Competition and Inter-Firm Credit: Theory and Evidence from Firm-level Data in Indonesia*

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Abstract

Using firm-level data we investigate the relationship between trade credit and suppliers' market structure and find a ∩-shaped relationship between competition and trade credit, with a discontinuous increase in credit provision between monopoly and duopoly. This "big jump" arises because monopolists are more likely to not offer *any* trade credit than firms in competitive environments. Our model exploits the fundamentally different nature between cash and trade credit sales, arguing that firms are unable to commit *ex ante* to a trade credit price. We show that monopolists will often sell only on cash, while credit is *always* provided in competitive environments.

JEL Classification: O16, O17, L10

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1 Introduction

Trade credit is arguably one of the principal sources of credit for firms in both developing and developed countries (Petersen and Rajan, 1995; Rajan and Zingales, 1995). Trade credit is the credit that is extended by suppliers of a good to buyers every time a delay of payment is granted. Typically suppliers can set distinct prices for up-front cash payments and for delayed payments. In countries with underdeveloped formal credit markets the significance of trade credit is particularly high: firms acting as financial intermediaries play a fundamental role as bank substitutes extending credit to other firms rationed in the formal credit sector (Demirgüç-Kunt and Maksimovic, 2002; Fisman and Love, 2003). Although a sizeable literature has paid attention to the determinants of trade credit, very few studies have addressed the particular question of how supplier competition affects inter-firm credit. This paper investigates the issue at both a theoretical and an empirical level.

In the empirical analysis we use a novel firm-level dataset from Indonesia, which combines two existing datasets, containing information on the trade credit policies of a sample of manufacturing firms. More importantly, however, we are able to recover the underlying competitive environment in which they operate. We find an inverted U-shaped relationship between competition and trade credit provision. In monopolistic environments very little trade credit is provided; however, there is a dramatic increase in trade credit provision for duopolies, followed by a more gradual increase in trade credit provision before finally decreasing as the environment becomes more and more competitive. The most striking finding, and the part we will dwell on, is what we call the big jump in trade credit provision between monopoly and duopoly: monopolists are more likely to provide *no* trade credit at all to their clients than firms in more competitive environments.

The fact that many monopolists appear unwilling to provide any trade credit to their clients seems particularly striking given that our data come from Indonesia — a country with poorly developed capital markets in which trade credit is often the only source of credit for small firms. Therefore, the monopolists in our sample would seem to be sacrificing profits by not extending trade credit to customers who cannot obtain bank finance.[1] What then is their motive, and why do firms in more competitive environments not make the same decision?

We construct a model in which suppliers initially post a cash price for up-front payments but are not able to commit *ex ante* to the terms of trade credit. Reminiscent of Coase's (1972) durable goods monopolist,[2] this lack of commitment can serve as a major handicap in setting cash prices. In particular, after a cash price is posted and the monopolist observes cash purchases, she may be tempted to loosen the terms of trade credit to attract those customers that could not afford to pay cash. Anticipating this, those that can afford to pay cash choose instead to wait and divert resources away from the monopolist's core business (cash sales). To avoid this outcome, the monopolist has two options: either distort the cash price or commit to only accepting cash payments. We show that often the firm is better off selling entirely on cash.

The conditions on the parameters that affect the shutdown zone are related to the parameters of the model in an interesting way: if a sufficiently large fraction of buyers can pay cash (say because banks do a good job of screening clients or buyers are self-financing) then the shutdown zone widens and the monopolist is more likely to offer no trade credit. More striking, however, the same result is true *even* if the monopolist is relatively efficient at providing trade credit: we show that the monopolist's ability to efficiently provide trade credit causes a greater distortion of her cash market and smaller revenues from that source, leading to a greater probability of shutdown.

With competition, commitment problems become irrelevant: Bertrand competition in the cash market pushes the cash price to marginal cost, leaving trade credit as the only source of profit for the supplier. This result follows from the fundamentally different nature between

[1]This is what makes our dataset particularly interesting: in the United States or other countries with well-developed credit markets, it is harder to argue that a firm, by not offering trade credit, is sacrificing profit.

[2]See also Stokey (1979, 1981), Bulow (1982) and Gul, Sonnenschein and Wilson (1986) for various formalisations of Coase's idea.

cash and trade credit. A buyer willing to pay cash for a homogenous product views suppliers as completely interchangeable and will choose the supplier with the lowest price, and the supplier will sell, without hesitation, to any such buyer. However, trade credit requires a closer relationship between buyer and seller, and the presence of supplier-client specific costs of credit provision prevent competition from driving trade credit margins to zero.

More generally, the model explains why trade credit may continue to grow with the number of competitors. This is driven by a more traditional competition effect: the entrance of a new competitor has no impact on the cash price, which is already at marginal cost, while it leads to a decrease in the equilibrium trade credit price. In the overall market the number of cash buyers does not increase, *but* more buyers have access to trade credit. Therefore, there is an increase in the proportion of goods sold on credit, and so, keeping loan enforcement problems out of the model, we predict an increasing relationship between competition and trade credit. However, when the number of competitors increases loan enforcement constraints become increasingly serious. The possibility of deterring defaults by threatening to cut buyers out of future credit is less effective the higher is the number of alternative suppliers. Also the formation of *social norms* which prescribe that defaulters be boycotted by the entire market is less likely if the number of competitors gets higher. The estimation suggests that the enforcement constraints start biting with more than four or five competitors causing firms to reduce their trade credit thereafter.

The rest of the paper is organized as follows: Section 2 examines the related literature, while Section 3 provides a brief preview of the empirical results. In Section 4 we describe the model and derive its main implications. We also provide a discussion of several alternative models and variations on our model. In particular, we show that the assumption that the supplier cannot commit to a trade credit price is crucial to generating the jump in credit provision going from monopoly to duopoly. Section 5 describes the dataset, while Section 6 lays out the empirical approach. In Sections 7 and 8 we provide the main empirical findings and the results of a battery of robustness checks. Section 9 concludes, while Appendix A contains all proofs and Appendix B contains relevant tables.

2 Related Literature

Three strands of related literature are relevant to our study: the literature on competition and formal credit provision, various studies of trade credit and the literature on durable goods in industrial organization, which was briefly discussed above.

The literature on bank credit provides conflicting conclusions about the relationship between creditors' market structure, access to credit and credit costs, with some studies conjecturing a negative correlation between competition and credit provision. Two sets of explanations are often proposed: those based on theories of the client-creditor relationship and those based on the loan enforcement argument. The literature on information asymmetries and agency problems has argued that competition is likely to reduce incentives to establish long-term relationships with the client which results in decreasing credit flows (Petersen and Rajan, 1995; Marquez, 2002). In competitive environments, creditors cannot expect to share the future surplus clients may generate. Similarly, studies on loan enforcement predict a negative relationship between competition and credit provisions pointing to the monopolist's ability to enforce payment by threatening to cut off future credit (Ghosh, Mookherjee and Ray, 2000). Conversely standard economic theory predicts a positive effect of competition on credit arguing that any deviation from perfect competition results in smaller loans to borrowers at a higher cost (see Guzman, 2000 and Heffernan, 1996).

There are many studies that have investigated both theoretically and empirically the determinants of trade credit, among others Cuñat (2007), Burkart and Ellingsen (2004), Biais and Gollier (1997), Petersen and Rajan (1997) and Mian and Smith (1992). However, none of these papers are able to explain why a monopolist supplier would find it optimal to *not* provide trade credit, while oligopolist suppliers do. For example, an early paper by Brennan, Maksimovic and Zechner (1988) shows, in a model with adverse selection and a competitive banking sector, that a monopolist supplier will always find it optimal to make cash and credit sales as a way to price discriminate. Moreover, they also show that under some circumstances in a duopoly, there is an equilibrium in which one firm specialises in cash sales, while the other extends credit to customers.[3] Instead, our paper focuses on explaining why a monopolist is more likely to sell only on a cash basis, while credit is much more often provided in more competitive environments.

The interest for trade credit in developing countries has grown in recent years (World Bank, 2004), given its important role as bank credit substitute and thanks to increasingly reliable firm-level datasets (Fafchamps, 2000). Nevertheless few empirical studies address the issue of competition and inter-firm credit provision, and those that have generally find somewhat conflicting results. On the one hand, McMillan and Woodruff (1999) use a survey collected in Hanoi and Ho Chi Minh City and find a negative correlation between the number of competitors operating within one kilometer of the firm and trade credit provided. On the other hand, Fisman and Raturi (2004) use a dataset from buyers in five sub-Saharan African countries and show that clients of monopolists have a significantly lower probability of receiving credit than firms that deal with more competitive suppliers.

Two studies by Fabbri and Klapper (2008) and Van Horen (2005) also show that firms with weak market power relative to their customers generally provide more trade credit.[4] Both papers also show that firms with strong market power relative to their suppliers also generally demand more trade credit. Fabbri and Klapper (2008) argue that this is due to a desire to balance the timing of accounts payable and accounts receivable. Our results will also show that such a desire may be present on the part of firms in our sample.

Given the apparent non-linear relationship between trade credit and competition, our results are consistent with the aforementioned papers and, in our opinion, provide a possible

[3]Thus we would expect to see more duopolists not providing an trade credit at all, and a correspondingly larger variance (than for monopolists) in the amount of credit provided, neither of which are supported in our dataset.

[4]In both papers, the authors' definition of market power takes the form of a discrete dummy variable; therefore, unlike in our study, amongst firms with market power, they are not able to distinguish those with relatively more and relatively less power.

reconciliation of their conflicting results. Indeed, if we use a linear specification for the effect of competition on trade credit, we also find a significantly negative correlation, as do McMillan and Woodruff. However, we show that a non-linear specification fits better the data. Our analysis suggests that their estimates may differ because of the limited cross-section geographical variation of their data. Their survey covers only two urban and intensively industrialized districts with presumably highly competitive markets. Our survey, instead, covers all the major districts in Indonesia — both rural and urban.

Both Fisman and Raturi's and Van Horen's datasets exploit remarkable cross-sectional variation. The former comes from a survey of as many as five Sub-Saharan countries, while the latter uses a sample of 18,000 firms from 42 countries. Their results are in contrast with McMillan and Woodruff's but consistent with our finding of lower trade credit offered by monopolists.[5] Our analysis, however, offers an important new insight on this issue. Using supplier data we can observe that the low probability of obtaining credit for monopolist's clients, found by Fisman and Raturi (2004), is due to the high number of monopolists that simply provide no credit to their clients. This requires, in our opinion, a radically new explanation from what has been so far conjectured by this literature. Our theoretical model sets out to reach this goal.

