows up on both sides of a firm's balance sheet. First, accounts receivable (AR) is the amount of money due to a firm for goods or services it delivered but has not yet been paid for by the customers. It measures the firm's gross lending of trade credit to other firms and appears as a current asset. Second, accounts payable (AP) is the amount a firm owes its suppliers for goods or services it has received. It measures the gross borrowing of trade credit from their suppliers, which is a current liability. Finally, a firm's net trade credit position (net AR=AR-AP) measures the net lending (if positive) or net borrowing (if negative) of trade credit. Naturally, the size of trade credit is closely linked to firms' production scale. I normalize AR, AP, and net AR by total sales in the empirical results. To limit the influence of outliers, I follow Kalemli-Ozcan et al. (2014) and winsorize the bottom and top 5 percent of the ratios I constructed (AR/sales, AP/sales, net AR/sales, and external financing/fixed assets, etc.).[2] The final sample consists of just over 30 thousand

[1] I restrict the sample to the period of 2000-2007 to exclude potential influences from the Global Financial Crisis (pre-2007) and to focus on a period when the measures of trade credit receivables are well-populated in the data (post-2000). The results are robust to including earlier sample periods.

[2] This trimming practice is employed to mitigate the impact of extreme values that could distort the analysis, especially those using the ratio of two variables, such as AR/sales and AP/sales. Excluding the

firm-quarter observations. Appendix table A.1 presents the summary statistics of the final sample.

**Results.** I begin by documenting the relationship between firms' trade credit choices, firm size, and age. This approach is motivated by findings in the literature suggesting that firm size and age are informative indicators of a firm's financial conditions, with larger and older firms being less constrained than their smaller and younger counterparts (Almeida and Campello, 2007; Hadlock and Pierce, 2010).[3] To do this, I first examine how trade credit varies across deciles of firm size and age. In the sample, firm age is constructed using a firm's first appearance in the Compustat dataset with a non-missing closing price, and firm size is measured using their total asset value.[4]

Figure 1 shows that larger and older firms are more likely to be net trade credit lenders (net AR $> 0$). For instance, while approximately 30% of the smallest decile firms are net trade credit lenders, more than 80% of the largest decile firms are. Similarly, while 65% of firms in the youngest decile are net trade credit lenders, that number rises to approximately 90% among the oldest decile. The increasing share of net trade credit lenders is driven primarily by decreasing AP/sales with firm size and age.[5] Given the documented empirical correlation between firm size and age with financial constraints, I interpret this as evidence suggesting that financially unconstrained firms are more likely to be net lenders of trade

top and bottom 5 percent of observations from these ratios helps ensure that our estimates are not skewed by outliers.

[3] In support of this relationship, I provide evidence from Compustat data that investment sensitivity to cash flow is higher among smaller and younger firms. See appendix section A.1.2.

[4] Given that the Compustat data starts from 1960, firm age measured in this manner is inherently right-truncated. For example, in the year 2000, the maximum firm age would be 40 years. However, I find that this issue does not significantly affect our results. In my sample, less than 1 percent of the firms have right-truncated age measures. Consequently, these firms all fall into the older decile in Figure 1. Additionally, in the regression analysis (table 1), I include an indicator for firms with right-truncated age measures and find minimal changes to the results. Two alternative sources are used by the literature to measure the age of public firms in the US. The first one is their IPO dates. The second one is a dataset of firm age constructed by Loughran and Ritter (2004) for a sample of public firms. These three measures are highly correlated, and the results are robust to both alternative measures.

[5] Murfin and Njoroge (2015) showed that the median net payable days declines with firm size in the Compustat dataset, except for the largest two deciles of firms. A similar, albeit less significant, pattern of average and median AP/sales can also be seen in figure 1 for the top two size deciles. See Appendix section A.1.3 for a detailed discussion.

**(a)** Size **(b)** Age

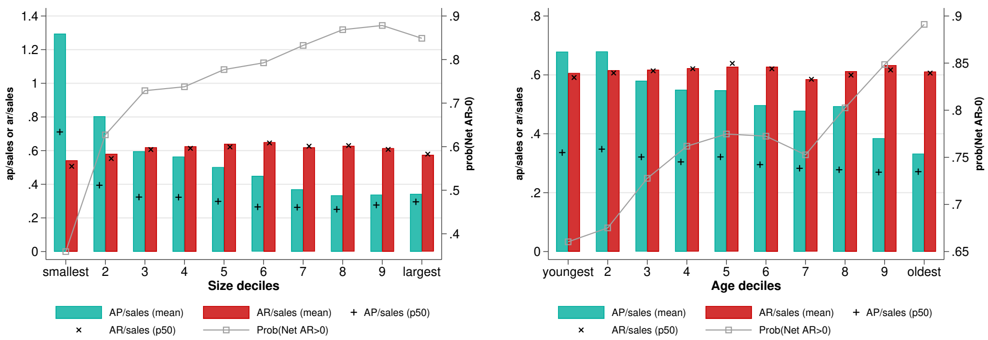



**Figure 1: Trade credit by firm age and size**

**Notes:** The sample includes all non-financial firms in the Compustat dataset for 2000-2007. The figures plot the choice of trade credit over firm size (panel a), and firm age (panel b). The bars reflect the mean and the (+ or x) reflect the median AP/sale and AR/sales for each decile, respectively. The gray line shows the probability of being a net trade credit lender (prob(net AR>0)) in each decile.

credit than their constrained counterparts.[6]

While informative, these simple statistics do not take into account any industry-specific trade credit practices, which may be affected by the industry's position in the supply chain (Kim and Shin, 2012) or any time-series variations. To control for these, I estimate the following equation at the quarterly frequency:

$$y_{it} = \alpha_1 \log(\text{age})_{it} + \alpha_2 \log(\text{size})_{it} + X_{it} + \epsilon_{it}, \tag{1}$$

where $y_{it}$ is one of four measures of trade credit for firm $i$ in quarter $t$: AP/sales, AR/sales, net AR/sales, and a net trade credit lender indicator $\mathbb{I}_{\text{net AR}>0}$. The regression also includes a vector $X_{it}$ of firm characteristics, such as industry-quarter fixed effects.

The regression results in Table 1 columns (1)–(4) corroborate the findings in the previous figures. After controlling for industry-quarter fixed effects, net trade credit lending (net AR/sales) is significantly higher among older and larger firms. The estimated coefficients are 0.066 and 0.068 on firm size and age, with both highly significant at the 1% level (column 3). A very similar pattern emerges in column (4), where the dependent variable is an indicator of whether the firm is a net trade credit lender (net AR>0). Furthermore, consistent with the

[6] Appendix section A.1.4 documents that these patterns hold conditional on firm age and size.

**Table 1: Trade credit and firm characteristics**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Firm size (log size) | -0.074*** | -0.001 | 0.066*** | 0.030*** | 0.072*** | 0.034*** |
| | (0.008) | (0.002) | (0.009) | (0.005) | (0.009) | (0.006) |
| Firm age (log years) | -0.070*** | 0.004 | 0.068** | 0.051*** | 0.074*** | 0.055*** |
| | (0.023) | (0.007) | (0.029) | (0.016) | (0.027) | (0.015) |
| Sales share | | | | | -0.150** | -0.080 |
| | | | | | (0.065) | (0.049) |
| Dependent variable | AP/Sales | AR/Sales | NetAR/Sales | $\mathbb{I}_{\text{NetAR}>0}$ | NetAR/Sales | $\mathbb{I}_{\text{NetAR}>0}$ |
| $N$ | 31943 | 31913 | 31852 | 31852 | 31852 | 31852 |
| $R^2$ | 0.085 | 0.003 | 0.071 | 0.038 | 0.075 | 0.040 |

**Notes**: The table displays results from regression equation 1. The sample includes all non-financial firms in the Compustat dataset for the period 2000-2007. All regressions include a set of 2-digit sic industry-quarter fixed effects. Standard errors are clustered two ways at the sector and quarter level.

findings in the previous figures, net trade credit lending is again driven mostly by borrowing trade credit (i.e., AP) rather than lending (i.e., AR). The estimates in column (1) show that firm size and age have a negative and significant correlation with the size of AP/sales. On the other hand, the estimated coefficients for AR/sales are insignificant for firm age, and their magnitude is only approximately 1/10 of the coefficients for AP/sales (column 2).

While the regression results underscore the significant influence of financial motives behind firms' trade credit decisions, research also finds that firms' market power can influence these decisions. For instance, large firms may exert market power over smaller ones and request more trade credit, despite the fact that smaller firms might be more financially constrained (Murfin and Njoroge, 2015 and Klapper et al., 2012). This dynamic may introduce an additional layer of complexity to trade credit decisions. To account for this, the regressions in columns (5)–(6) include a measure of firms' sales share within their 4-digit SIC industry, aiming to capture firms' market power within their respective industries. Compared to columns (3) and (4), which do not include this additional control, columns (5)–(6) show a noticeable increase in the correlations between firm size/age and net lending of trade credit. This result is reassuring as it suggests that the financial motives behind trade credit choices remain robust, even after controlling for firms' market power within their respective industries.[7]

The facts documented in this section align with previous findings in the literature that emphasize the financial motives behind trade credit (Meltzer, 1960, Schwartz, 1974, Petersen and Rajan, 1997).[8] While I have documented these facts using Compustat, supporting evidence for the financial motives behind trade credit can also be found in other datasets, such as the Survey of Small Business Finance and corporate tax return data. Furthermore, these patterns remain robust when additional controls such as inventory and return on assets are applied. Appendix sections A.1.5 to A.1.6 include discussions for these additional empirical exercises. Collectively, these findings provide strong evidence, corroborated by prior studies, that trade credit tends to flow in net terms from unconstrained to constrained firms.

## 2.2 Trade credit and financial shocks

Given the financial motive for trade credit documented above, one would expect that firms would borrow more trade credit from their suppliers and/or reduce their lending of trade credit when facing a negative financial shock.

I provide a simple test of this hypothesis by examining the events around the Lehman Brothers bankruptcy in 2008, using a strategy similar to that of Chodorow-Reich (2014).

[7] Recent studies such as Chod et al. (2019) and Giannetti et al. (2021) show that firms' market power at the customer level affects their incentive to lend trade credit as well. For instance, Chod et al. (2019) document that, suppliers are more likely to offer trade credit to retailers when they constitute a significant portion of those retailers' total input purchases. Although market power at the industry level might be somewhat correlated with that at the customer level, the analysis carried out in Table 1 is not conclusive and it does not fully capture the complex dynamics described in Chod et al. (2019) and Giannetti et al. (2021).

[8] Compared to existing evidence, AR varies less with firm size and age in the Compustat data as shown in Figure 1. For instance, Petersen and Rajan (1997) found a positive relationship between AR and firm age/size using the Surveys of Small Business Finances. One possible explanation for the weaker correlation in the Compustat dataset could be that public firms have better access to accounts receivable financing, which mitigates the liquidity loss from trade credit lending. According to the DealScan dataset, in the syndicated market frequented by many public firms, 46% of secured loans use AR as collateral, with an average advance rate of 87%. This indicates that lending one dollar of trade credit results in only a 13-cent loss of liquidity. In contrast, the advance rates are 59% for inventory and 29% for property, plant, and equipment among DealScan loans.

After the Lehman bankruptcy in 2008Q3, lending activities in the financial market contracted significantly. In particular, banks that co-syndicated more loans with Lehman Brothers also reduced their lending more than other banks (Ivashina and Scharfstein, 2010). Moreover, because it is costly/takes time for firms to switch to a new lender (Sufi, 2007 and Chodorow-Reich, 2014), their access to financing is disrupted when the bank they usually deal with (i.e., their relationship bank) tightens their lending. In other words, firms experienced differential exposure to the Lehman shock, depending on their banks' connections to Lehman before its bankruptcy. I exploit this as an exogenous financial shock and investigate how it impacts firms' lending and borrowing of trade credit.

**Data.** The analysis combines the Compustat dataset and the Thomson Reuters DealScan database, which reports information about loans issued in the syndicated loan market. The syndicated market is one of the most important places for large U.S. firms to obtain funding. According to Chodorow-Reich (2014), it accounts for almost half of all commercial and industrial lending. However, during 2007–09 financial crisis, there was a severe contraction in lending activities in the syndicated market with significant declines in the number, size, and maturity of new credit facilities (including AR-collateralized facilities), as shown in figures A.5 and A.6 in the appendix.

I follow Sufi (2007) and Chodorow-Reich (2014) to construct a sample of Compustat firms that borrow from the syndicated loan market and to identify firms' relationship banks before the Lehman bankruptcy. To do so, I focus on the loan facilities open from January 1, 2004, to December 31, 2006.[9] Focusing on loan facilities with a single lead lender, I use the link table provided by Chava and Roberts (2008) to match each loan facility's lead lender in the DealScan database with the borrower from the Compustat database. If a firm had only one open facility during this period, I would define the lead lender of this facility as the firm's pre-crisis relationship bank. If a firm had multiple facilities during that period, I would then define the newest facility's lead lender as its relationship bank.

[9]Focusing on this three-year window allows us to identify the relationship between firms and their lenders prior to the 2007-09 financial crisis. The results are robust if I extend the period to 2008Q2, the quarter before the bankruptcy of the Lehman Brothers.

Following Ivashina and Scharfstein (2010) and Chodorow-Reich (2014), I measure a firm's exposure to the Lehman shock using the fraction of its relationship bank's syndication portfolio in which Lehman Brothers had a lead role. As shown by Ivashina and Scharfstein (2010), this measure is negatively correlated with new lending activities. The data on banks' syndication portfolios are taken from Chodorow-Reich (2014), covering the 43 most active lenders. As a result, my analysis focuses on firms whose relationship bank is one of the 43 lenders. The above process yields a panel of 617 firm-bank pairs from 2005Q1 to 2010Q4 at the quarterly frequency. This sample closely mirrors the sectoral composition of the Compustat firms, though the average firm is eight times larger (in terms of assets) than the typical Compustat firm, suggesting that DealScan-Compustat sample consists of the largest firms in the US.

**Results.** I begin by categorizing firms into different groups based on their exposure to Lehman Brothers and examining the trade credit dynamics across these groups. The objective of this analysis is to investigate the differences in trade credit dynamics across groups and to understand how these differences correlate with exposure to Lehman.

Although the data exhibits some noise on a quarterly basis, Figure 2 shows that before the financial crisis, there were no significant pre-shock trend differences between the groups. This is reassuring, as it helps rule out any long-term trend differences between these groups. However, following the shock, a noticeable divergence appeared. Compared to less exposed firms, those more exposed significantly reduced their lending of trade credit and increased their borrowing to a greater extent. These patterns are consistent with the prediction that, facing a negative financial shock, firms would borrow more trade credit from their suppliers and reduce their lending to customers.

These figures offer an intuitive understanding of trade credit dynamics following the shock, but there might be other confounding factors, such as industry-specific factors, that would generate the differential trends after the shock. To control for these factors, I estimate

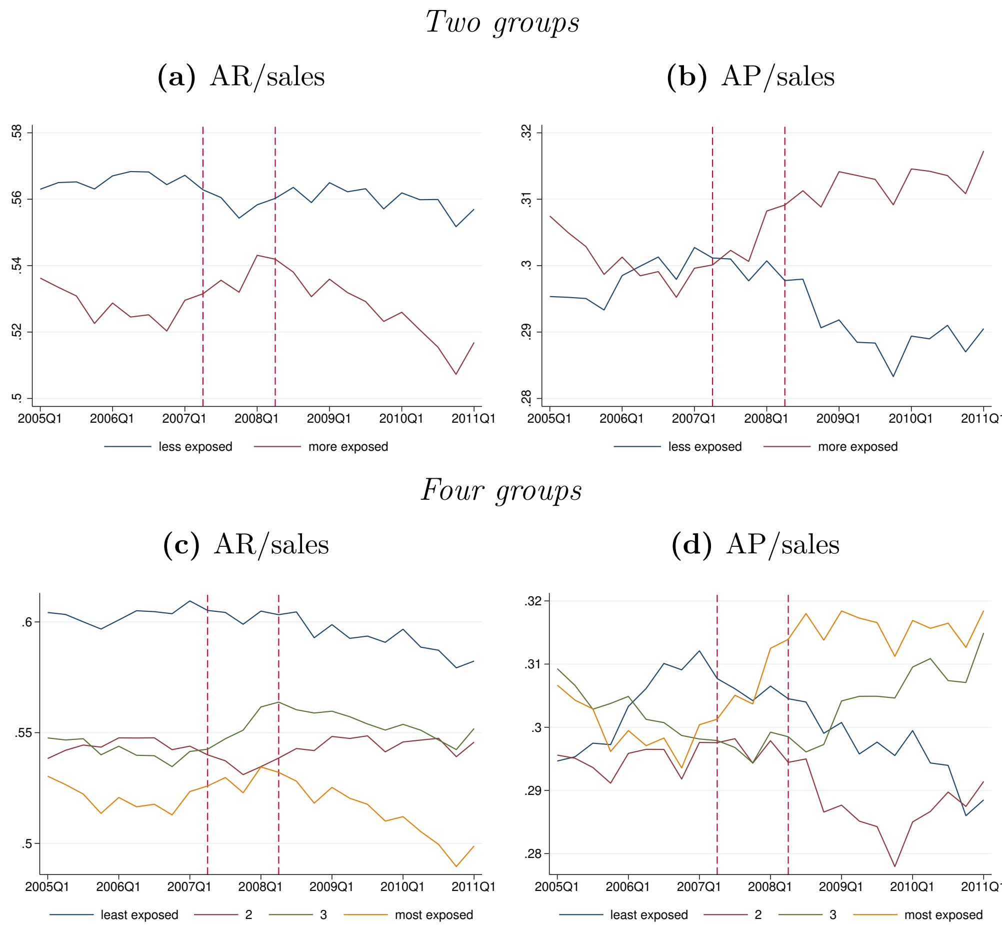



**Figure 2: Trade credit dynamics by exposure to Lehman**

**Notes**: This figure shows the average AR/sales and AP/sales for each group of firms based on their exposure to the Lehman shock. To adjust for the seasonality in trade credit measures, these figures display moving averages calculated over a four-quarter backward-looking window $[t-3,t]$. The two red vertical lines in each panel mark the quarters of 2007Q2 and 2008Q2, which are the quarters preceding the collapses of Bear Stearns (also the start of the NBER recession) and the Lehman bankruptcy, respectively.

the following equation at the quarterly frequency:

$$y_{it} = \alpha \text{PostLehman}_t + \beta \text{Exposure}_i + \gamma \text{Exposure}_i \times \text{PostLehman}_t + X_i + \Lambda_{it} + \varepsilon_{it}, \qquad (2)$$

where $y_{i,t}$ represents AR/sales or AP/sales for firm $i$ in quarter $t$. The control variables include PostLehman$_t$, an indicator assigned value of 0 for the pre-shock period (2005Q1-2008Q2) and a value of 1 for the post-shock period (2008Q3-2010Q4). The variable Exposure$_i$ measures firm $i$'s pre-shock exposure to Lehman. I use different ways to measure this exposure, as will be discussed in detail below. The coefficient $\gamma$ in front of the interaction between these two measures, $\text{Exposure}_i \times \text{PostLehman}_t$, is thus informative of how firms with different exposures to Lehman change their trade credit policies differently after the Lehman bankruptcy. Lastly, the regression includes a rich set of controls for characteristics of firms $X_i$ such as industry fixed effects, firm age, size, and indicators of having bond or commercial paper ratings. The vector $\Lambda_{it}$ includes a set of interactions between these characteristics (as contained in $X_i$) and $\text{PostLehman}_t$, capturing the possibility that firms of different characteristics react differently to the Lehman shock. For instance, the vector $\Lambda_{it}$ includes the interaction between industry fixed effects and $\text{PostLehman}_t$, which aims to control for the possibility that the Lehman bankruptcy's impact was particularly concentrated in some industries.

**Table 2: A regression analysis of trade credit responses to Lehman exposure**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Top quartile of exposure × PostLehman | -0.034** | 0.021*** | | | | |
| | (0.015) | (0.007) | | | | |
| Top 50% of exposure × PostLehman | | | -0.019* | 0.026*** | | |
| | | | (0.010) | (0.008) | | |
| Exposure to Lehman × PostLehman | | | | | -0.000 | 0.009* |
| | | | | | (0.009) | (0.005) |
| Dependent variable | AR/Sales | AP/Sales | AR/Sales | AP/Sales | AR/Sales | AP/Sales |
| $N$ | 11500 | 11406 | 11500 | 11406 | 11500 | 11406 |
| $R^2$ | 0.626 | 0.401 | 0.628 | 0.401 | 0.625 | 0.399 |

**Notes:** This table presents results from estimating equation 2. Displayed are the estimates of $\hat{\gamma}$, the coefficient for the interaction term $\text{Exposure}_i \times \text{PostLehman}_t$, where the firm's exposure to Lehman, $\text{Exposure}_i$, is measured in three different ways. Columns (1)–(2) use a dummy variable indicating whether firm $i$ belongs to the top quartile in terms of pre-shock exposure to the Lehman shock. Columns (3)–(4) use a dummy indicating if firms belong to the top 50% exposure to Lehman, and columns (5)–(6) utilize the raw measure of exposure to Lehman, defined as the fraction of a firm's relationship bank's syndication portfolio in which Lehman Brothers had a lead role. Standard errors are clustered at the ultimate lender level and are shown in parentheses.

Estimation results in Table 2 corroborate the observations from the previous figure, indicating that firms with higher exposure to the Lehman shock, compared to those with lower exposure, tend to increase their trade credit borrowing and decrease their trade credit lending significantly more. Specifically, the quartile of firms most exposed to Lehman increased their AP/sales, representing trade credit borrowing, by 2.1 percentage points more (column 1) and reduced their lending of trade credit, AR/sales, by 3.4 percentage points more (column 2) compared to the rest of the firms. This amounts to a 5.5 percentage points difference in net trade credit lending, giving the firms, through trade credit adjustments, an increase in liquidity equivalent to 5.5 percent of their revenue. In columns (3)–(4), the top 50% of firms by exposure are compared to the rest, we find a similar pattern, although, unsurprisingly, with a slightly smaller magnitude of estimate. Lastly, using the raw measures for firms' exposure to Lehman, columns (5)–(6) indicate that a one percent increase in exposure to Lehman is associated with a 0.9 percentage point decrease in trade credit lending.[10]

So far, the regression model divides the time into pre-shock and post-shock periods, with the dummy variable $\text{PostLehman}_t$ quantifying the average differences between these two periods. Next, I employ a regression to examine the trade credit differences between firms with high versus lower exposure to Lehman *in each quarter*. This approach tracks the evolution of these differences over time and around the Lehman bankruptcy, providing a clear view of both the pre- and post-shock effects. More formally, I estimate the following equation:

$$y_{it} = \gamma_t + \beta_t \text{Exposure}_i \times \gamma_t + X_i + \Lambda_{it} + \varepsilon_{it}, \tag{3}$$

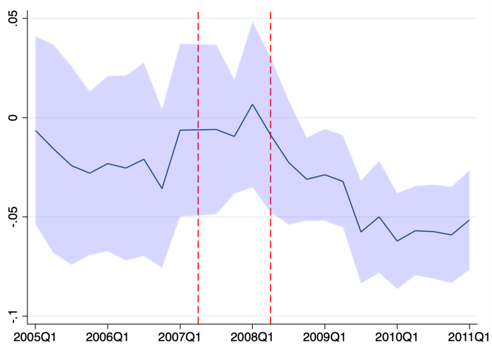
where $\gamma_t$ represents a set of indicators for each quarter in the sample. The interaction between the quarter indicators and the exposure measure $\text{Exposure}_i$ captures the differences in each quarter $t$ between firms highly exposed to Lehman and others.

