Trade Credit and Profitability in Production Networks*

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Abstract

We construct a sample of over 200,000 supply chains to conduct a chain-based analysis of trade credit. Our study uncovers novel stylized facts about trade credit both within and across supply chains. More upstream firms borrow more from suppliers, lend more to customers, and hold more net trade credit. This upstreamness effect in trade credit is weaker for more profitable firms and for longer chains. Firms in more central or more profitable chains provide more net trade credit. Our results are generally consistent with the recursive moral hazard theory of trade credit. Evidence for the financing advantage theory is mixed.

JEL classification: G32, L14, L15

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1 Introduction

Trade credit is a loan that a supplier provides to its customer. It constitutes a large part of firms' balance sheets.[1] Traditionally, trade credit studies often focus on a firm's role either as a lender or a borrower (e.g., Petersen and Rajan (1997); Burkart and Ellingsen (2004)). However, real-world firms generally comprise part of complex production networks. Within these networks, firms operate simultaneously as suppliers and customers in lengthy chains of production that start from the upstream sectors and end with the production of final consumption goods. They receive trade credit from some business partners and provide it to others. Studies based on bilateral supplier-customer relationships have difficulty capturing this important feature of trade credit.

This paper presents a supply chain-based study of trade credit. Using a comprehensive database of supplier-customer relationships from FactSet, we construct a sequence of firm-level production networks between 2003 and 2018. We develop a novel procedure to uncover the shortest distance supply chain from each upstream firm to the final consumption goods sector based on these networks. After deleting chains that are nested by other chains, this procedure leads to a sample of over 200,000 un-nested supply chains formed by more than 5,600 nonfinancial firms matched to the Compustat North America database. The number of firms in these chains varies from two to ten. Equipped with this comprehensive sample, we study trade credit and firm profitability both within and across supply chains.

Our approach captures the vertical dimension of the production network and provides a natural definition of a firm's upstreamness: a firm's vertical position in the supply chain. Firms at the bottom of the chain belong to the consumer discretionary and consumer staples sectors, and they are defined to have a vertical position of zero. The vertical positions of the other firms in the chain represent their shortest distance to the consumption goods sector, i.e., their upstreamness. Importantly, while a firm may belong to multiple chains, its upstreamness is the same across all those chains at a given time. By mapping firms to their supply chains, we can compare a firm's

[1] For example, Rajan and Zingales (1995) document that accounts receivable constitute 17.8% of total assets and accounts payable constitute 15% of total assets on average for non-financial firms in the United States. These ratios are more than double the ratio of short-term debt to total assets (7.4%) for the same sample.

provision and use of trade credit with those of its direct and indirect suppliers/customers, which allows us to uncover new patterns of trade credit along the vertical dimension of the economy.

The supply chain sample that we construct enables us to analyze many interesting questions about trade credit that would be otherwise difficult to address. For example, how do trade credit practices and profitability differ for firms operating at different production layers? Within each supply chain, which firms tend to be net trade credit users and which tend to be net trade credit providers? How do the distributions of profitability and financing capacity in a supply chain affect trade credit? What drives the variation of trade credit and profitability across chains? How do longer supply chains differ from shorter ones? How does the financial crisis affect the profitability and trade credit of firms at different vertical positions of the supply chain? The trade credit literature so far has provided little insight into these important questions. Our study fills this gap by documenting a rich set of stylized facts and performing model-based empirical tests.

We first exploit the within-chain variation to study how the use and provision of trade credit vary with firms' vertical position. We focus on three trade credit measures: accounts receivable normalized by total revenues (the provision of trade credit), accounts payable normalized by the cost of goods sold (the use of trade credit), and the difference between accounts receivable and payable normalized by total revenue (the net provision of trade credit). Our main finding is that all three trade credit measures are positively related to upstreamness. We refer to this pattern as the upstreamness effect in trade credit. Firms that are further from the consumption goods sector provide and receive more trade credit, and they have higher net receivables, even though they face stronger financial constraints based on the standard measures. These results hold for both the univariate and multivariate regressions with strong statistical and economic significance. In our baseline specification, as the vertical position increases by one, the accounts receivable-to-sales ratio increases by 3.0 percentage points, the accounts payable-to-COGS ratio by 2.4 percentage points, and the net receivables-to-sales ratio by 2.8 percentage points. These changes represent 30%, 8.3% and 28% of the standard deviations of these variables respectively. Further analysis shows that the positive relation between upstreamness and trade credit is weaker for more profitable firms and in chains with higher average profitability. The upstreamness effect in accounts receivable and net receivables is also weaker in longer chains, which tend to be more profitable. These results demonstrate rich interaction between trade credit and firm profitability.

We next turn to a cross-chain analysis of trade credit at the chain level. We find that firms in more profitable or more central chains provide more net trade credit, which is consistent with the idea that firms in such chains have easier access to other sources of financing. We also analyze how the distribution of financing capacity, measured by the profit margin and (inversely) by the WW-index (Whited and Wu, 2006) and the HP-index (Hadlock and Pierce, 2010) of financial constraints, is associated with trade credit at the chain level. We characterize these variables' distributions within the supply chain by calculating their rank correlations with the upstreamness measure. Somewhat surprisingly, based on these rank correlations, more trade credit is provided, both in gross and net terms, by firms belonging to chains in which the upstream firms have weaker financing capacity relative to the downstream firms. Furthermore, the average ratio of accounts payable is higher in more profitable chains, especially when the profit margin is higher in the downstream, suggesting that downstream firms with market power may extract rents from supplier through trade credit. These results suggest that the financing motive may not be the main driver of trade credit patterns in our sample.

Most trade credit theory does not provide a clear explanation of why upstream firms have more trade credit. The only theory of which we are aware that relates trade credit to a firm's position in a supply chain is Kim and Shin's (2012) recursive moral hazard theory. This theory predicts that upstream firms should have more incentives against shirking, which are measured by profits and net receivables. This theory also makes a strong prediction about the relation between receivables and payables: when both are normalized by production costs, a regression of accounts receivable on accounts payable should have a coefficient equal to one after controlling for the fixed effects of the vertical position. We test both predictions of the theory. We find strong evidence that incentives against shirking increase with the distance to final consumption, measured by either the vertical position, or an alternative measure that we design to capture the expected time before a firm's output reaches its final consumers. Our regressions of accounts receivable on accounts payable, both normalized by the cost of goods sold, generate coefficient estimates ranging from 0.81 to 0.95, indistinguishable from the predicted coefficient of one in most specifications.

The recursive moral hazard theory of trade credit describes a steady state equilibrium of incentives along the supply chain. Shocks such as the financial crisis of 2008-2009 can disproportionately affect upstream firms, disrupting their ability to provide net trade credit. For example, the model of Gofman, Segal, and Wu (2020) predicts that upstream firms are more exposed to aggregate shocks. In support of this prediction, we document that profit margins drop more for upstream firms than for downstream firms in 2008-2009. Consistent with the conjecture that this weakens upstream firms' ability to provide net trade credit, we find that upstream firms' net accounts receivable decrease during the crisis. Interestingly, we also find that the profit margins of central firms decline less while the profit margins of more financially constrained firms decline more during the financial crisis, and their net provision of trade credit changes accordingly. However, only a small part of the financial crisis' effects on the relations between trade credit and upstreamness, centrality, and financial constraints can be explained by the exposure of firms' profit margins to the financial crisis. Overall, our results suggest that financing capacity is a more important determinant of trade credit during the financial crisis than during the normal times.

We conduct a battery of additional tests to verify the robustness of the main stylized facts. We find that our results are robust to alternative model specifications, sample constructions, and estimation methods. To address the concern that our results may be driven by firms belonging to many supply chains, which we refer to as high-interlinkedness firms, we re-estimate our model using weighted regressions, in which an observation is weighted inversely by the number of chains to which a firm belongs. The results are very similar. Furthermore, the upstreamness effect in trade credit does not vary significantly across firms or chains with different degrees of interlinkedness, nor is it driven by firms at the top or the bottom of the supply chain. It remains highly significant after controlling for the industry fixed effects. An estimation of the relationship between trade credit measures and upstreamness using vertical position dummies show that the upstreamness effect is largely monotonic. Finally, we show that the positive relations between upstreamness and accounts receivable, accounts payable, and net receivables remain highly significant when we run regressions using firm-year observations ignoring information related to specific chains, although the economic magnitudes of the coefficient estimates are somewhat smaller.

Related Literature. Most of the existing literature on trade credit studies trade credit provision and use over a single supplier-customer link. The literature's goal is to understand why a supplier would provide trade credit to a customer and why a customer would want to borrow from a supplier. The lender-borrower relationship between suppliers and customers is puzzling because banks and capital markets are natural sources of funding for firms. To address this puzzle, the theoretical literature identifies a number of advantages to using suppliers, as opposed to banks, as providers of credit. Schwartz (1974) was among the first to introduce the financing advantage theory for trade credit. Subsequent studies have focused on different mechanisms for this advantage. For example, a supplier-customer relationship can generate an informational advantage about the customer's prospects (Smith, 1987; Biais and Gollier, 1997), allow better enforcement of repayment (Cuñat, 2007), provide an advantage in liquidating collateral (Mian and Smith, 1992; Frank and Maksimovic, 1998; Santos and Longhofer, 2003), allow a distressed customer to renegotiate with the lender at better terms (Wilner, 2000), or generate customer-specific inputs that are harder to divert relative to bank financing (Burkart and Ellingsen, 2004).

Empirically, Petersen and Rajan (1997) find that firms with better access to credit provide more trade credit, which supports the financing advantage theory. Recently, Amberg et al. (2021) provide additional support for this theory by showing that firms increase demand for trade credit when they experience a negative liquidity shock. Importantly, these studies cover mostly relatively small firms. In contrast, several recent studies show that relatively large firms with easy access to external finance also borrow substantially from suppliers, which challenges the financing advantage theory (Klapper, Laeven, and Rajan (2012), Murfin and Njoroge (2015)). We contribute to this literature by presenting new evidence for each side of the debate. On one side, we find that firms in more profitable and more central chains provide more net trade credit, consistent with the financing advantage theory. Furthermore, firms that are more resilient to the financial crisis provide more net trade credit during the financial crisis. On the other side, we show that more upstream firms provide more net trade credit despite facing stronger financial constraints. Furthermore, the average ratios of accounts receivable and net receivables are higher for supply chains in which downstream firms have stronger financing capacity than the upstream firms. More intriguingly, we show that firms borrowing more from suppliers also lend more to customers (almost dollar for dollar). These results suggest that we need to look beyond the financing motive to understand firms' trade credit policy.

The literature has also considered alternative frictions to explain trade credit. For example, Ferris (1981) argues that transaction costs are important in explaining the trade credit usage. Long, Malitz, and Ravid (1993) and Lee and Stowe (1993) propose that trade credit can serve as an implicit warranty when there is asymmetric information about the product quality. Desai, Foley, and Hines (2016) argue that taxation is another motive for firms to use trade credit. Similar to the literature about financing advantage theory, these papers study trade credit in a bilateral relationship. Kim and Shin (2012) consider moral hazard as a friction to explain trade credit use and provision. What sets their paper apart from the other theories of trade credit is that they study trade credit at the supply chain level. They predict that incentives against shirking (trade credit and profits) should be higher for more upstream firms because their shirking affects the final product with a delay. Their theory also predicts a one-for-one correspondence between changes in accounts receivable and accounts payable normalized by production costs after controlling for the vertical position fixed effects. Our supply chain-based analysis provides strong support for both predictions.

Strategic considerations related to the market structure and competition are also found to be important for understanding the role of trade credit in the economy. Brennan, Maksimovics, and Zechner (1988) show that suppliers with market power may find it optimal to use trade credit as a tool to price discriminate. Giannetti, Serrano-Velarde, and Tarantino (2020) find that suppliers offer trade credit to high-bargaining power customers instead of reducing the price because a price reduction would reduce profits from low-bargaining power customers. Chod, Lyandres, and Yang (2019) show that competition between suppliers can affect the suppliers' provision of trade credit to a customer firm. Lehar, Song, and Yuan (2020) show that trade credit can be used as a collusion mechanism in oligopolistic industries. Klapper, Laeven, and Rajan (2012) use detailed trade credit contract data to find that large creditworthy customers exercise their bargaining power to receive longer maturity trade credit contracts from their small customers. Murfin and Njoroge (2015) find similar results for large retailers. Consistent with these findings, we show that downstream firms with high profit margins not only provide more trade credit but also take more trade credit from suppliers. Furthermore, our within-chain analysis shows that firms with more competitors provide more net trade credit, suggesting that they may use trade credit as a strategic tool to gain market share.

Financial crises provide an important laboratory for studying trade credit because financing advantage theory would be more relevant when firms' access to bank credit or capital markets is restricted. Garcia-Appendini and Montoriol-Garriga (2013) find that during the 2008-2009 financial crisis, firms shared liquidity with their customers. Love, Preve, and Sarria-Allende (2007) find that there is an aggregate reduction in the supply of trade credit following a financial crisis. Costello (2020) uses firm-level data to show that suppliers that are negatively affected by reduction in bank credit reduce provision of trade credit to their customer firms. We contribute to this literature by showing that during the 2008-2009 financial crisis, upstream firms and more financially constrained firms experienced a larger drop in profitability and net trade credit. In contrast, central firms experienced less profit decline and extended more net trade credit during the crisis.

The remainder of the paper is organized as follows. The next section introduces the methodology used to construct supply chains and measure a firm's vertical position. Section 3 presents the data and the summary statistics. Section 4 presents the main stylized facts. In Section 5, we test the predictions of recursive moral hazard theory. Results for the financial crisis are in Section

6. Section 7 contains robustness tests. We conclude in Section 8.

2 Methodology

The first contribution of our paper is methodological. We develop a procedure to construct supply chains using supplier-customer relationships and introduce a measure of a firm's upstreamness in the production network. We describe our methodology in this section.

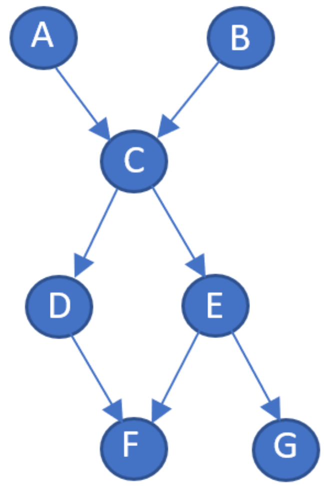
2.1 Supply Chain Construction

For a given time, let A be an $n \times n$ unweighted adjacency matrix, where n is the number of firms in the production network. Element $A_{i,j} = 1$ if firm i is a supplier to firm j. Otherwise, $A_{i,j} = 0$. Let Ω be a set of firms that are producers of final goods. These firms sell their goods and services directly to final consumers. Empirically, these firms can be identified based on the sector in which they operate. In our implementation, we define firms in the consumer discretionary sector (GICS code 25) and the consumer staples sector (GICS code 30) as producers of final goods.

We supply chains from matrix A. For each firm that is not in set Ω, we use the Bellman-Ford algorithm to identify all the shortest paths from this firm to all the firms in set Ω. Of all these shortest paths, we keep the path with the minimum shortest distance. (In the case of a tie, all paths with the minimum shortest distance are kept.) While this approach does not keep track of all supply chains in the production network, it covers the most direct connections between any non-consumption goods producer and the consumption goods sector. We then eliminate any supply chain that is a subchain of a longer chain. Doing so is important because it ensures that we correctly identify the whole supply chain and not merely a part of it. The final output of this procedure is a set of supply chains for each point-in-time snapshot.

Figure 1 provides an example of a production chain with seven firms. Firms F and G are the producers of final goods. The shortest chain from D to the set of final goods producers is $D \to F$.

Figure 1: **Example of a production network with six supply chains**



There are two shortest distance chains from C to F: $C \to D \to F$ and $C \to E \to F$. Notice that both $D \to F$ and $C \to D \to F$ are subchains of a longer chain $A \to C \to D \to F$, and so they will be eliminated. After the elimination procedure, the final set includes six chains: (i) $A \to C \to D \to F$, (ii) $A \to C \to E \to F$, (iii) $A \to C \to E \to G$, (iv) $B \to C \to D \to F$, (v) $B \to C \to E \to F$, and (vi) $B \to C \to E \to G$.

2.2 The Upstreamness Measure

Our methodology leads to a natural measure of a firm's upstreamness in the production network: its vertical position in the supply chain. This measure allows us to document novel stylized facts about trade credit and profitability along the vertical dimension of the economy. Such facts are important for testing theories of trade credit along supply chains.

Let S_i be supply chain i with m firms. Let b_i be the index of the firm at the bottom of supply chain S_i. An upstreamness measure of firm $j \in S_i$ is equal to the distance from firm j to firm b_i, where distance is measured by the number of supplier-customer links between j and b_i. Consequently, the upstreamness measure of firm b_i is 0 because it has zero distance to itself. A direct supplier to firm b_i has an upstreamness measure of 1. A supplier to the supplier of firm b_i has a vertical position of 2. In general, upstreamness of each firm in a supply chain is one unit above the upstreamness of its customer firm. The firm at the very top of the supply chain has the highest upstreamness measure. Naturally, the upstreamness of a supply chain's top firm is also equal to the length of the supply chain minus 1.

By definition, a firm's shortest distance to the bottom layer is unique. Therefore, even though a firm can have multiple equidistant shortest paths to the bottom layer, our method assigns a unique upstreamness measure for each firm at any given time. A firm can also belong to different chains with different lengths, but the variation in the length is driven by the number of firm's direct and indirect suppliers, which does not affect the firm's own upstreamness measure. In short, a firm's upstreamness measure is the same across all the chains to which it belongs at a given time.