3 Summary of the Empirical Results

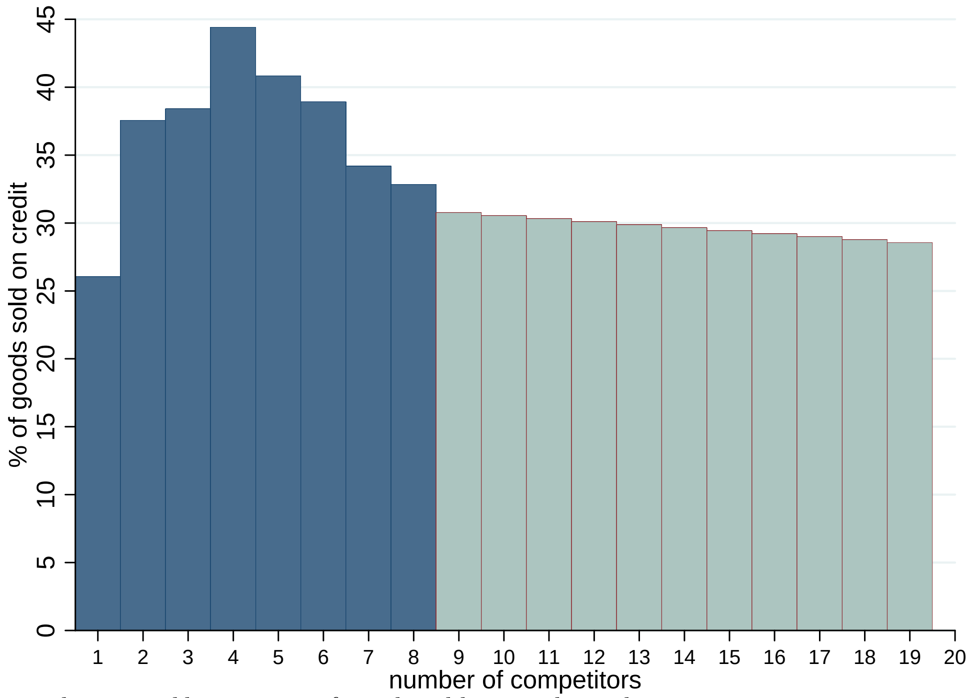
A thorough description of the dataset and details of the estimation and identification strategy are presented in Sections 5 and 6. Here we provide some evidence on the relationship between competition and the amount of trade credit provided by suppliers.

Figure 1 depicts the estimated proportion of goods sold on credit as a function of the number of competitors operating in the same subdistrict.[6] At least three features of the

[5] Like us, Fabbri and Klapper's data comes from a single country — in their case, China.

[6] For the purposes of our study, we say that two firms are competitors if they are located within the same subdistrict and whose main product has the same four-digit ISIC classification. Competitors are derived from the economic census conducted by the Indonesian Central Bureau of Statistics.

Figure 1: The effect of competition on trade credit



Dependent variable: percent of goods sold on trade credit.
Functional form: Step function as in (5), with dummy variables for whether there are n competitors ($n = 1, 2, \ldots, 8$) in a market and a linear term for 9 or more competitors. Additional control variables as in column (3) of Table 3, including three-digit ISIC sector dummies and district dummies.
Estimation method: double censored Tobit. Figure reports unconditional expected value of the dependent variable at the mean of the control variables.
Number of observations: 598.

estimation are striking. First, notice the sharp increase in trade credit provided to clients going from monopoly to duopoly. The average proportion of goods sold on credit when two firms compete is 42% higher than the same proportion when only one firm is active. Second, the trade credit granted increases gradually when a small number of firms compete reaching a peak at four competitors. Finally, the percentage of goods sold on credit decreases steadily when more than four competitors are active.

A closer investigation of the jump from monopoly to duopoly shows that, conditional on providing some positive trade credit, monopolists do not extend less credit than duopolists. Instead, what explains the jump is the fact that *suppliers with no competitors are more likely to provide no trade credit to their clients*. We think that this finding is not adequately explained by the traditional argument provided by the literature that predicts a positive relationship between competition and credit provision. Instead of observing monopolists that provide a lower amount of credit at a higher price, we find that monopolists are more likely to offer no credit and sell all their products for cash only. This is despite the fact that their enforcement power is much stronger than firms operating in more competitive settings.

In contrast, the negative part of the relationship is consistent with those of McMillan and Woodruff (1999), as well as the predictions of the loan enforcement in developing countries literature which argues that in economies with weak creditor protection, default is deterred mainly by the threat withholding future access to credit. This threat is particularly strong if the creditor is a monopolist in a given market. Also with a small number of creditors social norms can give rise to positive levels of borrowing and lending (Ghosh, Mookherjee and Ray, 2000). As the number of lenders increases, however, the threat of reducing or cutting access to future credit is less effective since borrowers can more easily find alternative sources of financing and social norms are less likely to arise — hence the higher presence of credit rationing in more competitive credit markets. This literature provides a convincing interpretation of the negative relationship between competition and trade credit provision that arises in our data with more then four competitors.

4 The Model

In this section we explain the model and derive the main results. The model intentionally ignores enforcement constraints. We first provide conditions under which a monopolist would choose a cash-only policy. We then extend the analysis to the case of more than one supplier, showing that it is never optimal to adopt such a policy; this leads to a large increase in the proportion of goods sold on credit from monopoly to duopoly.

4.1 Monopoly

There is a single supplier of an intermediate good who produces the good at no cost. There is also a continuum of buyers with unit mass; each buyer i demands one unit of the intermediate good, transforms it into a final product at no cost and sells it at price P_i. Each buyer knows his/her selling price, while the supplier only knows that selling prices are drawn from some distribution $F(P)$. The supplier can either sell the intermediate good for cash or on credit. If the supplier provides the intermediate good on credit she will incur a monitoring cost $m > 0$. This monitoring cost can be thought of as the cost to ensure that the delayed payment is eventually made. It can depend upon geographic distance or other buyer/seller-specific characteristics.

We assume that a fraction π of the buyers have adequate access to cash (say because they are self-financing or have sufficient, existing lines of formal credit from which they can readily draw), while the remaining $1 - \pi$ are unable to pay cash, and must rely entirely on trade credit. We also assume that π is independent of the value distribution, $F(P)$. We will call those buyers who can pay cash "non-rationed" and those buyers who cannot pay cash "rationed".[7] We also assume that the supplier cannot distinguish between rationed and non-rationed buyers; hence, the supplier must set the trade credit price based on her beliefs about the distribution of buyers who ask for trade credit.

The timing is as follows:

Stage 1: The supplier sets a cash price c;

Stage 2: The fraction of non-rationed buyers, π, decide whether to pay cash or to wait and purchase on trade credit;

Stage 3: Having observed cash sales, the supplier sets the trade credit price t;

Stage 4: Buyers decide whether or not to buy at this price and payoffs are realized.

[7] An alternative and equivalent assumption would be that all buyers must apply for bank finance in order to pay cash, and that loans are granted with probability $\pi > 0$.

The assumption that the trade credit price is set by the supplier only after buyers react to the cash price is critical to the model. In reality, it is more likely that a buyer sees both a cash and a trade credit price and then decides whether to pay cash or buy on credit. However, even in this situation it is likely that the final price for trade credit is not determined until final payment is actually made. For example, in the 1998 Survey of Small Business Finances, approximately 46% of buyers pay only after the agreed upon deadline and many of these same firms indicate that there are no penalties for late payment. This additional delay in payment can be thought of as a lower effective price than was initially agreed upon.[8] For example, Petersen and Rajan (1994) argue that many retail firms face trade credit terms of 10-2-30, which translates into an annualised interest rate of 44.6% if the borrower forgoes the 2% discount by paying after 10 days. They go on to note that, to the extent that there are no penalties for late payment (*i.e.,* payment after 30 days), payment after 36.9 days translates into an implicit interest rate of only 22.1%. While still quite a high rate of interest, by delaying the date of repayment, the borrower has effectively lowered its interest rate.

The results of the World Bank's Investment Climate Core survey indicate that late payment is a general phenomenon: Entrepreneurs report that almost half of the clients who receive trade credit settle their payment after the initial deadline. In the 2003 survey, among Indonesian firms that reported overdue payments, it takes, on average, 5.3 weeks to resolve an overdue payment dispute with a standard deviation of 5.8 weeks. In their sample of Chinese firms, Fabbri and Klapper (2008) indicate that between 20-27% of firms either make or receive late payments. They also report a similar percentage of disputes between buyer and seller and, when recourse to the courts is sought, 84% of the time the firm does not recover its losses.[9] In a study of small British firms, Howorth and Reber (2004, p. 480) argue that, "late paying firms had developed a detailed knowledge of their [suppliers'] credit management procedures and paid just in time to avoid enforcement action which usually took the

[8]See Cuñat (2007) for a reason why it may be optimal for a supplier to allow further delays in payment.

[9]Firms more frequently resort to negotiation to settle disputes and, in such cases, they recover the full value of their claim 80% of the time. However, even a negotiated settlement surely imposes other costs (*e.g.,* time and effort spent pursuing their claims) such that the effective price is still lower.

form of withheld supplies or, less frequently, penalty charges." They also provide evidence indicating that many firms are reluctant to enforce penalties for late payment (See Footnote 12). To reiterate, by granting any delay in payment, a supplier opens the door to further (non-negotiated) delays, effectively lowering the price she obtains. The model we present should be viewed as a convenient shorthand for a more general model in which buyers have some ability to stretch the repayment timetable.

In our model, we introduce one commitment device for the supplier. In particular, we allow her to close the trade credit window and commit to a cash-only policy. Formally, this amounts to the addition of an initial stage to the game: Stage 0, the supplier chooses whether or not to shut down the trade credit window.

We are now ready to demonstrate the main result of this section:

PROPOSITION 1. *For any given monitoring cost, m, there exists a threshold $\hat{\pi}(m)$, such that for $\pi > \hat{\pi}(m)$, the supplier will optimally decide not to offer credit and pre-commit to a "cash-only" policy. Furthermore, the threshold value is increasing in the monitoring cost.*

A formal proof is provided in Appendix A. Here we provide an example that illustrates the main intuition of the result and then we describe the key steps that lead to it. Consider first the case in which the supplier has full commitment power. It is easy to see that the supplier would never set the trade credit price, t, less than the cash price, c. If she did, all buyers would opt for trade credit, which is strictly less profitable for the supplier given the monitoring cost $m > 0$. Instead, by choosing $t > c$, all non-rationed buyers with a selling price $P \geq c$ (henceforth "high-price" types) will pay cash. Among the rationed buyers, those with $P \geq t$ will ask for trade credit, while those buyers with $P < c$ (henceforth "low-price" types) are left out of the market. In this full commitment scenario, the supplier is effectively able to separate the maximization problems for the cash and trade credit prices. Indeed, one can easily see that the optimal cash price, c^*, depends only on the distribution of buyer types, while the optimal trade credit price, t^*, depends on the distribution of buyer types and on the monitoring cost. Under standard regularity conditions on the profit function, both of these values are unique. Importantly, the fraction of buyers with access to cash plays no role in the maximization problem of the supplier, and trade credit is only extended to those buyers rationed in the formal credit sector.