Figure 3 panel (a) displays the estimated coefficient $\hat{\beta}_t$ associated with the interaction term, which quantifies the discrepancy in AR between firms in the top quartile of exposure to Lehman and the remaining firms. Before the shock, firms with high exposure to Lehman exhibit marginally lower AR/sales compared to those with low exposure, though this difference is not statistically significant. After the shock, this estimate becomes more negative and significant, suggesting that highly exposed firms experience a greater reduction

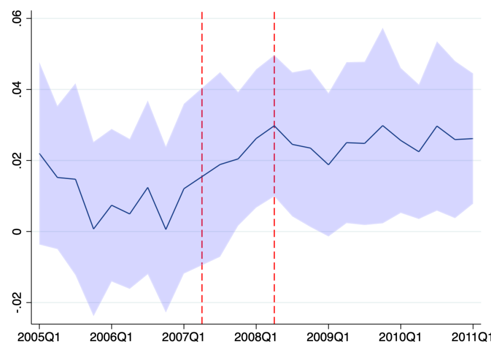
[10]To ensure the robustness of these findings, I further explore this relationship in appendix table A.4 which regresses the changes in median AR and AP between the pre- and post-Lehman bankruptcy periods for each firm on the indicators measuring firms' pre-shock exposure to Lehman. By taking the difference, this regression takes out any permanent pre-shock differences across firms. Furthermore, I also find similar patterns when adding fixed effects to the baseline specification in equation 2. The results are also robust to the inclusion of differential long-term trends, which control for any persistent trend differences across firm groups (appendix section A.2.3).

*Top quartile of exposure relative to the rest*

**(a)** AR/sales

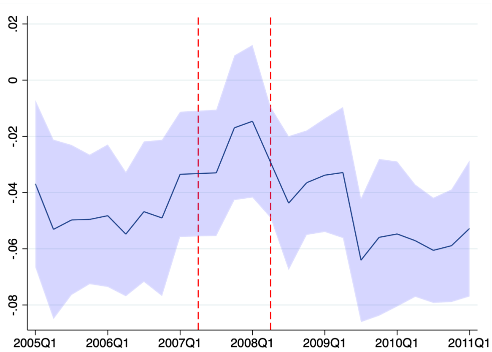



**(b)** AP/sales




*Top 50% of exposure relative to the rest*

**(c)** AR/sales




**(d)** AP/sales

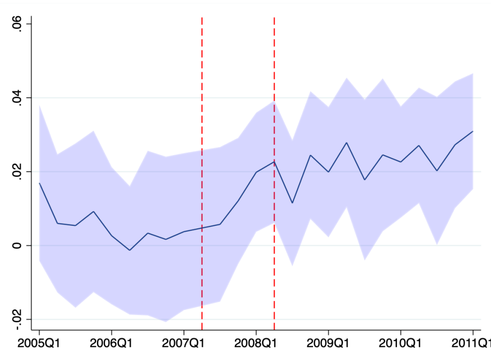



**Figure 3: Estimating differences in trade credit dynamics, $\hat{\beta}_t$**

**Notes:** These figures plot the estimates from regression equation 3. The lines represent the estimated coefficient $\hat{\beta}_t$ in front of the interaction term Exposure$_i \times \gamma_t$ for each quarter $t$ in the sample, using two definitions for Exposure$_i$. Panel (a) employs a dummy variable indicating that firm $i$ belongs to the top quartile in terms of its exposure to Lehman. Panel (b) uses a dummy variable indicating that firm $i$ falls within the top 50% of exposure to Lehman. The shaded areas represent the 95% confidence intervals of the estimates. Standard errors are clustered at the ultimate lender level. The two red vertical lines in each panel mark the quarters of 2007Q2 and 2008Q2, which are the quarters preceding the collapses of Bear Stearns (also the start of the NBER recession) and the Lehman bankruptcy, respectively.

in AR/sales than their less exposed counterparts. Conversely, prior to 2007Q2, there is no significant difference in AP/sales between high and low-exposure firms. After that, the disparity in AP/sales widens, with high-exposure firms exhibiting significantly higher AP/sales than the rest (panel b). A similar pattern emerges when comparing firms within the top half of exposure to Lehman against the rest (panels c and d).

Overall, these figures indicate a break in the trends of trade credit dynamics across firm groups. Although the exact timing of this trend break varies, all four panels reveal a significant shift around the shock: relative to firms with less exposure, those with greater exposure to the shock begin to borrow more trade credit and lend less, underscoring how trade credit policies are influenced by the degree of exposure to the financial shock. This suggests that the more exposed firms secured additional liquidity through these endogenous adjustments in trade credit, more so than their less exposed counterparts.

To summarize, the evidence highlighted in this section further supports the existence of financial motives behind trade credit choices. Firms in the DealScan-Compustat sample are very large, but they still adjust their trade credit positions in response to credit tightening, demonstrating the broad applicability of these financial considerations. In addition, these results illustrate the transmission of shocks from the financial sector to firms through endogenous trade credit channels. First, firms pass on the negative financial shock to their customers by cutting back their trade credit lending (AR), consistent with existing findings in Jacobson and von Schedvin (2015) and Costello (2020). Second, firms can adjust the other aspect of trade credit by borrowing more from suppliers (AP), potentially mitigating the effect of negative bank credit shocks. Both margins of adjustment play a role in shaping the impact of financial shocks on the real economy.

# 3 Model

Motivated by the empirical evidence, this section presents a dynamic general equilibrium model with heterogeneous entrepreneurs and financial frictions. In addition to production, entrepreneurs engage in trade credit lending and borrowing. Trade credit and bank credit coexist as two sources of funding, which is a crucial departure from the standard model with financial frictions and heterogeneity.

## 3.1 Economic environment

Time is discrete with an infinite horizon. There is one type of good, which is sold in a perfectly competitive market and used for consumption, investment, and intermediate input. There exists a unit measure of heterogeneous entrepreneurs who use capital ($k$), labor ($l$), and intermediate inputs ($x$) to produce. The entrepreneurs differ by wealth ($a$, endogenous) and productivity ($z$, exogenous).

There is a measure $N$ of homogeneous workers, who provide labor, receive wages, and consume. They have no access to asset markets and therefore consume their labor income every period; i.e., they are "hand-to-mouth."

**Preferences and endowments.** Worker preferences are time separable with instantaneous utility function $u(c_t^h, h_t)$ of the GHH form (Greenwood et al., 1988):

$$U^h(c^h, h) = \sum_t \beta^t u(c_t^h, h_t) = \sum_t \beta^t \left( c_t^h - \psi \frac{h_t^{1+\theta}}{1+\theta} \right)$$

where $\beta$ is the discount factor, $c_t^h$ is consumption, and $h_t$ is labor provided by the worker.

Entrepreneur preferences are time separable with an instantaneous utility function of $\log(c_t)$. The expected utility of the entrepreneur can be written:

$$U^e(c) = \mathbb{E} \sum_t \beta^t \log(c_t),$$

where the expectation is taken over the stochastic processes of productivity $z$ and wealth $a$.

**Production technology.** Entrepreneurs operate a decreasing returns to scale production technology ($\mu < 1$) that transforms capital, labor, and intermediate inputs into the final good:

$$y = Az \left( (k^\alpha l^{1-\alpha})^{1-\chi} x^\chi \right)^\mu$$

where $A$ is aggregate TFP and $z$ is idiosyncratic productivity that follows an exogenous Markov process $\Gamma_z(z'|z)$.[11] Since the production function is decreasing returns to scale, there is an optimal production scale for any given productivity $z$.

## 3.2 Financing production

Entrepreneurs deposit their wealth $a$ with perfectly competitive financial intermediaries (banks) and rent capital from them. The deposit rate is $r$, and the zero-profit condition gives a capital rental rate of $R = r + \delta$. In this case, the entrepreneur's net interest payment is $r(k - a)$. Notably, this setup of a capital rental market is equivalent to one where entrepreneurs own capital $k$, borrow an inter-temporal loan $d$ at interest rate $r$, and face no capital adjustment costs (Buera and Moll, 2015 and Zetlin-Jones and Shourideh, 2017). In this alternative setup, the entrepreneur's net worth is defined as $a = k - d$, and thus their interest payment is $rd = r(k-a)$, matching the outcomes of the current model. Accordingly, given the entrepreneur's net worth $a$ and capital $k$ in the current model, we can also derive the equivalent inter-temporal loan value $d$.

**Timing** At the beginning of each period, entrepreneurs enter with wealth $a$, and their productivity $z$ is realized. Consistent with the timing of the model in Jermann and Quadrini (2012), I assume that, after learning their productivity draw, firms choose their inputs ($k$, $l$, $x$), trade credit (to be introduced below), consumption $c$, and savings into the next period $a' - a$.

However, as in Jermann and Quadrini (2012) entrepreneurs need to pay for the cost of their labor, capital rental, intermediate goods, consumption, and investment before receiving this period's revenue. Therefore entrepreneurs must raise an intra-temporal loan $m$ to cover the timing mismatch in cash flows. The intra-temporal loan is repaid within the period, and

[11] The economy admits an aggregate value-added production function $Y = \bar{A}K^{\frac{\alpha(1-\chi)\mu}{1-\chi\mu}}L^{\frac{(1-\alpha)(1-\chi)\mu}{1-\chi\mu}}$, where $K$ and $L$ are the aggregate capital stock and labor inputs. In the absence of financial frictions, $\bar{A}$ is a function only of $A$ and the exogenous stationary distribution of $z$.

there is no interest. After obtaining financing, entrepreneurs produce, purchase goods for consumption, and save for the next period.

This brings us to the end of the period. At this point, entrepreneurs decide whether to repay their loans. Crucial to this model, the two sources of financing (bank loans and trade credit) differ in their exposure to moral hazard, which gives suppliers a comparative advantage in lending inputs to their customers. More specifically, I assume that entrepreneurs can default on bank loans, but trade credit is perfectly enforceable.

When deciding whether to default, the entrepreneur's assets consist of savings $a'$ and AR owed from customers, and its liabilities consist of bank loans $m$ and AP owed to suppliers. Under the assumption, the AP must be repaid, but the bank loan $m$ can be defaulted on. If the entrepreneur defaults, the bank can seize and liquidate the entrepreneur's assets ($a'$ and AR), but the liquidation is only successful with some probability. Therefore, when contracting the loans, the bank will foresee this and limit the size of the loan based on the anticipated proceeds from liquidation:

$$m \leq \gamma_1 a' + \gamma_2 \text{AR}. \tag{4}$$

where $\gamma_1$ and $\gamma_2$ are the probability of liquidating $a'$ and AR, respectively.[12] Figure 4 illustrates the timing of events.

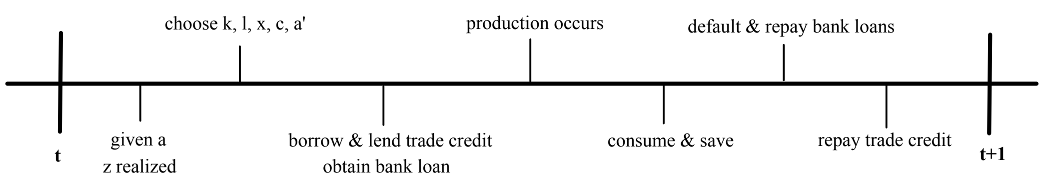



**Figure 4: Timing**

[12]It is important to note that if firms default on a bank loan, the bank's recovery will be based on AR, not on AR-AP. After production, entrepreneurs have the option to default on their bank loans. Should they choose to default, the bank is entitled to seize and liquidate the AR. At this juncture, although entrepreneurs owe their suppliers AP, this liability does not influence the bank's recovery process. The bank's focus is strictly on the value of AR, the asset over which it holds a claim, and its recovery decisions are not affected by other liabilities of the entrepreneur.

**Trade credit.** By nature, trade credit arises only in connection with the purchase of intermediate inputs. Recalling the intermediate inputs market is perfectly competitive; entrepreneurs who wish to borrow will therefore purchase inputs from the supplier who offers the most attractive trade credit terms. As a result, the trade credit interest rate will be equalized across all borrowers in equilibrium. A similar feature of the competitive input market can be found in the model of Burkart and Ellingsen (2004), which argues that the assumption is consistent with the empirical finding that trade credit terms look similar across borrowers within the same industry. As noted by Burkart and Ellingsen (2004), the trade credit interest rate reflects the financial condition of the *average* entrepreneur in the market rather than a specific seller and borrower.[13]

To formally model trade credit and input transactions, I assume a competitive market for intermediate inputs and trade credit. Entrepreneurs are price takers. They supply their output $y = Az\left((k^\alpha l^{1-\alpha})^{1-\chi} x^\chi\right)^\mu$ and offer a trade credit loan of size $\text{AR} \in [0, y]$. They also purchase intermediate goods of value $x$ and borrow trade credit of size $\text{AP} \in [0, x]$. Note that AR and AP are both non-negative and cannot exceed the value of goods sold or bought. Indeed, this tight connection between trade credit and the value of goods is an important feature that distinguishes trade credit from other types of inter-firm lending. At the end of the period, entrepreneurs collect a payment of $y - x + r^{tc}(\text{AR} - \text{AP})$ from the market, where $y - x$ is the profit from production, and $r^{tc}(\text{AR} - \text{AP})$ is the net interest from lending and borrowing trade credit. The entrepreneur's budget constraint can be written as:

$$c + a' = (1 + r)a + Az\left((k^\alpha l^{1-\alpha})^{1-\chi} x^\chi\right)^\mu - (r + \delta)k - wl - x + r^{tc}(\text{AR} - \text{AP}). \tag{5}$$

Before deriving the working capital constraint, a few remarks are in order on the modeling of trade credit. First, since the primary goal in this model is to capture the impact of trade

[13] Following Jermann and Quadrini (2012), the intra-temporal bank loan is assumed to carry an interest rate of zero. Although entrepreneurs can default on these loans, the bank loan contract is structured to prevent default in equilibrium. As a result, default risk does not increase the bank loan interest rate; instead, it places an upper limit on the amount of loans available to entrepreneurs. In contrast, trade credit interest rates can be positive because, unlike banks, some trade credit lenders (suppliers) are financially constrained. Therefore, to be willing to lend in equilibrium, they must be compensated with a positive interest rate.

credit on the entrepreneur's liquidity position, I abstract away from a real-world feature of trade credit. In reality, trade credit borrowing takes the form of a delay in payment rather than a direct loan. In Appendix section B.1, I construct an alternative model in which trade credit takes this form. Specifically, I assume that entrepreneurs carry their output into the following period and then decide whether to sell their goods on the spot or provide trade credit and delay receiving payment. I show this alternative specification is similar to the baseline model in capturing trade credit's impact on entrepreneurs' liquidity position. However, in this alternative model, the output of the previous period becomes an additional state variable for entrepreneurs, which makes the model computationally intractable. Therefore I opt for the current model set up to maintain tractability.

Second, the model builds on insights from the existing literature, which argues that trade credit exists because suppliers have a certain comparative advantage in lending to their customers over financial intermediaries (Biais and Gollier, 1997, Fabbri and Menichini, 2010, Burkart and Ellingsen, 2004 and Cuñat, 2007). I follow the papers emphasizing suppliers' comparative advantage in enforcing the repayment of trade credit loans. For instance, Cuñat (2007) argues that suppliers have a comparative advantage because they can stop supplying intermediate inputs.

Third, I abstract from modeling trade credit default, partly due to the difficulty of quantitatively separating default from liquidity loss in the model. In practice, firms often employ specific policies (non-recourse factoring or purchasing credit risk insurance) to manage trade credit default risk (Mian and Smith, 1992). With the help of these policies, firms can transform default risk into liquidity loss with certainty. Further, trade credit default in the data often refers to a delay of payment later than the pre-agreed dates. In sporadic cases, (2% among all defaults among French firms, calculated using data from Boissay and Gropp, 2007), trade credit default means non-payment because the customer becomes insolvent. A delay in payment does not hurt an unconstrained entrepreneur by much; only the constrained ones suffer from liquidity loss – this mechanism is already incorporated in the model. As shown later, the model is calibrated to match the quarterly data, longer than the usual trade credit terms. Thus, the calibrated model will likely have captured some of the default activities. Haven said these, existing literature has long recognized the importance of trade credit default in propagating financial shocks (see Kiyotaki and Moore, 1997, Jacobson and von Schedvin, 2015 and Mateos-Planas and Seccia, 2022). As a caveat to the analysis, I abstract from modeling default to maintain the model's tractability. In appendix section B.5, I discuss the implication of relaxing the assumption that entrepreneurs can not default on trade credit. I also delved deeper into the prevalence of trade credit defaults in the data, distinguishing between the types of defaults captured by my model and those from which I abstract, along with exploring the potential impacts of these abstractions.

**Working capital constraint.** According to the timing assumption, the entrepreneur's outlays must be financed in advance by $m$, such that

$$m = a' - a + c + r(k - a) + \delta k + wl + x + \mathrm{AR} - \mathrm{AP}.$$

The loan must cover the net interest payment $r(k-a)$, labor inputs $wl$, intermediate inputs $x$, capital depreciation $\delta k$, consumption $c$, and plus or minus any change in assets held $a' - a$. Compared to Jermann and Quadrini (2012), however, there is one additional term $\mathrm{AR} - \mathrm{AP}$, which is the entrepreneur's net trade credit position.

Using the budget constraint (equation 5), I can rewrite the size of the loan as

$$m = Az\left((k^{\alpha} l^{1-\alpha})^{1-\chi} x^{\chi}\right)^{\mu} + (1 + r^{tc})(\mathrm{AR} - \mathrm{AP}).$$

Plugging this into the bank loan limit (inequality 4), I derive the working capital constraint:

$$Az\left((k^{\alpha} l^{1-\alpha})^{1-\chi} x^{\chi}\right)^{\mu} + (1 + r^{tc})(\mathrm{AR} - \mathrm{AP}) \leq \gamma_1 a' + \gamma_2 \mathrm{AR}. \tag{6}$$

To see how trade credit affects the entrepreneur's liquidity position, consider what happens when I turn off trade credit by setting $\mathrm{AR} = \mathrm{AP} = 0$. In this case, the working capital constraint is simply $Az\left((k^{\alpha} l^{1-\alpha})^{1-\chi} x^{\chi}\right)^{\mu} \leq \gamma_1 a'$. Comparing this with constraint 6, I see that when trade credit is allowed, the entrepreneur's need for intra-temporal financing increases by $(1 + r^{tc})(\mathrm{AR} - \mathrm{AP})$, the net amount lent or borrowed via trade credit, and the borrowing limit increases by $\gamma_2\mathrm{AR}$, the collateral value of AR.[14]

### 3.3 Recursive competitive equilibrium

Workers solve a static optimization problem, which can be written as:

$$\max_{c^h,h} c^h - \psi\frac{h^{1+\theta}}{1+\theta}, \;\; s.t. \;\; c^h = wh. \tag{7}$$

The entrepreneur solves a dynamic problem, choosing production inputs $(k, l, x)$, trade credit (AR, AP), consumption $(c)$, and next period wealth $(a')$. These choices are subject to the budget constraint (equation 9), the working capital constraint (inequality 10), and the trade credit constraints (inequalities 11 and 12). I also require the entrepreneur's wealth to be non-negative.

I can write the entrepreneur's problem recursively as follows:

$$V(a,z) = \max_{c,k,l,x,\mathrm{AR},\mathrm{AP},a'} \log(c) + \beta\mathbb{E}_{z'|z}V(a',z'), \tag{8}$$

$$\begin{aligned}
s.t. \quad & c + a' = (1+r)a + Az\left((k^\alpha l^{1-\alpha})^{1-\chi}x^\chi\right)^\mu - (r+\delta)k - wl - x \\
& + r^{tc}(\mathrm{AR} - \mathrm{AP}), & (9)\\
& Az\left((k^\alpha l^{1-\alpha})^{1-\chi}x^\chi\right)^\mu + (1+r^{tc})(\mathrm{AR} - \mathrm{AP}) \le \gamma_1 a' + \gamma_2\mathrm{AR}, & (10)\\
& 0 \le \mathrm{AR} \le Az\left((k^\alpha l^{1-\alpha})^{1-\chi}x^\chi\right)^\mu, & (11)\\
& 0 \le \mathrm{AP} \le x, & (12)\\
& a' \ge 0.
\end{aligned}$$

[14] The working capital constraint indicates that net trade credit interest $r^{tc}(\mathrm{AR} - \mathrm{AP})$ needs to be covered by the intra-temporal loan. This is because, according to the timing of the events, $r^{tc}(\mathrm{AR} - \mathrm{AP})$ is budgeted as part of the current-period income to cover expenditure; therefore, it needs to be financed beforehand.

**Recursive competitive equilibrium.** The recursive competitive equilibrium consists of interest rate $r$, wage $w$, and trade credit rate $r^{tc}$; entrepreneur value function $V(a,z)$; entrepreneur policy functions $c(a,z)$, $k(a,z)$, $l(a,z)$, $x(a,z)$, $\text{AR}(a,z)$, $\text{AP}(a,z)$ and $a'(a,z)$; worker consumption and hours worked $(c^h, h)$; and a stationary distribution $\Phi(a,z)$, such that

**(i)** Given prices, the value function and policy functions solve the entrepreneur's problem 8.

**(ii)** Given prices, consumption, and hours worked solve the worker's problem 7.

**(iii)** Given prices, policy functions, and the stationary distribution, all markets clear

$$\begin{aligned}
&\text{[labor]} & \int l(a,z)d\Phi(a,z) &= Nh,\\
&\text{[capital rental]} & \int k(a,z)d\Phi(a,z) &= \int a d\Phi(a,z),\\
&\text{[trade credit]} & \int \text{AR}(a,z)d\Phi(a,z) &= \int \text{AP}(a,z)d\Phi(a,z),\\
&\text{[goods]} & \int y(a,z)d\Phi(a,z) &= Nc^h + \int [c(a,z) + \delta k(a,z) + x(a,z)]d\Phi(a,z).
\end{aligned}$$

**(iv)** The evolution of distribution across entrepreneurs satisfies:

$$\phi(a',z') = \int \mathbb{I}_{a'=a'(a,z)}\Gamma_z(z'|z)d\Phi(a,z).$$

### 3.4 Optimal trade credit choices

Let $F(k, l, x) = ((k^{\alpha} l^{1-\alpha})^{1-\chi} x^{\chi})^{\mu}$ denote the production function. The Lagrangian of the entrepreneur's problem can be written as

$$\begin{aligned}\mathcal{L} = & \log((1+r)a + AzF(k,l,x) - (r+\delta)k - wl - x + r^{tc}(\mathrm{AR} - \mathrm{AP}) - a') \\ & + \beta \mathbb{E}_{z'|z} V(a', z') + \xi(\gamma_1 a' + \gamma_2 \mathrm{AR} - AzF(k,l,x) - (1+r^{tc})(\mathrm{AR} - \mathrm{AP})) \\ & + \chi_1(AzF(k,l,x) - \mathrm{AR}) + \chi_2 \mathrm{AR} \\ & + \chi_3(x - \mathrm{AP}) + \chi_4 \mathrm{AP} \\ & + \tau a'.\end{aligned}$$

where $\xi$, $\chi_1, \chi_2, \chi_3, \chi_4$ and $\tau$ are the corresponding Lagrange multipliers for the working capital constraint, the trade credit constraints, and the non-negative wealth constraint, respectively.