Our methodology allows us to classify firms in a production network into layers of production based on the distance to the bottom layer firms. In the example of a production network in Figure 1, there are four layers of production. Firms F and G have a vertical position of 0. Firms D and E have a vertical position of 1. Firm C is at position of 2. Last, firms A and B have a vertical position of 3.

Upstreamness is a global network measure in the sense that it depends not only on a firm's direct supplier-customer relations, but also on the relations of its indirect suppliers and customers. The vertical position depends on technological factors. For example, a producer of oil drilling equipment cannot be a direct supplier to a car manufacturer. A firm at a vertical position of 5 does not have any direct link to any firm at a vertical position of 3 or lower. Therefore, the lack of links reveals information about a firm's technological position in the production process.

The upstreamness measure can also be calculated using the whole production network represented by adjacency matrix A without decomposing the network into supply chains. This is achieved by computing the minimum distance from each firm i to the firms that produce final goods (set Ω). Formally,

$$Upstreamness_i = \min_{j \in \Omega} D(i, j), \tag{1}$$

where $D(i, j)$ is the shortest distance between i and j. Conceptually, to find the solution to this formula, an algorithm searches through all possible supply chains that connect a firm to the bottom layer of production and returns the shortest distance as the output. This is the approach first developed in an early version of this paper and subsequently used in Gofman, Segal, and Wu (2020) to study the asset pricing implications of vertical positions. Our current methodology not only records the distance, but also keeps track of the shortest distance paths. This allows us to analyze trade credit and profitability along supply chains.

Our approach also gives rise to a novel measure of a firm's interlinkedness, which can be defined as the number of supply chains to which it belongs at a given time. This novel network measure is easy to compute once all the shortest distance supply chains are identified. For example, firm C in Figure 1 belongs to all six chains, making it the most interlinked of the seven firms.

3 Data and Summary Statistics

3.1 Data

The main data used in our empirical analysis are from the FactSet Revere relationships database (for information about suppliers, customers, and competitors) and the Compustat North America database (for accounting data). The FactSet Revere database is the most comprehensive one for firm-level supplier-customer relationships currently available.[2] The database reports the start date and the end date for each relationship, making it superior to alternative data sources for supplier-customer linkages that do not provide this information (e.g., Capital IQ). The primary source of this information is companies' financial reporting. Regulations require companies to report

[2]Recent publications using this database include Gofman, Segal, and Wu (2020), which studies creative destruction in supply chains, and Dai, Liang, and Ng (2020), which examines the influence of customers on suppliers' corporate social responsibility (CSR).

names of customers that generate above 10% of sales. FactSet supplements this information with companies' press releases, information on their websites, investor presentations and other public disclosures. Importantly, it also collects information about suppliers reported by customers, which is unavailable from alternative data sources such the Compustat Segment database. One limitation of this database is that the sale volume is unavailable for most supplier-customer relationships.

Our sample period starts in 2003, when the Revere database was initiated, and ends in 2018. Following the approach in Gofman, Segal, and Wu (2020), we combine multiple relationships between the same pair of supplier and customer over different time periods into one continuous relationship if the time gap between two consecutive relationships is 6 months or less. We use CUSIP as the main matching variable to merge the FactSet Revere database with the Compustat North America database, and use company name to verify the accuracy of the matches. We also identify some additional matches purely based on company name. We exclude firms in the financial and real estate industries (GICS code 40 or 60, or an SIC code between 6000 and 7000) and industrial conglomerates (GICS 201050). These procedures lead us to a sample of 121,556 supplier-customer links between 8,492 non-financial firms in the Compustat database. Based on the start and end dates of these links, we construct a snapshot of the supplier-customer relationships observed at the end of each calendar year. From these snapshots, we build a sequence of production networks at an annual frequency. Applying the methodology described in Section 2 to these networks, we identify 210,772 un-nested shortest distance supply chains during the 2003-2018 period. We treat chains observed in different years as distinct chains even if the lineup of firms in the chain is the same. This means that each supply chain is tied to a specific timestamp, and that year fixed effects are subsumed once we control for chain fixed effects.

We obtain annual financial data from the Compustat database. All dollar values are converted into 2004 dollar values using the GDP deflator. Numbers reported in Canadian dollars are first converted to US dollars using the exchange rate at the fiscal year end. We exclude firm-year observations with missing information about total revenue or total assets, with sales or assets of less than $1 million, or with a gross profit margin of less than -100%.

We match the annual fiscal year data to the closest production network snapshot. For example, fiscal years ending in January 2010 are matched to the December 2009 network snapshot. We delete the supply chains in which only one firm has financial data available. Our final sample consists of 35,167 firm-year observations from 5,623 non-financial firms matched to 203,722 shortest distance supply chains. The average number of firms in each annual snapshot of production network is about 2,200 firms. In any given annual snapshot, the average number of chains to which a firm belongs is 18 while the median number is 5.

3.2 Summary Statistics

3.2.1 Firm-year Observations

We first present summary statistics for all firm-year observations in Table 1. All the financial ratios are winsorized at the 1st and 99th percentiles, and variable definitions are provided in Table A.1 in Appendix A.1. On average, accounts receivable (the trade credit provided) are 15% of total revenues, with a median of 14%. Accounts payable (the trade credit received) constitute 21% (14%) of the cost of goods sold for the average (median) firm in the sample. Both the average and median ratios of net receivables (the trade credit provided minus the trade credit received) to total revenues are 6%.

The average vertical position is 1.46, which is about one and a half layers above the bottom layer. Nextera Energy Inc., electric services company, has a vertical position of 9 in 2003, which is the highest in our sample. Both the average and the median values of normalized centrality in our sample is 0.72. At the beginning of our sample IBM is the most central firm; at the end it is Amazon. The median firm size, measured by total assets, in the sample is $955 million, and the median firm age is 17 years. 20% of firm-year observations have investment grade rating (defined as the S&P domestic long term issuer credit rating being BBB- or above). The average number of competitors for a firm in the sample is 15.3, and the standard deviation is 20. Table 1 also reports the summary statistics for two commonly-used measures of financial constraints:

the WW-index (Whited and Wu (2006)) and the HP-index (Hadlock and Pierce (2010)). The HP-index is calculated purely based on firm size and firm age, while the WW-index takes into account, in additional to firm size, a firm's cash flows, long-term debt ratio, dividend payment, sale growth, and industry sales growth. For both indexes, a higher value means that a firm is more financially constrained.

Panel B of Table 1 reports the correlations between our main variables of interest. Accounts receivable and accounts payables have a correlation of 23%.[3] If trade credit mainly flows from firms with easier access to financing to firms that are more financially constrained, as suggested by the financing advantage theory of trade credit, then some firms should have high receivables but low payables, while other should have the opposite. The positive correlation means that firms simultaneously provide and use trade credit, suggesting either that trade credit is used for a different purpose than liquidity provision or that a firm can obtain liquidity from suppliers and pass it to direct and indirect customers, in which case one should go beyond bilateral relationships to study trade credit-based liquidity provision.

Upstreamness is positively correlated with all three trade credit measures and profit margins, but it is negatively correlated with centrality, size, and age. Not surprisingly, firm size is positively correlated with firm age, centrality, and the investment grade rating dummy.

3.2.2 Chain-level Summary Statistics

Table 2 reports the summary statistics at the supply chain level for the 203,722 shortest distance chains in our sample. Other than the chain length, which is measured by the number of firms in the chain, and the rank correlations, the chain-level variables are computed as simple averages across firms within the chain.

[3] We follow the convention in the literature (e.g., Love, Preve, and Sarria-Allende (2007)) to normalize accounts receivable by sales and accounts payable by the cost of goods sold (COGS) in our main tests, because receivables are associated with sales and payables are associated with purchases. When both are normalized by COGS, the correlation increases further to 0.49. In Section 5.3, we perform a test in which both accounts receivable and accounts payable are normalized by COGS based on the Kim and Shin (2012) model.

The average chain length is 3.3, and the standard deviation is 0.82. The shortest chain has two firms and the longest has ten. The average (median) centrality at the chain level is 0.8 (0.81), which is slightly higher than at the firm level. The average (median) firm size, firm age and fraction of firms with an investment grade rating are also higher than at the firm level. This is because large and central firms are more likely to belong to more chains. On the other hand, the average (median) trade credit measures and profit margin at the chain level are similar to those at the firm-level, which suggests that whether a firm belongs to many chains is not correlated with its trade credit practice or profit margin.

DTCs (Days-to-Consumers) is a new measure that we introduce in this paper to characterize a firm's distance to the consumers of the final product, i.e., upstreamness in the time dimension. This measure estimates the number of days before a firm's output reaches final consumers along each shortest distance chain. It is calculated by adding up days-in-inventory for the firm and all its downstream customers that belong to the supply chain. The average (median) DTCs across chains is 60 (55) days. Unlike the vertical position, which is constant across chain for a firm at a given time, DTCs is chain-specific. The correlation between these two measures is 0.47.

To characterize the distributions of trade credit and financing capacity within a supply chain, we compute the rank correlations of Upstreamness with the three trade credit measures and with firm characteristics that are likely related to financing capacity: profit margin, WW-index, HP-index, firm size, firm age, and asset tangibility. A rank correlation of 1 (-1) means that a variable increases (decreases) monotonically within a chain as the vertical position increases. The ratio of accounts receivable (net receivables) to sales has a rank correlation coefficients of 0.41 (0.40) with upstreamness. The ratio of accounts payable to COGS has a rank correlation of 0.09 with upstreamness. Consistent with the correlations at the firm-year level reported in Panel B of Table 1, these correlations further suggests that upstream firms not only extend more but also take more trade credit.

One may conjecture that the higher net trade credit extended by upstream firms may be due to their stronger financing capacity, as suggested by the financing advantage theory of trade credit.

However, the support for this conjecture is rather limited. While upstream firms tend to have higher profit margins (a rank correlation of 0.08 between upstreamness and profit margin), they also tend to be more financially constrained according to both the WW-index and the HP-index. The average rank correlations between upstreamness and these two indexes are 0.36 and 0.35, respectively. The rank correlations of upstreamness with firm size (-0.37) and firm age (-0.21) show more explicitly that upstream firms tend to be smaller and younger. Furthermore, the average rank correlation between upstreamness and tangibility is -0.19, suggesting that assets of upstream firms have lower pledgeability.

To summarize, a preliminary look at data at both at the firm and the supply chain level suggests that accounts payable and receivable are positively correlated. More upstream firms receive more trade credit, but they also provide more, in both gross and net terms. While upstream firms appear to be more profitable, they also tend to be smaller, younger, have lower asset tangibility, and face stronger financial constraints based on the standard measures. From the perspective of the financing advantage theory, it is puzzling why they tend to be net providers of trade credit.

4 Trade Credit in Supply Chains: Stylized Facts

In this section, we present novel facts about trade credit in supply chains using both within-chain and between-chain analysis.

4.1 Within-chain Analysis

4.1.1 The Upstreamness Effect in Trade Credit

Our within-chain analysis focuses on the relation between a firm's vertical position (i.e., upstreamness) in the supply chain and its provision and use of trade credit and how this relation varies with firm and chain characteristics. Our baseline specification takes the following form:

$$Y_{j,c} = \alpha + \beta * Upstreamness_{j,c} + \gamma * Controls_{j,c} + f_c + \epsilon_{j,c}, \tag{2}$$

where the dependent variable $Y_{j,c}$ is the scaled accounts payable, accounts receivable, or net receivables of firm j in chain c; f_c is the chain fixed effects. Note that because chains observed in different years are treated as distinct chains, even if they consist of the same set of firms, f_c subsumes the year fixed effects.[4]

Besides our main variable of interest, Upstreamness, another important network-based measure is centrality. There are various definitions of centrality. We adopt an intuitive and commonly used one: closeness centrality. It is calculated as the reciprocal of the sum of the shortest distance, measured by the number of links, between a firm and all other firms in the production network, multiplied by the squared fraction of firms connected to the firm.[5] We normalize this measure so that it is between zero and one in each year, with zero assigned to the firm with the lowest centrality in the year.

The other control variables in the baseline specification include the natural logarithms of firm size and firm age, and the investment grade rating dummy. These variables are meant to capture a firm's access to external financing. In addition, we control for the natural logarithms of inventory turnover and the number of competitors and whether a firm is headquartered outside the United States (the Foreign dummy).

We account for the triple clustering of standard errors in all of our within-chain analysis: by firm, by the firm at the top of the chain, and by the firm at the bottom. Clustering by firm is needed because the same firm can belong to multiple supply chains, either in a given year or over time. Clustering by the top and bottom firms accounts for the fact that two chains with the same origin or supplying to the same bottom layer firm are correlated. Specifically, clustering

[4] The within-chain analysis under our chain definition is equivalent to defining the chain by the lineup of firms in the chain and controlling for chain-by-year fixed effects.

[5] As an alternative, we have also used the eigenvector centrality measure. The results are similar.

by the top firm captures shocks that originate at the top of the chain and propagate downward, while clustering by the bottom firm captures shocks that originate at the bottom and propagate upward.

Table 3 presents the results from both the univariate and our baseline multivariate regressions. It shows three key findings: firms that are higher in the supply chain (i) provide more trade credit to their customers, (ii) obtain more trade credit from their suppliers, and (iii) provide more net trade credit relative to downstream firms. This upstreamness effect in trade credit is both highly statistically significant and economically large. Specifically, Column (1) shows a strongly positive univariate relation between the ratio of accounts receivable to sales (AR/Sale) and upstreamness. The coefficient on Upstreamness is 0.025 (with a t-stat of 4.92). In Column (2), this coefficient increases slightly to 0.30, with a t-stat of 7.75, as we include our standard set of controls. This means that as a firm moves up one position in the supply chain, the AR/Sale ratio increases by 3.0 percentage points, which is 30% of the standard deviation of this ratio at the firm-year level.

The next two columns show the relation between accounts payable (AP/COGS) and upstreamness, with and without controls. The results show that upstream firms not only provide more trade credit, they also obtain more. The coefficient is significant at 1% for both specifications. The point estimate in the baseline model (Column (4)) shows that as the vertical position moves up one position, the AP/COGS ratio increases by 2.4 percentage points, or 8.3% of the standard deviation of this variable across firm-years.

Because more upstream firms both provide and receive more trade credit, ex ante it is unclear whether they are net providers or net users of trade credit. The last two columns in Table 3 show that they tend to be net trade credit providers. The ratio of net receivables to sales (NAR/Sale) is strongly positively related to the upstreamness measure. The point estimate is 0.29 (t-stat 5.95) in the univariate regression (Column (5)) and 0.028 (t-stat 6.72) in the multivariate regression (Column (6)), suggesting that as the firm's vertical position increases by one, the NAR/Sale ratio increases by over a quarter of its standard deviation.

Among the other variables, Table 3 shows that more central firms, like more upstream firms, also provide and obtain more trade credit, and they tend to act as net trade credit providers. This suggests that central firms in production networks may play a role similar to that of central financial intermediaries in financial networks, channeling liquidity from one firm to another in the economy.

Older firms tend to have a lower AP/COGS ratio, suggesting that more established firms rely less on trade credit provided by suppliers. Somewhat surprisingly, firm size or having an investment-grade rating does not seem to have any significant effect on a firm's provision or use of trade credit. This result does not provide support for the financing advantage theory of trade credit.[6]

The last column of Table 3 also shows that firms with a higher inventory turnover rate or those that face more competitors have a higher net receivables-to-sales ratio. Firms with faster inventory turnover may be managed more efficiently and are thus able to provide more trade credit. Firms with more competitors are likely to use trade credit more extensively to gain market share.

In sum, we find a strong positive correlation between all the three trade credit measures and the upstreamness. In Section 7, we conduct an extensive set of additional tests to verify the robustness of this finding. The positive relation is consistent with the recursive moral hazard theory of Kim and Shin (2012), in which net receivables represent the "stake" that each firm holds in the supply chain. We will test this theory further in Section 5. The positive relation between firm centrality and net receivables suggests that more central firms are better positioned to be net providers of trade credit. We show in Section 6 that this role of central firms becomes more prominent during the financial crisis.

[6] One may wonder whether the lack of a significant size or rating effect is due to correlations between control variables. This is not the case. We do not find any significant relation between the trade credit ratios and Log(Assets), with or without controlling for chain fixed effects. The investment-grade rating dummy only has a marginally significant (at the 10% level) negative relation with net receivables in a univariate regression with chain fixed effects. However, we show in Section 6 that financial capacity plays a more important role in determining trade credit during the financial crisis.

4.1.2 Variation in the Upstreamness Effect in Trade Credit

We now investigate how the relation between trade credit and upstreamness varies with firm and chain characteristics. One particular variable of interest is firms' profit margin. On the one hand, firms with a high profit margin can generate more cash flows internally, which reduces their reliance on trade credit and enhances their ability to provide it. On the other hand, the recursive moral hazard theory of Kim and Shin (2012) suggests that more profitable firms have more incentive to sustain the supply chain and are less likely to shirk. Therefore, high profits reduce the amount of net trade credit that upstream firms need to hold in order to satisfy their incentive compatibility constraints.

Motivated by this consideration, we extend our baseline specification by adding profit margin and its interaction with upstreamness as explanatory variables. The results of the extended models are presented in the first three columns of Table 4. The coefficients on Upstreamness become slightly larger in magnitude relative to those in the baseline specification, while the coefficients on the baseline control variables remain largely unchanged. The coefficient on Profit Margin is significantly positive in all three columns. More interestingly, the coefficient on the interaction term is significantly negative in all three columns, suggesting an attenuation of the upstreamness effect in trade credit for more profitable firms. From the perspectives of most trade credit theories, it is not so obvious why this should be the case. However, this result is consistent with the recursive moral hazard theory of Kim and Shin (2012), which predicts that more profitable upstream firms rely less on trade credit to align incentives.