Suppose now that the supplier loses the ability to commit to a trade credit price. If $m > c^*$ it is obvious that $t > c^*$, since otherwise the monopolist would not even cover the monitoring cost. Thus she effectively has full commitment. Similarly, even if the monitoring cost were low, we could still have results identical to the full commitment case if the fraction of customers with access to cash were sufficiently low. In this case the distribution of buyers that ask for trade credit would have a large proportion of rationed, high-price buyers. The supplier would still find it optimal to set a trade credit price above the cash price and the full commitment scenario would be replicated.

The interesting range is then when m is low and π is relatively high. Indeed, consider the case in which $\pi \approx 1$. If all non-rationed buyers actually paid cash, then the distribution of buyers who apply for trade credit would be almost completely made of low-price buyers. At this point, te monopolist would find it optimal to set a trade credit price below the cash price, thus selling the product to those buyers who could not afford to pay cash in the first place. Anticipating this lower trade credit price, buyers will refuse to pay cash and demand trade credit. However, this breaks the full commitment equilibrium.

Proposition 1, demonstrates that if the π is *high enough* and the monitoring cost in *low enough*, the supplier is better off denying credit to her clients and committing to a cash-only policy. This, however, does not mean that when the full commitment equilibrium breaks the supplier immediately commits to a cash-only policy. Instead, she will first try to distort the cash price to convince some buyers to pay cash. Only when the cash price distortion becomes too costly will she commit to no credit.

We now highlight the key aspects of the game at each stage and proceed via backward induction to derive the supplier's optimal strategy for various parameter values.

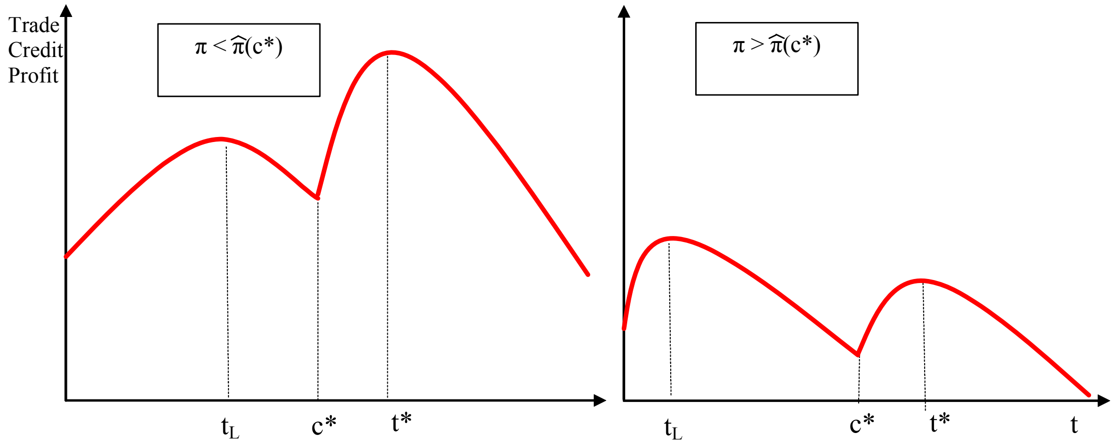
Stage 3: Determination of t. Since the supplier cannot tell whether those remaining after cash sales have been made were rationed or not, her decision on t depends upon her beliefs about who paid cash. We first examine the case in which the supplier believes that all non-rationed, high-price buyers (*i.e.,* buyers for which $P > c$) paid cash and low-price buyers did not, and show that there exists a threshold probability $\hat{\pi}(m, c)$ such that for any π larger than $\hat{\pi}(c, m)$ the supplier will optimally set trade credit price below the cash price.

Observation 1. *Assume that the supplier's belief is that all non-rationed, high-price types paid cash. Then there exists a threshold value $\hat{\pi}(c, m)$, such that for $\pi > \hat{\pi}(c, m)$, $t < c$, while for $\pi < \hat{\pi}(c, m)$, $t > c$. Furthermore, $\hat{\pi}(c, m)$ is strictly decreasing in c and strictly increasing m.*

The proof of this observation is in Appendix A; however, the intuition can be seen in Figure 2 where we show the supplier's trade credit profit function for the case in which the cash price was set at the "full commitment" level c^* and all the non-rationed, high-price buyers pay cash. Notice that for given values of π, the profit function has a double-hump shape. On the left side, we show a situation in which $\pi < \hat{\pi}(c, m)$. In this case, observe that the trade credit price would be set at the full commitment level t^*. On the right side, we show a case in which $\pi > \hat{\pi}(c, m)$ and the supplier will optimally set the trade credit price at t_L — below the cash price — and the full commitment equilibrium cannot be attained. Finally, note that, in the restricted domain $t > c$, profits are always maximised at $t = t^*$, and this value does not vary with π.

Observation 1 also asserts that the threshold value is increasing in c. This implies that there exists a critical value that we call $\hat{c}(m, \pi)$, such that for smaller cash prices the "left hump" is lower then the "right hump" and the supplier sets a trade credit price above the cash price. As we shall see in Stage 2, this suggests that for any fraction π larger than $\hat{\pi}(c^*)$, the supplier could set a cash price weakly less than the threshold $\hat{c}(m, \pi)$, thus inducing the Stage 3 incarnation of herself to set the trade credit price above the cash price. How much smaller this threshold value is than the full commitment optimal cash price c^* depends on

FIGURE 2: Typical Trade Credit Profit Functions



the parameters of the model, π and m. If the cash price is set, instead, greater than or equal to the optimal full commitment trade credit price t^*, the threshold probability is zero.

The fact that $\hat{\pi}(c, m)$ is decreasing in m shows that the lower is the monitoring cost the higher is the incentive for the supplier to set a trade credit price lower than the cash price. Interestingly, this result is different from what the literature on informal credit markets and on trade credit has traditionally argued. This literature has emphasized the fact that suppliers can rely on better knowledge of their clients or lower transaction costs in dealing with them than banks. Thanks to this advantageous position suppliers can bridge the gap between rationed borrowers and the formal credit sector. Our result, on the other hand, shows that if suppliers cannot commit to a trade credit price greater than the cash price, this very same advantage can turn against the supplier. The *closer* is the seller to the buyers, the greater is the temptation to lower the trade credit price below the cash price.

Before we proceed with our analysis of the previous step, we briefly look at the case in which no buyer pays cash. This would trivially lead to the same trade credit profit as the case of $\pi = 0$, which, under standard conditions on the distribution of buyers types, would have a unique maximum at t^*.

Stage 2: Buyers' Decision. Consider now a buyer who observes a cash price c. Her strategy can be defined as a probability of paying cash and is a function of her type, P, whether or not she is rationed (denote by ϕ_{nr} a buyer who is not rationed and ϕ_r a rationed buyer), the monitoring cost, m, and the cash price, c. Clearly, low-price types will ask for trade credit regardless of the values of the parameters. However, for high-price types, the decision depends on the parameters since such buyers must anticipate the eventual trade credit price. If the cash price they observe is less than or equal to the threshold cash price $\hat{c}(m, \pi)$, those who can will pay cash and the supplier will set the trade credit price at t^*. If, instead, they observe $c \geq t^*$ they will ask for trade credit with probability one and the supplier will charge a trade credit price equal to t^*. The question remains open regarding the equilibrium of the continuation game $c \in (\hat{c}(\pi, m), t^*)$. We show in Lemma 2 in Appendix A that if $c \in (\hat{c}(\pi, m), t^*)$, no pooling strategy for which all high-price types take the same action can be part of any equilibrium.

This leaves open the possibility that a strategy that is different among high-price buyers can be part of the equilibrium. More formally, say that buyers use type-contingent strategies if there exists types $P_i \neq P_j$, $P_i, P_j \geq c$, such that $\sigma(P_i, c, m, \phi_{nr}) \neq \sigma(P_j, c, m, \phi_{nr})$, where $\sigma(P, c, m, \phi_{nr})$ is the probability that a non-rationed buyer with selling price P facing parameters m and c actually pays cash. With non-degenerate type-contingent strategies it must be the case that all such buyers are indifferent between paying cash and asking for trade credit. Therefore, they must believe that the trade credit price will equal the cash price.[10] It can be shown that many equilibria with type-contingent strategies exist, but all are pay-off equivalent to the supplier. Thus we have the following:

Observation 2. *The following strategies are an equilibrium of the continuation game start-*

[10]This is proven in Lemma 3 in Appendix A. In Lemma 4, also in the in Appendix A, necessary and sufficient conditions are provided for type-contingent equilibrium strategies when $c \in (\hat{c}(\pi, m), t^*)$.

ing at stage 2:

$$\text{Buyers:}\begin{cases}\textit{Low-price types never pay cash} & \textit{for any } c\\ \textit{Non-rationed, high-price types pay cash} & \textit{if } c \leq \hat{c}(\pi, m)\\ \textit{Non-rationed, high-price types do not pay cash} & \textit{if } c \geq t^*\\ \textit{Non-rationed, high-price types use a type-contingent} & \textit{if } c \in (\hat{c}(\pi, m), t^*)\\ \quad \textit{mixed strategy, } \sigma(P, c, m, \phi_{nr}) \in (0,1) & \end{cases} \tag{1}$$

$$\textit{Supplier's trade credit price: } t = \begin{cases} t^* & \textit{if } c \geq t^* \textit{ or } c \leq \hat{c}\\ c & \textit{for } c \in (\hat{c}, t^*)\end{cases} \tag{2}$$

STAGE 1: THE DETERMINATION OF c. Naturally, if the value of $\pi < \hat{\pi}(c^*, m)$, the lack of commitment is not binding and we have the full commitment equilibrium. If, instead, $\pi > \hat{\pi}(c^*, m)$, the supplier will face three alternatives. First, she can set $c \leq \hat{c}(\pi, m)$ and commit to a trade credit price that is higher than the cash price, thereby ensuring that all high-price, non-rationed buyers pay cash. Alternatively, she can set $c \geq t^*$, thus inducing all the buyers' types to ask for trade credit. Finally, she can set $c \in (\hat{c}, t^*)$, to which the high-price buyers will respond with a type-contingent strategy $\sigma_m(P)$. It is shown in Lemma 5 that it is never optimal for the supplier to set a cash price $c \geq t^*$. However, whether $c = \hat{c}(\pi, m)$ or $c \in (\hat{c}(\pi, m), t^*)$ depends on the parameters and the distribution of buyer types. In any case we show that the equilibrium cash price will be different from the full commitment "unconstrained" optimal value c^*.