The FOCs of this optimization problem can be found in the appendix section B.2. For exposition purposes, I reproduce the FOCs w.r.t. AR and AP here:

$$[\mathrm{AR}] \qquad \frac{1}{c} r^{tc} = \xi(1 + r^{tc} - \gamma_2) + \chi_1 - \chi_2, \tag{13}$$

$$[\mathrm{AP}] \qquad \frac{1}{c} r^{tc} = \xi(1 + r^{tc}) - \chi_3 + \chi_4. \tag{14}$$

With the help of the FOCs, I will show in the following proposition that the optimal choice of trade credit follows a simple cut-off rule in entrepreneurs' wealth.

**Proposition 1.** *For given productivity $z$, there exist three cut-off values for entrepreneur wealth: $a_b(z)$, $a_{AR}(z)$, and $a_{AP}(z)$, such that*

1. *The working capital constraint is binding if and only if $a \leq a_b(z)$.*

2. *$AR > 0$ if and only if $a > a_{AR}(z)$.*

3. *$AP > 0$ if and only if $a < a_{AP}(z)$.*

*Proof.* See Appendix B.3.1. $\square$

The first wealth threshold $a_b(z)$ separates constrained from unconstrained entrepreneurs. Specifically, given productivity $z$, entrepreneurs become unconstrained when their wealth level exceeds threshold $a_b(z)$. One can show the Lagrange multiplier on working capital, $\xi$, which represents the shadow value of liquidity, declines monotonically with wealth for a given $z$, with $\xi$ reaching zero when wealth is high enough, and the entrepreneur becomes unconstrained.[15]

The second wealth threshold $a_{\text{AR}}(z)$ separates entrepreneurs who lend trade credit from those who do not. As shown in the FOC of AR (equation 13), the marginal benefit of lending trade credit is the trade credit interest rate multiplied by the marginal utility from consumption, while the marginal cost is the liquidity loss $1 + r^{tc} - \gamma_2$ multiplied by the shadow value of $\xi$. Since $\xi$ declines with wealth, there exists a threshold value for wealth above which the marginal benefit of lending trade credit exceeds the marginal cost, which corresponds to $a_{\text{AR}}(z)$.

The third wealth threshold $a_{\text{AP}}(z)$ separates entrepreneurs who borrow trade credit from those who do not. Using the FOC of AP (equation 14), a similar argument can be applied to understand the trade-offs behind $a_{\text{AP}}(z)$.

So far, I have discussed the cut-off rules behind the three decision functions separately. Next, I will show the relationship between these three wealth cut-offs. More specifically, the following proposition shows that, under relatively intuitive conditions, these three thresholds can be ranked based on their values.

**Proposition 2.** *If $r^{tc} \geq 0$ and $\gamma_2 \in (0, 1]$, the following inequality holds for any given $z$:*

$$a_{AR}(z) \leq a_{AP}(z) \leq a_b(z).$$

*Proof.* See Appendix B.3.2. $\square$

[15]The decrease of $\xi$ in wealth is not strictly monotone, and the function $\xi$ can be divided into several segments, each associated with different value ranges for AR and AP. I discuss this in detail in appendix figure C.4.

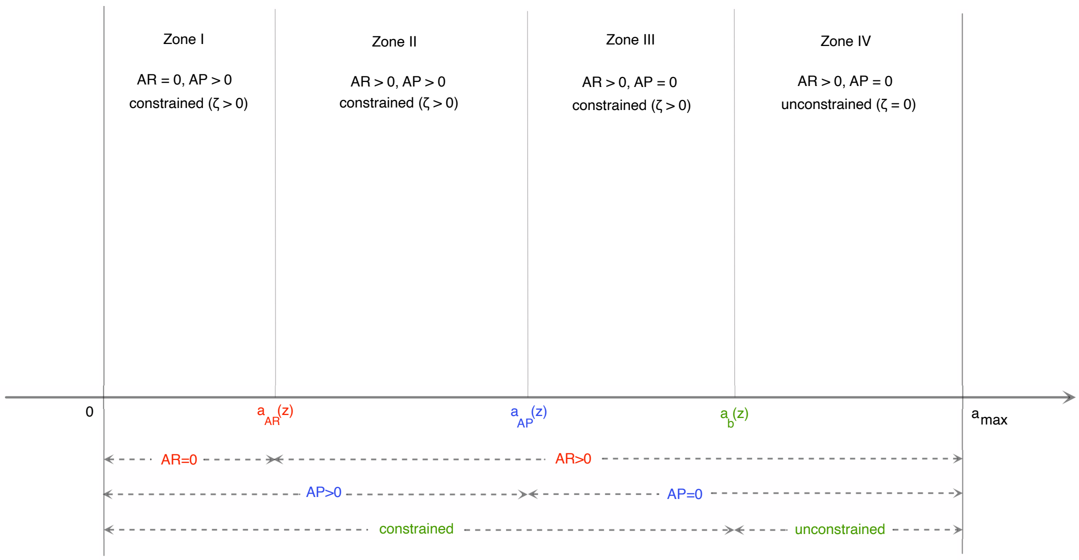



**Figure 5: The cut-off property of trade credit choices**

**Notes**: This figure shows the cut-off properties discussed in Propositions 1 and 2. For a given productivity $z$, there are three threshold values for $a$, $a_b(z)$ (green), $a_{\mathrm{AP}}(z)$ (blue), and $a_{\mathrm{AR}}(z)$ (red), which separate constrained entrepreneurs from unconstrained ones, entrepreneurs who borrow trade credit and those who do not, and entrepreneurs who lend trade credit and those who do not, respectively. These three thresholds divide the line of $a$ into four zones, which have different properties of trade credit choices and financial constraint.

Figure 5 illustrates the cutoff values of wealth $a$ for a given productivity $z$. These three cutoff values of wealth divide the line of $a$ into four zones. From low to high $a$, firms' trade credit choices can be broadly categorized into three types: (i) zone I, where AR $= 0$ and AP $> 0$; (ii) zone II, where both AR $> 0$ and AP $> 0$; and (iii) zones III and IV, where AR $> 0$ and AP $= 0$. While zones III and IV are characterized by the same trade credit choices, they are distinguished by the status of the working capital constraint: it is binding in zone III ($\xi > 0$) and non-binding in zone IV ($\xi = 0$). This figure also shows the funding sources across different zones. In the model, all firms obtain bank loans, and trade credit is a secondary option utilized only by firms with sufficiently low wealth (zones I and II). In other words, bank loans are the preferred funding source, with trade credit used only when firms reach the limits of their bank loan capacities.

With the help of this figure, I make the following observations about trade credit choices and firms' financial conditions: first, all unconstrained entrepreneurs provide AR to their customers. Second, some constrained entrepreneurs give AR to their customers. Third, unconstrained entrepreneurs do not take AP from their suppliers. Lastly, some entrepreneurs may give and receive trade credit simultaneously. This last point refers to zone II in Figure 5, where the zones of positive AR and positive AP overlap. A crucial parameter governing the size of zone II is $\gamma_2$, the collateral value of AR, which also captures the substitutability of trade credit for bank credit (Altinoglu, 2018).[16]

# 4 Quantitative Analysis

This section examines the quantitative implication of the model. I begin by discussing the calibration strategy and the results. Following it, I highlight the key mechanisms of the model and show how it generates outcomes consistent with the motivating facts.

## 4.1 Calibration

The model is calibrated to match key features in the US data.[17] I assume that each period in the model corresponds to one quarter. Since some data moments are only available at the annual frequency, calibrating to these data moments requires a temporal aggregation of the variables. For the stock variables, such as capital and labor, I take the average of the quarterly variables to construct the annual variables; for the flow variables, such as profit and output, I take the sum of the quarterly variables to create annual variables.

I discuss the calibration exercises in two parts: (i) parameters calibrated outside the model and (ii) parameters calibrated to target features in the data.

[16] With a slight abuse of notation, it is important to note that Zone II is bounded below by $a_{\text{AR}}(z) = \xi^{-1}\left(\frac{r^{tc}}{1-\gamma_2}; z\right)$ and above by $a_{\text{AP}}(z) = \xi^{-1}(r^{tc}; z)$, where $\xi(a; z)$ is a function of $a$ for a given $z$ and $\xi^{-1}$ is the inverse of this function. Accordingly, the value of $\gamma_2$ has a very direct influence on the zone size. In an extreme case, if $\gamma_2 = 0$, then $a_{\text{AR}}(z) = a_{\text{AP}}(z)$, rendering this zone an empty set—the regions with positive AR and positive AP do not overlap at all. As $\gamma_2$ increases, this zone expands, leading to larger overlapping regions of positive AR and AP.

[17] See appendix section C.1 for the algorithms to solve the model.

**Parameters calibrated outside the model.** I first set the values of several parameters outside the model following the standard practice of the literature. As shown in panel (a) of table 3, I set $\theta = 0.5$, which gives a Frisch elasticity of 2, a common value used in the literature and is well within the range of macro estimates (Chetty et al., 2011 and Keane and Rogerson, 2012). I fix the capital share $\alpha = 1/3$ in the production function. Consequently, the labor share is 2/3. Following Jones (2011), I fix $\chi$ so that the input's share in aggregate output is 0.43. Since the share of entrepreneurs in the data is around 10 percent and the measure of entrepreneurs in the model is 1, I set the workers' measure at $N = 9$. The capital depreciation rate $\delta$ is chosen to be 0.025, so the annual depreciation rate of capital is approximately 10 percent.

**Table 3: Calibration strategy**

| Parameter | | Value | Target/Source |
|---|---|---|---|
| **Pre-determined** | | | |
| $\theta$ | Frisher elasticity | 0.50 | standard |
| $\alpha$ | capital income share | 0.33 | capital share of 1/3 |
| $\chi$ | intermediate goods share | 0.43 | Jones (2013) |
| $N$ | measure of workers | 9 | share of entrepreneurs |
| $\delta$ | depreciation rate | 0.025 | 10% annual depreciation rate |
| **Calibrated** | | | |
| $\beta$ | discount factor | 0.92 | 4% annual risk-free interest rate |
| $\psi$ | disutility from working | 0.48 | hours worked |
| $\mu$ | scale parameter | 0.83 | top 5 percent earnings share |
| $\lambda$ | Pareto shape parameter | 4.3 | top 0.2 percent employment share |
| $\phi$ | productivity redraw shock | 0.1 | 1-year autocorrelation of profit rate |
| $\gamma_1$ | collateral value of wealth | 0.37 | ratio of debt to non-financial asset |
| $\gamma_2$ | collateral value of AR | 0.78 | ratio of AR to debt |

**Notes**: Panel (a) of this table lists all parameters that are set following the standard literature. Panel (b) of this table lists parameters that are calibrated to match specific features in the data.

**Parameters targeting features in the data.** I calibrate the remaining parameters to target specific data moments. The model assumes that the idiosyncratic productivity shocks follow a Pareto distribution with shape parameter $\lambda$, and the lowest productivity is normalized to 1. The idiosyncratic productivity is kept from one period to the next with probability $\phi$. With probability $1 - \phi$, the productivity needs to be redrawn from the distribution.

Seven parameters remain, and I calibrate them jointly to match seven data moments. These parameters are: (i) $\psi$, the disutility of providing labor in workers' utility function, (ii) $\beta$, the discounting factor of entrepreneurs, (iii) $\mu$, the span-of-control parameter in the production function, (iv) $\lambda$, the Pareto shape parameter, (v) $\phi$, the productivity redraw shock, (vi) $\gamma_1$, the collateral value of $a'$, and (vii) $\gamma_2$, the collateral value of AR.

Although the parameters are calibrated jointly, each is intuitively linked to a particular moment. The disutility from working, $\psi$, is closely related to the average hours worked in the data. I calibrate $\psi$ so that 30 percent of workers' time is spent working, i.e., $h = 0.3$. The discounting factor $\beta$ is calibrated to match an annual risk-free interest rate of 0.04.

The Pareto shape parameter $\lambda$ is sensitive to the employment share of the largest firms. I pick $\lambda$ so that the model matches the employment share of firms with 1000+ employees in the US economy. This data moment is calculated using the Business Dynamics Statistics dataset from 2005, which shows that these firms, although constituting only about 0.2% of all US firms, employ 44% of all workers. The span-of-control parameter $\mu$ is then calibrated to match the top 5 percent earnings share of 0.3 documented in Buera et al. (2015).

The productivity redraw shock affects the persistence of firm outcomes. Therefore the parameter $\phi$ is chosen to match the 1-year auto-correlation of the annual profit rate documented by Gourio (2018) using Compustat. Depending on the sample and the specification, Gourio (2018) estimates that the auto-correlation ranges from 0.68 to 0.79.

I pick $\gamma_1$, the collateral constraint on wealth $a'$, to match the ratio of credit market liabilities to non-financial assets in the US non-financial corporate sector. I follow Jermann and Quadrini (2012) to construct this data moment using the Flow of Funds dataset. Specifically, credit market liability equals the sum of "debt securities" and "loans." The non-financial assets include equipment, real estate, and intellectual property product (IPP). The ratio of credit market liabilities to non-financial assets averaged 0.36 from 2004 to 2006. At the same time, the collateral value of AR, $\gamma_2$, is calibrated to match the ratio of AR to credit market liabilities of the US non-financial corporate sector, which averaged 0.32 in the data during the same period.

**Table 4: Model and data moments**

| | Model | Data |
|---|---|---|
| Hours worked | 0.30 | 0.30 |
| Risk-free interest rate | 0.04 | 0.04 |
| Top 0.2 percentile employment share | 0.44 | 0.41 |
| Top 5 percentile earnings share | 0.30 | 0.32 |
| 1-year auto-correlation in profit | 0.76 | [0.68,0.79] |
| Ratio of debt to non-financial asset | 0.36 | 0.36 |
| Ratio of AR to debt | 0.32 | 0.32 |

**Notes**: The top 10 percentile employment share is computed using the Business Dynamics Statistics data. 1-year auto-correlation in profit rate follows the estimates in Gourio (2018). The s.d. of employment growth is estimated by Davis et al. (2007) for 2001. I take credit market liability from Flow of Funds Table L.103 line 23 and nonfinancial asset size from Flow of Funds Table B.103 line 2. Trade receivable is taken from Flow of Funds Table L.103 line 15.

Before discussing the calibration results, it is important to note that although the model is about the entire US economy, some data moments used in the calibration are derived from the Compustat database, which consists of the largest firms in the US. To ensure consistency between the model and data moments, I have drawn a subset from my model-generated data, comprising the largest firms, to serve as a comparator for the Compustat firms. I rely on two key pieces of information to guide the creation of this Compustat subsample. First, among the largest firms in the US, approximately 80% are public, and the remaining 20% are private.[18] Second, according to calculations by Schlingemann and Stulz (2022), public firms accounted for approximately 30% of employment in the US during the early to mid-2000s. Assuming that the ratio of public to private firms among the largest US firms also reflects their relative employment sizes, I can then infer that the Compustat subsample should be drawn from the top 38% (30/0.8) of the employment shares from my model-generated data.

Table 4 examines the implied moments of the model against the data and shows that the model matches data features well. I also compare, in Appendix section C.2, the model's fit to the observed untargeted firm size distribution. The results are reassuring: the model not only mirrors the data in terms of employment shares across each size category but also

[18]These figures are derived from leading company rankings by Fortune magazine and Forbes. Specifically, the 2022 Fortune 1000 lists the 1000 largest public companies, all with revenues above 2.1 billion. Meanwhile, Forbes identifies 258 of America's largest private companies, each generating over 2 billion annually. Collectively, these lists reveal that approximately 20% of the largest firms are private, while 80% are public.

matches how average employment increases with firm size.

## 4.2 Model implications related to the motivating facts

The model emphasizes the vital role of firms' heterogeneous financial conditions in determining the choice of trade credit. In this section, I argue that the model's predictions are consistent with the patterns highlighted in the empirical section and that heterogeneity in financial constraints is an important driver of the allocation of trade credit across firms.

### 4.2.1 Trade credit, financial constraint, and entrepreneur heterogeneity

To examine relationship between trade credit choice and firm-level financial constraints in the model, I begin by examining entrepreneurs' optimal policy functions. First, recall that the Lagrange multiplier $\xi$ in entrepreneurs' optimization problem represents the marginal value of liquidity. Panel (a) of figure 6 shows that $\xi$ is a decreasing in wealth for any given productivity level, and it shifts upward when productivity increases, indicating that, conditional on having the same wealth, higher-productivity entrepreneurs are more constrained than low-productivity entrepreneurs. Overall, this figure also illustrates how the model maps the $(a, z)$ space into different values of $\xi$, generating heterogeneity in financial constraints.

**(a)** $\xi$ **(b)** AR$/y$ **(c)** AP$/x$

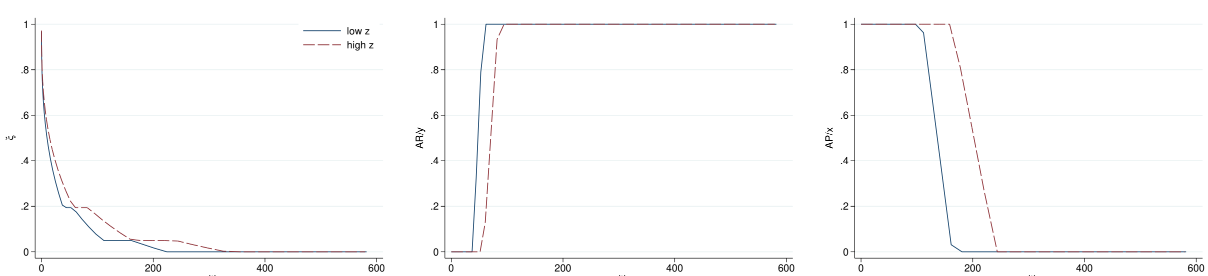



**Figure 6:** Policy functions for low and high values of $z$

**Notes**: Panel (a) plots the liquidity value $\xi$ as a function of entrepreneur wealth $a$ for a given productivity level (high or low). Panel (b) and (c) plot the lending of trade credit (i.e., AR$/y$) and the borrowing of trade credit (i.e., AP$/x$) as a function of wealth $a$, respectively.

Next, panels (b) and (c) in figure 6 plot firms' choice of trade credit – AR/$y$ and AP/$x$ – as a function of wealth. Both policy functions are bounded between 0 and 1.[19] Given productivity, trade credit lending AR/$y$ increases with wealth, while trade credit borrowing AP/$x$ decreases with wealth. As productivity increases, both functions shift outward. Compared with low-productivity entrepreneurs, high-productivity entrepreneurs with the same wealth, who are more financially constrained, would borrow more trade credit from suppliers and lend less to customers.

**Table 5:** Trade credit and firm size in the model and data

*Panel (a): Model*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Firm size (log size) | -0.012*** | 0.028*** | 0.040*** | 0.036*** |
| | (0.001) | (0.006) | (0.006) | (0.008) |
| Dependent variable | AP/Sales | AR/Sales | NetAR/Sales | $\mathbb{I}_{\text{NetAR}>0}$ |
| $N$ | 3360 | 3360 | 3360 | 3360 |
| $R^2$ | 0.079 | 0.006 | 0.012 | 0.006 |

*Panel (b): Data*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Firm size (log size) | -0.078*** | -0.001 | 0.068*** | 0.033*** |
| | (0.009) | (0.002) | (0.010) | (0.006) |
| Dependent variable | AP/Sales | AR/Sales | NetAR/Sales | $\mathbb{I}_{\text{NetAR}>0}$ |
| $N$ | 33608 | 33638 | 33605 | 33605 |
| $R^2$ | 0.076 | 0.004 | 0.062 | 0.030 |

**Notes**: Panel (a) estimates the relationship between trade credit policies on log firm size measured by assets in the model-generated Compustat sample. The Compustat sample is created by selecting the largest firms that constitute 38% of the total employment share in the model-generated data. Panel (b) estimates the relationship between trade credit and log firm size in the data using the estimation equation 1 (without controls for firm age).

Having discussed the policy functions, I now turn to examine the size relationship of trade credit in the steady state equilibrium. To do this, I regress firms' trade credit policies

[19] The policy functions in panels (b) and (c) show that some entrepreneurs choose not to lend or borrow trade credit (AR = 0 or AP = 0), which differs from the data, where it is rare to see firms with zero AR or AP on their balance sheet. One way to reconcile this discrepancy is to notice that the empirical measure of AR and AP is a snapshot of firms' activities; hence they likely reflect the averages of AR and AP over all the sales and purchases that overlapped in time. Similarly, suppose AR and AP in the model reflect the averages over several sales. In that case, I find that the policy functions no longer take corner solutions and thus can better mimic the observed patterns in the data (for more details, see appendix C.4).

on firm size in the model-generated Compustat sample and compare it with the actual data. Table 5 presents the estimation results in the model (panel a) and the data (panel b). Both the model and the data indicate larger firms tend to lend more trade credit on a net basis. The estimated coefficient between net AR/sales and firm size is 0.04 in the model, compared to 0.068 in the data. Additionally, the estimated coefficient for $\mathbb{I}_{\text{AR}>\text{AP}}$—the probability of being a net trade credit lender—and firm size is 0.036 in the model and 0.033 in the data. A notable difference, however, lies in the margins driving these outcomes: in the data, variations in net AR across firm sizes are mostly due to differences in the borrowing of trade credit (AP), whereas in the model, they occur through both borrowing and lending margins. This difference might indicate that the model does not fully capture all the determinants of trade credit policies among US public firms. Nonetheless, a comparison of these two panels reveals that the model generates a quantitatively similar pattern to that observed in the data, particularly in terms of net AR.[20]

#### 4.2.2 Heterogeneous exposure to financial shocks

Next, I study how entrepreneurs respond when they experience different degrees of financial shocks, as firms did after the bankruptcy of Lehman Brothers. I do so by introducing an unexpected negative financial shock to the economy, modeled as a reduction to the collateral values $\gamma_1$ and $\gamma_2$. Crucial to this experiment is that the magnitude of the shock differs across two ex-ante identical groups of entrepreneurs. The shock's magnitude is calibrated to match the observed decline in value-added output for two firm groups, differentiated by having exposures to the Lehman shock that are below and above the median, as detailed in the empirical section 2.2.

Figure 7 Panel (a) shows that, in the data, the average value-added output declined for

[20]The current model is not designed to capture firms' life cycle dynamics; therefore, it is not ideally suited for studying the effect of firm age on trade credit. However, the model can be expanded, following the approach in Ottonello and Winberry (2020), to incorporate life cycle patterns in financial constraints. This would involve assuming that new firms start smaller than their optimal scale, leading to younger firms being more constrained than older ones, even after controlling for firm size. Consequently, according to the mechanism highlighted in my model, younger firms would tend to borrow more and lend less trade credit than older firms.