The negative coefficient on the interaction term also implies that the positive relation between profitability and the trade credit ratios is substantially stronger for downstream firms than for upstream firms. The positive relation between net receivables and profit margins observed in the downstream firms (Column (3)) confirms a similar finding by Petersen and Rajan (1997), which they interpret as evidence for the price discrimination theory. Firms with high profit margins have an incentive to expand sales, and trade credit allows them to do so without cutting the price. This result is also consistent with the financing advantage theory, because more profitable firms are more able to finance trade credit cheaply, either through internal cash flows or external financing.

The reason for the positive relation between accounts payable and the profit margin for the downstream firms (Column (2)) is less clear. It may occur because more profitable downstream firms are viewed as more trustworthy by the suppliers, so it is easier for them to obtain trade credit. Alternatively, a high profit margin of a downstream firm may reflect its market power, which allows it to extract cheap trade credit from suppliers (Klapper, Laeven, and Rajan (2012), Murfin and Njoroge (2015)). Yet another possibility is that supplier shirking may be more costly for more profitable downstream firms and they, therefore, demand more trade credit to deter such behavior.

Table 4 also shows how profit margin is related to the upstreamness. The univariate relation, reported in Column (5), is positive, but it is statistically significant only at the 10% level. However, after adding the standard set of controls (Column (6)), this positive relation becomes much stronger (with a t-stat of 6.11). Interestingly, centrality is negatively associated with the profit margin, perhaps because high-centrality firms such as Walmart Inc., which has an average centrality measure of 0.95 out of 1, operate on large volumes and with relatively low profit margins. Firm asset size, on the other hand, is strongly positively related to the profit margin, which potentially reflects the pricing power of large firms as market leaders. Not surprisingly, the inventory turnover rate, which reflects a firm operational efficiency, is also positively related to the profit margin.

Table 5 shows how the upstreamness effect varies with the length and profitability of the supply chain. Chain profitability is measured by the average profit margin of all firms in the chain. For ease of interpretation, we subtract both chain characteristics by their median values across chains. Therefore, both interaction terms, Upstreamness * Adj. Chain Length and Upstreamness * Adj. Chain Profit, take a value of zero if the chain length and chain profit are at the median levels. Because we control for chain fixed effects, the direct effects of these chain characteristics are not estimated.

Columns (1) and (3) show a negative coefficient on the interaction term Upstreamness * Adj. Chain Length, suggesting that the positive relation between upstreamness and accounts receivable, gross and net, is weaker for longer chains. In other words, the provision of trade credit increases at a lower rate as the upstreamness increases in longer chains. This is not surprising, because otherwise the burden of providing trade credit may be too high for upstream firms in a long chain, making the chain not sustainable. On the other hand, the recursive moral hazard theory does imply that the incentive issue is more severe in longer chains. The weaker relation between the net receivables and the upstreamness in longer chains suggests that in order for longer chains to be sustained, they must be more profitable. In Table 6, we find this is indeed the case.

Columns (4) to (5) in Table 5 show a negative coefficient on the interaction term Upstreamness * Adj. Chain Profit, suggesting that the upstreamness effect in trade credit is attenuated by chain profitability. This is again consistent with the recursive moral hazard theory of trade credit, as discussed above.

To summarize, our within-chain analysis demonstrates a strong positive relation between upstreamness and both the provision (gross and net) and use of trade credit. Consistent with the recursive moral hazard theory, this positive relation is attenuated by both firm and chain profitability. The upstreamness effect in the provision of trade credit is also attenuated in longer supply chains.

4.2 Between-chains Analysis

4.2.1 Trade Credit, Profitability, and Chain Characteristics

We next focus on the comparison between different supply chains. Using the chain as the unit of observation, we investigate how trade credit and profitability measured at the supply chain level vary with chain characteristics. Because firms are generally a part of multiple chains, accounts receivable and accounts payable measured at the chain level generally do not balance out. If firms in a chain provide more trade credit than they receive, the chain is a net trade credit provider in the production network. In contrast, if firms on the chain obtain more trade credit than they provide, the chain is a net trade credit user.

We measure trade credit ratios at the chain level by taking the simple average across the firms in the chain. We consider three types of chain characteristics as explanatory variables. The first is chain length, measured by the number of firms in the chain. The second is a vector of firm characteristics aggregated to the chain level by taking a simple average across firms. The third type is variables designed to capture the within-chain distribution of financing capacity.

Table 6 shows how the chain-level accounts receivable, accounts payable, net receivables, and profit margin vary with chain length and other chain characteristics, including the average firm centrality, the average log firm size, the average log firm age, the fraction of firms with investment grade rating, the fraction of foreign firms, the average log inventory turnover, and the average log number of competitors. The results show that longer chains have on average higher payables, but not higher receivables or net receivables. Interestingly, longer chains also tend to have a higher profit margin. From the perspective of the recursive moral hazard theory, a higher profit margin makes long chains more sustainable. Without high profits, the amount of net trade credit required to satisfy the upstream firms' incentive compatibility constraints could be too to be economically feasible.

Another interesting fact is that chains composed of more central firms provide more and obtain more trade credit, highlighting the role of central firms as the nexus of the network. The former is statistically significant at the 1% level, the latter at the 10% level. Net receivables are positively related to centrality (t-stat 4.22) at the chain level, suggesting central chains are net trade credit providers. In contrast, the relation between chain-level net receivables and the average log firm size is significantly negative, suggesting that chains composed of large firms tend to obtain more trade credit than they provide. The average firm centrality and the average firm size in the chain also have opposite relations with average profit margin, even though size and centrality are positively correlated. While the size-profit relation is positive, the centrality-profit relation is strongly negative. These opposite relations highlight the distinct feature of centrality as a global network measure.

The average inventory turnover at the chain level has a positive relation with both net receivables (t-stat 2.46) and profit margin (t-stat 10.38), but not with receivables or payables. Chains with a high fraction of foreign firms have on average more receivables and payables (t-stats 5.13 and 6.31 respectively), but not significantly more net receivables. These results are consistent with those obtained from the with-chain analysis.

4.2.2 Effects of Within-Chain Distributions

We further examine whether trade credit measured at the chain level is related to the distribution of financing capacity within the chain. If the provision of trade credit is determined by the relative financing strength of the supplier and the customer, one would expect not only the average level but also the distribution of financial capacity to matter for accounts receivable and accounts payable observed at the chain level. If upstream firms can finance trade credit relatively cheaply, they would naturally extend trade credit to their customers, leading to high ratios of both accounts receivable and accounts payable at the chain level. In contrast, if upstream firms face stronger financial constraints than downstream firms do, then accounts receivable and accounts payable at the chain level will be lower, either because upstream firms have limited capacity to supply credit or because downstream firms have a low demand for it.[7]

We consider three indicators of firm's financing capacity: profit margin, which captures a firm's ability to generate cash flows internally and a firm's attractiveness to outside financiers; the WW-index and the HP-index of financial constraints. We use the rank correlation of each variable with the upstreamness measure to capture the distribution of the variable within the chain. A positive rank correlation between upstreamness and profit margin, $\rho_{\text{profit}} > 0$, means that upstream firms tend to be more profitable than are downstream firms. In contrast, a positive rank correlation between upstreamness and the WW-index or HP-index means that the upstream firms tend to be

[7]The effect of the distribution of financing capacity on net accounts receivable at the chain level is less clear because by taking an average across firms, high accounts receivable in the upstream may be offset by high accounts payable in the downstream.

more financially constrained relative to the downstream firms. We create a dummy variable for each rank correlation to indicate whether it is positive, and we include both the rank correlation dummies and the corresponding financing capacity variables in our specifications.[8]

The between-chain regression results reported in Table 7 show interesting effects of both the levels and the distributions of these variables. Columns (1), (4) and (7) show results for accounts receivable. The coefficients on the rank correlation dummies have signs opposite to what the financing advantage theory predicts. The coefficient on $D[\rho_{\text{profit}}]$ is significantly negative (Column (1), t-stat -6.02), suggesting that more trade credit is provided by firms in chains where the upstream firms are less profitable than the downstream firms. The coefficients on $D[\rho_{\text{WW}}]$ and $D[\rho_{\text{HP}}]$ are both significantly positive at the 1% level, suggesting more trade credit provision in chains where the upstream firms are more financially constrained than the downstream firms. The point estimate of the coefficient on $D[\rho_{\text{WW}}]$ (Column (4)) shows that in chains where the WW-index is higher in the upstream than in the downstream, the average accounts receivable ratio is 1.9 percentage points (13% of the standard deviation across chains) higher, relative to the chains with the opposite tilt in the distribution.

For accounts payable (Column (2), (5), (8)), the results are more mixed. On the one hand, Column (2) suggests that the average ratio of accounts payable is higher in more profitable chains (the coefficient on Profit Margin is significantly positive at the 1% level), and it is even higher if the downstream firms are more profitable than the upstream firms, because the coefficient on $D[\rho_{\text{profit}}]$ is significantly negative. This is inconsistent with the idea of profitable upstream firms providing financing to less profitable downstream firms. Instead, it is more consistent with the recent finding in the literature that downstream firms with market power extract rents from their suppliers through trade credit (e.g., Klapper, Laeven, and Rajan (2012), Murfin and Njoroge (2015), and Giannetti, Serrano-Velarde, and Tarantino (2020)). On the other hand, the coefficients on the two financial constraint indexes themselves are significantly positive, suggesting that in chains where firms are generally more financially constrained, more trade credit is obtained. This

[8] Because asset size is used as an input to compute the WW-index, we exclude it in the models with this index. Similarly, we exclude both firm size and firm age in the specifications with the HP-index.

result is consistent with the financing advantage theory.

Columns (3), (6) and (9) show the results for net receivables. The coefficients on the rank correlation dummies are similar to those obtained for gross account receivables. They suggest that firms in supply chains where financing capacity is stronger in the upstream are less likely to be net trade credit providers. Furthermore, Column (6) shows that the average chain-level WW-index of financial constraints is positively related to the average net trade credit provision. Both results are puzzling from the perspective of the financing advantage theory. However, Table (3) shows that the chain-level profit margin is strongly positively related to the chain-level net receivables, suggesting firms in more profitable chains supply more net trade credit relative to firms in less profitable chains. This is consistent with the financing advantage theory.

To summarize, our between-chain analysis shows that longer chains are associated with higher accounts payable and higher profit margins. Firms in central chains tend to act as net providers of trade credit, but they also tend to have lower profit margins. The relations between trade credit ratios observed at the chain level and the distribution of financing capacity within the chain are inconsistent with what the financing advantage theory predicts. However, there is a strong positive correlation between chain-level profitability and chain-level net trade credit provision, which supports the financing advantage theory.

5 Testing the Recursive Moral Hazard Theory

As we point out in several places, many of the stylized facts in Section 4 are consistent with the recursive moral hazard theory of trade credit of Kim and Shin (2012). In this section, we test two specific predictions of this model.

5.1 The Recursive Moral Hazard Theory of Trade Credit

We first briefly summarize the Kim and Shin (2012) model of trade credit. The model assumes a perfectly vertical supply chain, where each firm supplies inputs to the next firm in the chain, and the firm at the bottom of the chain produces the final good. Each firm can exert a high or a low level of effort in the production of its output. For example, we can interpret low effort as hiring employees with insufficient qualifications to lower production costs. The suboptimal hiring decision can result in the production of low quality output, which increases the final product's failure probability. If the final product fails, the chain breaks down.[9] Because a firm's effort is unobservable, the objective of a contract is to align the incentives of individual firms in the supply chain. As a result, a recursive moral hazard problem emerges where each intermediary firm acts as a principal with respect to its supplier and as an agent with respect to its customer. In Appendix A.2, we derive two empirical predictions from this theory. The first prediction is about the relation between a firm's level of incentives needed to avoid shirking and its upstreamness. The second prediction is about a one-to-one correspondence between receivables and payables after controlling for the fixed effects of the vertical position. Next we provide the intuition for the first prediction. We discuss and test the second prediction in Subsection 5.3.

Profit and the net trade credit a firm provides serve as incentives against shirking. If the a low-quality output leads to the breakdown of the whole supply chain, firms lose both their future profits and their net receivables. Therefore, if firms are more profitable, then they will have less incentive to shirk and threaten their future stream of profits. Similarly, if suppliers do not get paid immediately then they hold a stake in the success of the final good, which also makes them less likely to shirk.

The timing of the production is important for the heterogeneity in firms' incentives. In the model, each firm in a vertical supply chain requires one unit of time to produce its output. The cost of low effort is lower for firms that are further up in the chain because it takes more time for

[9]Hertzel et al. (2008); Boissay and Gropp (2013); Jacobson and Von Schedvin (2015); Barrot and Sauvagnat (2016); Carvalho et al. (2020) document how a negative shock to a customer can negatively affect other firms in the chain.

their effort level to affect the supply chain breakdown probability. However, the benefits of low effort are unrelated to a firm's position in the supply chain. The combination of lower costs and similar benefits from a low level of effort implies that firms at a higher vertical position need to have more incentives against shirking.

5.2 Upstreamness and Incentives

We show in Appendix A.2 that the theory implies the following empirical model specification for firm j in chain c:

$$log(\frac{NAR_{j,c} + Profit_{j,c}}{COGS_{j,c}}) = \alpha + \beta * Upstreamness_{j,c} + f_c + \epsilon_{j,c}, \tag{3}$$

where f_c captures the chain fixed effects. On the left hand side, we have the log of normalized incentives. Specifically, we add up net accounts receivable (NAR) and profit and then divide the sum by the cost of goods sold (COGS). We use two proxies for profit: EBITDA and EBIT. On the right hand side, we have a constant and a measure of distance to final consumers. Our main measure of the distance is upstreamness, which is used in Equation (3).

We also use a second measure for the distance to consumers (the upstreamness in the time dimension). Specifically, we estimate the time until a firm's output reaches consumers (DTCs). This is computed in two steps. First, we compute the days-in-Inventory for each firm in a supply chain as Inventory/Sales*365. This variable tells us the expected number of days for a firm to sell out its inventory. Second, a firm's DTCs along a supply chain is calculated as the sum of the days-in-inventory for the firm itself and for its downstream firms. For example, if A sells to B and B sells to C, then the DTCs for A is equal to the sum of the days-in-inventory for A, B and C. For B, it is the sum of the days-in-inventory for B and C. For bottom firm C, its DTCs is equal to its own days-in-inventory.

Table 8 shows how incentives against shirking vary with the vertical position. The first two columns show the results when profit is measured by EBIDTA. In Column (1), we estimate

Equation (3) without adding controls. The coefficient on Upstreamness is positive and statistically significant with a t-stat of 7.44, consistent with the the theory's prediction. Firms at a higher vertical position in a supply chain have higher incentives against shirking than do firms closer to the final consumers. In Column (2), we add the standard set of controls. The coefficient on Upstreamness is slightly higher and the t-stat increases to 9.13. The results are qualitatively similar when we use EBIT as a proxy for profits. For both the univariate (Column (3)) and the multivariate (Column (4)) models, the coefficient on Upstreamness is positive and highly significant (t-stats 6.17 and 6.90 respectively).

Models (5)-(8) in Table 8 repeat the analysis using the logarithm of the days-to-consumers (Log(DTCs)) instead of Upstreamness as the main explanatory variable. We find that Log(DTCs) is positively related to incentives in all specifications. This result further confirms that the incentives needed to avoid shirking is a function of a firm's distance to final consumption. Interestingly, the positive correlation between inventory turnover and incentives become even stronger when a firm's distance to final consumers is measured by the Log(DTCs) instead of the vertical position (columns (6) and (8)). Since inventory turnover is an inverse measure of the time needed for a firm's product to reach its own customers, results in Column (6) and (8) implies an interesting contrast: a positive correlation between incentives and the time to final customers and a negative correlation between incentives and the time to a firm's own customers. The time to final consumers reflects a firm's upstreamness, while the time to its own customers reflects operational (in)efficiency. Not surprisingly, they have different correlations with our incentive measure.[10]

5.3 Correlation Between Accounts Receivables and Accounts Payable

While most trade credit theories predict that firms either borrow or lend from their trade partners, the correlation matrix in Panel B of Table 1 shows that accounts receivable and payable are

[10]Because a firm's own days-in-inventory is a part of the DTCs, Log(DTCs) and Log(Inventory Turnover) have a negative correlation coefficient of -0.62. To address the concern for high multicollinearity, we have also tried a specification excluding Log(Inventory Turnover) from the controls. The coefficient on Log(DTCs) remains statistically significant at the 1% level, although the magnitude is smaller: 0.368 in Column (6) with a t-stat of 4.42 and 0.338 in Column (8) with a t-stat of 4.04.

positively correlated, suggesting that firms borrowing more from suppliers also lend more to their customers. The results in Section 4 further show that these two variables have similar correlations with other firm/chain characteristics.

As shown by Equation (A.10) in Appendix A.2, the Kim and Shin (2012) model not only implies a positive correlation between accounts receivable and payable, but also gives a sharp prediction that the coefficient β should be equal to one in the following linear regression model:

$$\frac{AR_{j,i}}{COGS_{j,i}} = \alpha + \beta \frac{AP_{j,i}}{COGS_{j,i}} + f_i + \epsilon_{j,i}, \tag{4}$$

where $\frac{AR_{j,i}}{COGS_{j,i}}$ and $\frac{AP_{j,i}}{COGS_{j,i}}$ are, respectively, accounts receivable and accounts payable normalized by the cost of goods sold for firm j in vertical position i, and f_i represents the fixed effects of the vertical position.