STAGE 0: OPENING OR CLOSING THE CREDIT WINDOW. It is by now clear that if the fraction of consumers with access to cash is high enough, the supplier must distort the cash price away from its unconstrained optimal value c^* in order to induce some of the buyers to pay cash. Nevertheless, if π were just above $\hat{\pi}(c^*, m)$ the distortion the supplier needed to make would not be very strong. She could lower the cash price to $\hat{c}(\pi, m)$ and still offer trade credit to her clients. Intuitively, the higher π, the more severe the cash price distortion will have to be and the lower the profits of the supplier. If π increases above a certain level and if a commitment device is available that allows the supplier to sell only on cash, she will use it. Hence the decision to shut down trade credit stated in Proposition 1.

4.2 Multiple Suppliers and the "Big Jump"

Now suppose there are N suppliers. If a supplier provides the intermediate good on credit to a buyer she will incur a buyer-specific monitoring cost which is distributed according to a distribution $I(\cdot)$.[11] Put differently, every buyer i draws N i.i.d. monitoring costs — one for each supplier from $I(\cdot)$. Every supplier now sets a cash price c and a trade credit price t which is buyer-specific. The rest of the model is identical to the monopoly case. The fact that the monitoring costs for the same buyer vary across suppliers reflects the presence of heterogeneous transaction costs in dealing with the client. For cash payments, instead, as in the monopoly case, there are no such costs. This captures the idea that a buyer willing to pay cash perceives suppliers of an identical product as perfect substitutes and is likely to trigger fierce competition among sellers. If, instead, trade credit is sought, transaction costs enter into play and the buyer is likely to face different terms from different suppliers.

In Appendix A, we prove the following result:

Proposition 2. *With two suppliers, the cash price is $c = 0$, each supplier's trade credit window is open and the trade credit price set by supplier $j = 1, 2$ for buyer i is $t_{ij} = \max\{m_{ij}, \min\{m_{i,-j}, t^*_{ij}\}\}$, where m_{ij} is the monitoring cost for supplier j of buyer i and $t^*_{ij} = argmax\{(t_{ij} - m_{ij})(1 - F(t_{ij}))\}$*

Hence, with more than one supplier, the commitment problem disappears, because cannibalisation of the cash market has left trade credit as the only avenue for profit. Moreover, trade credit is only extended to those buyers who are cash constrained.

[11] With many suppliers, it is now necessary to allow for supplier-buyer specific monitoring costs. However, it is not difficult to see that the monopoly model could also be extended to incorporate heterogenous monitoring costs. In this case we would have different threshold values of π that would induce the monopolist to shut the trade credit window.

We now provide an intuitive argument for the equilibrium trade credit prices. We could think of the monitoring cost as a measure of how close the supplier is to the buyer. For each supplier we can distinguish three sets of buyers. For supplier 1, for example, the first set corresponds to buyers that are too far from her competitor and for which the supplier can charge the optimal price $t^*(m_{1i})$. The second group consists of those buyers closer to supplier 1 but that are within reach of supplier 2. More formally those with $m_{1i} < m_{2i} < t^*(m_{1i})$. For this group supplier 1 will optimally set the trade credit price equal to her competitor's monitoring cost. Finally, for those buyers closer to supplier 2, the price is set to m_1.

What about the proportion of goods sold on trade credit conditional on providing some trade credit? Will a monopolist who sells both on credit and for cash would increase or decrease the proportion of goods sold on credit in response to the entry? Unfortunately, the answer to this question is ambiguous. In the duopoly case, if we look at the set of buyers who are too far from the competitor, Proposition 2 shows that their trade credit price equal to the monopolist's price. The cash price, instead, declines considerably leading to an overall lower proportion of goods sold on credit. The results on the other buyers more exposed to competition is less clear. Whether the proportion of them buying on credit over those paying cash increases depends on how much the trade credit price declines relative to the cash price, which ultimately depends on the distribution of monitoring costs.

Our final proposition states that, with more than one supplier, the proportion of goods sold on credit by each supplier increases with the number of suppliers. Intuitively the entrance of a new competitor has no effect on cash sales but exerts downward pressure on trade credit prices since now buyers can purchase from an additional supplier. The decrease in the trade credit price allows more buyers who are cash constrained to access trade credit.

Proposition 3. *With more than one supplier, an increase in the number of competitors leads to an increase in the proportion of good sold on credit by each of them.*

4.3 Discussion of the Model

The model that we have discussed makes sharp predictions and does a good job of explaining why a monopolist might be willing to pre-commit to cash-only sales and why such a pre-commitment is of no value when the level of competition increases. When our model is combined with the standard loan enforcement story, the hump-shaped relationship between competition and credit provision that we alluded to earlier and will presently show exists for a sample of Indonesian firms in our empirical analysis becomes clear. Before proceeding to the empirics, we discuss some extensions and alternative modeling choices.

The assumption driving our results is that the supplier cannot commit to a trade credit price before observing whether or not buyers pay cash. As we have said above, whether or not it is literally true that the supplier sets the trade credit price after observing how many buyers pay cash, so long as there exists the possibility of non-negotiated delays in repayment (something which seems likely in a developing country such as Indonesia), it will not affect our main result.[12] However, one might still question the validity of our assumption, or whether it is necessary for our results. We address these issues now.

For example, rather than suffering from any commitment problems, suppose that suppliers face a fixed cost of providing trade credit. Can this generate the big jump in credit provision from monopoly to duopoly? To be sure, in some cases, it is reasonable to assume that the extra profit generated from setting a trade credit price $t^* > c^*$ does not sufficiently compensate the monopolist supplier for the fixed cost of selling on credit. Therefore, the monopolist optimally sells only on cash. However, if this is true, then so is the following: As in our model, when the degree of competition increases, the cash price goes to zero and trade credit becomes the supplier's only source for profit. Moreover, it is not difficult to show that if the fixed cost induces the monopolist to sell only on a cash basis, then so too will

[12] Indeed, even in developed countries, firms often exploit another's inability of unwillingness to strictly enforce on-time repayments. Howorth and Reber (2004, p. 481) state that "the reason put forward by many of the firms that do not enforce their statutory right to interest is that it would have a negative impact on the relationship with their customer (and, presumably, future sales)." Surely such an effect is *even stronger* in a developing country with a less well-developed legal infrastructure.

oligopolists, *even though* the cash market has been cannibalised by Bertrand competition. Therefore, an explanation based on fixed costs will not do.

Although the supplier cannot commit to a trade credit price, she can commit to cash-only sales. Rather than this, one might imagine that the supplier can use reputation building as an alternative commitment device. For example, suppose that the buyer sets $(c, t) = (c^*, t^*)$ in every period; if she ever sets $t < c$, then the one-shot equilibrium we have derived ensues. This will be an equilibrium so long as the punishment for the one-shot deviation from (c^*, t^*) is higher than the one-shot gain. This punishment is no more than $\delta(t^*(1-F(t^*)(1-\pi))$, while the one-shot gain is $(1-\delta)\left[(t_L - m)(1 - F(t_L) - \pi(1 - F(c))) - (t^* - m)(1 - F(t^*))(1 - \pi)\right]$. Observe that an increase in π lowers the punishment and increases the one-shot gain. Therefore, while the threshold may be different from what we derived above, if π is close enough to one, the supplier still has the incentive to deviate and set $t < c$. Hence, reputation-building may not be enough and the monopolist may still find it optimal to commit to cash-only sales.

Another way in which our model is stylised is that we consider monopolistic or oligopolistic suppliers in a market with a continuum of customers, leaving consumers with very little power against a monopolist supplier. As both Van Horen (2005) and Fabbri and Klapper (2008) have empirically shown, market power on the part of buyers is also likely to affect trade credit provision. Instead of a continuum of consumers, consider the opposite extreme of a single buyer. Suppose also that this single buyer faces its own demand curve in the final goods market and purchases multiple units of the intermediate good from the supplier. With a single consumer, the monopolist supplier's commitment problem become irrelevant and, except for implausibly high values of the monitoring cost, it is difficult to imagine the monopolist shutting the trade credit window. First, the buyer is now on a more equal footing with the supplier and, when negotiating over terms of sale, is likely able to win some delay in payment. Second, one can view the cash and trade credit prices charged by the monopolist as contributing to the marginal cost of production of the buyer; therefore, the buyer would demand positive amounts of trade credit if she were denied bank credit. Third, even if she gets a loan, the buyer may be rationed by the bank and so may purchase some units from the monopolist on cash and some on credit. In this situation, we see that the monopolist is more likely to sell on credit, but what of the "big jump"? The exact same intuition tells us that two suppliers competing for the business of a single buyer are much more likely to sell on credit since now the buyer is in a much more advantageous position and can threaten to leave one supplier for another if generous credit terms are not provided.

5 The Data

In the empirical analysis we combine a firm-level survey in Indonesia sponsored by the World Bank in 1998 and conducted by the *Budan Pusat Statistik* (BPS), the Central Bureau of Statistics, and annual data by the same BPS covering all manufacturing establishments in Indonesia with at least 20 employees. The fact that the two datasets have been collected by the same agency using the same geographical and industrial classification codes, make them easy to be combined. In particular, both datasets contain detailed firm location codes and industrial sector codes for the main good produced. For every firm included in the survey sample it is, therefore, possible to retrieve a large set of information on their competitors operating in the same geographical area and to use this information to build measures of competition. We will come back to this in the identification strategy section. However, we first briefly discuss the two datasets.

The World Bank survey is part of a larger survey conducted in four East Asian countries in order to assess the effect of the Asian financial crises on the manufacturing sector and is described in Hallward-Driemeier (2001). Only in the Indonesian dataset is the detailed firm location information contained that is essential for our analysis.

The survey was conducted by the BPS with the help of the National Development Planning Agency (BAPPENAS) between November 1998 and February 1999. The original sample includes 955 manufacturing firms mainly from four manufacturing sectors (food processing, textiles, chemicals and processed rubber, electronics and others),[13] selected based on their importance to the economy in terms of value added, export orientation and employment, as well as being representative of the manufacturing sector in Indonesia. Individual firms were selected to ensure that the sample was a representative mix of firms of different size, location, ownership structure, and production orientation.

In our main specification we use a restricted sample which excludes those firms who declare that their biggest competitor is abroad, as well as those which export all their products. Our sample size is reduced to approximately 600 firms; however, the number varies in some specifications due to missing observations. The sample distribution is as follows: food processing 35%, chemicals/rubber 25%, textiles 29%, electronics 8%, others 3%. Small and medium firms (*i.e.,* employing between 20 and 150 workers) account for approximately 65% of the sample, while large firms account for approximately 35% of the sample. The sample is predominantly composed of non-exporters and single-establishment firms: 80% of the firms do not export at all and 90% export less than 30% of their production; approximately 90% of the firms in our sample have only one establishment.