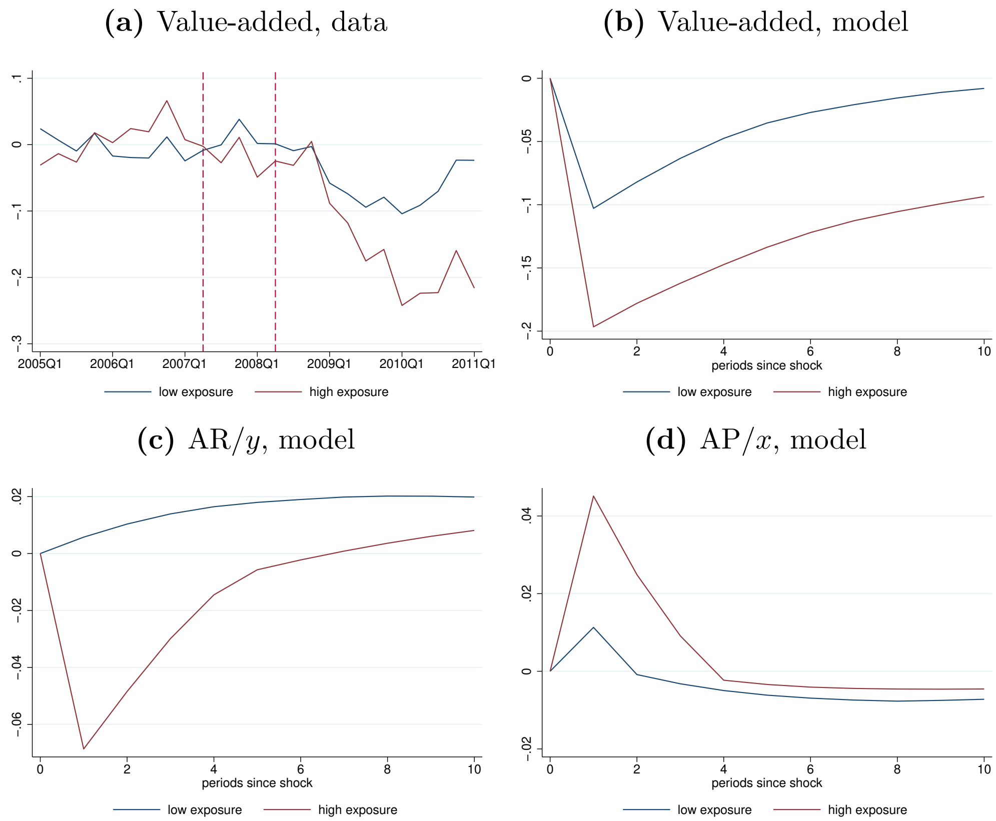



**Figure 7:** Changes in AR and AP by exposure to financial shock

**Notes**: Panel (a) shows the average value-added output for each group of firms based on their exposure to the Lehman shock. The two red vertical lines in each panel mark the quarters of 2007Q2 and 2008Q2, which are the quarters preceding the collapses of Bear Stearns (also the start of the NBER recession) and the Lehman bankruptcy, respectively. To adjust for the seasonality, this figure displays de-trended moving averages calculated over a four-quarter backward-looking window $[t-3, t]$. The value-added in 2007Q2 is normalized to 0 for both groups, with subsequent values showing the relative decline from this pre-shock level. Panel (b) illustrates that the model matches the observed relative decline in the average value-added output following the collateral shocks. Panels (c) and (d) detail the changes in average AR/y and AP/x after the shock, with dynamics expressed as percentage point differences from the pre-shock levels.

both firm groups. Firms with low Lehman exposure saw a 10% drop, while those with high exposure faced a 20% decrease, nearly doubling that of the low-exposure group. In panel (b), I apply collateral shocks to the two groups in the model, replicating the output declines seen in panel (a). The shocks decay geometrically with a half-life of one year. Panels (c) and (d) show the model dynamics for average AR/$y$ and AP/$x$. Panel (c) indicates that the high-exposure group cut their trade credit lending by over 6 percentage points, while the low-exposure group slightly increased theirs. Meanwhile, panel (d) reveals that the high-exposure group increased their borrowing of trade credit by more than 4 percentage points, compared to a 1 percentage point increase by the low-exposure group.[21] These figures show that, compared to firms with low exposure to Lehman, those with higher exposure reduce their trade credit lending more significantly and also increase their borrowing more.

We can also compare these trade credit dynamics to those in the data (top two panels in Figure 2). In the data, trade credit lending (AR) for low-exposure firms remains roughly unchanged, while high-exposure firms' AR declined by about 3 percentage points. Furthermore, trade credit borrowing increased by 1.5 percentage points for high-exposure firms and decreased by a similar margin for low-exposure firms. Overall, although the model generated a slightly larger impact compared to the data, the broad patterns are consistent, reflecting the differential impacts between high- and low-exposure firms. Specifically, I find that entrepreneurs facing more severe shocks reduce their lending to customers while increasing their borrowing from suppliers, in line with the evidence documented in the data.

# 5 Aggregate Implications of Trade Credit

In this section, I explore the aggregate implications of trade credit. I begin with a more formal evaluation of the allocative role played by trade credit in the steady state. Then, I examine the aggregate implications of financial shocks – shocks to all or a fraction of entrepreneurs – and focus on how the endogenous changes in trade credit affect the aggregate economy.

## 5.1 Reallocation effect of trade credit in normal times

I consider two counterfactual experiments to evaluate the allocative effect of trade credit in the steady state.[22] In the first experiment, I shut down the trade credit channel by setting AR = AP = 0. In the second experiment, the trade credit channel is still shut down, but I replace trade credit with bank credit by raising the collateral value $\gamma_1$ from 0.37 to 0.46 so

[21] Appendix section C.5 details the shifts in the policy functions for each firm group following the shock.

[22] See appendix section B.4 for the equilibrium definition of the counterfactual economy.

that the aggregate debt to capital stock ratio is the same as the benchmark model. While the first experiment quantifies the aggregate impact of the *existence* of trade credit, the second experiment examines how trade credit differs from bank credit in allocating resources across heterogeneous entrepreneurs.

Table 6 presents the differences between the benchmark and counterfactual economies in terms of the aggregate value-added output, hours, capital stock, and TFP. Shutting down trade credit leads to a 35.1% reduction in output, which can be decomposed into a 30.6% lower capital stock, a 30.5% lower hours worked, and a 10.9% lower aggregate TFP. Output is higher in the benchmark economy because trade credit relaxes the entrepreneurs' borrowing constraints and allows resources to be allocated more efficiently. This leads to higher aggregate productivity and, consequently, higher capital, labor, and output in the steady state.

**Table 6:** Difference between counterfactual and benchmark economy (%)

| Counterfactual | value-added | capital | labor | TFP |
|---|---|---|---|---|
| (1) shut down trade credit | -35.1 | -30.6 | -30.5 | -10.9 |
| (2) replace trade credit with bank credit | -10.3 | -8.1 | -8.6 | -3.3 |

**Notes**: This table displays the percent difference of the counterfactual economy relative to the benchmark economy. A negative number in the table suggests that the aggregate statistics of the counterfactual economy are lower than that of the benchmark economy. In the first counterfactual economy, I shut down trade credit by setting AR=AP=0 while keeping the other parameters fixed. In the second counterfactual economy, I increase $\gamma_1$ to 0.41 so that the aggregate debt-to-capital ratio is the same as the benchmark economy.

Replacing trade credit with bank credit also leads to lower aggregate economic activities, as shown in the second row of table 6, although compared with the previous experiment, the magnitude of the decline is smaller. The aggregate output is 10.3% lower, with an 8.1% smaller capital stock, 8.6% lower total hours, and 3.3% lower aggregate TFP. The lower aggregate TFP indicates that the allocative efficiency is worse in the counterfactual economy. Indeed, in the benchmark model, the correlation between log value-added output and log productivity is at its highest, at 0.82. In contrast, this correlation decreases to 0.77 when trade credit is replaced with bank credit in the counterfactual economy, and it declines further to 0.67 when trade credit is completely shut down.

**Table 7:** Distribution across productivity groups: benchmark v.s. counterfactual

| | Benchmark | | | Counterfactual (2) | | |
|---|---|---|---|---|---|---|
| | low | median | high | low | median | high |
| Number of entrepreneurs | 0.641 | 0.226 | 0.133 | 0.641 | 0.226 | 0.133 |
| Output per entrepreneur | 0.232 | 0.710 | 5.203 | 0.253 | 0.743 | 5.047 |
| Wealth per entrepreneur | 0.635 | 0.821 | 3.068 | 0.630 | 0.808 | 3.114 |

**Notes**: This table shows the distribution of entrepreneurs, wealth, and output across three productivity groups in the benchmark and the counterfactual economy in the second experiment where I replace trade credit with bank credit. Footnote 23 describes how I construct these three productivity groups. The first row shows the number of entrepreneurs in each group as a share of all entrepreneurs. The second row shows average wealth per entrepreneur in each productivity group with the aggregate wealth and number of entrepreneurs normalized to one. The third row shows average gross output per entrepreneur in each productivity group with the aggregate output and number of entrepreneurs normalized to one.

Table 7 compares the distribution across three productivity groups (low, median, and high) between the benchmark and the recalibrated counterfactual economies.[23] As shown in the first row, the share of entrepreneurs in each productivity group is identical across the two economies (because the same exogenous productivity process generates the distribution). In the benchmark economy, high-productivity entrepreneurs produce a larger share of aggregate output, despite having a lower wealth share than in the counterfactual economy. For instance, the average output (aggregate output and wealth normalized to one in both economies) of the most productive entrepreneurs is 3.1% higher in the benchmark economy (5.203) than in the counterfactual economy (5.047), whereas the average wealth is 1.5% lower (3.068 versus 3.114). The fact that output distribution is skewed towards more productive entrepreneurs in the benchmark model is consistent with its higher TFP. It indicates that trade credit performs better than bank credit in allocating resources to more productive entrepreneurs.

Trade credit plays a more significant role when the productivity distribution features a fatter tail. Suppose I lower $\lambda$, the Pareto shape parameter, from 4.3 to 4.1, and recalibrate all other parameters to match data moments. The difference in value-added between the counterfactual where trade credit is shut down and the benchmark increases from 35.1 percent to 37.9 percent. In the second counterfactual where trade credit is replaced by bank credit, this difference increases from 10.3 to 16.9 percent. This result is rather intuitive, given

[23] In the numerical solution, I discretize the productivity space $z$ into 10 grids. The median-productivity group consists of grid 4. Consequently, the low-productivity group consists of grids 1 to 3, and the high-productivity group consists of grids 5 to 10. The results are robust under alternative grouping schemes.

the reallocative role of trade credit. With different values of $\lambda$, each economy is calibrated to match other data moments, including the aggregate size of debt and trade credit. In economies where the productivity distribution is skewed towards the right tail, a larger share of trade credit is likely to benefit high-productivity firms by channeling resources to them. As a result, trade credit assumes a more important role; its absence would result in a more marked decline in economic activities.

## 5.2 Trade credit and financial shocks

I now investigate the role played by trade credit during a financial crisis – modeled as an unexpected shock to the collateral constraints of all entrepreneurs. To generate a financial shock of plausible magnitude, I reduce the collateral value $\gamma_1$ and $\gamma_2$ by 8% and 9%, respectively, to match the decrease in the credit of the U.S. non-financial corporate sector during the 2007–09 financial crisis.[24] The shocks decay geometrically with a half-life of one year (four periods), consistent with the duration of the banking crisis in advanced economies.

Figure 8 shows the model dynamics in credit market liability and trade credit following the shock. As shown in panel (a), the model generates a decrease in the ratio of credit market liabilities to capital stock, closely matching the 11 percent decrease from peak to trough in the data. Panel (b) shows that the decline in the ratio of trade credit to capital stock is approximately 11 percent, slightly lower than the 12 percent decrease in the data. The vertical dash line marks 2008Q2, the pre-crisis peak of credit market liability to capital stock ratio.

Figure 9 shows that the model can generate a sizable recession following the crisis, accounting for a significant fraction of the peak-to-trough decrease in output, TFP, hours, and

[24] The parameter $\gamma_2$ represents the collateral value of accounts receivable and captures the substitutability of trade credit for bank credit. Reducing $\gamma_2$ would therefore decrease entrepreneurs' willingness to lend trade credit, thereby limiting its role in mitigating financial shocks. The decision to reduce $\gamma_2$ alongside $\gamma_1$ aligns with empirical trends. Appendix figure A.5 shows that the volume of new loans secured by accounts receivable (AR) fell by approximately 40 percent from 2007 to 2008. Since $\gamma_2$ in the model reflects the collateral value of AR, it is reasonable to assume a decline in this value during a financial crisis. Moreover, the aggregate sizes of debt and trade credit are primarily determined by the collateral values $\gamma_1$ and $\gamma_2$. Consequently, both collateral values must be adjusted to reflect the observed reduction in the data.

**(a)** Credit market liability to capital stock ratio

**(b)** Trade credit to capital stock ratio

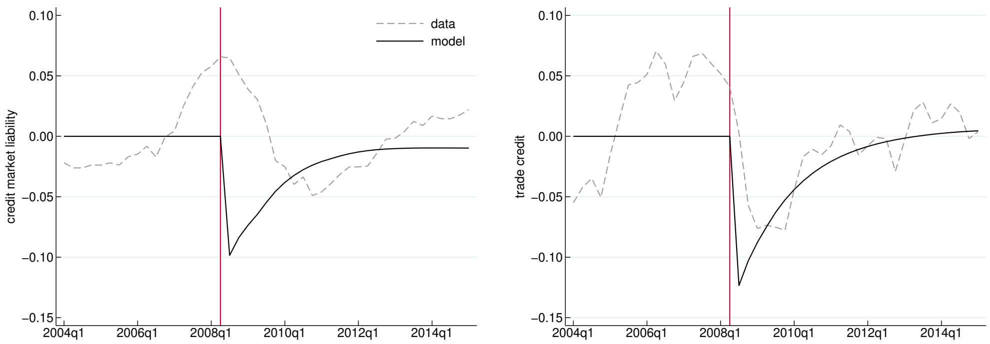



**Figure 8:** Dynamics of credit market liability and trade credit

**Notes**: The data used in the above figures are for the U.S. non-financial corporate sector. Among them, credit market liability is taken from Flow of Funds Table L.103 line 23. Trade credit is calculated as the average of trade payable (line 30 of Flow of Funds Table L.103) and trade receivable (line 15 of Flow of Funds Table L.103). The capital stock is constructed as the sum of equipment (line 46 of Flow of Funds Table B.103), intellectual property products (IPP) (line 47 of Flow of Funds Table B.103), and nonresidential structural capital (line 51 of Flow of Funds Table B.103), all valued at historical prices. Both credit market liability and trade credit to capital stock ratio are HP-filtered with a smoothing parameter of 1,600, and the percentage derivation from the trend is plotted in the figures. The corresponding model moments are normalized to 0 at $t = 0$. The red vertical line corresponds to $t = 0$ in the model and 2008Q2 in the data.

capital stock in the data.[25] Notably, output declined by 5.9%, approximately three quarters of what we observe in the data. Hours decreased by 8.8% compared to an 8.6% decline in the data. The model also generated a 6.3% decline in TFP and a 1.9% decline in capital stock. Overall, the model dynamics following the shock are consistent with the findings of the existing literature. The decline in aggregate TFP results from credit tightening in the presence of producer heterogeneity (Buera and Moll, 2015). In addition, there is a significant contraction in hours worked, which is also found in other models involving working capital constraints (Jermann and Quadrini, 2012).

Figure 10 examines the dynamics of trade credit. Following the shock, entrepreneurs become more constrained: they are less willing to lend trade credit and more eager to borrow. The inward shift in the supply of trade credit and the outward shift in demand for trade credit leads to an increase in the trade credit interest rate (panel a) and, under the calibrated parameters, a decrease in trade credit relative to output (panel b). Through the lenses of the

[25]The vertical dash line marks 2008Q2. Despite the official NBER recession starting in 2007Q4, the initial drop in output was small. The most significant decrease in all four series happened in 2008Q3 or 2008Q4.

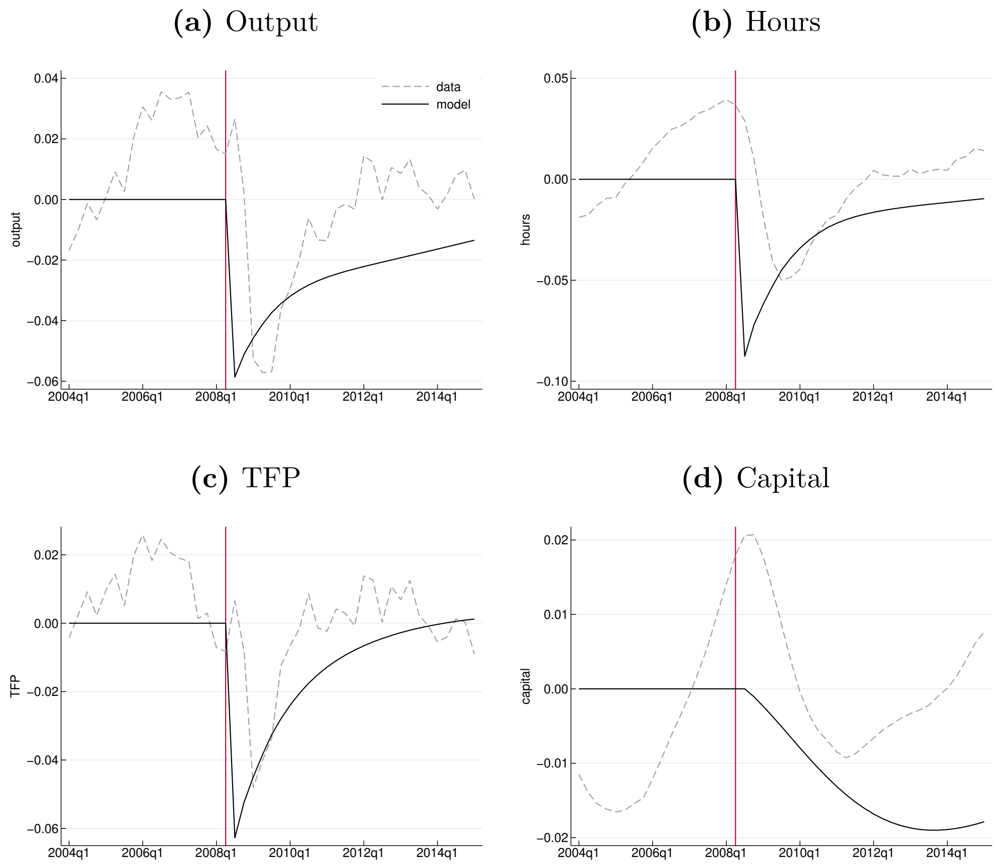



**Figure 9:** Dynamics of the aggregate variables

**Notes**: The data used in the above figures are for the U.S. nonfinancial corporate sector. Among them, output (gross value added) is taken from NIPA Table 1.14 line 17. Data for hours worked is an index taken from the Bureau of Labor Statistics Labor Productivity and Costs database (BLS code PRS88003033). Data for capital stock are constructed in the same way as Figure 8. TFP is then constructed as a Solow-type residual using output, hours, and capital stock. The corresponding model moments are normalized to 0 at $t = 0$. The red vertical line corresponds to $t = 0$ in the model and 2008Q2 in the data.

model, a direct consequence of these changes in trade credit is that, as trade credit becomes costlier and scarcer during the financial crisis, some of the constrained entrepreneurs can no longer rely on trade credit from their suppliers to finance their production. That is, the reallocation role played by trade credit during normal times, as discussed in the previous section, is impaired by the financial shock.

**(a)** Trade credit interest rate **(b)** Trade credit relative to output

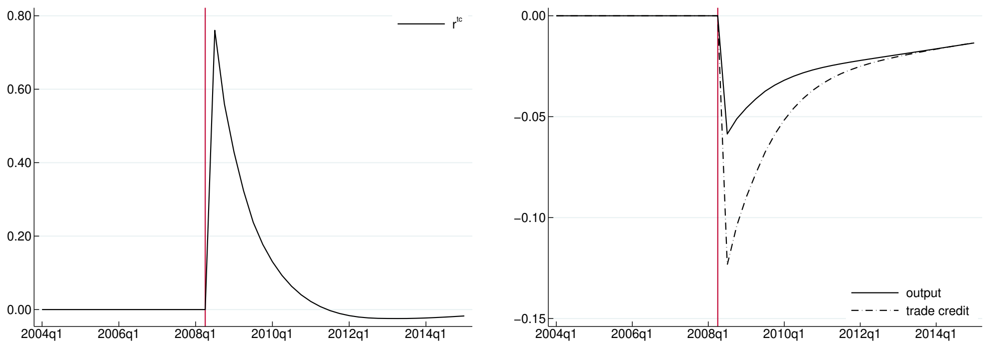



**Figure 10:** Trade credit interest rate and size

**Notes**: The two panels in this figure plot the dynamics in trade credit following the financial shock. Panel (a) shows the trade credit interest rate $r^{tc}$ and panel (b) shows total trade credit (aggregate AR or AP) and value-added output. The values at $t = 0$ are normalized to 0. The red vertical line corresponds to $t = 0$ in the model and 2008Q2 in the data.

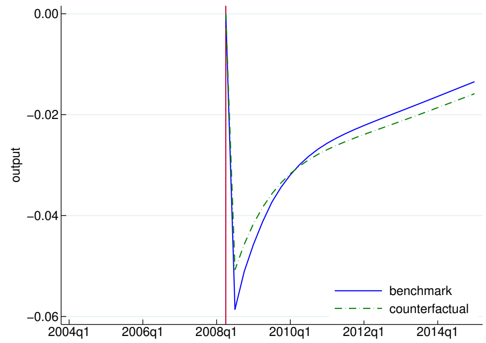
### 5.2.1 Aggregate financial shocks and the amplification effect

In this section, I quantify trade credit's role during the 2007–09 financial crisis by introducing the same financial shock to the counterfactual economy without trade credit and comparing the dynamics of the two economies following the shock. The counterfactual economy, as described in section 5.1, is recalibrated to match the steady-state debt-to-capital ratio in the benchmark model.

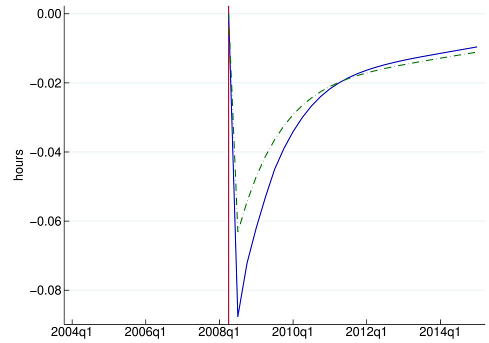
Figure 11 shows recession generated by the same shock is greater in the benchmark economy than in the counterfactual economy, with a total output reduction 0.8 percentage points larger, or a 16 percent larger decline than in the counterfactual. In particular, the benchmark economy sees a greater decline in aggregate TFP and hours worked than the counterfactual economy. However, compared with the counterfactual case, the decline in capital stock is milder in the benchmark model. Overall, the exercise suggests that the steeper decline in TFP and hours quantitatively dominates, and consequently, the presence of trade credit amplifies the output loss during the financial crisis.