The intuition for the positive relation between $\frac{AR}{COGS}$ and $\frac{AP}{COGS}$ is easy to understand given the role of trade credit in relaxing the incentive compatibility constraints of firms in a supply chain. Receivables and payables are positively related because it is important that each firm maintains a stake in the production process. If a firm's payables increase (to provide incentives to suppliers) but its receivables do not, then its stake in the production chain shrinks and its incentives cease to be aligned.

We test this prediction in Table 9 using both univariate and multivariate regressions. In the first two columns, we control for the vertical position fixed effects and the year fixed effects. In the next two columns, we control for the vertical position fixed effects and the chain fixed effects. In the last two columns, we perform between-chain regressions, controlling for the year fixed effects. In the last row, we report the p-value of the F-test for the null hypothesis that the coefficient on $\frac{AP_{j,i}}{COGS_{j,i}}$ is equal to 1. Under all specifications, this coefficient is strongly positive, with t-stats varying from 8.8 to 15.3. The point estimate ranges from 0.81 (Column (4)) to 0.95 (Column (5)). Only results from the models with the chain fixed effects (Column (3) and (4)) reject the null hypothesis of $\beta = 1$ at the conventional 5% significance level. In three out of the six models

(Columns (1), (5), and (6)), the p-value for the F-test is above 10%. These results provide strong support for the recursive moral hazard theory.

Overall, the results presented in this section provide additional empirical support for the role of trade credit as an incentive device in supply chains. Even though these results are not sufficient to establish a causal effect of upstreamness on trade credit and profitability, the two powerful tests we perform in this section enhance the plausibility of the recursive moral hazard theory.

6 Effects of the Financial Crisis

In this section, we examine the role of firms' financing capacity in their provision and use of trade credit by exploring the effects of the 2008-2009 global financial crisis. Intuitively, because external financing is much more challenging during a financial crisis, we expect financing advantage to play a more important role in determining the pattern of trade credit during the crisis period. Specifically, we expect firms that were hit harder by the financial crisis to reduce while firms less affected by the financial crisis to increase their net supply of trade credit.

We first examine how the upstreamness effect in trade credit varies between the normal and the crisis years. Gofman, Segal, and Wu (2020) show, both theoretically and empirically, that relative to downstream firms, upstream firms are more exposed to the aggregate shocks. This implies that the position of upstream firms as net trade credit providers should be weakened during the financial crisis. To examine whether this is indeed the case, we create a crisis dummy that equals one for the years 2008 and 2009 and zero for all other years, and we extend our baseline models in Table 3 by adding an interaction term of the crisis dummy with Upstreamness as a regressor.[11] Panel A in Table 10 presents the results for both trade credit and profitability.

Consistent with the theory of Gofman, Segal, and Wu (2020), upstream firms indeed suffer a larger decline in both the EBITDA profit margin (Column (4)) and the net profit margin

[11] Because we control for chain fixed effects, the crisis dummy itself, which does not vary within a chain, is subsumed in these models.

(Column (5)) during the crisis. The coefficient on the interaction term Crisis * Upstreamness is significantly negative in both columns. The point estimates in Column (4) suggest that while a one unit increase in upstreamness is associated with a 3.4 percentage point increase in the EBITDA profit margin, this effect is reduced to 2.1 percentage points during the crisis. Interestingly, while the crisis does not affect the relation between upstreamness and the AR/Sale ratio (Column (1)), it increases the AP/COGS ratio (Column (2)) and reduces the NAR/Sale ratio (Column (3)) of upstream firms. This suggests that upstream firms' larger profit margin decline indeed weakens their positions as net credit providers, which provides support for the financing advantage theory.

Panel B in Table 10 shows how the financial crisis affects the central firms' trade credit and profitability. In contrast to the profit margins of upstream firms, the profit margins of central firms enjoy a relative boost during the crisis, as indicated by the strongly positive coefficient on the interaction term Crisis * Centrality in Columns (4) and (5). Correspondingly, the position of central firms as net trade credit providers is strengthened. In fact, while the coefficient on the interaction term Crisis * Centrality in Column (3) is strongly positive (t-stat 2.92), the coefficient on Centrality itself is statistically insignificant, suggesting that central firms act as net trade credit providers mainly during the crisis. Using industry-level measure of centrality (based on the BEA Input-Output Tables), Gao (2020) finds that central firms' profitability are more procyclical and their trade credit provision is more counter-cyclical relative to non-central firms. Our firm-level centrality measure reveals a similar pattern in central firms' net trade credit provision but an opposite pattern in their profitability.

Panel C shows how the financial crisis affects the trade credit and profitability of firms that face different degrees of financial constraints, as measured by the WW-index. We drop Log(assets) from the models because it is included in the WW-index. Columns (4) and (5) show that firms that are more constrained have a significantly lower EBITDA profit margin and net margin, and that these margin gaps are even more pronounced during the financial crisis. Columns (1) to (3) show that the WW-index of financial constraints is not significantly related to any of the three trade credit variables during the normal times—the coefficients on WW-index are indistinguishable from zero. However, during the financial crisis its correlations with accounts payable and net receivables are significantly stronger, and the signs are consistent with what the financing advantage theory predicts: the coefficient on the interaction term Crisis*WW-index is significantly positive for accounts payable (Column (2)) and significantly negative for net receivables (Column (3)). Table OA.1 in Online Appendix shows very similar results using the HP-index to measure financial constraints.

The results above suggest that firms whose profit margins get a harder hit by the financial crisis reduce the provision of net trade credit in the crisis period. These results are consistent with the finding of Love, Preve, and Sarria-Allende (2007), who show that firms that are more vulnerable to financial crises reduce the provision of trade credit relatively more after a crisis using data from six emerging economies. An interesting question is whether the crisis affects net trade credit provision mainly through the profit channel. In Panel D of Table 10, we reexamine the interaction effects of crisis with upstreamness, centrality, WW-index, and HP-index on net accounts receivable by adding profit margin as a control. Compared to the results not controlling for the profit margin, the statistical significance of the coefficients on each interaction term remains unchanged, and the magnitude declines only slightly by 13%-18% (for example, the coefficient on Crisis * Upstreamness changes from -0.009 to -0.008). This suggests that only less than 20% of the interaction effects documented in previous panels can be explained by the direct impact of the crisis on firms' profitability.

Taken together, the contrast between the crisis and the normal years suggests that the financing strength plays a more important role in determining the trade credit patterns during the financial crisis.

7 Robustness

We conduct a battery of robustness checks for our main stylized facts. Table 11 reports abbreviated regression results. The full regression results are reported in the online appendix (Tables

OA.2 to OA.9). We control for chain fixed effects in all panels except in Pane H.

One potential concern about our supply chain-based analysis is that our results may be driven by firms with high interlinkedness, i.e., firms that appear in many chains. To address this concern, we rerun our main specifications in Table 3 using weighted regressions, in which each observation is weighted inversely by a firm's interlinkedness (using one over the number of chains to which it belongs at a given time). Panel A of Table 11 presents the results from this alternative estimation method. We find that all our main results continue to hold, both in univariate regressions and in baseline multivariate specifications. All the three trade credit ratios are positively correlated with the upstreamness measure. The coefficient estimates for Upstreamness are very similar to those in Table 3 in economic magnitude, and stronger in statistical significance. Furthermore, there is a significantly positive relation between a firm's centrality and its provision and use of trade credit. These results show that the trade credit patterns we document are not due to the large weight of firms belonging to many chains.

In Panel B (C) of Table 11, we further study whether the upstreamness effect in trade credit varies with the degree of firm (chain) interlinkedness. We define a chain's interlinkedness as the average interlinkedness of the firms in the chain. A high interlinkedness suggests that a network is more densely populated. We define a dummy variable, D(HI Firm), that equals one if a firm's interlinkedness is above the median. Similarly, we define D(HI Chain) as a dummy variable that equals one if a chain's interlinkedness is above the median. We interact Upstreamness with these dummies to check whether the role of Upstreamness is different for more populated networks. We find no evidence that it is. In Panels B and C, the coefficient on the interaction term is indistinguishable from zero. This also explains why our results remain largely unchanged when we rerun our regressions using weighted observations in Panel (A).

In Panel D, we study whether the upstreamness effect in trade credit remains after controlling for industry fixed effects. We use the Fama-French 49-industry classification scheme to classify firms (based on the mapping between the historical SIC code and the Fama-French industry definitions). Because a firm's position in the supply chain is largely a function of the industry to which it belongs, we expect our results to be weaker after controlling for industry fixed effects. Nevertheless, we find that the upstreamness effect is statistically significant even after controlling for both industry and chain fixed effects, although its economic magnitude shrinks substantially. This shrinkage is not surprising because a large portion of upstreamness effect is absorbed by industry fixed effects. The coefficient on Upstreamnness is positive and statistically significant at the 1% level in all the models except the univariate model for accounts payable, where the coefficient is positive but statistically insignificant. This result highlights the importance of analyzing firm-level data about supplier-customer relationships, because industry-level data would miss the effects of within-industry variation in the upstreamness.

Another concern about our main stylized facts may be that bottom layer firms may mechanically have more receivables or top layer firms may mechanically have less payables. This concern is mitigated by the presence of the upstreamness effect in both receivables and payables. To further address this possibility, in Panels E and F of Table 11, we exclude firms at the bottom and top of each chain, respectively. Because we control for the chain fixed effects, dropping either the top firms or the bottom firms automatically exclude chains with only two layers from the estimation. Thus these alternative sample constructions also address the concern that our results may be driven by chains with only two firms. The coefficient on Upstreamness is positive and statistically significant at the 1% level for all specifications except for Model (3) in Panel F. We therefore conclude that the upstreamness effect that we document is not driven by firms at the top or bottom of the supply chain, or chains with only two firms. On the other hand, the centrality effect becomes largely insignificant in Panels E and F, suggesting that it is not as robust as the upstreamness effect.

In our benchmark models we assume a linear relation between the trade credit ratios and upstreamness. In Panel G of Table 11, we estimate the non-parametric relations between the trade credit ratios and Upstreamness using dummy variables. We create dummies that indicate whether a firm's vertical position is 1,2,3, 4, or 5 and above, using the bottom layer as the base case. We group vertical positions 5 or above into one category because of the small number of observations with a vertical position above 5. We regress the trade credit variables on these dummies, with or without the standard set of controls. The coefficient on each dummy measures the differences in the trade credit ratios between firms in the corresponding vertical position and those in the bottom layer. The results show that for accounts receivables (Columns (1) and (2)) and net receivables (Columns (5) and (6)), the coefficients on the upstreamness dummies increase monotonically as the vertical position increases, with or without controls. This suggests that there is a strictly monotonic relation between upstreamness and accounts receivable, gross or net of accounts payable. The monotonicity also holds for accounts payable up to layer 4 in the absence of controls and up to layer 3 after including the standard set of controls. These results further confirm a strong upstreamness effect in firms' provision and use of trade credit.

Finally, despite the advantages of our within-chain analysis, one may wonder whether our results are specific to this approach. To answer this question, we rerun our main specifications in Table 3 using firm-year observations instead of the firm-by-chain observations. This means that in any given year, each firm appears in the sample only once. Our focus on the shortest distance chains guarantees that a firm has a unique upstreamness measure across all the chains to which it belongs in a given year, which makes this alternative estimation easy to implement. Instead of controlling for chain fixed effects, in this analysis we control for year fixed effects, and cluster standard errors by firm. Panel H of Table 11 presents the results from the firm-year observations. We find that all our main results continue to hold, in both the univariate regressions and baseline specifications. The ratios of accounts receivable and net receivables to sales are strongly positively related to Upstreamness, as is the payables-to-COGS ratio. Compared to Table 3, the statistical significance of the upstreamness effect in each regression is even stronger (with t-stats ranging from 7.30 to 17), although economic magnitudes is somewhat smaller. For example, in the benchmark model for accounts receivable, the coefficient on Upstreamness declines from 0.030 to 0.022. Panel H also shows that there is a significantly positive relation between a firm's centrality and its provision and use of trade credit, as in Table 3. These results show that the trade credit patterns we document are not specific to the empirical method we adopt for our analysis. The smaller coefficient estimates on Upstreamness in Panel H relative to Table 3 further demonstrate the power of our within-chain analysis. Unlike the more traditional approach used in Panel H, which compares a firm with all firms above or below its layer, the within-chain analysis compares a firm with its own upstream and downstream firms. Not surprisingly, it is more effective in detecting the upstreamness effect in trade credit.

8 Conclusion

We conduct a supply chain-based study of trade credit and firm profitability. Using comprehensive firm-level data about supplier-customer relationships, we construct at an annual frequency a sequence of production networks from 2003 to 2018. We develop a novel procedure to uncover the shortest distance supply chain from each upstream firm to the final consumption goods sector based on these networks. After deleting the chains that are nested by other chains, we build a sample of over 200,000 un-nested supply chains formed by more than 5,600 nonfinancial firms.

We analyze trade credit and profitability both within and across chains. Within-chain analysis shows that firms further away from the final consumption goods sector provide and obtain more trade credit, and have higher net receivables. A battery of additional tests confirm the robustness of these novel stylized facts with respect to sample construction, model specification, and estimation method. Further analysis shows that the positive relation between upstreamness and trade credit is weaker for firms that are more profitable and for chains with a higher average profit margin. It is also weaker for longer chains, which tend to be more profitable.

Between-chain analysis shows that firms in more central or more profitable chains tend to be net trade credit providers, consistent with the idea that firms in these chains have stronger financing capacity. More trade credit, both in net and gross terms, is provided by firms belonging to chains where the upstream firms have a weaker financing capacity relative to the downstream firms based on a number of measures. Furthermore, the average ratio of accounts payable is higher in more profitable chains, especially when the profit margin is higher in the downstream, suggesting that downstream firms with market power may extract rents from suppliers through trade credit.

The recursive moral hazard theory of trade credit of Kim and Shin (2012) predicts that upstream firms should have more incentives against shirking because shirking is less costly for them due to the longer time required for their output to be incorporated in the final product. Both profit and net trade credit act as such incentives. This theory also makes a sharp prediction about the relation between normalized receivables and payables after controlling for fixed effects of vertical positions. We test these predictions and find supportive empirical evidence for both of them.

Our sample period includes the financial crisis of 2008-2009. We explore whether firms at different vertical positions adjust their trade credit practice differently during the crisis. We find that the profit margins of upstream firms took a harder hit during the crisis. These firms increased borrowing from suppliers and decreased net provision of trade credit. This result suggests that liquidity shocks can disrupt the long-term role of trade credit as an incentives device. We also find that central firms and firms less financially constrained firms were less affected by the financial crisis, and their positions as net providers of trade credit strengthened.

Overall, our chain-based analysis generates many novel stylized facts about trade credit. These stylized facts not only shed new light on existing theories, they also establish a fruitful ground for future theoretical work. Furthermore, the methodology we develop to construct vertical chains based on production networks can be used to examine many other economic and finance questions related to supply chains.

Appendix

A.1 Variable definitions

Table A.1: **Variable definitions**

This table summarizes the variable definitions. The Compustat data items used to contruct the variables are indicated in parentheses. All ratios are winsorized at the 1st and 99th percentiles. Variables with Log in the name, which are not included in this table, are the natural logarithm of the corresponding variable.

Variable	Description
Upstreamness	A firm's vertical position in a supply chain, which is 0 for the firm at the end of the chain, 1 for its immediate supplier, 2 for its supplier's supplier, and so on.
Chain Length	The number of firms in a supply chain.
Centrality	Inverse sum of the shortest distances from a firm to other firms in the production network multiplied by the squared fraction of firms connected to the firm. Normalized to be in the interval between zero and one in each year.
AR/Sale	Trade accounts receivables (rectr) divided by sales. When rectr missing, we substitute it by total accounts receivables (rect) minus the income tax refund (txr).
AP/COGS	Trade accounts payable (ap) divided by the cost of goods sold (cogs).
NAR/Sale	Net receivables (rectr − ap) divided by sales.
Assets	Total book assets (at), measured in year 2004 US dollar values.
Age	Number of years since a firm first appeared in Compustat +1.
Ncompetitor	Number of competitors reported in the Factset Relationships database.
Investment Grade	A dummy variable that equals 1 if the S&P Domestic Long Term Issuer Credit Rating is BBB- or above, 0 if the rating is below BBB- or missing.
Profit Margin	Earnings before interest, taxes, depreciation and amortization (ebitda) divided by sales.
Net Margin	Net income (ni) divided by sales.
Inventory Turnover	Sales divided by inventories (invt).
Foreign	A dummy variable that equals 1 if a firm's headquarter is outside the US.
Tangibility	Property, plant, and equipment (ppent) divided by total book assets (at).
WW-index	Financial constraint index based on Whited and Wu (2006), calculated as $-0.091 * CF - 0.062 * DIVPOS + 0.021 * (TLTD) - 0.044 * LNTA + 0.102 * ISG - 0.035 * SG$, where CF is the ratio of cash flow to total assets [(ib+dp) /(at)]; DIVPOS is an indicator that takes the value of one if the firm pays cash dividends; TLTD is the ratio of the long-term debt to total assets (dltt/at); LNTA is the natural log of total assets (at), ISG is the firm's 3-digit industry sales growth; SG is firm sales growth.