What makes the survey particularly suited for our purposes is the detailed section on trade credit, which includes questions on the percentage of goods sold on credit, the average number of days before payment is due — both before and after the Asian Financial Crisis, although our study focuses entirely on the pre-crisis data.[14] The questions suffer from the usual memory recall and measurement error bias that characterize this kind of survey. The memory recall bias is likely to affect the change in the percentages and days reported for before and after the crisis, especially if the effect of the crisis on trade credit is not of great magnitude. Since we are focusing only on the period before the financial crisis, however, the

[13]Our sample contains firms in the following three-digit ISIC sectors: 311, 312, 313, 321, 322, 324, 351, 352, 355, 356, 381, 382, 383 and 384.

[14]The questionnaire also asked for the average discount offered for early payments. However, the ambiguity of the question, which does not give room to identify the kind of discount offered, led only very few firms to answer, making the data uninformative.

cross-sectional variation exploited for the identification of the parameters is less likely to be significantly affected by this kind of error. A potentially more relevant issue is the possible survival bias coming from the fact the only those firms active in the aftermath of the Asian financial crisis are included; however, in Section 8 we use the information contained in the census dataset before and after the crisis and show that survival bias is not a significant problem.

The census data by the BPS contains a complete enumeration of all manufacturing establishments in Indonesia with more than 20 employees and includes precise location codes, 4 digit classification (ISIC 2^{nd} Rev.) of the main good produced and some detailed quantitative information such as short form income statements and balance sheets. No data on the firms' trade credit policies is contained in this survey. We use the BPS data to retrieve information on the competitive environment in which the firms in the World Bank Survey operate and derive a set of control variables.

Table 1.A reports summary statistics of the data included in our study averaged over all firms, while Table 1.B provides greater detail on some variables by reporting summary statistics for monopolist and duopolist firms. Foreshadowing the results to come, notice that duopolist firms sell a larger percentage of goods on trade credit than do monopolists (49.5% vs. 37.8%); indeed, we can easily reject the null hypothesis that the two means are equal in favour of the one-sided alternative that duopolists provide more credit ($|t| = 2.09$, $p = 0.0187$). It is also apparent that duopolists are substantially more likely to provide trade credit than are monopolists (70.1% vs 52.5%), and this difference is also statistically significant at the 1% level ($|z| = 2.68$, $p < 0.01$). Finally, observe that the difference in trade credit provision between monopolists and duopolists appears largely due to the fact that monopolists are less likely to provide any credit at all. If we condition on some credit being granted, then there is no significant difference between the percentage of goods sold on credit by duopolists and monopolists (70.7% vs 72.7%, $|t| = 0.64$).[15]

[15] If we look at the number of days of credit granted by monopolists and duopolists, we see that monopolists are less likely to grant any delay, but that conditional on some delay in payment being granted, there is no

Table 2 provides a correlation matrix for the same set of variables as in Table 1.A. Looking at the correlation between the percentage of goods sold on trade credit and the number of competitors in the subdistrict, one sees that it is -0.038. Taken together with Table 1.B, this suggests a non-linear relationship between the two variables. Indeed, if we re-calculate the correlation matrix restricting attention to only those firms with 4 or fewer competitors (as suggested by our estimates below), then the correlation becomes 0.1185. Finally, looking once again at Table 1.B, it does appear that there are differences between subdistricts which contain a monopolist firm and those which contain a duopolist firm: subdistricts with a monopolist appear to be somewhat smaller as measured by sales and number of firms. However, as we will presently show, *even controlling for such differences*, we observe a ∩-shaped relationship between competition and trade credit.

REMARK 1. *As can be seen in Table 1.B, approximately 25% of the firms in our sample are classified as monopolists (i.e., no other firm in the subdistrict has the same four-digit ISIC code). Moreover, of the fourteen three-digit ISIC sectors represented in our data, eleven of them contain some monopolists. Furthermore, the monopolists in our sample are also fairly dispersed geographically, being present in 37 of the 50 subdistricts in our sample.*

6 Empirical Approach

Our main goal is to accurately capture the functional form of the relation between competition and trade credit provision while controlling for unobserved heterogeneity potentially correlated with the level of competition.

The equation we want to estimate is the following partially linear model:

$$TC_{ips} = f(C_{ps}) + \eta' X_{ips} + \alpha' Z_s + \varepsilon_{ips} \tag{3}$$

where TC_{ips} is the proportion of goods sold on credit by firm i, producing product p in

difference between the two.

geographical area s. C_{ps} is a measure of competition in the production of good p in area s. X_{ips} are firm level characteristics, while Z_s are area characteristics. In order to estimate (3), we will use different specifications of $f(\cdot)$ to capture the possible nonlinearity of the effect of competition on trade credit.

The dependent variable of our estimates is a proportion with many observations at 0 and 100%; therefore, we will use a two-limit Tobit estimation procedure. When estimating the full relationship between competition and trade credit provision, the non-linear nature of the double-censored Tobit estimation makes it difficult to deal with potential unobserved heterogeneity at the level of the industrial sector or sub-district. Therefore, we also present results of OLS fixed effects estimation. Since we are also interested in the "big jump", we will devote attention to the binary decision to provide trade credit. This has the advantage of making it easier to control for unobserved heterogeneity. We will discuss this more below, but now turn our attention to the measure of competition used in our estimates.

Measure of Competition. The first step in estimating the empirical relationship between competition and trade credit policies is to define a measure of competition in trade credit supply. We will use mainly the number of "competitors" in the sub-district where the firm operates. For the analysis we define competitors as those firms producing the same product, as classified at the four-digit ISIC level. The usual problems connected with the use of sector classification to measure competition apply here. The relevant market might include products classified in different sectors but perceived as substitutes by the buyers. Our assumption is that, on average, the sector classification adequately captures product classification.

A crucial condition underlying the use of our measure of competition is that markets for trade credit provision be predominantly local. That is, trade credit should be provided, at least with greater probability, to clients who operate in close proximity to the supplier. While predominantly local markets is a sufficient condition, it is not necessary, especially in contexts where information and enforcement problems are significant: geographical vicinity makes information flows between the borrower and lender easier and often turns out to be crucial in mitigating obstacles to credit provision.

We will see that the estimates show consistent evidence in favor of the local trade credit market hypothesis: only local competition and the local characteristics of the area help to significantly explain trade credit provision. Indeed, the characteristics of the Indonesian economy and of the firms in our sample provide further clues that local markets are actually prominent. First, the country's widespread island archipelago geography and generally poor transportation infrastructure is often quoted as a reason that makes local markets significant in Indonesia (Blalock-Gertler, 2003). Second, given the aforementioned restrictions on our dataset, those that remain are mainly small-to-medium, single-establishment firms selling domestically.

The extension of the geographical area that covers the relevant market for trade credit provision must take into account the characteristics of the data. The available data are organized in administrative units which include provinces (*propinsi*), districts (*kabupaten*) sub-districts (*kecamatan*) and villages (*desa*). The choice of sub-districts as the relevant area has been mainly driven by the empirical analysis on different geographical levels. In Section 8 we show that once we include the number of competitors in the sub-district, the number of competitors in the district, province or country have no explanatory power on the amount of trade credit granted to clients. This result suggests that trade credit markets *are* actually local. There are around 4,000 subdistricts in the country with an average of 20 villages each. In our sample we have 50 subdistricts, 35 districts and nine provinces.

To be sure, the number of competitors is not necessarily the best measure of competition but seems particularly well-suited to our problem. When we examine the robustness of our results we also use market share as an alternative measure of competition and show that the qualitative results do not change. This measure, however, is more likely to be affected by problems of endogeneity due to a reverse causality between trade credit and market shares:

sales as well as market shares are affected by the trade credit policies.

Functional Form. We will use a parametric approach to estimate (3), which allows us to deal more effectively with issues of endogeneity or unobserved heterogeneity. In this paper, we focus on a log-quadratic specification:

$$TC_{ips} = \alpha + \beta_1 \log(C_{ps}) + \beta_2 \log(C_{ps})^2 + \eta' X_{ips} + \alpha' Z_s + \varepsilon_{ips} \tag{4}$$

where all the variables are as previously defined. We take the log-quadratic because it is better-suited to capture an asymmetric non-linear relationship between competition and trade credit than is a quadratic specification. The strong concavity of the log function also captures the fact that, beyond a certain number of competitors, adding another competitor does not alter the environment in an economically appreciable way.

We have also estimated (3) with other parametric specifications, as well as semi-parametrically, which can more effectively capture the predicted non-monotonicity of $f(C_{ps})$ without making any assumptions on the precise nature of any non-monotonicity. Specifically, the other specifications that we estimated were a linear spline specification with knots at $C_{ps} = C_{pc}^{j*}$, $j = 1, \ldots, K$:

$$TC_{ips} = \alpha + \beta_1 C_{ps} + \sum_{j=1}^{K} \beta_{j+1} I(C_{ps} \geq C_{ps}^{j*})(C_{ps} - C_{ps}^{j*}) + \eta' X_{ips} + \alpha' Z_s + \varepsilon_{ips} \tag{5}$$

and a step function given by:

$$TC_{ips} = \alpha + \sum_{j=1}^{H} \beta_j I(C_{ps} = C_{ps}^{j*}) + \beta_{H+1} \log(C_{ps} I(C_{ps} > C_{ps}^{H*})) + \eta' X_{ips} + \alpha' Z_s + \varepsilon_{ips}. \tag{6}$$

As we will presently see, estimates using (5) or (6) provide qualitatively identical results.

Identification Strategy: Unobserved Heterogeneity. Our identification strategy relies on the ability of our cross-sectional estimates to control for potential sources of endogeneity, with two of the most relevant being subdistrict-level and firm-specific unobserved heterogeneity correlated with competition.[16] The possible correlation of those factors determining the location of the firm with variables correlated to trade credit provision can be a serious problem that we have to deal with in our identification.[17]

In particular, the decision of the firm to locate in a certain subdistrict might be influenced by some unobserved characteristics potentially correlated with credit supply. Urban or intensely populated areas, for example, may attract firms for the size of the market or the endowment of infrastructure but may also have more effective legal enforcement systems which could facilitate the provision of credit (Fisman-Raturi, 2004). This kind of heterogeneity might introduce a positive bias on the estimates of the coefficient of competition. Put differently, in areas with a high number of firms we should observe, all else equal, a higher amount of trade credit. Naturally other subdistrict specific characteristics might be at work which affect the coefficient in the opposite direction.