To summarize, the benchmark and counterfactual economies differ in two important ways. First, the benchmark model features more significant productivity losses, suggesting

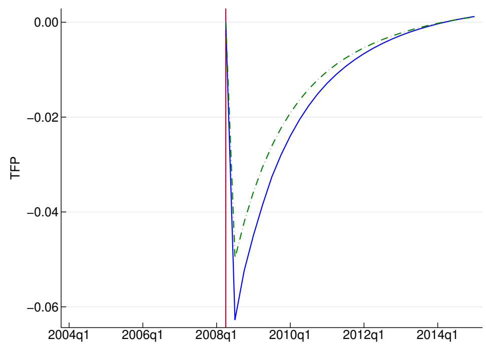
**(a)** Output




**(b)** Hours




**(c)** TFP




**(d)** Capital

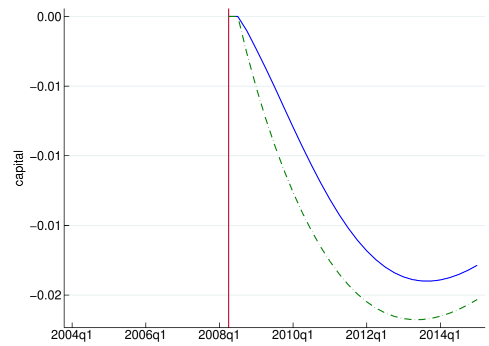



**Figure 11:** Dynamics of the aggregate variables: benchmark vs. counterfactual

**Notes**: The figures show the changes in the aggregate economy in terms of output, hours, aggregate TFP, and capital stock after the financial crisis. All lines are normalized to 0 at the beginning of the crisis. Each line in the figure represents a model economy: benchmark economy (blue) and counterfactual economy without trade credit (green).

a more severe misallocation of resources. What causes the more severe misallocation in the benchmark economy? In both economies, after the shock, resources are reallocated from high-productivity entrepreneurs to low-productivity entrepreneurs. For instance, figure 12 shows that, in both models, the average output of low-productivity entrepreneurs (those with a below-median $z$) increases while that of high-productivity entrepreneurs decreases. However, this reallocation toward low-productivity entrepreneurs is more pronounced in the benchmark economy, which can be attributed to two forces associated with trade credit. On the one hand, compared with a contraction in bank credit, a contraction in trade credit is disproportionately borne by the most constrained entrepreneurs (because they are the ones using it). On the other hand, a higher trade credit interest rate benefits unconstrained

**(a)** Low productivity **(b)** High productivity

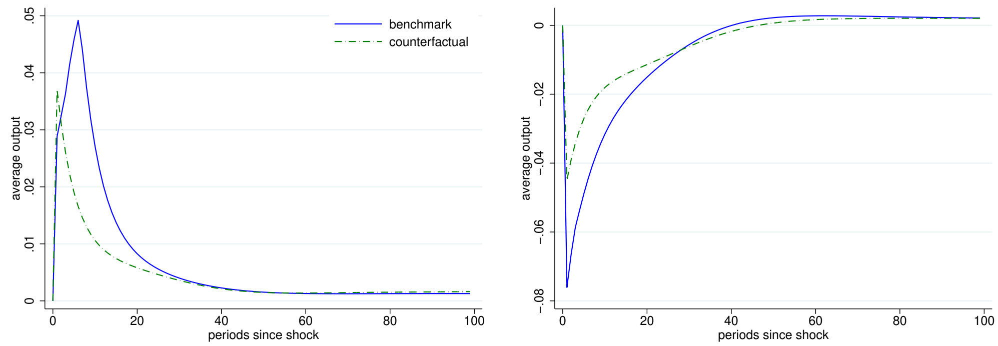



**Figure 12:** Average output for low and high productivity entrepreneurs

**Notes**: The two panels show the average output per entrepreneur of low productivity (below-median $z$) and high productivity (above-median $z$). The average output at $t = 0$ is normalized to 0. Each line in the figure represents a model economy: benchmark economy (blue) and counterfactual economy without trade credit (green).

entrepreneurs (lenders of trade credit) by raising their profitability. Both forces lead to more misallocation across entrepreneurs.

**(a)** Interest rate $r$ **(b)** Value of liquidity $\xi$

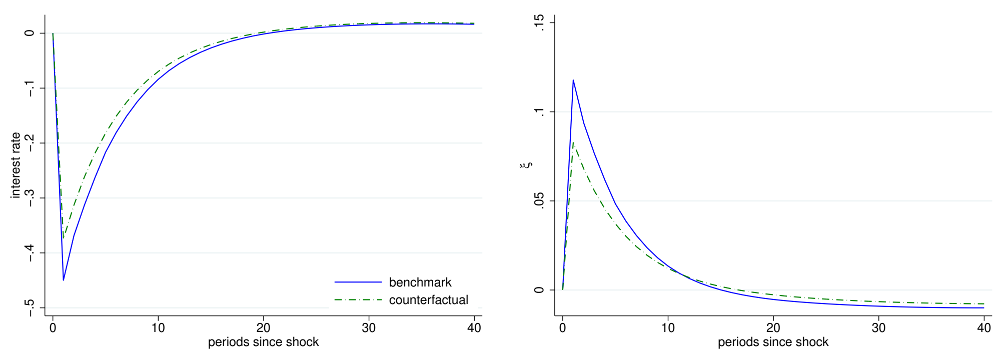



**Figure 13:** Incentives for saving: interest rate and value of liquidity

**Notes**: Panel (a) shows the dynamics of interest rate $r$, and panel (b) shows the value of liquidity $\xi$. The values at $t = 0$ is normalized to 0. Each line in the figure represents a model economy: benchmark economy (blue) and counterfactual economy without trade credit (green).

Second, entrepreneurs have a greater incentive to save in the benchmark model. Entrepreneurs' incentive to save depends on (i) interest rate $r'$ and (ii) liquidity value $\xi$. In the benchmark model, the interest rate falls more than in the counterfactual case, as shown in panel (a) of figure 13. A lower interest rate discourages saving. On the other hand, the value of liquidity $\xi$ increases more in the benchmark economy than in the counterfactual economy (panel b). A higher liquidity value indicates that entrepreneurs are more constrained, incentivizing them to save more to ease the borrowing constraint. Overall, the impact of higher liquidity values dominates, resulting in more savings in the benchmark economy.

### 5.2.2 Financial shocks to a fraction of entrepreneurs and the mitigation effect

The previous section illustrates how changes in trade credit amplify an aggregate financial shock that affects *all* entrepreneurs. Suppose instead that only a fraction of entrepreneurs are affected by the financial shock; what role does trade credit play here? As evidenced by empirical evidence, when the financial shock is heterogeneous across entrepreneurs, trade credit flows to those facing more severe shocks. Consequently, one might expect trade credit to mitigate the impact of such shocks. In this section, I investigate the mitigation effect of trade credit by introducing the same collateral-constraint shock as in the previous section to *some*, but not all, entrepreneurs. Moreover, I randomly assign the shock to entrepreneurs; in other words, entrepreneurs face the same probability of receiving the shock ex-ante.

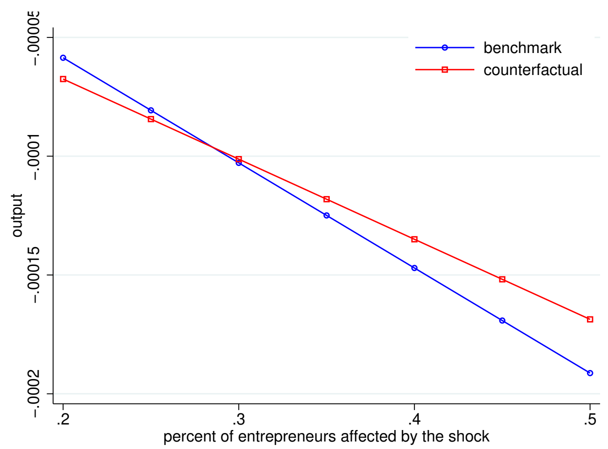



**Figure 14:** Output loss and share of entrepreneurs facing negative financial shocks

**Notes**: These figures plot the output (vertical axis) from a shock to $x$ percent of entrepreneurs in the economy (horizontal axis). The pre-shock output is normalized to 0. The two lines in the figures represent two model economies: benchmark (blue) and counterfactual economy without trade credit (red).

Figure 14 shows the (upon impact) output loss following the shock. When the shock hits a small fraction of the entrepreneurs, the benchmark economy experiences a smaller output loss than the counterfactual economy, consistent with the idea that the presence of trade credit mitigates the impact of idiosyncratic financial shocks. As more entrepreneurs are affected by the shock, however, the benchmark economy's output declines more steeply than the counterfactual economy. In fact, when the share of affected entrepreneurs exceeds a threshold – approximately 0.3%, the benchmark economy suffers a more significant output loss than the counterfactual case. Such a reversal indicates that the mitigation effect, which depends on trade credit flowing from unaffected to affected entrepreneurs, is most powerful when the shock only impacts a small percentage of entrepreneurs. As the shock spreads and fewer entrepreneurs can lend trade credit, trade credit's mitigation effect weakens. When the share of affected entrepreneurs exceeds a threshold value, the amplification effect of trade credit dominates the mitigation effect, resulting in a greater loss of output in the benchmark economy. This is a rather intuitive result: as the shock affects more and more entrepreneurs, trade credit plays an increasingly similar role as it does during an aggregate financial shock.

Compared with the counterfactual model, the output loss *accelerates* in the benchmark model as more entrepreneurs are affected by the financial shock. In other words, in the presence of trade credit, output loss is more "backloaded" as the shock spreads gradually throughout the economy. To illustrate this, figure 15 panel (a) compares the increments in output loss in the two economies as the shock hits an increasing number of entrepreneurs. For a more transparent comparison, I normalize the output losses in both economies to 1 when the shock hits all entrepreneurs. As shown in the figure, the benchmark economy experiences an output loss of 0.179 when the first 20 percent of entrepreneurs are affected by the financial shock. Each subsequent 20 percent of entrepreneurs affected by the shock results in an increasingly larger increment in output loss, reaching 0.224 when the shock hits the last 20 percent of entrepreneurs. In contrast, the increments in output loss associated with the first 20% and last 20% of entrepreneurs are much more similar in the counterfactual model (0.195 versus 0.205).

Because the mitigation effect hinges on trade credit flowing from unaffected to affected entrepreneurs, the volume of such flows is an intuitive indicator of its strength. Panel (b) of figures 15 plots the net trade credit borrowing (AP − AR) of the affected group

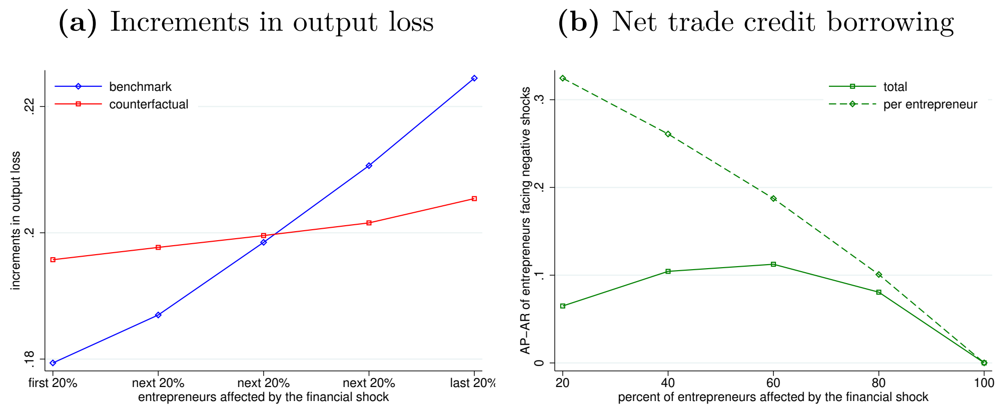



**Figure 15:** Acceleration of output loss and trade credit borrowing of affected entrepreneurs

**Notes**: Panel (a) plots the increments in output loss as the financial shock hits 20%, 40%, 60%, 80% and 100% of the entrepreneurs in the economy. The output loss when the financial shock hits 100% entrepreneurs is normalized to 1 in both economies. The two lines in the figures represent two model economies: benchmark (blue) and counterfactual economy without trade credit (red). Panel (b) plots the average and total net trade credit borrowing (AP − AR) against the share of entrepreneurs affected by the shock.

of entrepreneurs. A positive value of AP − AR, as shown in the figure, indicates that these affected entrepreneurs become net trade credit borrowers after being hit by the shock. In particular, as more entrepreneurs are affected by the shock, the amount of net trade credit borrowed per affected entrepreneur decreases, reaching zero when every entrepreneur in the economy is affected. In the meantime, as the financial shock spreads, the total net trade credit borrowed by the affected entrepreneurs exhibits an inverted-U shape due to a decline in net trade credit borrowing per entrepreneur as well as an increase in the number of entrepreneurs affected. Taken together, the intuitive relationship between the volume of trade credit flows and the scope of the financial shock, as shown in the figure, further illustrates why trade credit's mitigation effect diminishes as the number of affected entrepreneurs increases.

# 6 Conclusion

In this paper, I document empirical evidence supporting the existence of a financial motive behind trade credit. Motivated by this, I build trade credit into a heterogeneous entrepreneur model with financial friction and the co-existence of trade credit and bank credit. The model generates a cross-sectional distribution of trade credit across firm sizes consistent with the empirical regularities. It also shows that trade credit flows, in net terms, to firms facing more significant financial shocks, in line with the observed pattern after the Lehman bankruptcy.

I use the model to study the aggregate implications of trade credit. Trade credit helps alleviate the misallocation of production factors. This channel, however, is dependent on suppliers' access to financing. During a financial crisis where all entrepreneurs experience a tightening in their borrowing constraint, their access to financing is disrupted, resulting in a decrease in trade credit lending, a reduction in the effectiveness of the trade credit reallocation channel, and an amplification of the original financial shock. On the other hand, when only a small fraction of entrepreneurs experience financial shocks, trade credit is shown to help entrepreneurs in distress overcome financial constraints, thus mitigating the negative impact of the shock. But this mitigation effect diminishes as financial shocks become more widespread.

While the paper highlights the financial motives behind trade credit using a dynamic model of heterogeneous firms with financial frictions, several potential extensions of the current framework could provide more comprehensive understanding of trade credit and its contribution to the aggregate economy.

First, the empirical literature on trade credit has shown that "there are multiple, not mutually exclusive, rationales for extending trade credit" (Klapper et al., 2012). Incorporating these additional, non-financial, factors into the current model could provide additional insights. For instance, studies indicate that firms' market power at the customer or industry level affects their trade credit choices. Chod et al. (2019) find that suppliers are more likely to extend trade credit to retailers if they constitute a larger share of the retailer's input purchases, while Klapper et al. (2012) document that large retailers request trade credit from their smaller suppliers as a way to guarantee quality of the goods. In the current model, trade credit flows from relatively more constrained to less constrained firms. One possible outcome of incorporating these additional motivations into the model is that it could counteract the reallocative effects of trade credit, and when a negative financial shock hits the economy, these additional factors might lead to changes in trade credit that further deteriorate resource allocations.

Second, while the current model features input-output linkages, it lacks a realistic input-output network with multiple sectors. Incorporating such a network would offer interesting insights into the quantitative implications of trade credit dynamics. From this paper, we learn that trade credit, predominantly flowing from suppliers to customers, is significantly influenced by firms' financial conditions. These conditions may vary markedly between firms in upstream and downstream sectors, thereby affecting the flows of trade credit across sectors and their overall impact. With this in mind, exploring these asymmetries in financial conditions across sectors could yield valuable insights into the quantitative implications of trade credit.

Overall, this paper establishes that the financial motive behind trade credit is a crucial and ubiquitous factor influencing trade credit decisions, with potentially significant aggregate implications. Introducing the aforementioned additional dimensions into the framework would enable a more comprehensive analysis of trade credit and its aggregate effects. These topics, rich with interesting applications, will be the focus of future research.

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# Online Appendix

## Aggregate Fluctuations and the Role of Trade Credit

# A Empirical appendix

## A.1 Trade credit in the cross section

This appendix section A.1 provides additional results to support evidence documented in section 2.1 of the paper.

### A.1.1 Summary statistics.

Table A.1 displays the summary statistics of the Compustat sample.

**Table A.1:** Summary statistics

| Variables | mean | sd | min | max |
|---|---|---|---|---|
| Total assets | 1,486.21 | 5,947.84 | 0.02 | 78,942.00 |
| Firm age | 13.65 | 10.02 | 1.00 | 47.00 |
| AR receivable - trade | 176.19 | 710.51 | 0.00 | 8,547.22 |
| AP payable - trade | 114.20 | 476.23 | 0.01 | 6,274.78 |
| Sales | 350.90 | 1,361.96 | 0.00 | 15,495.43 |
| AR to sales ratio | 0.57 | 0.28 | 0.00 | 1.36 |
| Net AR to sales ratio | 0.10 | 0.63 | -4.37 | 0.89 |
| AP to sales ratio | 0.48 | 0.65 | 0.06 | 5.34 |

### A.1.2 Evidence of relationship between firm size/age and financial constraint

Previous studies have documented that firm size and age are reliable indicators of a firm's financial constraints. To provide some evidence for this relationship in the Compustat data, I performed an analysis to investigate the investment sensitivity to cash flow, stratified by the age and size quartiles of firms. The regression equation used for this analysis is as follows:

$$I/K_{i,t} = \beta_1 \text{Cash Flow}/K_{i,t} + \beta_2 Q_{i,t} + \chi_i + \gamma_t + \varepsilon_{i,t},$$

In this equation, $I/K_{i,t}$ represents the investment rate, Cash Flow$/K_{i,t}$ denotes the firm's cash flow normalized by the capital stock, and $Q_{i,t}$ corresponds to the measured Tobin's Q, which captures the firm's growth opportunities. The terms $\chi_i$ and $\gamma_t$ are firm fixed effects and time fixed effects, respectively. The coefficient of primary interest, $\hat{\beta}_1$, is associated with Cash Flow$/K_{i,t}$ and measures the responsiveness of investment to cash flow.

The equation is estimated across eight subsamples of firms, divided into quartiles based on size and age, in addition to the full sample. Table A.2 displays the estimated coefficient $\hat{\beta}_1$ for these categories. Panel (a) shows that, in the full sample (column 1), both cash flow and Tobin's Q are positively associated with investment rates. This is commonly interpreted in the literature to indicate that financial frictions and future investment opportunities are positively linked with a firm's propensity to invest. Crucially, there is a notable decrease in investment sensitivity to cash flows, from 0.023 (highly significant) to -0.001 (not significant), as we move from the smallest to the largest firms. Likewise, Panel (b) reveals that the estimated investment sensitivity to cash flow diminishes from 0.027 to 0.008 when comparing the youngest to the oldest firms. The results from this table generally support the conclusion that younger and smaller firms are subject to more financial constraints than their older and larger counterparts, which is reflected in their greater investment sensitivity to cash flows.

**Table A.2:** Investment sensitivity to cash flows

Panel (a): Size groups

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| cash flow/K | 0.021*** | 0.023*** | 0.014*** | 0.009* | -0.001 |
| | (0.001) | (0.002) | (0.003) | (0.005) | (0.011) |
| Tobin's Q | 0.068*** | 0.040*** | 0.143*** | 0.146*** | 0.078*** |
| | (0.004) | (0.008) | (0.008) | (0.008) | (0.008) |
| Sample | All | Q1 (smallest) | Q2 | Q3 | Q4 (largest) |
| $N$ | 123735 | 30934 | 30935 | 30933 | 30933 |
| $R^2$ | 0.230 | 0.272 | 0.395 | 0.382 | 0.275 |

Panel (b): Age groups

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| cash flow/K | 0.021*** | 0.027*** | 0.029*** | 0.022*** | 0.008* |
| | (0.001) | (0.003) | (0.003) | (0.003) | (0.004) |
| Tobin's Q | 0.068*** | 0.016 | -0.004 | 0.028*** | 0.043*** |
| | (0.004) | (0.010) | (0.011) | (0.011) | (0.010) |
| Sample | All | Q1 (youngest) | Q2 | Q3 | Q4 (oldest) |
| $N$ | 123735 | 33767 | 32108 | 27937 | 29923 |
| $R^2$ | 0.230 | 0.483 | 0.411 | 0.298 | 0.202 |

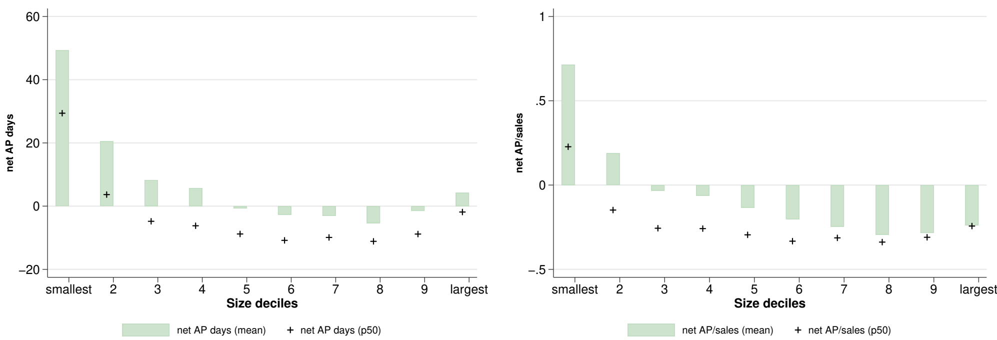
**Notes**: The sample includes all but financial firms in the Compustat dataset for the period 1960-2007 at the annual frequency. Cash flow of a firm is the net cash flows (`oancf`). Tobin's Q is calculated as `(prcc_f*csho+at-ceq)/at`, where `prcc_f*csho` is the market value, `at` is total asset and `ceq` is the common equity.

### A.1.3 Net accounts payable among largest firms

In this section, I examine in detail the trade credit activities of the top two size deciles firms in the Compustat dataset, motivated by the findings in Murfin and Njoroge (2015). In particular, Murfin and Njoroge (2015) finds that net payable days decrease with firm size, except for the largest two deciles of firms. In panel (a) of figure A.1, I replicate their result using our Compustat sample, where net payable days is defined as payable days (AP/cogs × 365) minus receivable days (AR/sales × 365).[26] In addition, in panel (b), I present the relationship with firm size using our preferred measure of net accounts payable (i.e., net AP/sales).

**Figure A.1:** Net accounts payable and firm size: two measures

**(a)** Net payable days **(b)** Net AP/sales




**Notes**: The sample includes all but financial firms in the Compustat dataset for 2000-2007. The figures plot net payable days and net AP/sales within each decile of size distribution. Net payable days is defined as payable days (AP/cogs × 365) minus receivable days (AR/sales × 365). Panel (a) plots the mean and median net payable days in each size decile. Panel (b) plots each size decile's mean and median net AP/sales.

The relationship between median net payables days and size deciles are very similar in panel (a) and table 1 of Murfin and Njoroge (2015). Specifically, the net payable days of the top two deciles of firms are in fact higher than some of the smaller firms. For instance, the median net payable days of the largest decile firms are even slightly higher than that of the third decile. Additionally, I show in panel (a), that this reversal, albeit not as strong, is also present for the average net payable days. The average net payable days of the largest firms, for instance, is shorter than that of the 4th decile. Similarly, there is also a slight reversal in the net AP/sales among the top two size deciles, as shown in panel (b), but the magnitude of the reversal is even less significant than net payable days. The difference between these two panels is due to the fact that in panel (a), AP is normalized by cogs (cost of goods sold) and in panel (b) it is normalized by sales.

A few remarks regarding these findings are in order. First, the decline of net payable or payable in firm size is fast when firms are small, and the decline slows down as firms grow larger. In other words, the overall decline in net payable is driven by the difference between the smallest versus larger firms. This same pattern is also present in the model (see, for instance, figure C.11). Partly due to this, I note that the negative relationship between net payables and firm size is rather robust, especially comparing the smallest firms versus the rest, despite the reversal among the largest firms.

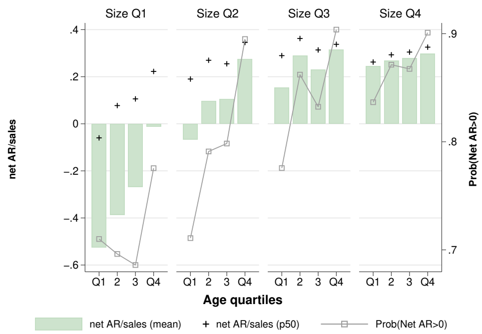
Second, as argued by Murfin and Njoroge (2015), there is a non-financial motive at play when it comes to the trade credit choices of the largest firms in Compustat. Using a sample of large retailers and their suppliers, Murfin and Njoroge (2015) show these largest buyers use a substantial amount of trade credit from their small suppliers. Similarly, Klapper et al. (2012) document that large buyers tend to get long trade credit terms from smaller suppliers. Both papers argue that these patterns are consistent with a non-financial motive to countervail frictions between suppliers

[26] Our Compustat sample excludes financial-sector firms, same as Murfin and Njoroge (2015).