Table A.1 continued

HP-index	Financial constraint index based on Hadlock and Pierce (2010), calculated as $(-0.737 * Size) + (0.043 * Size^2) - (0.040 * Age)$, where $Size$ is the log of inflation adjusted (to 2004) book assets capped at \$4.5 billion, and Age is firm age capped at 37.
$\frac{\text{Incentive1}}{\text{COGS}}$	Sum of net receivables and earnings before interest and taxes, depreciation and amortization (ebitda) divided by the cost of goods sold (cogs).
$\frac{\text{Incentive2}}{\text{COGS}}$	Sum of net receivables and earnings before interest, taxes (ebit) divided by the cost of goods solds (cogs).
DTCs	Expected number of days it takes for a firm's output to reach the consumers of the final product along the shortest-distance supply chain. The expected number of days in each stage of the supply chain is estimated as the inventory-to-sales ratio times 365 (known as Days in Inventory).
D(HI Firm)	A dummy variable indicating whether a firm is a high-interlinkedness firm, i.e., whether the number of chains to which it belongs is above the median.
D(HI Chain)	A dummy variable indicating whether a supply chain is a high-interlinkedness chain, i.e., whether the average interlinkedness across the firms in the chain is above the median.
$\rho_{\text{AR}}, \rho_{\text{AP}}, \rho_{\text{NAR}}, \rho_{\text{profit}}, \rho_{\text{WW}}, \rho_{\text{HP}}, \rho_{\text{size}}, \rho_{\text{age}}, \rho_{\text{tangibility}}$	Within-chain rank correlations between Upstreamness and AR/Sale, AP/COGS, NAR/Sale, Profit Margin, WW-index, HP-index, Log(Assets), Log(Age), and Tangibility, respectively.

A.2 Derivation of the relation between incentives and upstreamness

We derive two testable empirical predictions of the recursive moral hazard theory of trade credit proposed by Kim and Shin (2012). The first prediction concerns the relation between the level of a firm's incentives against shirking and its upstreamness. The second addresses the relation between accounts receivable and accounts payable.

A.2.1 Incentives and Upstreamness

To derive the first prediction, we use the fact that in the model's solution the incentive compatibility constraint (Equation (8) in Kim and Shin (2012)) is binding. The equilibrium relation between net receivables, profits and the firm's vertical position in the supply chain can therefore be described by:

$$a_i p_i - a_{i+1} p_{i+1} + (p_i - p_{i+1} - w_i) = b_i w_i, \tag{A.1}$$

where $a_i p_i$ ($a_{i+1}p_{i+1}$) is firm i's outstanding balance of accounts receivable (payable), p_i denotes its revenues, p_{i+1} is the cost of inputs paid by firm i to its supplier firm $i+1$, and w_i is firm i's cost of production. The intuition behind Equation (A.1) is that net accounts receivable ($a_i p_i - a_{i+1}p_{i+1}$) and profits ($p_i - p_{i+1} - w_i$) need to be sufficiently large to ensure that firm i decides to exert the first-best effort rather than to shirk and get a one period benefit of bw_i. The definition of b_i is given by Equation (6) in Kim and Shin (2012):

$$b_i = b\frac{\pi^H}{(\pi^L - \pi^H)(1-\pi^H)^i}. \tag{A.2}$$

In Equation (A.2), $b > 0$ is the per-period private benefit (as a percent of a firm's production costs) that a firm enjoys if it exerts low effort. Private benefits parameter b is assumed to be common to all firms in the chain. If all firms in the supply chain exert high effort, then the probability that the chain is liquidated will be π^H. If any of the firms exerts low effort, then the probability will be $\pi^L > \pi^H$.

In the model, firm i's output is sold as a part of the final product in i periods because each firm requires one period to produce its output and there are i firms down the chain (firms at positions: $i-1$, ..., 0). Under this assumption, firm i's incentive compatibility constraint should include a term that accounts for the fact that the cost of shirking (an increase in the probability that chain will break down) occur i periods after the benefits of shirking (bw_i) are realized. This cost difference is embedded in the $(1-\pi^H)^i$ term in Equation (A.2), which is similar to the compounded discount rate with i being the number of compounding periods.

To derive testable empirical specifications, we divide both sides of Equation (A.1) by w_i and substitute out b_i using Equation (A.2):

$$\frac{a_i p_i - a_{i+1}p_{i+1} + (p_i - p_{i+1} - w_i)}{w_i} = b\frac{\pi^H}{(\pi^L - \pi^H)(1-\pi^H)^i}. \tag{A.3}$$

Equation (A.3) relates the normalized incentives of each firm to its vertical position in the supply chain. The normalized level of incentives are composed of profits and net receivables (accounts receivable - accounts payable) divided by the production cost.

We take the logs of both sides of Equation A.3 to make incentives linear in the vertical position:

$$log(\frac{a_i p_i - a_{i+1} p_{i+1} + (p_i - p_{i+1} - w_i)}{w_i}) = log(\frac{b\pi^H}{\pi^L - \pi^H}) - log(1 - \pi^H)i \tag{A.4}$$

For each term in Equation (A.4), we construct an empirical counterpart. Equation (A.4) then leads us to the following empirical specification:

$$log(\frac{NAR_j + Profit_j}{COGS_j}) = \alpha + \beta * i_j + \epsilon_j \tag{A.5}$$

where j is the index of a firm, i_j is the vertical position of firm j, and ϵ_j is the noise term. We use the cost of goods sold (COGS) as a proxy for the production costs (w_i). Ideally, we would use a proxy for production costs that excludes costs of inputs, but this information is not available in Compustat. Table A.2 provides the mapping between the theoretical variables and the empirical proxies used in the regressions in Table 8.

Table A.2: **Definition of the variables for the regressions in Table 8 and Table 9**

This table presents the mapping between the theoretical variables and the empirical proxies used in the regressions in Table 8 and in Table 9.

Variable	Full Name	Short Name
$a_i p_i$	Accounts Receivable per period	AR
$a_{i+1} p_{i+1}$	Accounts Payable per period	AP
$a_i p_i - a_{i+1} p_{i+1}$	Net Accounts Receivable	NAR
w_i	Cost of Goods Sold	COGS
$p_i - p_{i+1} - w_i$	Profit	EBITDA or EBIT
i	Vertical position	Upstreamness

A.2.2 Relationship Between Receivables and Payables

The second empirical prediction follows from Equation (9) in Kim and Shin (2012).

$$a_i p_i = a_{i+1} p_{i+1} + \beta_i w_i, \tag{A.6}$$

where $\beta_i = b_i - \left(\pi^H/(1-\pi^H)\right)$ and b_i is given in Equation (A.2). This equation is derived by combining Equation A.1 with the optimal transaction price given by

$$p_i = \sum_{k=i}^{N} \frac{1}{(1-\pi^H)^{k-i+1}} w_k, \tag{A.7}$$

Given these transaction prices, firm i's profit becomes

$$p_i - p_{i+1} - w_i = \frac{\pi^H}{(1-\pi^H)} w_i. \tag{A.8}$$

When we substitute out the profit in Equation (A.1) using (A.8) and rearrange terms, we get Equation (A.6).

If we divide both sides of Equation (A.6) by w_i and substitute out b_i using Equation (A.2), we get

$$\frac{a_i p_i}{w_i} = \frac{a_{i+1} p_{i+1}}{w_i} + b \frac{\pi^H}{(\pi^L - \pi^H)(1-\pi^H)^i} - \frac{\pi^H}{(1-\pi^H)}, \tag{A.9}$$

The empirical counterpart to Equation (A.9) is given by

$$\frac{AR_{j,i}}{COGS_{j,i}} = \alpha + \beta \frac{AP_{j,i}}{COGS_{j,i}} + f_i + \epsilon_{j,i}, \tag{A.10}$$

for firm j in vertical position i. In this specification, we proxy for the production cost (w_i) with COGS and include fixed effects (f_i) for each vertical position to absorb the second term in the right hand side of equation (A.9), which is a nonlinear function of vertical position i.

The quantitative prediction of the model is that $\beta = 1$. We test this prediction in Table 9, using the mapping between the theoretical variables and the empirical proxies provided in Table

9. We also estimate this equation by including the standard set of controls, as well as chain fixed effects. In addition, we estimate this equation at the chain level by computing the average ratios of accounts receivable and accounts payable to COGS for each chain.

References

Amberg, N., Jacobson, T., Von Schedvin, E., Townsend, R., 2021. Curbing shocks to corporate liquidity: The role of trade credit. Journal of Political Economy 129, 000–000.

Barrot, J.-N., Sauvagnat, J., 2016. Input specificity and the propagation of idiosyncratic shocks in production networks. Quarterly Journal of Economics 131, 1543–1592.

Biais, B., Gollier, C., 1997. Trade credit and credit rationing. Review of Financial Studies 10, 903–937.

Boissay, F., Gropp, R., 2013. Payment defaults and interfirm liquidity provision. Review of Finance 17, 1853–1894.

Brennan, M. J., Maksimovics, V., Zechner, J., 1988. Vendor financing. Journal of Finance 43, 1127–1141.

Burkart, M., Ellingsen, T., 2004. In-kind finance: A theory of trade credit. American Economic Review 94, 569–590.

Carvalho, V. M., Nirei, M., Saito, Y. U., Tahbaz-Salehi, A., 2020. Supply chain disruptions: Evidence from the great east japan earthquake. Quarterly Journal of Economics .

Chod, J., Lyandres, E., Yang, S. A., 2019. Trade credit and supplier competition. Journal of Financial Economics 131, 484–505.

Costello, A. M., 2020. Credit market disruptions and liquidity spillover effects in the supply chain. Journal of Political Economy 128, 3434–3468.

Cuñat, V., 2007. Trade credit: Suppliers as debt collectors and insurance providers. Review of Financial Studies 20, 491.

Dai, R., Liang, H., Ng, L., 2020. Socially responsible corporate customers. Journal of Financial Economics forthcoming.

Desai, M. A., Foley, C. F., Hines, J. R., 2016. Trade credit and taxes. Review of Economics and Statistics 98, 132–139.

Ferris, J., 1981. A transactions theory of trade credit use. Quarterly Journal of Economics 96, 243–270.

Frank, M., Maksimovic, V., 1998. Trade credit, collateral, and adverse selection, Working Paper, University of Maryland.

Gao, J., 2020. Managing liquidity in production networks: The role of central firms. Review of Finance, Forthcoming .

Garcia-Appendini, E., Montoriol-Garriga, J., 2013. Firms as liquidity providers: Evidence from the 2007–2008 financial crisis. Journal of Financial Economics 109, 272–291.

Giannetti, M., Serrano-Velarde, N. A. B., Tarantino, E., 2020. Cheap trade credit and competition in downstream markets. Journal of Political Economy, forthcoming .

Gofman, M., Segal, G., Wu, Y., 2020. Production networks and stock returns: The role of vertical creative destruction. Review of Financial Studies 33, 5856–5905.

Hadlock, C. J., Pierce, J. R., 2010. New evidence on measuring financial constraints: Moving beyond the KZ index. Review of Financial Studies 23, 1909–1940.

Hertzel, M. G., Li, Z., Officer, M. S., Rodgers, K. J., 2008. Inter-firm linkages and the wealth effects of financial distress along the supply chain. Journal of Financial Economics 87, 374–387.

Jacobson, T., Von Schedvin, E., 2015. Trade credit and the propagation of corporate failure: an empirical analysis. Econometrica 83, 1315–1371.

Kim, S., Shin, H. S., 2012. Sustaining production chains through financial linkages. American Economic Review 102, 402–06.

Klapper, L., Laeven, L., Rajan, R., 2012. Trade credit contracts. Review of Financial Studies 25, 838–867.

Lee, Y. W., Stowe, J. D., 1993. Product risk, asymmetric information, and trade credit. Journal of Financial and Quantitative Analysis 28, 285–300.

Lehar, A., Song, V. Y., Yuan, L., 2020. Industry structure and the strategic provision of trade credit by upstream firms. Review of Financial Studies 33, 4916–4972.

Long, M. S., Malitz, I. B., Ravid, S. A., 1993. Trade credit, quality guarantees, and product marketability, Financial Management 22, 117-127.

Love, I., Preve, L. A., Sarria-Allende, V., 2007. Trade credit and bank credit: Evidence from recent financial crises. Journal of Financial Economics 83, 453–469.

Mian, S. L., Smith, C. W., 1992. Accounts receivable management policy: theory and evidence. Journal of Finance 47, 169–200.

Murfin, J., Njoroge, K., 2015. The implicit costs of trade credit borrowing by large firms. Review of Financial Studies 28, 112–145.

Petersen, M. A., Rajan, R. G., 1997. Trade credit: theories and evidence. Review of Financial Studies 10, 661–691.

Rajan, R., Zingales, L., 1995. What do we know about capital structure? Some evidence from international data. Journal of Finance 50, 1421–1460.

Santos, J., Longhofer, S., 2003. The paradox of priority. Financial Management 32, 69–81.

Schwartz, R. A., 1974. An economic model of trade credit. Journal of Financial and Quantitative Analysis 9, 643–657.

Smith, J. K., 1987. Trade credit and informational asymmetry. Journal of Finance 42, 863–872.

Whited, T. M., Wu, G., 2006. Financial Constraints Risk. Review of Financial Studies 19, 531–559.

Wilner, B. S., 2000. The exploitation of relationships in financial distress: The case of trade credit. Journal of Finance 55, 153–178.

Table 1: **Summary statistics at the firm-year level**

This table shows the summary statistics of our Compustat-FactSet-matched sample at the firm-year level. The sample includes a total of 5,623 unique nonfinancial firms that belong to at least one of the shortest distance supply chains that we identify from the snapshots of supplier-customer relationships. The snapshots are taken at the end of each year from 2003 to 2018 using the FactSet Revere Relationship database. A supply chain ends when it reaches the first consumption goods producer. Upstreamness is defined as a firm's position in a supply chain relative to the consumption goods producer at the end of the chain, which has an upstreamness measure of zero. Because we focus on the shortest distance chains, a firm's upstreamness measure is the same across all the chains to which it belongs in a given snapshot. Panel A reports the mean, median, standard deviation, minimum, maximum, and number of observations of each variable. Panel B reports the correlations between the key variables. Table A.1 provides detailed variable definitions.

Panel A. Summary statistics

	mean	sd	min	p50	max	count
AR/Sale	0.15	0.10	0.00	0.14	0.63	34,958
AP/COGS	0.21	0.29	0.01	0.14	2.58	35,090
NAR/Sale	0.06	0.10	-0.38	0.06	0.44	34,893
AR/COGS	0.42	0.51	0.00	0.28	3.36	34,951
Upstreamness	1.46	1.06	0.00	1.00	9.00	35,167
Centrality	0.72	0.09	0.00	0.72	1.00	35,068
Assets	8,116.39	25,359.52	1.02	955.23	410,177.50	35,167
Log(Assets)	6.86	2.22	0.02	6.86	12.92	35,167
Age	22.03	16.56	1.00	17.00	70.00	35,167
Log(Age)	2.81	0.78	0.00	2.83	4.25	35,167
Ncompetitor	15.34	19.68	1.00	10.00	313.00	31,606
Log(Ncompetitor)	2.24	1.03	0.00	2.30	5.75	31,606
Investment Grade	0.20	0.40	0.00	0.00	1.00	35,167
Profit Margin	0.13	0.22	-0.78	0.13	0.73	35,126
Net Margin	-0.01	0.25	-1.36	0.04	0.56	35,167
Inventory Turnover	39.29	95.49	1.67	11.10	742.83	28,517
Log(Inventory Turnover)	2.70	1.16	0.51	2.41	6.61	28,517
Foreign	0.21	0.41	0.00	0.00	1.00	35,167
WW-index	-0.33	0.12	-0.65	-0.33	0.08	34,763
HP-index	-3.83	0.97	-6.33	-3.66	-0.77	35,167
Tangibility	0.27	0.25	0.00	0.18	0.93	35,155
$\text{Log}(\frac{\text{Incentive1}}{\text{COGS}})$	-0.85	1.18	-4.41	-0.83	2.01	30,131
$\text{Log}(\frac{\text{Incentive2}}{\text{COGS}})$	-1.13	1.23	-4.93	-1.09	1.83	28,024

Panel B. Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) AR/Sale	1.00											
(2) AP/COGS	0.23	1.00										
(3) NAR/Sale	0.71	-0.28	1.00									
(4) Profit Margin	-0.06	0.09	0.01	1.00								
(5) Upstreamness	0.17	0.08	0.12	0.08	1.00							
(6) Centrality	0.10	-0.00	0.09	-0.00	-0.31	1.00						
(7) Log(Assets)	-0.09	0.02	-0.15	0.43	-0.12	0.28	1.00					
(8) Log(Age)	-0.06	-0.07	-0.05	0.10	-0.07	0.14	0.31	1.00				
(9) Log(Ncompetitor)	0.08	0.04	0.05	0.05	-0.04	0.39	0.33	0.10	1.00			
(10) Investment Grade	-0.04	0.02	-0.09	0.21	-0.05	0.21	0.60	0.37	0.23	1.00		
(11) Log(Inventory Turnover)	-0.07	0.04	0.00	0.21	0.04	0.05	0.11	-0.11	-0.01	0.04	1.00	
(12) Foreign	0.09	0.14	-0.06	0.11	0.03	0.02	0.23	-0.13	0.08	0.13	0.09	1.00

Table 2: **Summary statistics at the chain level**

This table presents summary statistics for the 203,722 un-nested shortest distance supply chains in our sample. The chains are identified from snapshots of supplier-customer relationships taken at the end of each year from 2003 to 2018 using the FactSet Revere Relationships database. A supply chain ends at the first consumption goods producer it reaches. The chain length is defined as the number of firms in the chain, ρ_{AR}, $\rho_{\text{AP/COGS}}$, $\rho_{\text{NAR/Sale}}$, ρ_{profit}, ρ_{WW} ρ_{HP}, ρ_{size}, ρ_{age}, and $\rho_{\text{tangibility}}$ are within-chain rank correlations of upstreamness with AR/Sale, AP/COGS, NAR/Sale, Profit Margin, WW-index, HP-index, Log(Assets), Log(Age), and Tangibility, respectively. All other variables are averages across the firms in the chain. Table A.1 provides detailed variable definitions.