To deal with this, in all specifications we use district level dummies along with three-digit sector dummies. Unfortunately, this is not enough because the variation in firms' location within a district could still introduce a bias. When analysing the full relationship between competition and trade credit, it is not possible to condition out subdistrict fixed effects due to the highly non-linear nature of the Tobit. Furthermore, any attempt to directly estimate ξ_s along with $f(C_{ps})$ might introduce an incidental parameter problem which could undermine the consistency of $f(C_{ps})$ (Greene, 2004). Therefore, to handle this, we also use OLS to estimate our model with subdistrict and four-digit ISIC product fixed effects. On the other hand, when we study the binary decision to grant trade credit we have considerably more freedom to handle unobserved heterogeneity at the product and subdistrict level. In

[16]Industrial sector heterogeneity is also relevant. It is well-documented that trade credit varies substantially across industrial sectors according to specific characteristics of the products or of the production process. We control for differences among products using three-digits ISIC sector dummies in all the specifications. In the robustness checks we also check possible interactions with the level of competition.

[17]A direct "reverse causality" argument seems less relevant for our estimates. Although trade credit provision might be a non-negligible source of revenue, we believe that a vast majority of manufacturing firms decide where to locate their activity based on other factors than direct trade credit opportunities in the specific geographical area.

particular, we are able to estimate a logit subdistrict fixed-effects model, thereby conditioning out any unobserved heterogeneity at the subdistrict level. Beyond this, we also estimate a random-effects logit model à la Chamberlain (1980) in which we allow for correlation between unobserved effects and competition.

As for firm-level heterogeneity, we include a large set of firm-level control variables capturing the financial situation of the firm, its size, its productivity shocks as well as the propensity to export. The basic identification assumption is that, conditioning on our control variables at the firm and subdistrict level, the variation in the number of competitors operating in each subdistrict is exogenous to trade credit and is enough to identify the effect of competition on trade credit provision.

7 Results

7.1 The Full Relationship

Table 3 shows the estimation results for (4), the log-quadratic specification, which was estimated via a double censored Tobit. We report the results as marginal effects on the unconditional expected value of trade credit at the mean of the control variables reported. In brackets, we report the absolute value of t-statistics for the estimated coefficients which account for clustering at the subdistrict level. Except in specification (4), all of the coefficients on competition are individually significant at the 1% level, and in all cases, they are jointly significant at the 1% level. Importantly, all specifications show that trade credit provision is first increasing in the number of competitors, reaches a maximum and then declines steadily thereafter.

In the first specification, besides the log of the number of competitors and its square, we include three firm-level control variables: the percentage of goods exported, the log of sales and the log value of fixed assets. In the second, we include subdistrict level characteristics such as log total number of manufacturing firms and log total sales as well as the average percentage of goods exported in the subdistrict, which has the effect of reducing the coefficient of competition. We also included a measure of firm turnover in the subdistrict in 1996 — specifically, the proportion of firms which started operating in the subdistrict in 1996 plus the proportion of those which exited in the same year.[18] This variable has a negative and significant impact on the amount of trade credit provided, signalling that suppliers are more wary to provide trade credit in those districts where the turnover of new and old firms is higher.[19] In the third specification in column (3), we include a set of additional firm level control variables including age, interest expenses on sales, percentage of capacity usage and change in the capacity usage from the previous year. The inclusion of these control variables does not appreciably affect the estimated coefficients on the number of competitors. In these specifications, the proportion of goods sold on trade credit reaches a maximum when there are approximately four active competitors in the subdistrict and declines thereafter.

Column (4) includes the proportion of goods purchased on credit as a control variable. This was done because, as suggested by Fabbri and Klapper (2008), firms may wish to balance accounts payable with accounts receivable. We see that the estimated coefficient is positive and highly significant, indicating that firms may indeed have such a motive. As the reader can see, the inclusion of the proportion of goods bought on credit reduces somewhat the significance of the coefficients on competition — though they are still significant at the 5% level or better — and lowers the number of competitors at which the maximum is obtained by approximately 0.3 firms. This suggests that there might be an interaction between competition and the percentage of goods bought on trade credit. Indeed, if we interact the percentage of goods bought on credit with a dummy for whether the firm was a monopoly we find a significantly positive coefficient (see column (5)). Therefore, monopolists may be in a better position (due to greater bargaining power) to balance accounts payable

[18] The number of entries and exits is computed looking at the firms operating in the subdistricts at the end of 1995 and comparing them with those operating at the end of 1996. The firms included in the survey are those with more than 20 workers. Consequently some of the entries and exits might reflect an increase or decrease in employment by a firm above or below the threshold for inclusion in the survey.

[19] If we break the turnover measure in its two components, proportions of new entries and exits, the coefficients of the two variables are both negative and significant.

and accounts receivable. Notice also that once we include this interaction, the direct effect of the number of competitors on credit provision increases in significance and returns to its previous magnitude.

In Table 4, we provide results based on the estimation of the best linear spline, which turns out to be the one that has a single knot at four competitors. As can be seen, the qualitative features are identical to those reported in Table 3. The main differences are that the coefficients on competition are somewhat less significant and the overall goodness of fit seems worse (although the two coefficients are still jointly significant at the 1% level), which suggests that the log-quadratic specification better captures the relationship between competition and credit provision.[20] We attribute this to the fact that the relationship between the two variables is rather non-linear (recall Figure 1), and the log-quadratic specification is better able to handle such non-linearities.

Before turning to our analysis of the binary decision of whether to grant trade credit, we first discuss two issues regarding the robustness of our results. Further robustness checks can be found in the next section. First, while the estimations reported in Tables 3 and 4 included district dummies and three-digit ISIC sector dummies, it is still possible that there is unobserved heterogeneity at the subdistrict and/or product level. As we discussed above, due to the non-linear nature of the Tobit model, we cannot condition out any subdistrict fixed effects. Therefore, to deal with this issue, we obtained OLS estimates with both subdistrict and four-digit ISIC product fixed effects. The results of this exercise are reported in columns (3) and (6) of Table 6 for the log-quadratic and linear spline specifications, and in column (9) of Table 7 for the step function (*i.e.,* (6)) specification. As can be seen, the results are qualitatively similar to the Tobit estimates, suggesting that unobserved heterogeneity at the subdistrict level is not a big issue.

Second, since some subdistricts in Indonesia can be rather small, one might wonder

[20] Of course, the two models are not nested so one should be careful when comparing log-likelihoods. However, if one includes the log number of competitors into the linear spine specification, the coefficient is significant. On the other hand, adding the linear terms in the log-quardratic specification does not lead to an improvement in fit.

whether the same pattern holds at the district level. In Table 9, we report estimation results of the Tobit model for both the log-quadratic and linear spline specifications in which we take the number of competitors at the district level as a control variable. We also control for the population of the district in these regressions. As can be seen, firms in more heavily populated districts generally provide more trade credit. Importantly, however, in both cases, we continue to find the hump-shaped relationship between trade credit provision and the number of competitors at in a district.[21] Table 9 also provides results for district fixed-effects regressions. As can be seen, our results on trade credit provision remain intact.

7.2 The Big Jump

As the reader is by now well aware — and can see from column (9) of Table 7 — the most dramatic change in trade credit provision is going from monopoly to duopoly. One might imagine that this is so for two reasons. It may be that monopolists provide less trade credit at a higher price than do duopolists, or rather that they simply do not provide *any* trade credit. We now show that the latter explanation holds true in our dataset. To do this, we break the analysis into two parts. First, we look at the binary decision to grant trade credit and second, we examine the relationship between competition and credit provision *conditional on providing some trade credit.*

In column (1) of Table 5, one can see that what explains the discontinuous increase in trade credit provided is the probability of offering some positive trade credit. The estimates indicate that a duopolist has a substantially higher probability of providing trade credit than does a monopolist; indeed, the probability of providing trade credit is increasing in the number of competitors until approximately five (*i.e.,* four other competitors) and declining thereafter. Moreover, as can be seen from column (2), conditional on providing some trade credit, the number of competitors does not appear to have a significant effect on how much

[21] While it is comforting to know that our results are not affected by whether we use the number of competitors at the subdistrict or district level, in the next section, we provide evidence which supports our use of the subdistrict as the correct unit of analysis.

trade credit is provided.

As with the full relationship, it appears that there is a motive to balance accounts payable and accounts receivable. Moreover, the positive and significant interaction term in column (1) suggests that the effect is even stronger for monopolists. This is likely due to the monopolist's greater ability to dictate the terms of both credit granted and credit received.[22] Interestingly, the difference only manifests itself in the decision to grant credit. Conditional upon providing some credit, there is no significant difference between monopolists and other firms in the relationship between credit granted and credit received.

In the third column of Table 5 we estimate a logit model including only a dummy variable for monopoly as measure of competition. This specification is similar to the one used by Fisman and Raturi (2004) and the results are consistent with theirs. Nevertheless, the analogy cannot be pushed too far. Fisman and Raturi look at buyers' data and find that the probability of obtaining credit is lower if the supplier is a monopolist. Their result, therefore, does not rule out a scenario in which monopolists offer lower trade credit to their clients. However, looking at data from the suppliers' side, we find something profoundly different and yet consistent with their observations: suppliers with no competitors are more likely not to provide trade credit at all.

In order to control for unobserved heterogeneity at the subdistrict level, we estimate fixed- and random-effects logit models on the binary decision to grant some positive or no trade credit. The logit is among the very few non-linear models that allow to difference out the fixed effect. One can see from columns (1) and (2) of Table 6 that the random-effects estimates are very close to the fixed-effects estimates, suggesting that our subdistrict level control variables do a good job in controlling for unobserved heterogeneity. Moreover, we see that the identical relationship holds — monopolists are simply less likely to offer any trade credit than firms in competitive settings. In columns (4) and (5) of Table 6 and columns (7) and (8) of Table

[22] Admittedly, we do not know how much bargaining power firms have with respect to their suppliers, but it seems likely that a monopolist (in its output market) should command more power than would a duopolist firm in the same market.

7, we also present results of both fixed and random effects estimations for the linear spline and step function specifications. The results are qualitatively similar, but the differences between the random and fixed effects estimates are somewhat more pronounced. Finally, in Table 8 we report the results of a series of fixed effects estimations including only a dummy variable for whether the firm was a monopolist. Column (1) provides the logit estimates for the binary decision to grant trade credit. The estimate is negative and similar in magnitude to that reported in Table 5, though the level of significance has dropped somewhat. In columns (2) and (3) we report OLS fixed effects results. Specifically, column (2) includes all observations and indicates that monopolists generally provide less trade credit. Column (3) restricts attention to only those firms that offer some trade credit. Unlike the Tobit results reported in Table 5, the coefficient on the monopoly dummy is now negative; like the Tobit results, the coefficient is not significantly different from zero.