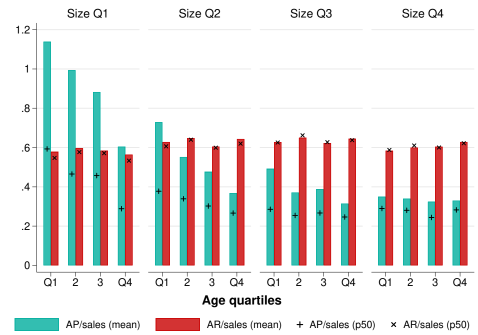
## Figure A.2: Trade credit within each age/size quartile

*Within each size quartile*

**(a)** Net AR

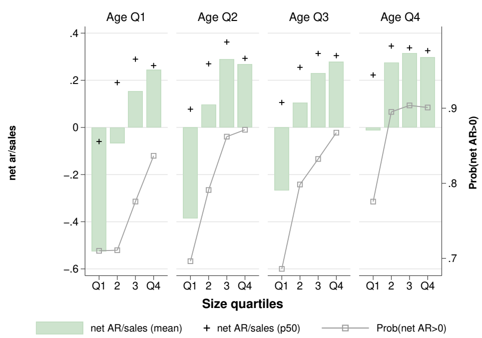



**(b)** AR and AP

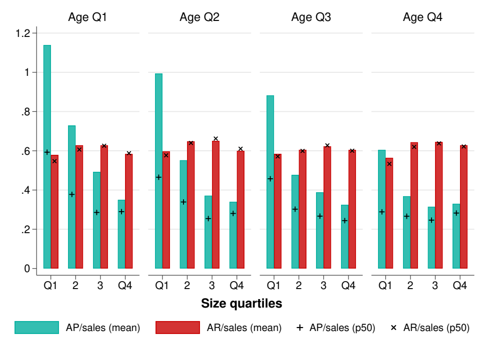



*Within each age quartile*

**(c)** Net AR




**(d)** AR and AP




**Notes**: The sample includes all but financial firms in the Compustat dataset for the period 2000-2007. The two figures in the upper panel plot net AR/sales (panel a), AP/sales, and AR/sales (panel b) within each quartile of firm size distribution. The two figures in the lower panel plot net AR/sales (panel c), AP/sales and AR/sales (panel d) within each quartile of firm age distribution.

and buyers related to product quality. As a caveat to our analysis, I focus on the financial motives that I view as particularly important and relevant.

### A.1.4 Conditional on firm age or firm size

Section 2.1 of the paper documents that older and larger firms in net terms lend more trade credit, and are more likely to be trade credit lenders. Here, Figure A.2 show that these patterns still hold even conditional on firm size or age. The age gradients of net trade credit lending hold separately within each size quartile (panels a and b); similarly, the size gradients hold separately within each age quartile (panels c and d). Further, the age gradients are less steep among large firms than small firms; and the size gradients are less steep among old than young firms. For instance, as shown in panel (a), within the smallest quartile of firms (size Q1), the difference in average net AR/sales between the youngest (age Q1) and oldest firms (age Q4) is -0.51. In contrast, within the largest quartile (size Q4), the difference is only -0.05, comparing the same two age groups. These patterns are consistent with the fact that firm size and age both contain relevant information about financing frictions.

### A.1.5 Controlling for inventory and ROA

Table A.3 results from the regressing equation 1 while controlling for firms' return on assets (ROA) or inventory-to-sale ratios. Due to data limitations, these regressions are carried at using Compustat data at the annual frequency. The baseline results carry through with these additional controls with the magnitude of the estimates slightly lower than the baseline regressions.

**Table A.3: Net AR and firm characteristics, controlling for ROA & inventory**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Firm size (log size) | 0.028*** | 0.007*** | 0.008*** | 0.055*** | 0.021*** | 0.022*** |
| | (0.004) | (0.002) | (0.002) | (0.006) | (0.005) | (0.005) |
| Firm age (log years) | 0.022*** | 0.021*** | 0.015*** | 0.066*** | 0.060*** | 0.052*** |
| | (0.006) | (0.005) | (0.005) | (0.010) | (0.011) | (0.010) |
| ROA | | 0.207*** | 0.184*** | | 0.355*** | 0.342*** |
| | | (0.035) | (0.033) | | (0.036) | (0.035) |
| inventory/sales | 0.193 | | 0.181* | 0.317 | | 0.275 |
| | (0.123) | | (0.101) | (0.254) | | (0.220) |
| Dependent variable | NetAR/Sales | NetAR/Sales | NetAR/Sales | $\mathbb{I}_{\text{NetAR}>0}$ | $\mathbb{I}_{\text{NetAR}>0}$ | $\mathbb{I}_{\text{NetAR}>0}$ |
| $N$ | 14052 | 13262 | 12688 | 14052 | 13262 | 12688 |
| $R^2$ | 0.191 | 0.285 | 0.283 | 0.213 | 0.280 | 0.275 |

**Notes**: The table displays results from regression equation 1 while controlling for firms' ROA (returns on assets) and the ratio of inventory to sales. The sample includes all non-financial firms in the Compustat dataset for the period 2000-2007. All regressions include a set of industry-quarter fixed effects. Standard errors are clustered two ways at the industry and time level and shown in parentheses.

### A.1.6 Corporate tax return data

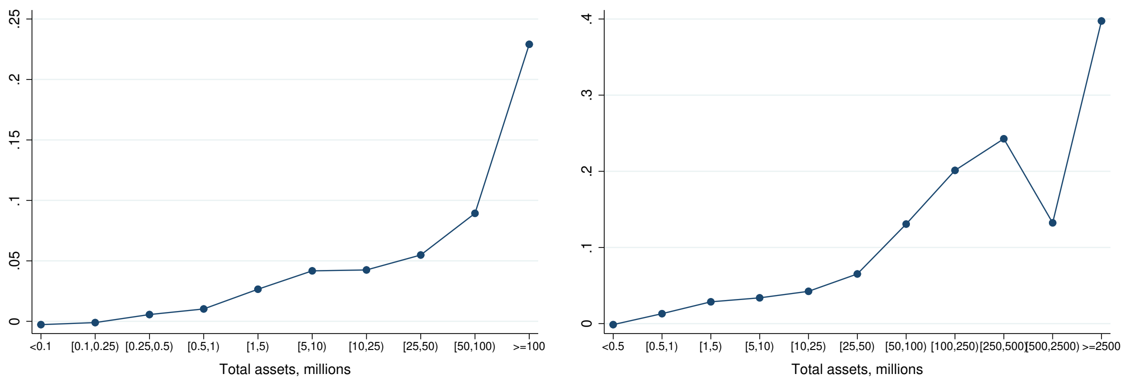
Section 2.1 provides empirical evidence of the financial motives behind firms' choice of trade credit using the Compustat data. Previous papers such as Petersen and Rajan (1997) utilize data from the Survey of Small Business Finances (SSBF). Both datasets have the limitation that they are not representative of the firms in the US economy. In this appendix section, we utilize the Business Tax Statistics dataset, an *aggregate* dataset that covers a broader spectrum of firms. It categorizes firms into different groups based on asset sizes and reports aggregate statistics on balance sheets and income information. A key strength of this dataset is its extensive coverage across all US corporations.

As the first pass of the data, Figure A.3 displays net AR/sales (with sales measured using business receipts) for each firm size group for S and C corporations, respectively. For both types of firms, it is evident that net AR/sales increases with firm size, indicating that, in net terms, larger firms extend more trade credit than smaller firms. This finding aligns with the observations in both

Compustat and SSBF datasets. While C corporations include very large firms within the economy, hence their asset size groupings are relatively broad, S corporations are generally smaller in size, resulting in more detailed size groupings, especially at the lower end. Nevertheless, regardless of the firm type or the different size grouping schemes, both figures reveal a consistent pattern of increasing net trade credit lending with firm size, supporting the financial motive behind trade credit.

**Figure A.3:** Relationship between net AR/sales and firm size

**(a)** S Corporations **(b)** C Corporations




**Notes**: Data in these figures are taken from the Business Tax Statistics from IRS for year 2005. Panel (a) plots the statistics for all S corporations by different size groups. Panel (b) plots the statistics for all C corporations by different asset size groups. Sales in these figures are measured using total business receipts.

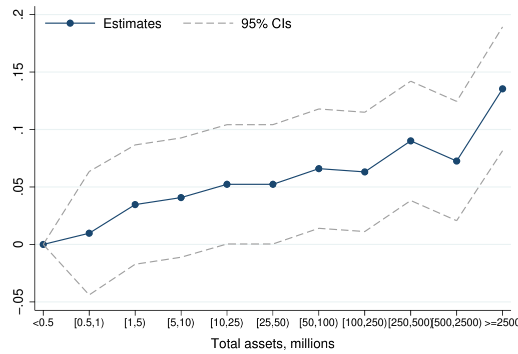
One concern with the findings from the previous figures is that they do not control for the industrial composition of firms within each size category. Consequently, the observed increase in firm size might also reflect differences in industry composition. For C corporations, data are available separately for major sectors of the economy. This allows me to carry out a simple regression of net AR/sales against firm-size group indicators while including sector-fixed effects as controls:

$$\text{net AR/Sales}_{i,f} = \alpha + \left( \sum_{f \in \mathcal{S}} \beta_f \mathbb{I}_f \right) + \chi_i + \varepsilon_{i,f}, \tag{A.1}$$

where net AR/Sales$_{i,f}$ represents the net AR/sales ratio for firm size group $f$ in sector $i$. The term $\mathbb{I}_f$ is a dummy indicator for firm size group $f$, and $\mathcal{S}$ denotes the set of these firm size groups $\{(0,0.5), [0,5,1), [1,5), [5,10), [10,25), [25,50), [50,100), [100,250), [250,500), [500,2500), [2500,\infty)\}$. The variable $\chi_i$ is the sector fixed effects, and $\varepsilon_{i,f}$ is the error term. The object of interest is the coefficients in front of the firm-size groups, $\hat{\beta}_f$. Figure A.4 shows estimated coefficients $\hat{\beta}_f$ and the 95% confidence intervals, with $\hat{\beta}_f$ of the smallest group normalized to zero. It shows that larger firms have higher net trade credit lending, with the largest firms' net AR/sales about 15 percentage points higher than the smallest firms.

To summarize, these analyses utilizes Business Tax Return data to corroborate the financial rationale behind firms' trade credit decisions. Despite its caveat of not being at the firm-level, results from this dataset complement the evidence provided by Compustat.

**Figure A.4:** Relationship between net AR/sales and firm size, $\hat{\beta}_f$




**Notes**: This figure reports the estimation results from equation A.1. The sample includes 16 industries for the year 2005. These industries are ASWM services, Accommodation and food service, Agriculture etc, Art, entertainment, and recreation, Construction, Education services, Health care and social assistance, Information, Manufacturing, Mining, Other services, PST services, Real Estate Rental and Leasing, Utility, Wholesale and retail trade, and Transportation and warehouse.

## A.2 Trade credit and financial shocks

This appendix section A.2 provides additional results to support evidence documented in section 2.2 of the paper.

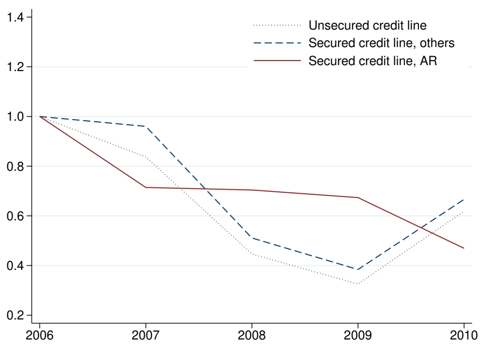
### A.2.1 Syndicated market around Lehman bankruptcy

In this section, I examine the changes in the syndicated loan market during the 2007–09 financial crisis. Figure A.5 illustrates the changes in various types of new credit line facilities. A key observation from these figures is that credit facilities secured by accounts receivable (AR) display dynamics similar to those of unsecured credit lines, as well as facilities secured by other types of assets.

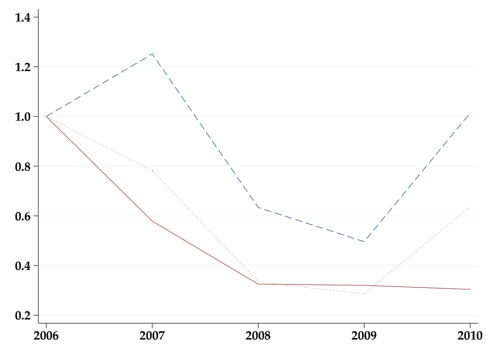
Additionally, Figure A.6 plots the number and the total size of facilities on a quarterly basis. Panel (a), plotting the characteristics of new facilities, reveals that the decline began around 2007Q3, coinciding with the collapse of Bear Stearns, which also marked the onset of the recession designated by the NBER. The downturn continued to deepen after the Lehman bankruptcy in 2008Q3 and reached its nadir a year later. Conversely, the number and size of all open facilities in the market, as shown in Panel (b), started their decline slightly later, around 2008Q1, reaching their lowest point in 2011Q1.

**Figure A.5:** Characteristics of new credit line facilities by type

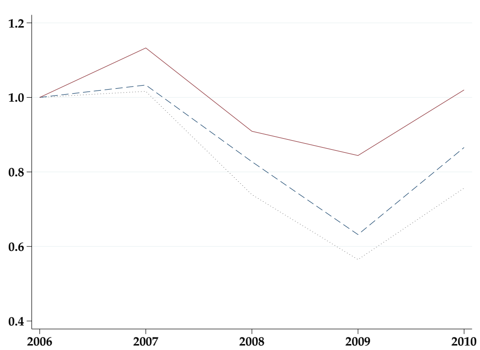
**(a)** Number of new facilities



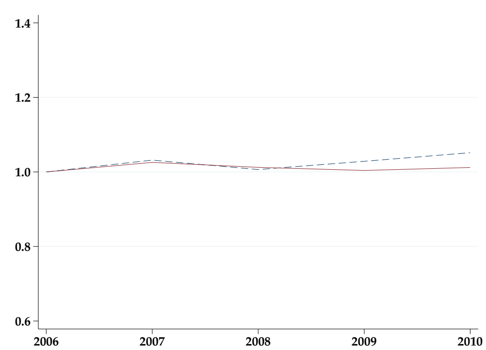

**(b)** Total facility size




**(c)** Maturity



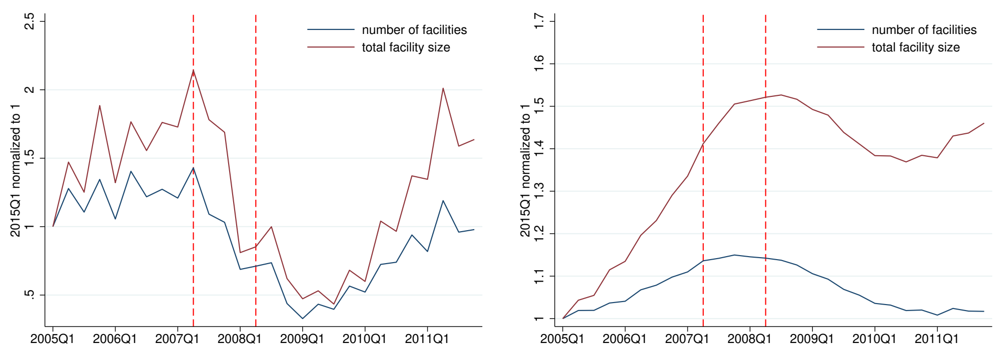

**(d)** Borrowing base percentage




**Notes**: I compute the characteristics of the newly opened credit line facilities of each year as the average of all new credit line facilities with non-financial borrowing firms using Thomson Reuters DealScan dataset. The solid lines in these figures are credit line facilities that require accounts receivable as collateral. The dashed lines are credit line facilities that require other types of assets as collateral. The dotted lines are unsecured credit line facilities. The time series are normalized such that they are 1 in year 2006.

**Figure A.6:** Syndicated market during the crisis, quarterly data

**(a)** New facilities **(b)** All facilities




**Notes**: These figures plot the number and total size of new facilities (panel a) and all currently open facilities (panel b) to non-financial borrowing firms in the syndicated loan market during the 2007-09 crisis. The two red vertical lines in each panel mark the quarters of 2007Q2 and 2008Q2, which are the quarters preceding the collapses of Bear Stearns (also the start of the NBER recession) and the Lehman bankruptcy, respectively.

### A.2.2 Changes in trade credit as dependent variables

Table A.4 presents another method for estimating how changes in trade credit correlate with firms' exposure to Lehman, where the dependent variables are the changes in trade credit from pre- to post-Lehman shock. Formally, I run the following regression:

$$\Delta y_i = \gamma \text{Exposure}_i + X_i + \varepsilon_i, \tag{A.2}$$

where the dependent variable represents the changes in the median value of AR/sales or AP/sales between the pre-Lehman and post-Lehman periods. This approach removes permanent level differences between firms. The controls for firm characteristics in $X_i$, identical to those used in regression equation 2, account for variations that could be attributed to factors such as industry affiliation or access to bond and commercial paper markets. What remains, captured by the Exposure$_i$ indicator, are therefore changes in trade credit attributable to the different exposure to Lehman. Reassuringly, results from table A.4 shows a very similar pattern as the baseline estimation in table 2.

**Table A.4:** Changes in trade credit and exposure to Lehman

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Top quartile of exposure | -0.032** | 0.015* | | | | |
| | (0.014) | (0.008) | | | | |
| Top 50% of exposure | | | -0.022* | 0.014* | | |
| | | | (0.012) | (0.007) | | |
| Exposure to Lehman | | | | | -0.005 | 0.013** |
| | | | | | (0.009) | (0.005) |
| Dependent variable | Δ AR/Sales | Δ AP/Sales | Δ AR/Sales | Δ AP/Sales | Δ AR/Sales | Δ AP/Sales |
| $N$ | 617 | 613 | 617 | 613 | 617 | 613 |
| $R^2$ | 0.384 | 0.349 | 0.379 | 0.349 | 0.374 | 0.352 |

**Notes:** This table presents estimates $\hat{\gamma}$ from estimating equation A.2. Firm's exposure to Lehman, Exposure$_i$, is measured in three different ways. Columns (1)–(2) use a dummy variable indicating whether firm i belongs to the top quartile in terms of pre-shock exposure to the Lehman shock. Columns (3)–(4) use a dummy indicating if firms belong to the top 50% exposure to Lehman, and columns (5)–(6) utilize the raw measure of exposure to Lehman, defined as the fraction of a firm's relationship bank's syndication portfolio in which Lehman Brothers had a lead role. Standard errors are clustered at the ultimate lender level and shown in parentheses.

### A.2.3 Controlling for differential trends

One potential factor that could lead to differential changes in trade credit following the Lehman shock is the presence of distinct long-term trends in trade credit choices among these groups. Although figure 2 indicate no significant pre-shock trend differences, it remains prudent to formally control for such possibilities in the regression analysis.

To address this, I incorporated linear trends into the estimation equation 2, allowing them to vary among firms with different levels of exposure to the Lehman shock. Specifically, I introduced two linear trend terms into the estimation equation: (i) a general linear trend, represented as $t-t_0$, where $t_0$ marks the beginning of the sample period and $t$ denotes the current period, and (ii) an interaction term between the linear trend $t-t_0$ and the indicator variable $\text{Exposure}_i$, which signifies whether a firm is in the top quartile or half in terms of exposure to Lehman. This latter interaction term is designed to capture the potential differential trend between firm groups. More formally, I estimate the following equation:

$$\begin{aligned} y_{it} = \quad & \alpha \text{PostLehman}_t + \beta \text{Exposure}_i + \gamma \text{Exposure}_i \times \text{PostLehman}_t \\ & + (t - t_0) + \phi \text{Exposure}_i \times (t - t_0) + X_i + \Lambda_{it} + \varepsilon_{it}, \end{aligned} \tag{A.3}$$

Table A.5 shows that, after controlling for differential linear trends, the patterns previously observed still hold. Notably, firms with greater exposure to Lehman experienced a steeper decline in their trade credit lending, by 2.5 to 2.9 percentage points (pps) more than their less exposed counterparts (columns 1 and 3). They also experience a more pronounced increase in their trade credit borrowing by 0.6 to 0.9 pps more (columns 2 and 4) than less exposed firms.

The regressions also reveal that there is no significant differences in these long-term trends across firm groups. The coefficients in front of the interaction between the linear trends and $\text{Exposure}_i$ are small and mostly insignificant. Column 3 suggest that firms in the top half of exposure might actually experience significantly faster growth in AR/sales compared to those with lower exposure. This suggests that the notable decline observed in these groups post-Lehman shock is even more striking as it represents a reversal of the long-run trends.

**Table A.5:** Trade credit and exposure to Lehman, controlling for differential trends

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Top quartile exposure × trend | 0.000 | 0.001 | | |
| | (0.000) | (0.000) | | |
| Top quartile exposure × PostLehman | -0.029*** | 0.006 | | |
| | (0.010) | (0.005) | | |
| Top 50% exposure × trend | | | 0.001** | 0.001 |
| | | | (0.000) | (0.000) |
| Top 50% exposure × PostLehman | | | -0.025** | 0.009* |
| | | | (0.009) | (0.005) |
| Depdent variable: | AR/Sales | AP/Sales | AR/Sales | AP/Sales |
| $N$ | 16338 | 16186 | 16338 | 16186 |
| $R^2$ | 0.625 | 0.372 | 0.627 | 0.372 |

**Notes:** This table shows results from estimating equation A.3. Estimates displayed here are the $\hat{\phi}$ and $\hat{\gamma}$. The firm's exposure to Lehman, $\text{Exposure}_i$, is measured in three different ways. Columns (1)–(2) use a dummy variable indicating whether firm i belongs to the top quartile in terms of pre-shock exposure to the Lehman shock. Columns (3)–(4) use a dummy indicating if firms belong to the top 50% exposure to Lehman. Standard errors are clustered at the industry level and shown in parentheses.

# B Model appendix

## B.1 An alternative model of trade credit

In this section, I present an alternative model in which I treat trade credit as a delay in payment. To do so, I need to adopt a different timing in which output is carried over and sold at the beginning of the next period. The output can be sold on the spot market to generate immediate cash flow, or it can be extended as a trade credit loan.

**Timing.** Entrepreneurs carry over their wealth $a$ and output $y$ from the previous period. After the idiosyncratic productivity shock $z$ is realized, entrepreneurs sell their output to generate cash flow: they can choose to extend some goods as trade credit loans $\mathrm{AR} \in [0, y]$, and the remaining goods will generate an immediate cash flow $y - \mathrm{AR}$, which can be used to finance working capital. Additionally, entrepreneurs make decisions about their current period production $(k, l, x)$ and whether they will borrow trade credit $\mathrm{AP} \in [0, x]$. Based on these choices, entrepreneurs obtain the required intra-temporal working capital bank loan $m$. At that point, entrepreneurs decide whether to default on their bank loans. If an entrepreneur decides to default, a renegotiation process occurs between the entrepreneur and the bank, with the ultimate settlement determined by the bank's expected proceeds from liquidating the entrepreneur's collateral. Using the cash flow generated at the beginning of the period and the bank loan, entrepreneurs invest in working capital and production occurs. After entrepreneurs settle the bank loan, collect AR, and repay AP, they consume $c$ and invest in their wealth $a'$. This period's output is carried over into the next period as $y'$.