	mean	sd	min	p50	max	count
Chain Length	3.31	0.82	2.00	3.00	10.00	203,722
AR/Sale	0.15	0.06	0.00	0.14	0.63	203,718
AP/COGS	0.21	0.15	0.01	0.18	2.58	203,722
NAR/Sale	0.05	0.07	-0.33	0.05	0.44	203,718
Centrality	0.80	0.06	0.00	0.81	1.00	203,722
Assets	41,636.71	39,471.36	5.07	29,877.19	314610.56	203,722
Log(Assets)	8.48	1.24	1.29	8.50	12.65	203,722
Age	28.28	11.08	1.50	27.50	69.00	203,722
Log(Age)	3.07	0.46	0.35	3.08	4.23	203,722
Ncompetitor	41.22	30.91	1.00	33.00	296.00	203,614
Log(Ncompetitor)	2.95	0.70	0.00	2.98	5.69	203,614
Investment Grade	0.44	0.25	0.00	0.50	1.00	203,722
Profit Margin	0.14	0.10	-0.78	0.15	0.62	203,722
Log(Inventory Turnover)	2.80	0.73	0.51	2.65	6.61	201,931
Foreign	0.25	0.28	0.00	0.25	1.00	203,722
WW-index	-0.41	0.07	-0.64	-0.41	-0.01	203,717
HP-index	-4.58	0.59	-6.33	-4.58	-1.57	203,722
Tangibility	0.25	0.15	0.01	0.21	0.87	203,722
DTCs	60.79	37.37	0.49	55.25	422.00	201,931
Log(DTCs)	3.74	0.81	-0.71	3.89	5.96	201,931
ρ_{AR}	0.41	0.70	-1.00	0.50	1.00	199,963
ρ_{AP}	0.09	0.78	-1.00	0.40	1.00	203,140
ρ_{NAR}	0.40	0.70	-1.00	0.50	1.00	199,485
ρ_{profit}	0.08	0.77	-1.00	0.40	1.00	202,715
ρ_{WW}	0.36	0.65	-1.00	0.50	1.00	198,553
ρ_{HP}	0.35	0.65	-1.00	0.50	1.00	203,225
ρ_{size}	-0.37	0.65	-1.00	-0.50	1.00	203,722
ρ_{age}	-0.21	0.72	-1.00	-0.50	1.00	202,094
$\rho_{\text{tangibility}}$	-0.19	0.78	-1.00	-0.50	1.00	203,677

Table 3: **Upstreamness and trade credit: within-chain analysis**

This table shows how accounts receivable (AR/Sale), accounts payable (AP/COGS), and net receivables (NAR/Sale) are related to a firm's upstreamness in the supply chain. Variable descriptions are provided in Table A.1. We control for chain-fixed effects in all regressions. t-statistics, based on standard errors triple-clustered by firm, by the top and bottom of the chain, are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1) AR/Sale	(2) AR/Sale	(3) AP/COGS	(4) AP/COGS	(5) NAR/Sale	(6) NAR/Sale
Upstreamness	0.025***	0.030***	0.020***	0.024***	0.029***	0.028***
	(4.92)	(7.75)	(3.63)	(3.88)	(5.95)	(6.72)
Centrality		0.217***		0.186*		0.097*
		(4.17)		(1.80)		(1.93)
Log(Assets)		-0.002		-0.001		-0.003
		(-0.54)		(-0.39)		(-0.84)
Log(Age)		0.002		-0.024**		0.007
		(0.30)		(-2.52)		(1.09)
Investment Grade		-0.013		0.014		-0.020
		(-0.92)		(0.66)		(-1.44)
Log(Inventory Turnover)		-0.001		-0.004		0.010***
		(-0.40)		(-0.54)		(2.63)
Log(Ncompetitor)		0.007		0.010		0.010**
		(1.47)		(1.51)		(2.03)
Foreign		0.032***		0.038**		0.013
		(2.69)		(2.16)		(1.04)
Constant	0.114***	-0.075	0.191***	0.082	0.017***	-0.115**
	(17.41)	(-1.29)	(26.90)	(0.86)	(2.66)	(-2.00)
Observations	610291	487835	613976	491487	609757	487569
R^2	0.406	0.459	0.386	0.420	0.407	0.445

Table 4: **Profit and the upstreamness effect in trade credit**

This table shows how a firm's profit margin is related to its upstreamness in the supply chain and how profit margin affects the relation between the trade credit variables (AR/Sale, AP/COGS), and NAR/Sale) and the upstreamness. Variable descriptions are provided in Table A.1. We control for chain-fixed effects in all regressions. t-statistics, based on standard errors triple-clustered by firm, by the top and bottom of the chain, are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1) AR/Sale	(2) AP/COGS	(3) NAR/Sale	(4) Profit Margin	(5) Profit Margin
Upstreamness	0.035***	0.029***	0.031***	0.008*	0.033***
	(8.88)	(5.01)	(7.18)	(1.79)	(6.11)
Profit Margin	0.077*	0.323***	0.160***		
	(1.87)	(3.48)	(3.27)		
Upstreamness * Profit Margin	-0.044***	-0.086**	-0.045***		
	(-3.40)	(-2.43)	(-2.82)		
Centrality	0.216***	0.244**	0.124***		-0.335***
	(4.38)	(2.51)	(2.67)		(-4.28)
Log(Assets)	-0.002	-0.008**	-0.006		0.043***
	(-0.40)	(-2.26)	(-1.44)		(11.22)
Log(Age)	0.002	-0.021**	0.008		-0.010
	(0.42)	(-2.46)	(1.34)		(-1.48)
Investment Grade	-0.014	0.017	-0.018		-0.025
	(-0.94)	(0.84)	(-1.27)		(-1.62)
Log(Inventory Turnover)	-0.002	-0.010	0.007*		0.030***
	(-0.52)	(-1.30)	(1.75)		(8.42)
Log(Ncompetitor)	0.006	0.008	0.009*		-0.004
	(1.24)	(1.39)	(1.86)		(-0.51)
Foreign	0.033***	0.041***	0.015		-0.016
	(2.74)	(2.67)	(1.25)		(-1.11)
Constant	-0.083	0.071	-0.121**	0.136***	-0.031
	(-1.43)	(0.81)	(-2.08)	(20.65)	(-0.45)
Observations	487312	490357	487046	613362	490663
R^2	0.462	0.433	0.455	0.303	0.509

Table 5: **Chain characteristics and the upstream effect in trade credit**

This table shows how the relation between the trade credit ratios (AR/Sale, AP/COGS, and NAR/Sale) and a firm's upstreamness in the supply chain depends on the chain's length and profitability. Chain length is defined as the number of firms in the chain; chain profit as the average profit margin across the firms in the chain. Adj. Chain Length and Adj. Chain Profit are chain length and chain profit subtracted by the corresponding median values across chains. Variable descriptions are provided in Table A.1. We control for chain-fixed effects in all regressions. Therefore, regressors that are constant within a chain are subsumed (including Adj. Chain Length and Adj. Chain Profit). t-statistics, based on standard errors triple-clustered by firm, by the top and bottom of the chain, are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	AR/Sale	AP/COGS	NAR/Sale	AR/Sale	AP/COGS	NAR/Sale
Upstreamness * Adj. Chain Length	-0.006***	-0.001	-0.007***			
	(-3.00)	(-0.36)	(-3.46)			
Upstreamness * Adj. Chain Profit				-0.055***	-0.148***	-0.046**
				(-3.51)	(-3.99)	(-2.37)
Profit Margin				0.005	0.192***	0.084***
				(0.19)	(4.00)	(2.88)
Upstreamness	0.035***	0.025***	0.035***	0.030***	0.020***	0.026***
	(6.62)	(3.41)	(6.11)	(8.88)	(2.99)	(6.48)
Centrality	0.188***	0.182*	0.064	0.208***	0.224**	0.117**
	(3.34)	(1.79)	(1.20)	(4.20)	(2.30)	(2.49)
Log(Assets)	-0.001	-0.001	-0.002	-0.001	-0.007**	-0.006
	(-0.29)	(-0.34)	(-0.52)	(-0.31)	(-1.98)	(-1.37)
Log(Age)	0.002	-0.024**	0.007	0.002	-0.022**	0.008
	(0.28)	(-2.53)	(1.07)	(0.35)	(-2.49)	(1.27)
Investment Grade	-0.011	0.014	-0.018	-0.013	0.017	-0.018
	(-0.78)	(0.68)	(-1.28)	(-0.92)	(0.85)	(-1.25)
Log(Inventory Turnover)	-0.001	-0.004	0.010***	-0.001	-0.009	0.008*
	(-0.44)	(-0.54)	(2.60)	(-0.38)	(-1.23)	(1.90)
Log(Ncompetitor)	0.007	0.010	0.010*	0.007	0.009	0.010**
	(1.40)	(1.50)	(1.94)	(1.32)	(1.46)	(1.98)
Foreign	0.032***	0.038**	0.012	0.032***	0.040**	0.014
	(2.65)	(2.15)	(0.98)	(2.66)	(2.52)	(1.16)
Constant	-0.061	0.084	-0.099*	-0.074	0.090	-0.111*
	(-1.00)	(0.90)	(-1.67)	(-1.26)	(0.99)	(-1.90)
Observations	487835	491487	487569	487312	490357	487046
R^2	0.462	0.420	0.448	0.461	0.433	0.453

Table 6: **Trade credit, profit, and chain characteristics: between-chain analysis**

This table shows how profit margins, accounts receivable (AR/Sale), accounts payable (AP/COGS), and net accounts receivable (NAR/Sale) measured at the supply chain level are related to chain characteristics. The chain length is defined as the number of firms in the chain. All other variables are defined as the averages across the firms in the chain. Details of variable definitions are provided in Table A.1. We control for year fixed effects in all regressions. t-statistics, based on standard errors double-clustered by the top and bottom of the chain, are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1) AR/Sale	(2) AP/COGS	(3) NAR/Sale	(4) Profit Margin
Chain Length	-0.001	0.010***	-0.001	0.009***
	(-0.65)	(2.76)	(-0.66)	(4.84)
Centrality	0.319***	0.151*	0.235***	-0.297***
	(5.57)	(1.72)	(4.22)	(-7.17)
Log(Assets)	-0.004	-0.005	-0.008**	0.038***
	(-1.11)	(-1.56)	(-2.33)	(17.42)
Log(Age)	-0.001	-0.021**	-0.000	-0.008*
	(-0.15)	(-2.27)	(-0.03)	(-1.74)
Investment Grade	-0.007	0.022	-0.005	-0.037***
	(-0.47)	(1.16)	(-0.36)	(-3.75)
Log(Inventory Turnover)	-0.003	-0.003	0.007**	0.024***
	(-1.48)	(-0.84)	(2.46)	(10.38)
Log(Ncompetitor)	-0.002	0.008	0.004	0.006*
	(-0.54)	(1.01)	(1.01)	(1.77)
Foreign	0.044***	0.079***	0.011	-0.008
	(5.13)	(6.31)	(1.10)	(-1.11)
Constant	-0.059	0.126***	-0.095	-0.019
	(-0.89)	(3.00)	(-1.62)	(-0.55)
Observations	201820	201824	201820	201824
R^2	0.101	0.104	0.079	0.238

Table 7: **Trade credit at the chain level: effects of the within-chain distribution of financing capacity**

This table shows how trade credit at the chain level depends on the distribution of financing capacity within the chain, where financing capacity is measured by the profit margin, and the WW-index and HP-index of financial constraints. D[ρ_{profit}>0], D[ρ_{WW}>0], D[ρ_{HP}>0] are dummy variables equal to one if the rank correlation between the corresponding variable and upstreamness is positive and zero if it is negative (chains with zero rank correlations are excluded). All other variables are the averages across the firms in the chain. Variable definitions are provided in Table A.1. We control for year fixed effects in all regressions. t-statistics, based on standard errors double-clustered by the top and bottom of the chain, are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	AR/Sale	AP/COGS	NAR/Sale	AR/Sale	AP/COGS	NAR/Sale	AR/Sale	AP/COGS	NAR/Sale
D[ρ_{profit}>0]	-0.014***	-0.016***	-0.011***						
	(-6.02)	(-2.59)	(-4.13)						
D[ρ_{WW}>0]				0.019***	0.002	0.015***			
				(3.38)	(0.49)	(2.86)			
D[ρ_{HP}>0]							0.015***	0.005	0.012**
							(2.82)	(1.06)	(2.34)
Profit Margin	0.017	0.137***	0.086***						
	(0.68)	(3.62)	(3.69)						
WW-index				0.089	0.122**	0.143**			
				(1.37)	(1.98)	(2.37)			
HP-index							0.008	0.019***	0.013
							(0.85)	(2.78)	(1.59)
Chain Length	-0.001	0.009***	-0.002	-0.001	0.010***	-0.001	-0.001	0.010***	-0.002
	(-0.56)	(2.64)	(-1.01)	(-0.36)	(2.78)	(-0.58)	(-0.65)	(2.83)	(-0.96)
Centrality	0.307***	0.175*	0.248***	0.306***	0.149*	0.215***	0.307***	0.148*	0.215***
	(5.81)	(1.90)	(4.82)	(5.25)	(1.72)	(3.84)	(5.39)	(1.73)	(3.82)
Log(Assets)	-0.003	-0.008**	-0.010**						
	(-0.64)	(-2.27)	(-2.36)						
Log(Age)	-0.001	-0.020**	0.001	-0.000	-0.021**	0.000			
	(-0.13)	(-2.21)	(0.08)	(-0.04)	(-2.11)	(0.01)			
Investment Grade	-0.009	0.025	-0.003	-0.005	0.028	-0.004	-0.009	0.019	-0.008
	(-0.54)	(1.30)	(-0.23)	(-0.31)	(1.42)	(-0.26)	(-0.57)	(0.99)	(-0.53)
Log(Inventory Turnover)	-0.004	-0.007*	0.004*	-0.002	-0.003	0.007***	-0.003	-0.002	0.006**
	(-1.64)	(-1.69)	(1.66)	(-1.10)	(-0.89)	(2.69)	(-1.47)	(-0.46)	(2.42)
Log(Ncompetitor)	-0.003	0.006	0.003	-0.002	0.007	0.004	-0.002	0.009	0.004
	(-0.71)	(0.81)	(0.79)	(-0.52)	(0.94)	(1.03)	(-0.43)	(1.13)	(1.10)
Foreign	0.045***	0.080***	0.012	0.044***	0.080***	0.011	0.041***	0.083***	0.005
	(5.27)	(6.56)	(1.24)	(4.98)	(6.40)	(1.03)	(4.47)	(6.37)	(0.48)
Constant	-0.053	0.134***	-0.089	-0.071	0.129***	-0.104*	-0.065	0.096*	-0.094*
	(-0.79)	(3.18)	(-1.49)	(-1.02)	(2.98)	(-1.69)	(-1.04)	(1.93)	(-1.66)
Observations	198165	198169	198165	193087	193091	193087	197332	197336	197332
R^2	0.111	0.110	0.093	0.119	0.106	0.088	0.111	0.102	0.080

Table 8: **Upstreamness and Incentives**

This table shows the results for a test of the recursive moral hazard theory of Kim and Shin (2012). The dependent variable is the natural logarithm of incentives normalized by the cost of goods sold. Two alternative measures of incentives are used: Incentive1 is the sum of net receivables and EBITDA, while Incentive2 is the sum of net receivables and EBIT. Upstreamness is defined as the position of a firm in a supply chain relative to the end of the chain. Log(DTCs) is the natural logarithm of the expected number of days needed for a firm's output to reach final consumers. Details of variable definitions are provided in Table A.1. We control for chain-fixed effects in all regressions. t-statistics, based on standard errors triple-clustered by firm, by the top and bottom of the chain, are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	$\text{Log}(\frac{\text{Incentive1}}{\text{COGS}})$		$\text{Log}(\frac{\text{Incentive2}}{\text{COGS}})$		$\text{Log}(\frac{\text{Incentive1}}{\text{COGS}})$		$\text{Log}(\frac{\text{Incentive2}}{\text{COGS}})$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Upstreamness	0.418***	0.484***	0.361***	0.415***				
	(7.44)	(9.13)	(6.17)	(6.90)				
Log(DTCs)					0.424***	0.692***	0.369***	0.620***
					(4.23)	(7.91)	(3.66)	(6.55)
Centrality		-0.944		-0.588		-2.601***		-1.943***
		(-1.38)		(-0.88)		(-4.00)		(-3.12)
Log(Assets)		0.088***		0.077**		0.094***		0.085***
		(2.83)		(2.38)		(2.92)		(2.59)
Log(Age)		-0.114*		-0.093		-0.105		-0.084
		(-1.75)		(-1.35)		(-1.60)		(-1.22)
Investment Grade		-0.055		0.016		-0.028		0.036
		(-0.44)		(0.12)		(-0.22)		(0.28)
Log(Inventory Turnover)		0.258***		0.207***		0.527***		0.445***
		(7.40)		(5.62)		(11.42)		(8.70)
Log(Ncompetitor)		0.225***		0.192***		0.248***		0.202***
		(3.21)		(2.76)		(3.38)		(2.83)
Foreign		0.020		-0.142		-0.002		-0.164
		(0.16)		(-1.08)		(-0.02)		(-1.23)
Constant	-1.453***	-2.663***	-1.662***	-2.860***	-2.583***	-4.325***	-2.636***	-4.457***
	(-19.38)	(-4.91)	(-20.65)	(-5.01)	(-6.73)	(-6.52)	(-6.79)	(-6.33)
Observations	508766	397897	453625	352073	487847	397897	434797	352073
R^2	0.422	0.535	0.443	0.528	0.369	0.527	0.409	0.527