8 Robustness Checks

We have also conducted a number of different checks to assess the robustness of our results, including the estimation of alternative functional forms and specifications. We now highlight the results of this exercise.[23]

Alternative Measures of Competition. In addition to estimating our model using district level data (results discussed above and in Table 9, we estimated our empirical model using alternative geographical areas to assess the importance of competition at these other levels of aggregation; specifically, we included the number of competitors in the country, province, district and village. The results of this exercise can be found in Table 10. Importantly, once we control for the number of competitors in the subdistrict, the other variables do not have additional explanatory power — a result confirmed by a likelihood ratio test. Moreover, the relationship between competition (at the subdistrict level) and credit provision

[23] More details will be provided upon request.

still shows the characteristic hump-shape. In our view, this further substantiates our use of the subdistrict and suggests that markets are, indeed, predominantly local in our sample of Indonesian firms.

Second, in Table 11, we use market shares in the subdistrict as opposed to the number of competitors. This has the advantage of capturing possible differences in the relative size of competitors at the cost of increased problems of endogeneity. The estimates confirm the non-linear hump-shaped relationship between competition and trade credit provision. As an additional check we include the market share in the country, province and district. In no case are these variables significant, nor do they alter the magnitude or significance of the coefficients on market shares at the subdistrict level.

Industry Analysis. One concern is that we may be biasing our results by pooling across different industries with a wide variety of products and different competitive features: n competitors in electronics may have a very different impact than n competitors in food processing. To explore this issue we ran the estimations by industry. The results are in Table 12. Qualitatively the relationship is the same as the pooled estimation, even if the reduced sample size makes the estimates less accurate and more noisy. We also estimated the model excluding the metal tools and structure sector where the effect of competition on trade credit is particularly pronounced. The effect of competition is dampened, but remains significant.

Days of Credit Granted. Rather than using the percentage of goods sold on trade credit as the dependent variable, we also estimated the model using the number of days for which trade credit is granted. We would expect to find a similar relationship in which the number of days allowed before repayment is due initially increases and then decreases. Indeed, this is precisely what we find. Estimating the full relationship, it appears that monopolists grant extend credit for shorter periods of time. However, just as with the results that we have presented thus far, what explains this difference is that monopolists are more likely to not grant any delay at all (*i.e.,* not offer any trade credit). Conditional on granting some delay, we find that there is no significant relationship between the number of competitors and the length of trade credit terms.

Survival Bias. Another concern comes from the fact that the World Bank survey was conducted after the Asian financial crisis with only surviving firms sampled. If competition is correlated with the likelihood that a firm exits the market after the financial crisis our estimates might be biased. In particular, if monopolists and duopolists experienced different mortality rates we could confound the differences in trade credit for the remaining sample with the inherent differences in the population. We address this issue using the BPS census data for before and after the financial crisis. We estimate a logit model to determine the effect of the competition in the subdistrict before the financial crisis on the probability of firms' death. After conditioning on firm size and the same set of control variables used in our main estimation we find that monopolists are not more likely to survive than firms operating in more competitive settings. Therefore, we do not feel that survival bias is a concern.

9 Conclusions

In this paper we explored the relationship between trade credit and competition. In the empirical analysis we combined a World Bank Survey conducted in Indonesia with a comprehensive dataset from the Indonesian Central Bureau of Statistics (BPS) which contains a complete enumeration all Indonesian manufacturing firms with more than 20 workers. The use of the two datasets allowed us to combine data on the trade credit policies of a sample of firms with detailed information on the competitive environment in which each of them operate. The estimates revealed a $\cap$-shaped relation between credit provision and competition. In our sample, the amount of trade credit provided by suppliers increases sharply going from monopoly to duopoly and more gradually up to four competitors, before declining steadily thereafter. We argued that the decreasing part of the relationship is consistent with previous studies and in line with the literature on loan enforcement in developing countries.

However, the increasing part and in particular the "big jump" from monopoly to duopoly is particularly striking. Indeed, it is not that monopolists offer less trade credit at a higher price, but that they are much more likely to offer no trade credit at all to their clients. Importantly, this empirical result survives a number of robustness checks — among them, controlling for unobserved heterogeneity at the level of the market where the firms operate. This result cannot be explained with traditional arguments provided from the literature, but instead requires a radically different explanation.

Consistent with others (*e.g.,* Fabbri and Klapper (2008) and Van Horen (2005)), we have also shown that firms may have a desire to balance accounts payable and accounts receivable. Our results also indicate that monopolists appear better able — perhaps due to their great bargaining power — to accomplish this goal.

To explain the big jump, we provided a model in which suppliers are able to post cash prices but are unable to commit *ex ante* to the terms of trade credit. This lack of commitment is a natural consequence of the fundamentally different nature between trade credit and cash. Cash payment represents a completely impersonal relationship between buyer and seller, whereas trade credit is much more demanding in terms of the buyer-seller relationship. Indeed, since payment is delayed (often beyond what was originally agreed upon), the terms of trade credit are effectively determined only after the good is delivered.

By simply allowing for some lack of commitment in setting trade credit price we showed that monopolists may be tempted to use trade credit as a tool for price discrimination and this possibility can seriously jeopardize their core business. This happens because borrowers, in anticipation of favorable trade credit conditions, decide not to pay cash. In this case suppliers may prefer to protect their main activity by accepting only cash payment. In the theoretical model we also demonstrated that this is more likely to happen if the market for "informal credit" is thin because the banks do relatively little credit rationing or if the supplier is particularly efficient in providing credit. Interestingly, this latter point suggests that, in the presence of commitment problems, the very same advantage that make suppliers ideal informal creditors can turn out to be detrimental to them and cause them to shun this extra role.

This result makes a contribution to the literature on informal credit markets. This literature, in line with the studies in corporate finance, has pointed out that suppliers can leverage the relationship with their clients and act as informal creditors, extending credit to borrowers who are rationed in the formal sector. Most of the advantages of suppliers over banks, such as lower monitoring costs, easier liquidation of inventories in case of default or higher enforcement power given by lock-in effects, are strongest when the supplier is a monopolist. Here we document empirically that monopolists often decide to give up their role as informal creditors and focus only on their core business.

While one should be cautious in making sweeping conclusions regarding welfare, two points do arise from our study. First, above and beyond the direct welfare loss of monopolies, there is a further effect due to the decreased likelihood that the monopolist will provide trade credit to its customers. Therefore, the final goods sector will be smaller (due to credit constraints) than in a more competitive environment. Second, the process of gradual improvement of formal credit markets may inflict an interim cost on the economy, by worsening the outcomes of those who still rely on the informal sector since, with credit more freely available, monopolist suppliers may actually be less likely to extend informal financing. Therefore, our results on small firms in Indonesia may serve as an example of what could happen in other less-developed or transition economies where formal credit is starting to be increasingly more available.

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Appendix A: Omitted Proofs

Proof of Observation 1: Let us focus on the subgame in which the supplier fixes t. For given c and m the suppliers will choose a t which maximizes the following profit function:

$$H(t) = \begin{cases} (t-m)(1-F(t))(1-\pi), & \text{if } t \geq c \\ (t-m)(1-F(t)-\pi(1-F(c))), & \text{if } t \leq c \end{cases} \tag{7}$$

Let t_L denote the trade credit price which maximizes $H(t)$ on the domain $[0,c]$, t_H the trade credit price which maximizes $H(t)$ on the domain $[c,\infty)$ and $\hat{t}$ the trade credit price which maximizes $H(t)$ on $\mathbb{R}_+$. Also observe that $t_H = \max\{c, t^*\}$, where $t^* = \text{argmax}(t-m)(1-F(t))(1-\pi)$ and that t^* is independent of c and π, while t_L depends is a function of both. We aim to show that there is a threshold, $\hat{\pi}(c,m)$ such that for all $\pi \leq \hat{\pi}(c,m)$, $\hat{t} = t_H$ and for all $\pi < \hat{\pi}(c,m)$, $\hat{t} = t_L < c$. In order to do so, define

$$Z(\pi) = (t_H - m)(1-F(t_H))(1-\pi) - (t_L - m)(1-F(t_L) - \pi(1-F(c)))$$

We will prove the existence of a unique point $\hat{\pi}(c,m)$ such that $Z(\hat{\pi}(c,m)) = 0$, and for π above this threshold, $Z(\pi) < 0$, while for π below this threshold $Z(\pi) > 0$.

First notice that $Z(0) > 0$ and $Z(1) > 0$. Therefore, since $Z(\pi)$ is continuous, the claim is proven if we can demonstrate that $Z'(\pi) < 0$.

$$Z'(\pi) = -\pi(t_H - m)(1-F(t_H)) + \pi(t_L - m)(1-F(c)) + \frac{\partial t_L}{\partial \pi}\frac{\partial Z}{\partial t_L}$$

We claim that the last term is zero and that the sum of the first two terms is negative. Consider the former claim. If we let x^* denote the unconstrained argmax of $(x-m)(1-F(x)-\pi(1-F(c))$, we see that one of two things may happen: either $x^* = t_L$, in which case $\frac{\partial Z}{\partial t_L} = 0$ or $x^* > t_L$, in which case $\frac{\partial t_L}{\partial \pi} = 0$. In either case, our claim is proven. Now consider the sum of the first two terms and notice that for all $\pi > 0$, $x^* < t^*$. Therefore, if $t_H = c$, $t_L < t_H$ and we are done. If $t_H > c$ and $t_L \leq c$, since $Z(0) > 0$, we are also done.

The next part of the proof requires us to show that $\hat{\pi}(c,m)$ is increasing in m and decreasing in c. Observe that $\frac{\partial Z(\hat{\pi}(c,m))}{\partial m} = (1-F(t_H))(1-\pi)) + \frac{\partial t_H}{\partial m}\frac{\partial Z}{\partial t_H} + (1-F(t_L) - \pi(1-F(c))) + \frac{\partial t_L}{\partial m}\frac{\partial Z}{\partial t_L}$. It can be easily shown that $\frac{\partial t_H}{\partial m}\frac{\partial Z}{\partial t_H} = 0$ and $\frac{\partial t_L}{\partial m}\frac{\partial Z}{\partial t_L} = 0$. Furthermore at $\pi = \hat{\pi}$ it must be that $(1-F(t_H))(1-\pi) <$

$1 - F(t_L) - \pi(1 - F(c))$. Hence, we have shown that $\frac{\partial Z(\hat{\pi}(c,m))}{\partial m} > 0$, which together with $\frac{\partial Z(\pi)}{\partial \pi} < 0$ implies that $\frac{\partial \hat{\pi}(c,m)}{\partial m} > 0$.

To show that $\hat{\pi}(c,m)$ is decreasing in c, notice that $\frac{\partial Z(\hat{\pi}(c,m))}{\partial c} < 0$. This together with $\frac{\partial Z}{\partial \pi} < 0$ shows the last part of the lemma.