**Financial frictions and the existence of trade credit** Without loss of generality, assume that working capital includes interest $rk$, wage bills $wl$, and inputs $x$. The entrepreneurs can finance working capital using: i) bank loans, ii) cash flow generated by selling goods on the spot market, and iii) trade credit. As discussed in the benchmark model, the bank loan limit is equal to the expected liquidation value of the collateral $\gamma_1 a + \gamma_2 \mathrm{AR}$.[27] On the other hand, I assume that the repayment of trade credit can be enforced perfectly.

Therefore, I can write the working capital constraint of the entrepreneurs as follows:

$$
\begin{aligned}
rk + wl + x - \mathrm{AP} &\leq \underbrace{\gamma_1 a + \gamma_2 \mathrm{AR}}_{bank\ loan} + \underbrace{y - \mathrm{AR}}_{cash\ flow}, \\
\Longrightarrow rk + wl + x + (\mathrm{AR} - \mathrm{AP}) - y &\leq \gamma_1 a + \gamma_2 \mathrm{AR}.
\end{aligned}
$$

It captures the impact of trade credit on entrepreneurs' liquidity position similar to the benchmark model. Consider the case without trade credit, and the working capital constraint can be written as follows:

$$rk + wl + x - y \leq \gamma_1 a.$$

By comparing the two inequalities, I see that the introduction of trade credit changes the entrepreneurs' liquidity position in two ways: the entrepreneurs' needs for bank loans increase by $\mathrm{AR} - \mathrm{AP}$, while their bank loan limit increases by $\gamma_2 \mathrm{AR}$, as is the case in the benchmark model.

[27] Note that due to the difference in timing, the collateral available at the time of default is this period's wealth $a$ and not $a'$ as in the benchmark model.

Although the two models capture a similar mechanism, compared to the benchmark model, this alternative model of trade credit is less tractable computationally as it introduces another state variable $y$ (output carried over from the previous period).

**Recursive representation of entrepreneurs' problem.** To summarize, in this alternative model, entrepreneurs are characterized by three state variables $(a, z, y)$. I write their problem recursively as follows:

$$
\begin{aligned}
V(a,z,y) = &\max u(c) + \beta \mathbb{E}_{z'|z}(a', z', y'), \\
s.t. \quad & c + a' + rk + wl + x = (1+r)a + r^{tc}(\mathrm{AR} - \mathrm{AP}) + y, \\
& rk + wl + x + (\mathrm{AR} - \mathrm{AP}) - y \leq \gamma_1 a + \gamma_2 \mathrm{AR}, \\
& 0 \leq \mathrm{AR} \leq y, \\
& 0 \leq \mathrm{AP} \leq x, \\
& y' = AzF(k,l,x), \\
& a' \geq 0.
\end{aligned}
$$

## B.2 First-order conditions

Here, I present the entrepreneur's optimization problem and derive the first-order conditions (FOCs). The value function of entrepreneurs is

$$
\begin{aligned}
V(a,z) \quad = \quad & \max_{c,k,l,AR,AP,a'} \mathbb{E}_{z'|z} log(c) + \beta \mathbb{E}_{z'|z} V(a', z') \\
s.t. \quad & c + a' = (1+r)a + Az\left((k^{\alpha} l^{1-\alpha})^{1-\chi} x^{\chi}\right)^{\mu} - (r+\delta)k - wl - x \\
& + r^{tc}(AR - AP), \qquad \text{(B.1)} \\
& Az\left((k^{\alpha} l^{1-\alpha})^{1-\chi} x^{\chi}\right)^{\mu} + (1 + r^{tc})(AR - AP) \leq \gamma_1 a' + \gamma_2 AR, \qquad \text{(B.2)} \\
& 0 \leq AR \leq Az\left((k^{\alpha} l^{1-\alpha})^{1-\chi} x^{\chi}\right)^{\mu}, \\
& 0 \leq AP \leq x, \\
& a' \geq 0.
\end{aligned}
$$

Denote $F(k,l,x) = \left((k^{\alpha} l^{1-\alpha})^{1-\chi} x^{\chi}\right)^{\mu}$ as the production function. The Lagrangian of the problem can be written as,

$$
\begin{aligned}
\mathcal{L} \quad = \quad & log((1+r)a + AzF(k,l,x) - (r+\delta)k - wl - x + r^{tc}(AR - AP) - a') \qquad \text{(B.3)} \\
& + \beta \mathbb{E}_{z'|z} V(a', z') + \xi(\gamma_1 a' + \gamma_2 AR - AzF(k,l,x) - (1+r^{tc})(AR - AP)) \\
& + \chi_1(AzF(k,l,x) - AR) + \chi_2 AR \\
& + \chi_3(x - AP) + \chi_4 AP \\
& + \tau a'.
\end{aligned}
$$

The FOCs are:

$$\begin{aligned}
k: &\quad AzF_k = \frac{r+\delta}{1-c\xi+c\chi_1} \\
l: &\quad AzF_l = \frac{w}{1-c\xi+c\chi_1} \\
x: &\quad AzF_x = \frac{1-c\chi_3}{1-c\xi+c\chi_1} \\
AR: &\quad \frac{1}{c}r^{tc} = \xi(1+r^{tc}-\gamma_2)+\chi_1-\chi_2 \\
AP: &\quad \frac{1}{c}r^{tc} = \xi(1+r^{tc})-\chi_3+\chi_4 \\
a': &\quad \frac{1}{c} = \beta\mathbb{E}_{z'|z}V_{a'}(a',z')+\xi\gamma_1+\tau
\end{aligned}$$

The envelope theorem is

$$V_a(a,z) = \frac{1}{c}(1+r)$$

That gives the Euler equation

$$\frac{1}{c} = \beta\mathbb{E}_{z'|z}\frac{1}{c'}(1+r')+\xi\gamma_1+\tau \tag{B.4}$$

In addition, according to the Kuhn-Tucker condition, the Lagrangian multipliers and the constraints have the following properties:

$$\begin{aligned}
&\xi \geq 0, \gamma_1 a' + \gamma_2 AR - AzF(k,l,x) - (1+r^{tc})(AR-AP) \geq 0, \\
&\chi_1 \geq 0, AzF(k,l,x) - AR \geq 0, \\
&\chi_2 \geq 0, AR \geq 0, \\
&\chi_3 \geq 0, x \geq AR, \\
&\chi_4 \geq 0, AP \geq 0, \\
&\tau \geq 0, a' \geq 0,
\end{aligned}$$

with complementary slackness.

## B.3 Proofs of propositions 1 and 2

Before proceeding to the proofs of the propositions, I first prove the monotonicity of the optimal policy function in a lemma. To do this, I rewrite the value function as

$$\begin{aligned}
V(a,z) &= \max_{c,a'} u((1+r)a+\pi(z,a')-a')+\beta\int_{z'}V(a',z')d\lambda(z',z) \\
s.t. &\qquad a' \geq 0.
\end{aligned} \tag{B.5}$$

where given $a'$,

$$\begin{aligned}
\pi(z,a') &= \max_{k,l,x,AR,AP} Az\left((k^{\alpha}l^{1-\alpha})^{1-\chi}x^{\chi}\right)^{\mu} - (r+\delta)k - wl - x + r^{tc}(AR - AP) \\
s.t. \quad & Az\left((k^{\alpha}l^{1-\alpha})^{1-\chi}x^{\chi}\right)^{\mu} + (1+r^{tc})(AR-AP) \leq \gamma_1 a' + \gamma_2 AR, \\
& 0 \leq AR \leq Az\left((k^{\alpha}l^{1-\alpha})^{1-\chi}x^{\chi}\right)^{\mu}, \\
& 0 \leq AP \leq x. \qquad\qquad (B.6)
\end{aligned}$$

Essentially, I am breaking down this dynamic problem into two problems and proving the monotonicity property in each one. First, given $a'$, the static production optimization problem is established in B.6, which gives the optimal profit function $\pi(z,a')$ for a given $z$. Second, the dynamic problem of choosing next period wealth $a'$, taken as given the function $\pi(z,a')$ as shown in B.5.

**Lemma 1.** *The value function $v(a,z)$ is supermodular in $a$ and has increasing differences in $(a,z)$. Given $z$, the policy functions $k(a,z)$, $l(a,z)$, $x(a,z)$, $AR(a,z)$, $-AP(a,z)$ and $a'(a,z)$ increase in $a$.*

*Proof.* First, I consider the optimization problem B.6: I intend to show that the optimal policy increase with $a'$ for a given $z$ using Theorem 2.8.1 from Topkis (1998).[28] It is easy to verify that the feasibility set increases strictly with $a'$; therefore I only need to show that inequality 2.8.1 from Topkis (1998) is satisfied.

Denote $W(k,l,x,AR,AP) = AzF(k,l,x) - (r+\delta)k - wl - x + (r^{tc}(AR-AP))$. Given any $\{k_1,l_1,x_1,AR_1,AP_1\}$ and $\{k_2,l_2,x_2,AR_2,AP_2\}$, I need to show that

$$\begin{aligned}
& W(k_1,l_1,x_1,AR_1,AP_1) + W(k_2,l_2,x_1,AR_2,AP_2) \\
\leq \; & W(k_1\wedge k_2, l_1\wedge l_2, x_1\wedge x_2, AR_1\wedge AR_2, AP_1\wedge AP_2) + \\
& W(k_1\vee k_2, l_1\vee l_2, x_1\vee x_2, AR_1\vee AR_2, AP_1\vee AP_2),
\end{aligned}$$

which reduces to

$$\begin{aligned}
& zAF(k_1,l_1,x_1) + zAF(k_2,l_2,x_2) \\
\leq \; & zAF(k_1\wedge k_2, l_1\wedge l_2, x_1\wedge x_2) + zAF(k_1\vee k_2, l_1\vee l_2, x_1\vee x_2).
\end{aligned}$$

This is straightforward to prove because function $F(\cdot,\cdot,\cdot)$ features strictly increasing differences in its inputs. Following Theorem 2.8.1 of Topkis (1998), I know that the optimal policy increases with $a'$.

For the next step, I move on to the optimization problem B.5. Following Proposition 2 in Hopenhayn and Prescott (1992), I will show the supermodularity of the value function $V(a,z)$ and policy function $a'(a,z)$ increase with $a$.

I need to verify the following three conditions using equations B.5 and B.6. First, $u((1+r)a + \pi(z,a') - a')$ is supermodular in $(a,a')$ and has increasing differences in $(a,a')$ given any $z$. Second, the graph of the feasibility set $\{a'|a' \geq 0\}$ is a sublattice. Third, $\lambda(\cdot,z)$ is increasing in $z$ with respect to the first-order stochastic dominance. The second and third conditions are straightforward in this

[28] Topkis, D. M. (1998). Submodularity and Complementarity. Princeton University Press.

case. I next need to show that the first condition holds, which is equivalent to showing $\frac{\partial^2 u}{\partial a \partial a'} \geq 0$.

$$\frac{\partial^2 u}{\partial a \partial a'} = u''(c)(1+r)(\pi_{a'}(z,a') - 1).$$

Since $u''(\cdot) < 0$, it is sufficient to show that $\underline{\pi_{a'}(z,a') \leq 1}$.

Write the the Lagrangian of the problem B.6 as follows:

$$\begin{aligned}
\mathcal{L} \quad = \quad & AzF(k,l,x) - (r+\delta)k - wl - x + r^{tc}(AR - AP) \\
& +\xi(\gamma_1 a' + \gamma_2 AR - AzF(k,l,x) - (1+r^{tc})(AR - AP)) \\
& +\chi_1(AzF(k,l,x) - AR) + \chi_2 AR + \chi_3(x - AP) + \chi_4 AP.
\end{aligned}$$

Note that this is different from the Lagrangian of the full dynamic problem B.3. With a slight abuse of notation, I use the same $(\xi, \chi_1, \chi_2, \chi_3, \chi_4)$ to represent the Lagrangian multipliers in both problems.

The FOCs are:

$$k: \qquad AzF_k = \frac{r+\delta}{1-\xi+\chi_1} \tag{B.7}$$

$$l: \qquad AzF_l = \frac{w}{1-\xi+\chi_1} \tag{B.8}$$

$$x: \qquad AzF_x = \frac{1-\chi_3}{1-\xi+\chi_1} \tag{B.9}$$

$$AR: \qquad r^{tc} = \xi(1+r^{tc}-\gamma_2) + \chi_1 - \chi_2 \tag{B.10}$$

$$AP: \qquad r^{tc} = \xi(1+r^{tc}) - \chi_3 + \chi_4 \tag{B.11}$$

There are two cases I need to investigate. The first one is if the borrowing constraint is not binding ($\xi(a', z) = 0$) and the second one is if it is binding ($\xi(a', z) > 0$).

### (1) $\xi = 0$

If $\xi = 0$, from equation B.10 and B.11, I know that $\chi_1 = r^{tc}$, $\chi_2 = 0$, $\chi_3 = 0$ and $\chi_4 = r^{tc}$. Therefore equation B.7, B.8 and B.9 become

$$\begin{aligned}
k: \qquad & AzF_k = \frac{r+\delta}{1+r^{tc}} \\
l: \qquad & AzF_l = \frac{w}{1+r^{tc}} \\
x: \qquad & AzF_x = \frac{1}{1+r^{tc}}
\end{aligned}$$

Denote the solution to the above system of equations as $k^*, l^*, x^*$ and the corresponding output $y^* = AzF(k^*, l^*, x^*)$. Because $x_1 > 0$ and $x_4 > 0$, the complementary slackness conditions imply that $AR = y^*$ and $AP = 0$. As a result, given $z$, $\pi(z, a')$ does not change with $a'$, as a result, $\pi_{a'}(z, a') = 0$.

**(2)** $\xi > 0$

If $\xi$, I know that the borrowing constraint holds with equality. That is,

$$y + (1 + r^{tc})(AR - AP) = \gamma_1 a' + \gamma_2 AR \Longrightarrow y = \gamma_1 a' - (1 + r^{tc} - \gamma_2)AR + (1 + r^{tc})AP$$

By definition, $\pi(z, a') = y - (r + \delta)k - wl - x + r^{tc}(AR - AP)$. Replacing $y$ using the above equation yields

$$\pi(z, a') = \gamma_1 a' - (1 - \gamma_2)AR + AP - (r + \delta)k - wl - x$$

Since I have shown that $\frac{dk}{da'} \geq 0, \frac{dl}{da'} \geq 0, \frac{dx}{da'} \geq 0$, $\frac{dAR}{da'} \geq 0$ and $\frac{dAP}{da'} \leq 0$, and because $\gamma_1 < 1$, I have $\pi_{a'}(z, a') < 1$. *Q.E.D.* □

### B.3.1 Proof of Proposition 1

**Cut-off for financial constraint** Given $z$, define set $\mathbf{U}^z = \{a|\xi(a, z) = 0\}$. I intend to show that the set $\mathbf{U}^z$ is in the following form $(\underline{a}, \infty)$.[29] To do this, I first show that $\mathbf{U}^z$ has the following property: if $a \in \mathbf{U}^z$ and $\hat{a} > a$, then $\hat{a} \in \mathbf{U}^z$.

Let $a \in \mathbf{U}^z$. According to the definition of $\mathbf{U}^z$, I know that $\xi(a, z) = 0$. The complementary slackness condition then implies that for entrepreneur $(a, z)$, the working capital constraint is not binding,

$$AzF(k, l, x) + (1 + r^{tc})(AR - AP) < \gamma_1 a' + \gamma_2 AR.$$

According to equation B.4 and B.4, $\xi = 0$ implies that $\chi_2 = 0$, $\chi_1 = \frac{1}{c} r^{tc}$, $\chi_3 = 0$ and $\chi_4 = \frac{1}{c} r^{tc}$. Taking the value of $\xi, \chi_1, \chi_2$ back into equations B.4, B.4 and B.4, I get

$$\begin{aligned} k: \quad & AzF_k = \frac{r + \delta}{1 + r^{tc}}, \\ l: \quad & AzF_l = \frac{w}{1 + r^{tc}}, \\ x: \quad & AzF_x = \frac{1}{1 + r^{tc}}. \end{aligned}$$

Since production function $F$ is decreasing return to scale, there exist optimal $k$, $l$ and $x$ that solve the above system of three equations. Denote the solution as $k^*$, $l^*$ and $x^*$. Since $\chi_1 > 0$ and $\chi_4 > 0$, the complementary slackness condition implies that $AR = AzF(k^*, l^*, x^*)$ and $AP = 0$.

Let $m = Az\left((k^\alpha l^{1-\alpha})^{1-\chi} x^\chi\right)^\mu - (r + \delta)k - wl - x$, and the budget constraint B.1 can be re-written as,

$$c + a' = (1 + r)a + m.$$

It is clear that $m$ is maximized when $k = k^*$, $l = l^*$, $x = x^*$, $AR = AzF(k^*, l^*, x^*)$ and $AP = 0$. In other words, entrepreneurs will always choose $k = k^*$, $l = l^*$, $x = x^*$, $AR = AzF(k^*, l^*, x^*)$ and $AP = 0$ if they are feasible under the working capital constraint (equation B.2).

[29] This statement is equivalent to the first part of Proposition 1.

Consider the entrepreneur with productivity $z$ and wealth $\hat{a} > a$. According to Lemma 1, $a'(\hat{a}, z) \geq a'(a, z)$. Therefore, since $k = k^*$, $l = l^*$, $x = x^*$, $AR = AzF(k^*, l^*, x^*)$ and $AP = 0$ are feasible for entrepreneur $(a, z)$, they must be feasible for entrepreneur $(\hat{a}, z)$ as well. Following the above analysis, I know that entrepreneurs will choose $k = k^*$, $l = l^*$, $x = x^*$, $AR = AzF(k^*, l^*, x^*)$ and $AP = 0$, and the working capital constraint holds with strict inequality. Using the complementary slackness condition, this implies that $\xi(\hat{a}, z) = 0$.

With the help of this property, I show that $\mathbf{U}^z$ is an interval. Suppose that it is not; then there exists $x < w < y$, such that $x, y \in \mathbf{U}^z$ but $w \notin \mathbf{U}^z$. This violates the property, since it means $x \in \mathbf{U}^z$, $w < x$, but $w \notin \mathbf{U}^z$. I can also show that $\mathbf{U}^z$ is unbounded from above. Suppose that it is not; then there exists $w \notin \mathbf{U}^z$ but $w > a$ for all $a \in \mathbf{U}^z$, which violates the property.

**Cut-off for AR** Define a set $\mathbf{H}^z = \{a | AR(a, z) > 0\}$. I show that $\mathbf{H}^z$ is in the form of $(\underline{a}, \infty)$. The proof is very similar. Essentially, I need to prove that the set $\mathbf{H}^z$ has the following property: if $a \in \mathbf{H}^z$ and $\hat{a} > a$, then $\hat{a} \in \mathbf{H}^z$. It is clear that this property holds since according to Lemma 1, $AR(a, z)$ is an increasing function in $a$. Therefore, for any $\hat{a} > a$, I have $AR(\hat{a}, z) \geq AR(a, z) > 0$.

**Cut-off for AP** Similarly, define a set $\mathbf{W}^z = \{a | AP(a, z) = 0\}$. I can show that $\mathbf{W}^z$ is in the form of $(\underline{a}, \infty)$. According to Lemma 1, $AP(a, z)$ is a decreasing function in $a$. Therefore for any $\hat{a} > a$, I have $0 \leq AP(\hat{a}, z) \leq AP(a, z) = 0$. As a result, $AP(\hat{a}, z) = 0$. *Q.E.D.*

### B.3.2 Proof of Proposition 2

Proving this proposition is equivalent to showing that $\mathbf{U}^z \subseteq \mathbf{W}^z \subseteq \mathbf{H}^z$. I do it in two steps.

**$\mathbf{U}^z \subseteq \mathbf{W}^z$** Take any $a \in \mathbf{U}^z$ and $\xi$ be the Lagrangian multiplier associated with it; I know that $\xi = 0$ according to the definition of $\mathbf{U}^z$. According to equation B.4, if $\xi = 0$ then $\frac{1}{c(a,z)} r^{tc} = \chi_4(a, z) - \chi_3(a, z)$. Since $\frac{1}{c(a,z)} r^{tc} > 0$, it has to be the case that $\chi_4(a, z) = \frac{1}{c(a,z)} r^{tc}$ and $\chi_3(a, z) = 0$. Apply the complementary slackness condition, I know $AP(a, z) = 0$, which means $a \in \mathbf{W}^z$.

**$\mathbf{W}^z \subseteq \mathbf{H}^z$** For any $a \in \mathbf{W}^z$, I know $AP(a, z) = 0$, thus the complementary slackness condition implies that $\chi_4(a, z) > 0$ and $\chi_3(a, z) = 0$. Therefore equation B.4 implies $\frac{1}{c} r^{tc} > \xi(1 + r^{tc})$. As a result, $\frac{1}{c} r^{tc} > \xi(1 + r^{tc} - \gamma)$ because $\xi(a, z) \geq 0$. Take $\frac{1}{c} r^{tc} > \xi(1 + r^{tc} - \gamma)$ back to equation B.4, I get $\chi_1(a, z) > 0$ and $\chi_2(a, z) = 0$. The complementary slackness condition implies that $AR(a, z) > 0$, which means $a \in \mathbf{H}^z$. *Q.E.D.*

## B.4 Equilibrium definition of the counterfactual economy

The stationary equilibrium of the counterfactual economy without trade credit is defined as follows:

**Definition.** The recursive competitive equilibrium consists of interest rate of rental capital $r$, wage rate $w$; value function of the entrepreneurs $V(a, z)$; policy functions $c(a, z)$, $k(a, z)$, $l(a, z)$,

$x(a,z)$, and $a'(a,z)$; consumption and hours of the workers $(c^h, h)$; and the CDF of the stationary distribution $\Phi(a,z)$, such that

1. Given prices, the value functions, and policy functions solve the entrepreneurs' problem.

$$\begin{aligned} V(a,z) &= \max_{c,k,l,x,AR,AP,a'} log(c) + \beta \mathbb{E}_{z'} V(a', z'), \\ s.t. \quad & c + a' = (1+r)a + Az((k^\alpha l^{1-\alpha})^{1-\chi} x^\chi)^\mu - (r+\delta)k - wl - x, \\ & Az((k^\alpha l^{1-\alpha})^{1-\chi} x^\chi)^\mu \leq \gamma_1 a', \ a' \geq 0. \end{aligned}$$

2. Given prices, the consumption and hours of the workers solve the workers' problem.
3. Labor market clears
$$\int l(a,z) d\Phi(a,z) = N \cdot h.$$
4. Rental capital market clears
$$\int k(a,z) d\Phi(a,z) = \int a d\Phi(a,z).$$
5. Goods market clear
$$\int y(a,z) d\Phi(a,z) = N \cdot c^h + \int [c(a,z) + a'(a,z) - a + x(a,z)] \Phi(a,z).$$

## B.5 Trade credit default

My model assumes that trade credit does not suffer from moral hazard issues and that it is always repaid. This is a simplifying assumption that can potentially be relaxed. For instance, Altinoglu (2018), which introduces an interesting trade credit contract structure, where firms can divert trade credit from suppliers. Although the cost of this diversion remains constant, the marginal benefit increases with the proportion of inputs purchased on trade credit. Based on these principles, suppliers are likely to restrict the size of trade credit they offer, ensuring that the marginal cost always exceeds the marginal benefit.