Table 9: **The relation between accounts receivable and accounts payable**

This table shows the positive correlation between accounts receivable (AR/COGS) and accounts payable (AP/COGS) predicted by the recursive moral hazard theory of Kim and Shin (2012). Columns (1) and (2) shows the results after controlling for vertical position fixed effects and year fixed effects. Columns (3) and (4) show the results after controlling for vertical position fixed effects and chain fixed effects (subsuming year fixed effects). Columns (5) and (6) show the result from the between-chain regressions. The last row of the table shows the p-values for F-tests of the hypothesis that the coefficient on AP/COGS is equal to one. Details of variable definitions are provided in Table A.1. t-statistics in parentheses are based on standard errors triple-clustered by firm and by the top and bottom of the chain in Columns (1) to (4), and based on standard errors double-clustered by the top and bottom of the chain in Columns (5) and (6). Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	AR/COGS				AR/COGS(Between)	
	(1)	(2)	(3)	(4)	(5)	(6)
AP/COGS	0.905***	0.840***	0.876***	0.812***	0.945***	0.906***
	(13.71)	(8.80)	(14.18)	(9.88)	(16.42)	(15.25)
Centrality		0.249		0.358*		0.822***
		(1.04)		(1.66)		(4.47)
Log(Assets)		-0.035***		-0.030***		-0.052***
		(-3.86)		(-3.61)		(-6.02)
Log(Age)		0.011		0.002		-0.029*
		(0.67)		(0.18)		(-1.81)
Investment Grade		-0.028		-0.051		0.024
		(-0.79)		(-1.56)		(0.66)
Profit Margin		0.483***		0.476***		0.407***
		(4.96)		(5.40)		(6.82)
Log(Inventory Turnover)		0.037***		0.043***		0.025**
		(2.65)		(3.51)		(2.39)
Log(Ncompetitor)		0.066***		0.061***		0.038***
		(4.31)		(4.15)		(3.28)
Foreign		0.037		0.038		0.020
		(1.12)		(1.29)		(0.79)
Constant	0.197***	-0.113	0.203***	-0.206	0.192***	-0.185
	(12.07)	(-0.55)	(14.63)	(-1.03)	(13.51)	(-1.22)
Vertical Position FE	Yes	Yes	Yes	Yes	No	No
Year FE	Yes	Yes	Subsumed	Subsumed	Yes	Yes
Chain FE	No	No	Yes	Yes	No	No
Observations	610179	512634	609699	487028	203718	201820
R^2	0.284	0.348	0.557	0.603	0.238	0.294
p-value($\beta_{AP/COGS}$=1)	.149	.095	.046	.022	.337	.116

Table 10: **Trade credit and the financial crisis**

This table shows how the relation between trade credit, profit margins, and firms' network characteristics change during the global financial crisis. Crisis is a dummy variable equal to 1 for the years 2008 and 2009 and 0 for all other years. In Panel A, we interact the crisis dummy with the upstreamness measure; in Panel B, we interact it with the centrality measure; in Panel C, we interact it with the WW-index of financial constraints; in Panel D, we examine the effect of crisis on net receivable after controlling for profit margins. Details of variable definitions are provided in Table A.1. We control for chain-fixed effects in all regressions. Therefore, regressors that are constant within a chain (e.g., the crisis dummy itself) are subsumed. t-statistics, based on standard errors triple-clustered by firm, by the top and bottom of the chain, are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A. The financial crisis and the upstreamness effect

	(1) AR/Sale	(2) AP/COGS	(3) NAR/Sale	(4) Profit Margin	(5) Net Margin
Crisis * Upstreamness	-0.002	0.018***	-0.009**	-0.013**	-0.018**
	(-0.63)	(2.70)	(-2.44)	(-2.25)	(-2.29)
Upstreamness	0.030***	0.022***	0.029***	0.034***	0.005
	(7.56)	(3.39)	(6.67)	(6.38)	(1.17)
Centrality	0.217***	0.183*	0.099**	-0.333***	-0.145**
	(4.19)	(1.77)	(1.97)	(-4.27)	(-2.50)
Log(Assets)	-0.002	-0.001	-0.003	0.043***	0.028***
	(-0.54)	(-0.36)	(-0.85)	(11.20)	(8.89)
Log(Age)	0.002	-0.024**	0.007	-0.010	0.004
	(0.30)	(-2.52)	(1.08)	(-1.48)	(0.82)
Investment Grade	-0.013	0.014	-0.020	-0.025	0.008
	(-0.92)	(0.67)	(-1.45)	(-1.63)	(0.71)
Log(Inventory Turnover)	-0.001	-0.004	0.010***	0.030***	0.011***
	(-0.40)	(-0.54)	(2.63)	(8.40)	(3.63)
Log(Ncompetitor)	0.007	0.010	0.010**	-0.003	-0.006
	(1.47)	(1.48)	(2.04)	(-0.50)	(-1.16)
Foreign	0.032***	0.038**	0.013	-0.016	-0.011
	(2.69)	(2.15)	(1.04)	(-1.11)	(-1.13)
Constant	-0.075	0.083	-0.116**	-0.032	-0.133***
	(-1.30)	(0.88)	(-2.02)	(-0.47)	(-2.67)
Observations	487835	491487	487569	490663	491793
R^2	0.459	0.421	0.445	0.510	0.443

Panel B. The financial crisis and the centrality effect

	(1) AR/Sale	(2) AP/COGS	(3) NAR/Sale	(4) Profit Margin	(5) Net Margin
Crisis * Centrality	0.027	-0.080	0.117***	0.286***	0.337***
	(0.68)	(-1.20)	(2.92)	(4.10)	(4.03)
Upstreamness	0.030***	0.024***	0.028***	0.033***	0.003
	(7.75)	(3.88)	(6.71)	(6.11)	(0.71)
Centrality	0.214***	0.194*	0.085	-0.366***	-0.184***
	(4.02)	(1.82)	(1.64)	(-4.73)	(-3.21)
Log(Assets)	-0.002	-0.001	-0.003	0.043***	0.028***
	(-0.54)	(-0.40)	(-0.83)	(11.25)	(8.97)
Log(Age)	0.002	-0.024**	0.007	-0.010	0.004
	(0.29)	(-2.50)	(1.06)	(-1.54)	(0.74)
Investment Grade	-0.013	0.014	-0.020	-0.025	0.008
	(-0.92)	(0.66)	(-1.44)	(-1.62)	(0.75)
Log(Inventory Turnover)	-0.001	-0.004	0.010***	0.030***	0.011***
	(-0.41)	(-0.53)	(2.60)	(8.37)	(3.58)
Log(Ncompetitor)	0.007	0.010	0.010**	-0.004	-0.006
	(1.47)	(1.51)	(2.03)	(-0.51)	(-1.20)
Foreign	0.032***	0.038**	0.013	-0.016	-0.011
	(2.70)	(2.15)	(1.04)	(-1.12)	(-1.14)
Constant	-0.075	0.081	-0.114**	-0.029	-0.129***
	(-1.29)	(0.85)	(-1.98)	(-0.42)	(-2.63)
Observations	487835	491487	487569	490663	491793
R^2	0.459	0.420	0.446	0.511	0.444

Panel C. The financial crisis and the effect of financial constraints

	(1) AR/Sale	(2) AP/COGS	(3) NAR/Sale	(4) Profit Margin	(5) Net Margin
Crisis * WW-index	-0.010	0.089**	-0.066**	-0.108**	-0.258***
	(-0.33)	(1.96)	(-2.18)	(-2.28)	(-4.19)
WW-index	0.067	0.019	0.068	-0.922***	-0.741***
	(1.08)	(0.25)	(1.17)	(-11.71)	(-11.91)
Upstreamness	0.029***	0.024***	0.028***	0.034***	0.006
	(7.32)	(3.81)	(6.41)	(6.71)	(1.47)
Centrality	0.223***	0.184*	0.094*	-0.338***	-0.204***
	(3.98)	(1.80)	(1.78)	(-4.65)	(-3.79)
Log(Age)	0.003	-0.023**	0.007	-0.016**	-0.005
	(0.50)	(-2.46)	(1.09)	(-2.41)	(-0.86)
Investment Grade	-0.009	0.016	-0.018	-0.048***	-0.024**
	(-0.68)	(0.69)	(-1.29)	(-2.93)	(-2.00)
Log(Inventory Turnover)	-0.001	-0.004	0.010***	0.028***	0.009***
	(-0.29)	(-0.61)	(2.67)	(8.33)	(2.89)
Log(Ncompetitor)	0.008*	0.010	0.010**	-0.003	-0.008*
	(1.65)	(1.46)	(2.12)	(-0.45)	(-1.95)
Foreign	0.034***	0.037**	0.014	-0.025*	-0.026***
	(2.85)	(2.14)	(1.12)	(-1.86)	(-2.85)
Constant	-0.078	0.084	-0.114*	-0.007	-0.103**
	(-1.32)	(0.89)	(-1.96)	(-0.12)	(-2.29)
Observations	484165	487213	483906	487512	487512
R^2	0.460	0.421	0.446	0.535	0.476

Panel D. The effect of financial crisis after controlling for profit

	(1) NAR/Sale	(2) NAR/Sale	(3) NAR/Sale	(4) NAR/Sale
Crisis * Upstreamness	-0.008**			
	(-2.21)			
Crisis * Centrality		0.096***		
		(2.64)		
Crisis * WW-index			-0.057**	
			(-2.01)	
Crisis * HP-index				-0.007**
				(-2.26)
WW-index			0.141*	
			(1.86)	
HP-index				0.007
				(0.92)
Profit Margin	0.074***	0.073***	0.080***	0.062***
	(2.77)	(2.76)	(2.94)	(2.71)
Upstreamness	0.026***	0.026***	0.025***	0.027***
	(6.37)	(6.42)	(6.00)	(6.09)
Centrality	0.123***	0.111**	0.122**	0.114**
	(2.64)	(2.33)	(2.52)	(2.23)
Log(Assets)	-0.006	-0.006		
	(-1.44)	(-1.42)		
Log(Age)	0.008	0.008	0.008	
	(1.22)	(1.20)	(1.30)	
Investment Grade	-0.018	-0.018	-0.014	-0.018
	(-1.25)	(-1.24)	(-0.95)	(-1.26)
Log(Inventory Turnover)	0.008*	0.008*	0.008*	0.007*
	(1.95)	(1.94)	(1.96)	(1.75)
Log(Ncompetitor)	0.011**	0.010**	0.010**	0.009**
	(2.10)	(2.09)	(2.20)	(2.10)
Foreign	0.014	0.014	0.016	0.008
	(1.16)	(1.15)	(1.28)	(0.61)
Constant	-0.113*	-0.112*	-0.114*	-0.099*
	(-1.94)	(-1.91)	(-1.94)	(-1.74)
Observations	487046	487046	483906	487046
R^2	0.452	0.452	0.453	0.449

Table 11: **Robustness checks**

This table presents the results from a battery of robustness checks. Panel A repeats the baseline regressions in Table 3 using weighted regressions, in which each observation is weighted by one over the number of chains a firm belongs to in a given year. Panel B (C) allows the relations between the trade credit variables and upstreamness to vary depending on the degree of a firm's (chain's) interlinkedness. A firm's interlinkedness is measured by the number of chains to which it belongs in a given year. D(HI Firm) is a dummy variable that equals one if a firm's interlinkedness is above the median and zero otherwise. D(HI Chain) is a dummy variable that equals one if the average interlinkedness of firms in a chain is above the median value across all the chains and zero otherwise. Panel D adds industry fixed effects to the baseline models as additional controls. Panel E (F) re-estimates the baseline models excluding firms at the bottom (top) of the supply chains. Panel G uses upstreamness dummies to indicate a firm's position in the supply chain (the omitted base case is Upstreamness=0). Panel H repeats the baseline regressions in Table 3 using firm-year observations, which means that each firm has one observation per year. In panel H, we control for year fixed effects and cluster standard errors by firm. In all other panels, we control for chain fixed effects and triple-cluster standard errors by firm and by the top and bottom firms in the chains. Details of variable definitions are provided in Table A.1. We report t-statistics in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A. Baseline models using weighted regressions

	(1) AR/Sale	(2) AR/Sale	(3) AP/COGS	(4) AP/COGS	(5) NAR/Sale	(6) NAR/Sale
Upstreamness	0.025***	0.027***	0.017***	0.020***	0.026***	0.024***
	(11.31)	(12.41)	(4.45)	(4.90)	(12.21)	(10.81)
Centrality		0.251***		0.271***		0.125***
		(8.02)		(3.12)		(4.58)
R^2	0.672	0.701	0.709	0.718	0.681	0.691
Other Controls						
Observations	610291	487835	613976	491487	609757	487569

Panel B. High-interlinkedness vs. low-interlinkedness firms

	(1) AR/Sale	(2) AR/Sale	(3) AP/COGS	(4) AP/COGS	(5) NAR/Sale	(6) NAR/Sale
Upstreamness	0.027***	0.033***	0.019***	0.021***	0.026***	0.029***
	(12.92)	(9.80)	(4.30)	(4.19)	(11.77)	(8.40)
Upstreamness * D(HI Firm)	-0.001	-0.011	0.003	0.003	0.004	-0.005
	(-0.10)	(-1.14)	(0.35)	(0.41)	(0.45)	(-0.47)
D(HI Firm)	0.005	-0.008	-0.002	-0.027*	-0.010	-0.012
	(0.30)	(-0.50)	(-0.15)	(-1.93)	(-0.59)	(-0.83)
Centrality		0.254***		0.227**		0.129***
		(5.17)		(2.18)		(2.69)
Other Controls	No	Yes	No	Yes	No	Yes
Observations	610291	487835	613976	491487	609757	487569

Panel C. High-interlinkedness vs. low-interlinkedness chains

	(1) AR/Sale	(2) AR/Sale	(3) AP/COGS	(4) AP/COGS	(5) NAR/Sale	(6) NAR/Sale
Upstreamness	0.024***	0.028***	0.019***	0.023***	0.026***	0.025***
	(5.99)	(9.00)	(4.48)	(4.66)	(6.97)	(7.62)
Upstreamness * D(HI Chain)	0.003	0.004	0.002	0.002	0.005	0.007
	(0.85)	(1.04)	(0.31)	(0.35)	(1.35)	(1.58)
Centrality		0.219***		0.187*		0.101**
		(4.28)		(1.81)		(2.02)
Other Controls	No	Yes	No	Yes	No	Yes
Observations	610291	487835	613976	491487	609757	487569

Panel D. Baseline models with industry fixed effects

	(1) AR/Sale	(2) AR/Sale	(3) AP/COGS	(4) AP/COGS	(5) NAR/Sale	(6) NAR/Sale
Upstreamness	0.013***	0.017***	0.009	0.016***	0.014***	0.012***
	(5.18)	(5.25)	(1.26)	(3.04)	(5.84)	(3.76)
Centrality		0.125***		0.141		0.047
		(2.76)		(1.59)		(1.12)
Other Controls	No	Yes	No	Yes	No	Yes
Observations	610291	487835	613976	491487	609757	487569

Panel E. Baseline models excluding bottom firms

	(1) AR/Sale	(2) AR/Sale	(3) AP/COGS	(4) AP/COGS	(5) NAR/Sale	(6) NAR/Sale
Upstreamness	0.013***	0.013***	0.010	0.025***	0.019***	0.019***
	(3.47)	(3.66)	(1.55)	(2.90)	(4.91)	(4.32)
Centrality		-0.001		0.121		-0.050
		(-0.03)		(1.21)		(-1.13)
Other Controls	No	Yes	No	Yes	No	Yes
Observations	377595	285256	379775	287451	376967	284948

Panel F. Baseline models excluding top firms

	(1) AR/Sale	(2) AR/Sale	(3) AP/COGS	(4) AP/COGS	(5) NAR/Sale	(6) NAR/Sale
Upstreamness	0.029***	0.023***	0.034***	0.031***	0.028***	0.021***
	(3.83)	(3.58)	(4.08)	(4.33)	(3.98)	(3.33)
Centrality		0.268***		0.086		0.106
		(3.71)		(0.62)		(1.46)
Other Controls	No	Yes	No	Yes	No	Yes
Observations	407714	337806	412180	341962	407390	337586

Panel G. Regressions using upstreamness dummies

	(1) AR/Sale	(2) AR/Sale	(3) AP/COGS	(4) AP/COGS	(5) NAR/Sale	(6) NAR/Sale
D(Upstreamness=1)	0.053***	0.028	0.037***	0.024*	0.049***	0.022
	(3.66)	(1.48)	(2.61)	(1.81)	(3.51)	(1.24)
D(Upstreamness=2)	0.063***	0.059***	0.051***	0.057***	0.074***	0.062***
	(4.44)	(5.82)	(3.40)	(3.99)	(5.63)	(5.88)
D(Upstreamness=3)	0.075***	0.099***	0.058***	0.071***	0.076***	0.085***
	(5.15)	(11.57)	(2.95)	(3.50)	(5.55)	(8.24)
D(Upstreamness=4)	0.076***	0.110***	0.061***	0.064***	0.083***	0.096***
	(4.83)	(8.31)	(2.63)	(2.59)	(5.55)	(6.70)
D(Upstreamness≥5)	0.079***	0.116***	0.046**	0.056**	0.089***	0.107***
	(4.37)	(7.01)	(1.97)	(2.17)	(5.42)	(6.37)
Centrality		0.235**		0.167		0.110
		(2.19)		(1.63)		(1.12)
Other Controls	No	Yes	No	Yes	No	Yes
Observations	610291	487835	613976	491487	609757	487569

Panel H. Baseline regressions with firm-year observations

	(1) AR/Sale	(2) AR/Sale	(3) AP/COGS	(4) AP/COGS	(5) NAR/Sale	(6) NAR/Sale
Upstreamness	0.016***	0.022***	0.021***	0.018***	0.013***	0.018***
	(13.14)	(16.96)	(7.44)	(7.30)	(9.94)	(13.68)
Centrality		0.184***		0.129**		0.113***
		(8.56)		(2.37)		(5.76)
Other Controls	No	Yes	No	Yes	No	Yes
Observations	34958	25600	35090	25728	34893	25569

Online Appendix

We present additional tables in this Online Appendix. Table OA.1 repeats the tests in Panel C of Table 10 using the HP-index (Hadlock and Pierce (2010)) to measure financial constraints. Tables OA.2 to OA.9 show the full regression results for robustness checks summarized in Table 11.