**Relaxing the assumption.** Incorporating the moral hazard problem described by Altinoglu (2018) into my model is feasible, because these two models share some similar structures. This modification would effectively introduce an additional constraint on the size of trade credit available. Specifically, it would cap the amount of trade credit such that AP $\leq \gamma_3 x$ and AR $\leq \gamma_3 y$, where $\gamma_3 < 1$. For context, under my current setup without moral hazard considerations, trade credit is only limited by its natural feasibility, which dictates that AP $\leq x$ and AR $\leq y$. This is equivalent to the case where $\gamma_3 = 1$ and I will call this the benchmark model in the discussion below.

Next, I will explore the addition of this extra constraint to my model. This will effectively transform the firms' problem into the following:

$$
\begin{aligned}
V(a,z) = & \max_{c,k,l,x,\text{AR},\text{AP},a'} \log(c) + \beta \mathbb{E}_{z'|z} V(a',z'), \\
s.t. \quad & c + a' = (1+r)a + Az\left((k^{\alpha}l^{1-\alpha})^{1-\chi}x^{\chi}\right)^{\mu} - (r+\delta)k - wl - x \\
& + r^{tc}(\text{AR} - \text{AP}), \\
& Az\left((k^{\alpha}l^{1-\alpha})^{1-\chi}x^{\chi}\right)^{\mu} + (1+r^{tc})(\text{AR} - \text{AP}) \leq \gamma_1 a' + \gamma_2 \text{AR}, \\
& 0 \leq \text{AR} \leq \gamma_3 Az\left((k^{\alpha}l^{1-\alpha})^{1-\chi}x^{\chi}\right)^{\mu}, \qquad \text{(B.12)} \\
& 0 \leq \text{AP} \leq \gamma_3 x, \qquad \text{(B.13)} \\
& a' \geq 0.
\end{aligned}
$$

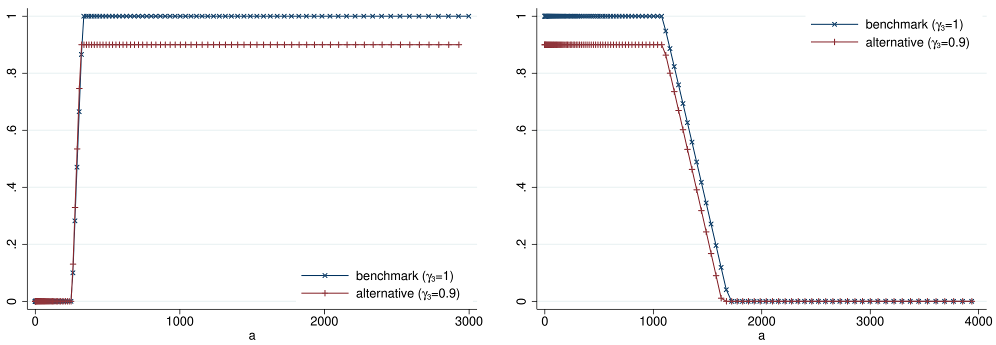
Notice the changes to the two constraints B.12 and B.13 with the addition of $\gamma_3$. This problem's FOCs can be written as the following:

$$
\begin{aligned}
k : AzF_k &= \frac{r+\delta}{1-\mu_1+\chi_1\gamma_3}, \\
l : AzF_l &= \frac{w}{1-\mu_1+\chi_1\gamma_3}, \\
x : AzF_x &= \frac{1-\chi_3\gamma_3}{1-\mu_1+\chi_1\gamma_3}, \\
AR : r^{tc} &= \mu_1(1-\gamma_2) + \chi_1 - \chi_2, \\
AP : r^{tc} &= \mu_1 - \chi_3 + \chi_4.
\end{aligned}
$$

Compared to the previous first-order conditions, we observe that the equations with respect to $k$, $l$, and $x$ now include the additional $\gamma_3$ term, while those with respect to AR and AP remain unchanged. Therefore, the analysis concerning the cut-off values for the AR and AP choices proceeds in the same manner as in the old model. However, the only difference is that the upper bounds of AR and AP, should firms decide to borrow or lend trade credit, will be lower than before, binding at $\gamma_3 y$ and $\gamma_3 x$ instead of $y$ and $x$.

To illustrate the changes in the trade credit policy function, Figure B.7 below displays the trade credit policy functions AR/y and AP/x, for the benchmark case $\gamma_3 = 1$ and the alternative case $\gamma_3 = 0.9$, under the same prices. This figure clearly shows the changes in policy functions. Notably, the upper bounds for the trade credit choices have been reduced from the benchmark $\gamma_3 = 1$ to the alternative setup $\gamma_3 = 0.9$, however, the threshold value of wealth remains roughly unchanged. Importantly, even with $\gamma_3 = 0.9$, for a given $z$, the lending of trade credit still increases with $a$ while the borrowing of trade credit decreases with $a$. In equilibrium, trade credit continues to flow from relatively unconstrained to constrained firms, and the redistributive effects of trade credit are maintained in the model.

In my model, the production function is decreasing returns to scale and there exists a continuum of heterogeneous firms. As a result, the aggregate trade credit size can attain an interior value. Specifically, its size in equilibrium is predominantly determined by two critical factors: the financial conditions of the firms, which are influenced by parameters $\gamma_1$ and $\gamma_2$, and the prevailing price of trade credit in the market. Incorporating the exogenous constraint $\gamma_3$ into the model does not alter the key mechanisms that I have previously highlighted; however, it adds complications to the calibration process. This complexity arises because any changes to $\gamma_3$ tend to have offsetting effects




**(a)** AR/y **(b)** AP/x

**Figure B.7:** Trade credit choice in the benchmark and alternative models

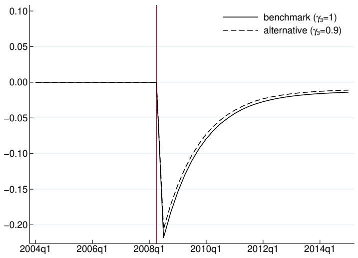
on $\gamma_1$ and $\gamma_2$. For instance, a reduction in $\gamma_3$ would require corresponding increases in $\gamma_1$ and $\gamma_2$ to ensure the model matches trade credit and bank loan sizes observed in the data. As a result, attempting to calibrate the model can often lead to indeterminate outcomes.

Given the calibration challenges, in the next exercise, I opted to fix $\gamma_3$ at 0.9 and recalibrate the remaining parameters. In this recalibrated alternative model, I introduced shocks to $\gamma_1$ and $\gamma_2$, which produced a drop in bank and trade credit similar to that in the benchmark model (see Figure B.8 panels a-b). The output dynamics following these shocks show a similar magnitude of decline in both models (panel c). A breakdown of different inputs reveals that while the dynamics in total factor productivity (TFP) are very similar, there are slight differences in labor and capital inputs, potentially due to variations in the calibrated discount factor $\beta$ and Frisch elasticity $\psi$. In short, this exercise reveals that both models exhibit comparable dynamics following financial shocks. However, due to the complications that the additional constraint of $\gamma_3$ introduces, I prefer to retain the benchmark model as is, to maintain transparency and straightforwardness in the calibration process.

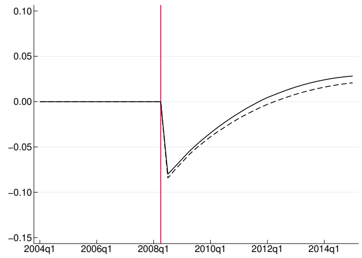
**Default in the data.** Another feature that my model shares with Altinoglu (2018) is the absence of trade credit default in *equilibrium*, as the trade credit contract precludes such occurrences. It is therefore worthwhile to examine the prevalence of trade credit default in the data and to discuss whether this is a reasonable assumption.

Often in the data, firms are labeled as having 'defaulted on trade credit,' which might imply one of two scenarios: (i) delays in payment beyond pre-agreed dates, or (ii) complete default or non-payment. Essentially, the first type of 'default' serves as a means for firms to extend their borrowing from suppliers by delaying payment. Importantly, my model captures this type of 'default,' as it manifests in an increase in the size of accounts receivable on firms' balance sheets. Through the lenses of the model, the nature of this type of default is that it leads to delayed cash flow for suppliers who extend trade credit, and this delay is costly for suppliers who are financially constrained, but less so for those who are not. The option to delay payments to suppliers is compensated by an interest rate on trade credit, which offset the loss of liquidity for constrained suppliers.

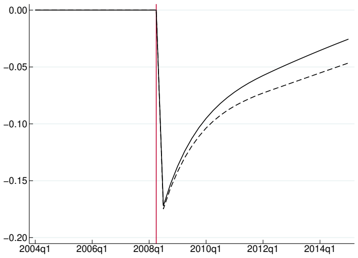
In contrast, the second type of 'default' – non-payment – is not captured by the model, as including it would require allowing trade credit defaults in equilibrium. However, from what I see



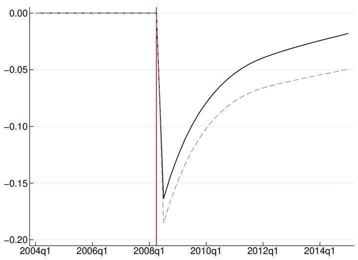

**(a)** Credit market liability to capital stock ratio



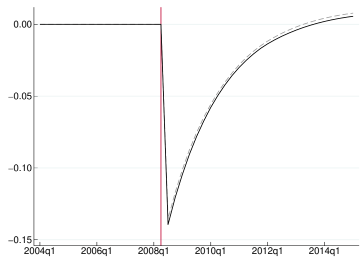
**(b)** Trade credit to credit market liability ratio



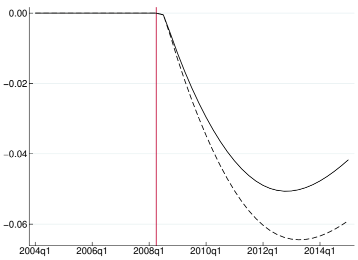
**(c)** Output



**(d)** Hours



**(e)** TFP



**(f)** Capital

**Figure B.8:** Model dynamics following financial shocks

from the existing literature, this type of default is not very prevalent in the data. For instance, Boissay and Gropp (2007) report that of all recorded trade credit default cases, only approximately 2% are due to insolvency leading to non-payment. The authors also document that, at the quarterly frequency, the average default-to-payable ratio is approximately 2%, indicating that the loss from true non-payment of trade credit is about 0.04%. The size of this loss is rather small compared to the trade credit interest rate in the model, which is approximately 4%. Considering the relatively minor impact indicated by these figures, the inclusion of equilibrium default in the current model would not substantially modify its quantitative properties.

# C Quantitative analysis appendix

## C.1 Algorithms

In this section, I describe the algorithms for computing the benchmark model. The algorithms to compute the counterfactual model are very similar to the benchmark model, only with different sets of FOCs, budget constraints, and working capital constraints. Hence they are omitted here.

### C.1.1 Stationary equilibrium

- Guess equilibrium prices $r, w, r^{tc}$.
- Given the prices, solve the household problem.
- Given the prices, solve the entrepreneurs' problem as follows:
  - Discretize the state space.
  - Guess policy function $c(a, z)$.
  - For each $(a, z)$, assume that the entrepreneur is unconstrained, i.e., $\mu(a, z) = 0$. Solve for the system of equations that consists of FOCs and budget constraints.
  - Check whether the working capital constraint is satisfied with the solution to the above system of equations.
  - If the working capital constraint is not satisfied, it means that $\mu(a, z) > 0$ and working capital constraint holds with equality. Solve the system of equations that consists of FOCs, budget constraints, and working capital constraints (with equality).
  - Use the Euler equation to update the policy function $c(a, z)$ until it converges.
- Given any arbitrary distribution of $(a, z)$, iterate using the policy functions derived above until a stationary distribution is reached.
- Generate the aggregate statistics of the three markets: capital, labor, and trade credit market.
- Update $(r, w, r^{tc})$ until the markets clear simultaneously.

### C.1.2 Transitional dynamics

To compute the transitional dynamics of the economy, I consider a transition path of $T = 100$ periods. The economy is at the initial stationary equilibrium level in period $t = 1$, and I assume that it converges back to the initial stationary equilibrium at period $t = T$.

- Guess a sequence of prices $\{r_t, w_t, r_t^{tc}\}_{t=2}^{T-1}$.
- Backward induction. For each $t = T-1, T-2, ..., 2$,
  - Discretize the state space.
  - Given prices, solve the household problem for the period $t$.

- Given prices, solve the entrepreneurs' policy functions for the period $t$.
    1. Guess $c_t(a,z)\mu_t(a,z) = 0$, solve the system of equations that consists of FOCs of period $t$, budget constraint, and Euler equations (with the next period policy function $c_{t+1}(a,z)$ known).
    2. Check whether the working capital constraint is satisfied under the above solution.
    3. If the working capital is not satisfied, $c_t(a,z)\mu_t(a,z) > 0$ and the working capital constraint holds with equality. Solve the system of equations that consists of FOCs of period $t$, budget constraint, Euler equations (with the next period policy function $c_{t+1}(a,z)$ known), and working capital constraint with equality.

- Forward induction. The first period stationary distribution $\Phi_1(a,z)$ is set to be the stationary equilibrium distribution. Using the policy functions for period $t = 2, ..., T-1$, compute the distribution along the transition path $\Phi_t(a,z)$.

- Generate aggregate statistics for the four markets in every period $t = 2, ..., T-1$ using the policy functions and the distributions.

- Update $\{r_t, w_t, r_t^{tc}\}_{t=2}^{T-1}$ until the four markets clear simultaneously in each period $t = 2, ..., T-1$.

## C.2 Firm size distribution in the model and data

This section compares the firm-size distribution between the model-generated data and the Business Dynamics Statistics (BDS) database, which covers the universe of firms in the US. To operationalize the comparison, I focus on four size categories. These size categories are firms with 1 to 0 employees, 10-99 employees, 100-999 employees, and 1000+ employees. According to the BDS, the fraction of firms in these four categories in 2005 was 76, 22, 1.8, and 0.2 percent. Firms in our model are then categorized into four groups to match this distribution, once they are sorted by size. As discussed in Section 4.1, I calibrate the Pareto shape parameter of the firm productivity distribution to match the employment share of the largest firm size categories. Figure C.9 compares the full distribution between the model and the BDS data. It shows that the mapping between the two is reassuring: not only is the firm grouping similar to the data in terms of the percentage of firms in each size category (panel a) but also in terms of how average employment increases over the size categories (panel b).

## C.3 The shadow value of liquidity function

I begin by looking at how the shadow value of liquidity $\xi$ varies with wealth $a$ for a given productivity level. Figure C.10 shows that $\xi$ decreases in $a$, indicating that producers are less constrained with higher wealth. Notably, $\xi$ is not strictly monotone; the function is divided into six segments by three values of $\xi$: $\{0,\ r^{tc},\ r^{tc}/(1-\gamma_2)\}$. Each segment is associated with different value ranges for AR and AP.

**(a)** Firm and employment shares **(b)** Average employment

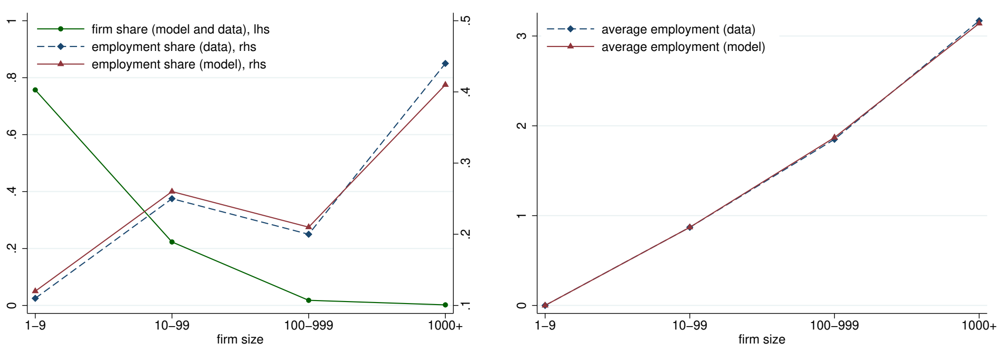



**Figure C.9:** Firm size distribution in the data and model

**Notes**: Panel (a) shows the share of firms in each size category in the model and the Business Dynamics Statistics (BDS) data (left axis) and the corresponding employment shares (right axis). Panel (b) shows the (logarithms of) average employment by size categories, with the smallest category normalized to 0.

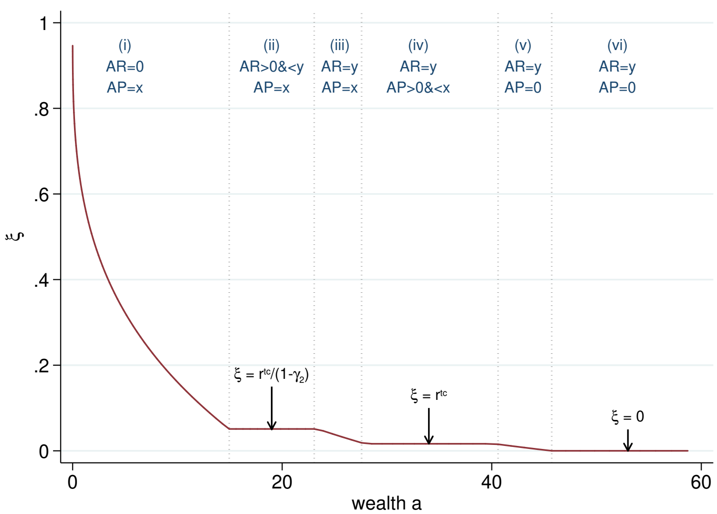



**Figure C.10:** Shadow value of liquidity and its role in determining trade credit choices

**Notes**: This figure plots the liquidity value $\xi$ as a function of wealth $a$ for a given $z$. The function $\xi$ decreases in $a$, but not strictly decreasing. There are three regions where $\xi$ is constant, marked by $\xi \in \{r^{tc}/(1-\gamma_2), r^{tc}, 0\}$. As such, the function $\xi$ is divided into six segments, each associated with a different value range for AR and AP.

## C.4 Policy functions

The policy functions of AR and AP as shown in figure 6 indicate that some entrepreneurs choose not to lend or borrow trade credit (AR = 0 or AP = 0). In the data, however, it is very rare for firms to have zero AR or AP on their balance sheet. In this section, I show that this discrepancy can be solved by recognizing that measured AR and AP are a snapshot of firms' activities and they likely reflect the averages of AR and AP over several sales and purchases that overlapped in time.

In figure C.11, I plot AR/$y$ and AP/$x$ averaged over three sales/production cycles. More specifically, I track each entrepreneur over three periods and use average $\{\text{AR}, \text{AP}, x, y, a\}$ to plot this figure. The shapes of AR/$y$ and AP/$x$ can more closely resemble the data patterns. In particular, they no longer take the corner values as before.

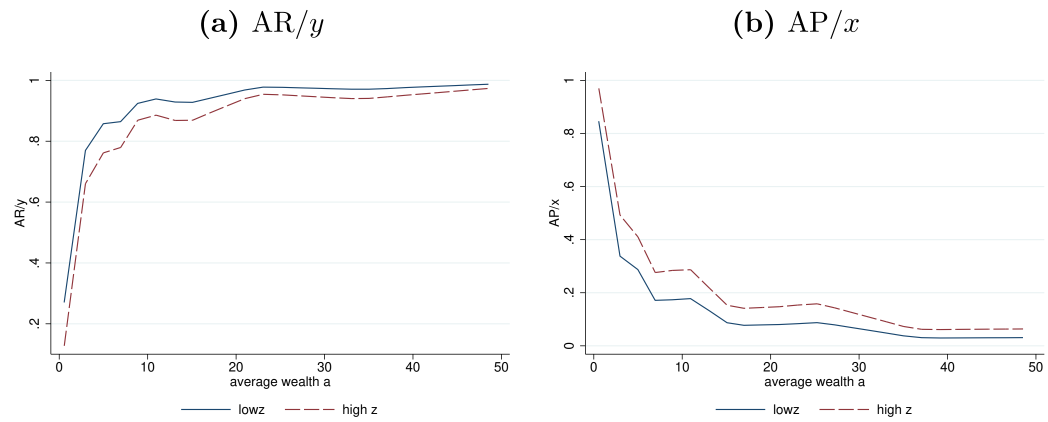



**Figure C.11:** Trade credit choice, average over three periods

**Notes**: This figure displays trade credit choices as a function of wealth $a$ for given low and high values of $z$. Panel (a) shows the average AR/average output over three periods. Panel (b) shows the average AP/average input costs over three periods.

In the data, firms might make multiple sales and purchases that overlap in time; therefore, the observed AR and AP may reflect the average of these sales and purchases. In this exercise, I consider the case where AR, AP, and sales reflect the averages of three cycles of sales/production. Although in the model, I do not explicitly model the *overlap* of these sales, this exercise conveys the simple idea that, in the presence of idiosyncratic productivity randomness (shocks to $z$), taking averages smooths out the policy functions; hence they can better mimic the data.

## C.5 Shifts in policy functions following the Lehman shock

Figure C.12 shows the policy functions for the two groups before and immediately after the collateral shock. Panel (a) shows the $\xi$ function shifts upward for both groups, indicating an increased value for liquidity. Panel (b) shows that, after the shock, there is a leftward shift in AR/$y$ of the low-exposure group and a rightward shift of the high-exposed group. In other words, the low-exposure entrepreneurs increase while the high-exposure ones cut back their lending of trade credit. Interestingly, as shown in panel (c), there is a slightly different pattern for AP/$x$. The curve of AP/$x$ shifts to the right – the borrowing of trade credit increases – for both groups. Importantly, the increase in AP/$x$ is more significant for the high-exposure than the low-exposure entrepreneurs.

The fact that the low-exposure group increased their their lending of trade credit (panel b, blue line) and their borrowing of trade credit (panel c, blue line) simultaneously reveals the intertwined nature of AR, AP, and production in equilibrium. Following a negative financial shock, trade credit becomes more expensive due to decreased supply and increased demand for trade credit. In turn, the higher trade credit interest rate has two opposing effects on the choice of AP. On the one hand, as trade credit becomes more costly, entrepreneurs would want to borrow less of it. On the other hand, higher trade credit interest rates also raise entrepreneurs' profitability (if they lend trade credit), increasing the optimal production scale. To expand production, some entrepreneurs need to borrow more trade credit.

**(a)** $\xi$ **(b)** AR/$y$ **(c)** AP/$x$

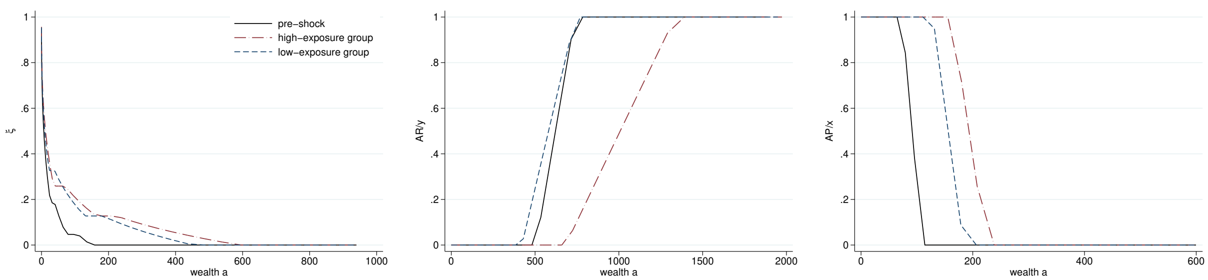



**Figure C.12:** Shifts in policy functions by the severity of the financial shock

**Notes**: These figures illustrate the shift in policy function after the negative shock for the low-exposure group (blue line) and the high-exposure group (red line). The black line shows the pre-shock policy function. Panel (a) plots the liquidity value as a function of wealth for a given productivity. Panels (b) and (c) show the lending and borrowing of trade credit, respectively.