Table OA.1: **Trade credit and financial crisis: HP-index of financial constraints**

This table repeats the regressions in Panel C of Table 10 using the HP-index to measure financial constraints. We exclude Log(Assets) and Log(Age) from the list of explanatory variables because they are incorporated in the HP-index. Details of variable definitions are provided in Table A.1. We control for chain-fixed effects in all regressions. Therefore, regressors that are constant within a chain (e.g., the crisis dummy itself) are subsumed. t-statistics, based on standard errors triple-clustered by firm, by the top and bottom of the chain, are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1) AR/Sale	(2) AP/COGS	(3) NAR/Sale	(4) Profit Margin	(5) Net Margin
Crisis * HP-Index	-0.002	0.010**	-0.008**	-0.011**	-0.023***
	(-0.56)	(2.00)	(-2.38)	(-2.14)	(-3.51)
HP-index	0.005	0.014	0.003	-0.060***	-0.045***
	(0.66)	(1.38)	(0.48)	(-7.75)	(-7.60)
Upstreamness	0.030***	0.023***	0.029***	0.026***	-0.001
	(7.15)	(3.62)	(6.40)	(4.62)	(-0.14)
Centrality	0.223***	0.191*	0.099*	-0.265***	-0.107*
	(3.97)	(1.82)	(1.84)	(-3.01)	(-1.71)
Investment Grade	-0.011	0.015	-0.019	-0.014	0.015
	(-0.83)	(0.63)	(-1.36)	(-0.87)	(1.29)
Log(Inventory Turnover)	-0.002	-0.002	0.009**	0.037***	0.015***
	(-0.58)	(-0.34)	(2.55)	(9.13)	(4.66)
Log(Ncompetitor)	0.007	0.012*	0.009**	0.005	-0.001
	(1.62)	(1.83)	(2.12)	(0.69)	(-0.27)
Foreign	0.030**	0.046***	0.008	0.016	0.005
	(2.54)	(2.86)	(0.67)	(1.07)	(0.52)
Constant	-0.071	0.054	-0.104*	-0.077	-0.149***
	(-1.27)	(0.58)	(-1.89)	(-1.01)	(-2.81)
Observations	487835	491487	487569	490663	491793
R^2	0.459	0.419	0.444	0.474	0.434

Table OA.2: **Baseline models using using weighted regressions**

This table repeats the baseline regressions in Table 3 using weighted regressions. Each observation is weighted by one over the number of chains a firm belongs to in a given year. We control for chain fixed effects in all models. Details of variable definitions are provided in Table A.1. t-statistics, based on standard errors triple-clustered by firm, by the top and bottom of the chain, are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	AR/Sale	AR/Sale	AP/COGS	AP/COGS	NAR/Sale	NAR/Sale
Upstreamness	0.025***	0.027***	0.017***	0.020***	0.026***	0.024***
	(11.31)	(12.41)	(4.45)	(4.90)	(12.21)	(10.81)
Centrality		0.251***		0.271***		0.125***
		(8.02)		(3.12)		(4.58)
Log(Assets)		-0.008***		-0.003		-0.008***
		(-5.36)		(-1.53)		(-5.30)
Log(Age)		0.001		-0.012**		0.004
		(0.33)		(-2.06)		(1.42)
Investment Grade		0.004		0.011		0.003
		(0.83)		(1.15)		(0.47)
Log(Inventory Turnover)		-0.005***		-0.003		0.005**
		(-3.03)		(-0.85)		(2.50)
Log(Ncompetitor)		0.007***		0.002		0.009***
		(3.53)		(0.55)		(4.35)
Foreign		0.039***		0.069***		0.006
		(7.43)		(6.80)		(1.14)
Constant	0.114***	-0.032	0.188***	0.021	0.025***	-0.062**
	(34.26)	(-1.19)	(33.65)	(0.36)	(7.94)	(-2.43)
Observations	610291	487835	613976	491487	609757	487569

Table OA.3: **High-interlinkedness vs. low-interlinkedness firms**

This table repeats the within-chain regressions in Table 3 with one variation: we allow the relations between the trade credit variables and upstreamness to be different for high- and low-interlinkedness firms. D(HI firm) is a dummy variable that equals 1 if the number of chains a firm belongs to in a given year is above the median and 0 otherwise. We control for chain fixed effects in all regressions. Details of other variable definitions are provided in Table A.1. t-statistics, based on standard errors triple-clustered by firm, by the top and bottom of the chain, are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	AR/Sale	AR/Sale	AP/COGS	AP/COGS	NAR/Sale	NAR/Sale
Upstreamness	0.027***	0.033***	0.019***	0.021***	0.026***	0.029***
	(12.92)	(9.80)	(4.30)	(4.19)	(11.77)	(8.40)
Upstreamness * D(HI Firm)	-0.001	-0.011	0.003	0.003	0.004	-0.005
	(-0.10)	(-1.14)	(0.35)	(0.41)	(0.45)	(-0.47)
D(HI Firm)	0.005	-0.008	-0.002	-0.027*	-0.010	-0.012
	(0.30)	(-0.50)	(-0.15)	(-1.93)	(-0.59)	(-0.83)
Centrality		0.254***		0.227**		0.129***
		(5.17)		(2.18)		(2.69)
Log(Assets)		-0.001		-0.000		-0.002
		(-0.34)		(-0.07)		(-0.65)
Log(Age)		0.002		-0.024***		0.007
		(0.28)		(-2.61)		(1.06)
Investment Grade		-0.012		0.015		-0.019
		(-0.87)		(0.71)		(-1.40)
Log(Inventory Turnover)		-0.002		-0.004		0.010**
		(-0.59)		(-0.58)		(2.52)
Log(Ncompetitor)		0.007		0.009		0.010**
		(1.61)		(1.44)		(2.12)
Foreign		0.032***		0.038**		0.013
		(2.73)		(2.15)		(1.04)
Constant	0.111***	-0.106*	0.191***	0.061	0.023***	-0.137**
	(18.18)	(-1.75)	(26.94)	(0.64)	(3.86)	(-2.29)
Observations	610291	487835	613976	491487	609757	487569

Table OA.4: **High-interlinkedness vs. low-interlinkedness chains**

This table repeats the within-chain regressions in Table 3 with one variation: we allow the relations between the trade credit variables and upstreamness to be different for firms in high- and low-interlinkedness chains. D(HI Chain) is a dummy variable that equals 1 if the average interlinkedness, measured by the number of chains a firm belongs to in a given year, of firms in the chain is above the median and 0 otherwise. We control for chain fixed effects in all regressions. Details of other variable definitions are provided in Table A.1. t-statistics, based on standard errors triple-clustered by firm, by the top and bottom of the chain, are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	AR/Sale	AR/Sale	AP/COGS	AP/COGS	NAR/Sale	NAR/Sale
Upstreamness	0.024***	0.028***	0.019***	0.023***	0.026***	0.025***
	(5.99)	(9.00)	(4.48)	(4.66)	(6.97)	(7.62)
Upstreamness * D(HI Chain)	0.003	0.004	0.002	0.002	0.005	0.007
	(0.85)	(1.04)	(0.31)	(0.35)	(1.35)	(1.58)
Centrality		0.219***		0.187*		0.101**
		(4.28)		(1.81)		(2.02)
Log(Assets)		-0.002		-0.001		-0.003
		(-0.54)		(-0.39)		(-0.83)
Log(Age)		0.002		-0.024**		0.007
		(0.30)		(-2.53)		(1.09)
Investment Grade		-0.013		0.014		-0.020
		(-0.92)		(0.67)		(-1.44)
Log(Inventory Turnover)		-0.001		-0.004		0.010***
		(-0.40)		(-0.54)		(2.64)
Log(Ncompetitor)		0.007		0.010		0.010**
		(1.45)		(1.51)		(2.00)
Foreign		0.032***		0.038**		0.013
		(2.70)		(2.16)		(1.03)
Constant	0.114***	-0.077	0.191***	0.081	0.017***	-0.118**
	(17.33)	(-1.34)	(26.76)	(0.84)	(2.64)	(-2.05)
Observations	610291	487835	613976	491487	609757	487569

Table OA.5: **Baseline models with industry fixed effects**

This table repeats the within-chain regressions in Table 3 with one variation: in addition to controlling for the chain fixed effect, we also control for the industry fixed effects, where industry is defined according to the Fama and French 49-industry classification. Details of variable definitions are provided in Table A.1. t-statistics, based on standard errors triple-clustered by firm, by the top and bottom of the chain, are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	AR/Sale	AR/Sale	AP/COGS	AP/COGS	NAR/Sale	NAR/Sale
Upstreamness	0.013***	0.017***	0.009	0.016***	0.014***	0.012***
	(5.18)	(5.25)	(1.26)	(3.04)	(5.84)	(3.76)
Centrality		0.125***		0.141		0.047
		(2.76)		(1.59)		(1.12)
Log(Assets)		-0.002		0.005*		-0.002
		(-1.12)		(1.68)		(-1.31)
Log(Age)		0.002		-0.018***		0.005
		(0.38)		(-2.71)		(1.21)
Investment Grade		0.002		0.017		-0.005
		(0.23)		(0.88)		(-0.49)
Log(Inventory Turnover)		-0.008***		-0.013		0.006
		(-2.78)		(-1.65)		(1.33)
Log(Ncompetitor)		-0.001		-0.007		-0.002
		(-0.34)		(-1.41)		(-0.58)
Foreign		0.014		0.017		-0.003
		(1.49)		(1.40)		(-0.28)
Constant	0.130***	0.055	0.204***	0.134	0.034***	-0.013
	(36.22)	(1.10)	(21.65)	(1.65)	(9.80)	(-0.26)
Observations	610291	487835	613976	491487	609757	487569

Table OA.6: **Baseline models excluding bottom firms**

This table repeats the within-chain regressions in Table 3 after excluding firms at the bottoms of supply chains. We control for chain fixed effects in all regressions. Details of variable definitions are provided in Table A.1. t-statistics, based on standard errors triple-clustered by firm, by the top and bottom of the chain, are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1) AR/Sale	(2) AR/Sale	(3) AP/COGS	(4) AP/COGS	(5) NAR/Sale	(6) NAR/Sale
Upstreamness	0.013***	0.013***	0.010	0.025***	0.019***	0.019***
	(3.47)	(3.66)	(1.55)	(2.90)	(4.91)	(4.32)
Centrality		-0.001		0.121		-0.050
		(-0.03)		(1.21)		(-1.13)
Log(Assets)		-0.007***		0.002		-0.009***
		(-5.58)		(0.67)		(-5.80)
Log(Age)		0.010***		-0.010		0.012***
		(2.85)		(-1.37)		(2.86)
Investment Grade		-0.004		-0.024*		-0.009
		(-0.79)		(-1.65)		(-1.25)
Log(Inventory Turnover)		0.001		0.015***		0.008**
		(0.27)		(2.93)		(2.12)
Log(Ncompetitor)		0.014***		0.013*		0.020***
		(4.01)		(1.68)		(4.49)
Foreign		0.015**		0.038***		-0.003
		(2.51)		(3.08)		(-0.46)
Constant	0.138***	0.119***	0.209***	0.012	0.032***	0.029
	(15.97)	(2.86)	(15.11)	(0.14)	(3.43)	(0.65)
Observations	377595	285256	379775	287451	376967	284948

Table OA.7: **Baseline model excluding top firms**

This table repeats the within-chain regressions in Table 3 after excluding firms at the tops of supply chains. We control for chain fixed effects in all regressions. Details of variable definitions are provided in Table A.1. t-statistics, based on standard errors triple-clustered by firm, by the top and bottom of the chain, are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1) AR/Sale	(2) AR/Sale	(3) AP/COGS	(4) AP/COGS	(5) NAR/Sale	(6) NAR/Sale
Upstreamness	0.029***	0.023***	0.034***	0.031***	0.028***	0.021***
	(3.83)	(3.58)	(4.08)	(4.33)	(3.98)	(3.33)
Centrality		0.268***		0.086		0.106
		(3.71)		(0.62)		(1.46)
Log(Assets)		-0.000		-0.003		-0.000
		(-0.06)		(-0.64)		(-0.08)
Log(Age)		-0.002		-0.025*		0.003
		(-0.34)		(-1.87)		(0.39)
Investment Grade		-0.016		0.023		-0.027*
		(-1.00)		(0.87)		(-1.75)
Log(Inventory Turnover)		0.000		-0.013		0.013***
		(0.09)		(-1.31)		(2.72)
Log(Ncompetitor)		0.009		0.014*		0.014**
		(1.42)		(1.71)		(2.20)
Foreign		0.032**		0.023		0.017
		(2.32)		(0.98)		(1.21)
Constant	0.109***	-0.128*	0.184***	0.196	0.013**	-0.147**
	(17.47)	(-1.69)	(26.63)	(1.60)	(2.17)	(-1.97)
Observations	407714	337806	412180	341962	407390	337586

Table OA.8: **Baseline regressions using upstreamness dummies**

This table repeats the within-chain regressions in Table 3 with one variation: instead of using the upstreamness measure directly as an independent variable, we create five dummy variables indicating whether a firm's upstreamness measure is 1, 2, 3, 4, 5 or above (with the omitted base case being 0). We control for chain fixed effects in all regressions. Details of variable definitions are provided in Table A.1. t-statistics, based on standard errors triple-clustered by firm, by the top and bottom of the chain, are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	AR/Sale	AR/Sale	AP/COGS	AP/COGS	NAR/Sale	NAR/Sale
D(Upstreamness=1)	0.053***	0.028	0.037***	0.024*	0.049***	0.022
	(3.66)	(1.48)	(2.61)	(1.81)	(3.51)	(1.24)
D(Upstreamness=2)	0.063***	0.059***	0.051***	0.057***	0.074***	0.062***
	(4.44)	(5.82)	(3.40)	(3.99)	(5.63)	(5.88)
D(Upstreamness=3)	0.075***	0.099***	0.058***	0.071***	0.076***	0.085***
	(5.15)	(11.57)	(2.95)	(3.50)	(5.55)	(8.24)
D(Upstreamness=4)	0.076***	0.110***	0.061***	0.064***	0.083***	0.096***
	(4.83)	(8.31)	(2.63)	(2.59)	(5.55)	(6.70)
D(Upstreamness=5)	0.079***	0.116***	0.046**	0.056**	0.089***	0.107***
	(4.37)	(7.01)	(1.97)	(2.17)	(5.42)	(6.37)
Centrality		0.235**		0.167		0.110
		(2.19)		(1.63)		(1.12)
Log(Assets)		-0.002		-0.001		-0.003
		(-0.72)		(-0.27)		(-1.00)
Log(Age)		0.002		-0.023**		0.007
		(0.30)		(-2.45)		(1.15)
Investment Grade		-0.013		0.016		-0.019
		(-0.89)		(0.74)		(-1.36)
Log(Inventory Turnover)		-0.001		-0.004		0.011***
		(-0.33)		(-0.53)		(2.85)
Log(Ncompetitor)		0.007*		0.010		0.011**
		(1.77)		(1.50)		(2.46)
Foreign		0.032***		0.037**		0.012
		(2.79)		(2.12)		(1.00)
Constant	0.103***	-0.088	0.183***	0.089	0.007	-0.129
	(11.06)	(-0.90)	(20.43)	(1.03)	(0.84)	(-1.45)
Observations	610291	487835	613976	491487	609757	487569

Table OA.9: **Baseline models using firm-year observations**

This table repeats the baseline regressions in Table 3 using firm-year observations, which means each firm has one observation per year. We control for year fixed effects instead of chain fixed effects. Standard errors are clustered by firm. Details of variable definitions are provided in Table A.1. The t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1) AR/Sale	(2) AR/Sale	(3) AP/COGS	(4) AP/COGS	(5) NAR/Sale	(6) NAR/Sale
Upstreamness	0.016***	0.022***	0.021***	0.018***	0.013***	0.018***
	(13.14)	(16.96)	(7.44)	(7.30)	(9.94)	(13.68)
Centrality		0.184***		0.129**		0.113***
		(8.56)		(2.37)		(5.76)
Log(Assets)		-0.008***		-0.005**		-0.009***
		(-9.11)		(-2.48)		(-9.53)
Log(Age)		0.002		-0.014***		0.007***
		(0.91)		(-3.21)		(3.27)
Investment Grade		0.007		0.025**		0.002
		(1.61)		(2.46)		(0.39)
Log(Inventory Turnover)		-0.006***		-0.001		0.003**
		(-4.83)		(-0.47)		(2.23)
Log(Ncompetitor)		0.007***		0.009***		0.008***
		(5.31)		(3.01)		(6.09)
Foreign		0.037***		0.084***		0.002
		(8.56)		(7.45)		(0.52)
Constant	0.128***	0.027	0.182***	0.115***	0.046***	-0.034*
	(49.44)	(1.54)	(33.68)	(3.09)	(17.62)	(-1.96)
Observations	34958	25600	35090	25728	34893	25569