Finally, if $c > t^*$ notice that for all $t < c$, $(t - m)(1 - F(t) - \pi(1 - F(c))) > (t - m)(1 - F(t))(1 - \pi)$. Therefore, when $t_H = c$, $Z(\pi) < 0$ for all π and it follows that $\hat{\pi} = 0$. □

We state, without proof, the following simple result:

Lemma 1. *Let c be the cash price fixed by the supplier. Suppose that the supplier holds the belief that all buyer types apply for trade credit. Then the optimal trade credit price is $t^* = \hat{t}$.*

Let the $\sigma_i(P, c, m, \phi_{nr})$ the probability that buyer i, with price P and access to cash, facing a cash price of c and a monitoring cost of m pays cash. Define a *pooling* strategy to be one in which for buyers i and j with $P_i, P_j > c$ and $P_i \neq P_j$, $\sigma_i(P_i, c, m) = \sigma_j(P_j, c, m) = \sigma(P)$.

Lemma 2. *If $c \in (\hat{c}, t^*)$ no pooling strategy can be part of an equilibrium of the continuation game.*

Proof. Suppose that a buyer of type $P > c$ observes $c \in (\hat{c}, \hat{t})$ and $\sigma(P) = 1$. Given her strategy, she must believe that $t > c$. On the other hand, given the proposed strategy of all high-price buyers, the supplier believes that such buyers actually pay cash. Therefore, by Observation 1, she will choose a trade credit price $t^* = t_L < c$ — a contradiction. Alternatively assume that the buyer observes $c \in (\hat{c}, \hat{t})$ and $\sigma(P) = 0$. In this case, she must anticipate $t \leq c$. In this proposed equilibrium, the supplier should correctly believe that all buyer types ask for trade credit. Therefore, by Lemma 1, she will set a trade credit price $t^* = \hat{t} > c$, again contradicting the presumption that we had an equilibrium.

The final case is the one in which $\sigma(P) \in (0, 1)$. In this case, high-price buyers must anticipate that $t = c$. The supplier's trade credit profit function at $t = c$ is $H(c) = (c - m)(1 - F(c))(1 - \pi\sigma(P))$. Now it can be easily seen that $H(c) < H(\hat{t})$, where $\hat{t}$ is as defined in Observation 1 — the unique argmax of the trade credit profit function. □

Lemma 3. *In any equilibrium with type-contingent strategies $t = c$, unless $\pi = 0$.*

Proof. The result is trivial for strictly mixed strategies. Therefore, consider the case in which two high-price buyers P_i and P_j adopt different pure strategies. Without loss of generality let $\sigma(P_i) = 0$ and $\sigma(P_j) = 1$. Define $\mathbb{E}[\Pi(\sigma(P_k)]$ to be the expected profit of buyer k conditional on his strategy, $\sigma(P_k)$. Suppose to the contrary that $t > c$. Clearly, this cannot be an equilibrium since $\mathbb{E}[\Pi(0)] = P_i - t < \pi(P_i - c) + (1 - \pi)(P_i - t) =$

$\mathbb{E}[\Pi(1)]$ unless $\pi = 0$. Next suppose that $t < c$. Analogously, we have $\mathbb{E}[\Pi(1)] = \pi(P_i - c) + (1-\pi)(P_i - t) < P_i - t = \mathbb{E}[\Pi(0)]$. □

Lemma 4. *A type-contingent strategy profile $\sigma(P)$, $P \in supp(F)$, is is part of a type-contingent equilibrium if and only if:*

$$\sigma(c) = 0 \tag{8}$$

$$\pi \int_c^{\infty} \sigma(P) f(P) dP = 1 - F(c) - f(c)(c - m) \tag{9}$$

Proof. From the previous lemma we know that a necessary condition for any type-contingent equilibrium strategy is that $t = c$. We now show that (8) and (9) are necessary and sufficient to induce the supplier to optimally set $t = c$.

Consider the supplier profit function from trade credit:

$$(t - m)[1 - F(t) - \pi \int_t^{\infty} \sigma(x) f(x) dx] \tag{10}$$

The demand for trade credit in square bracket can be seen as the mass of people with $P > t$ minus those who already paid cash. Recall that $\sigma(P) = 0$ for $\forall P < c$. The left derivative of (10) at $t = c$ is equal to

$$1 - F(c) - \pi \int_c^{\infty} \sigma(x) f(x) dx - f(c)(c - m) \tag{11}$$

while the right derivative is:

$$1 - F(c) - \pi \int_c^{\infty} \sigma(x) f(x) dx - f(c)(c - m) + \pi \sigma(c) f(c)(c - m) \tag{12}$$

Given that (10) is continuous and concave, the function obtains its maximal value at $t = c$ if and only if (11) ≥ 0 and (12) ≤ 0. The result easily follows from this. □

Given the continuation strategy profile by buyers given by (1) and the supplier's response given by (2), let $G(c)$ denote the profit function of the supplier as a function of the cash price. Furthermore, define $\tilde{c} = \text{argmax}_{c \in (\hat{c}, t^*]} G(c)$.[24]

[24] Under standard conditions, $\tilde{c}$ is assured to exist.

Lemma 5. *$G(\tilde{c}) > G(t^*)$.*

Proof. With some effort, one can show that for all $c \in (\hat{c}, t^*)$, $G(c) = (c-m)(1-F(c)) + mf(c)(c-m)$. Therefore, it is obvious that $G(\tilde{c}) = \max_{c \in (\hat{c}, t^*]}(c-m)(1-F(c)) + mf(c)(c-m) > \max(t-m)(1-F(t)) = G(t^*)$. □

Lemma 6. *The supplier's equilibrium strategy is:*

$$\begin{aligned}
(c,t) &= (c^*, t^*), \quad \text{if } \hat{c} \geq c^* \\
(c,t) &= (\tilde{c}, t^*), \quad \text{if } \hat{c} < c^* \text{ and } G(\hat{c}) < G(\tilde{c}) \\
(c,t) &= (\hat{c}, t^*), \quad \text{if } \hat{c} < c^* \text{ and } G(\hat{c}) \geq G(\tilde{c})
\end{aligned} \tag{13}$$

Proof. The supplier's total profit function is:

$$G(c,t) = c\pi \int_0^\infty \sigma(P)f(P)dP + (t-m)[1 - F(t) - \pi \int_0^\infty \sigma(P)f(P)dP]$$

which, upon plugging the strategies into (1) and (2), and simplifying, can be written as:

$$G(c) = \begin{cases} c\pi(1-F(c)) + (t^*-m)(1-F(t^*))(1-\pi) & \text{for } c \leq \hat{c} \\ (c-m)(1-F(c)) + m\pi \int_c^\infty \sigma(P)f(P)dP & \text{for } c \in (\hat{c}, t^*] \\ (t^*-m)(1-F(t^*)) & \text{for } c \geq t^* \end{cases} \tag{14}$$

To prove the optimality of the first equation in (13) suppose that $\hat{c} \geq c^*$. Then $\max G(c)$ for $c \leq \hat{c}$ is $G(c^*) = c^*(1-F(c^*))\pi + (t^*-m)(1-F(t^*))(1-\pi) \geq (t^*-m)(1-F(t^*))$ if and only if $c^*(1-F(c^*)) \geq (t^*-m)(1-F(t^*))$, which is easily seen to be the case. We must also show that $G(c^*) \geq G(\tilde{c})$. Rewrite $G(c)$ for $c \in (\hat{c}, t^*]$:

$$c(1-F(c)) - m\int_c^\infty (1 - \pi\sigma(P))f(P)dP \tag{15}$$

which can be shown to be scriptsizeer than $c(1-F(c))\pi + (c-m)(1-F(c))(1-\pi)$.[25]

To prove the optimality of the second equation in (13) recall from Lemma 5 that $G(\tilde{c}) \geq (t^*-m)(1-F(t^*))$. It is easily verified that if standard concavity conditions apply to the cash and trade credit profit functions and $\hat{c} < c^*$, then $\hat{c} = \text{argmax}_{c \leq \hat{c}} G(c)$. Therefore, if $G(\tilde{c}) \geq G(\hat{c})$ then $G(\tilde{c}) = \max G(c)$. The optimality of the third equation in (13) for the case in which $G(\hat{c}) \geq G(\tilde{c})$ follows easily. Finally, note that for $c \geq t^*$, $G(c)$ is constant. □

[25] Observe that $-m\int_c^\infty (1-\pi\sigma(P))f(P)dP \leq -m(1-\pi)(1-F(c))$; upon rearranging terms, the inequality becomes clear.

Proof of Proposition 1.

The proof of this result proceeds by showing the existence of two thresholds, π_1 and π_2, such that if $\pi > \pi_1$, the supplier would rather close the trade credit window rather than choose $c = \tilde{c}$, while if $\pi > \pi_2$, the supplier would rather close the trade credit window rather than choose $c = \hat{c}$. Then, the threshold as claimed in the statement of the proposition is $\hat{\pi}(m) = \max\{\pi_1, \pi_2\}$.

First, observe that the profit obtained by closing the trade credit window and choosing the optimal cash price is: $G(c^*|\text{cash only}) = \pi c^*(1 - F(c^*))$. Furthermore, recall that:

$$G(\tilde{c}) = \tilde{c}(1 - F(\tilde{c})) - mf(\tilde{c})(\tilde{c} - m) \quad (16)$$

$$G(\hat{c}) = \hat{c}(1 - F(\hat{c}))\pi + (t^* - m)(1 - F(t^*))(1 - \pi) \quad (17)$$

That $G(c^*|\text{cash only}) \geq$ (16) for π large enough is obvious once one realises that $\tilde{c}$ does not depend upon π. Therefore, we have that $\pi_1 = \frac{\tilde{c}(1-F(\tilde{c}))-mf(\tilde{c})(\tilde{c}-m)}{c^*(1-F(c^*))} < 1$.

That $G(c^*|\text{cash only}) \geq$ (17) for π large enough is also a straightforward calculation. Define $V(\pi) = \pi c^*(1 - F(c^*)) - \pi\hat{c}(1 - F(\hat{c})) - (t^* - m)(1 - F(t^*))(1 - \pi)$, and notice that $V(\pi)$ is continuous, $V(1) > 0$ and $V(0) < 0$. It can further be seen that $V'(\pi) > 0$ — hence the existence of π_2.

Finally, that the threshold is increasing in m, can easily be seen by examining (16) and (17) and observing that since both $\tilde{c}$ and $hatc$ are less than c^*, they are increasing in m. □

Proof of Proposition 2

Proof. First, observe that in equilibrium $c = 0$. If not, it can easily be seen that one supplier will always undercut the other so as to capture the entire cash market. To see that $t_{ij} = \max\{m_{ij}, \min\{m_{i,-j}, t^*_{ij}\}\}$ consider, WLOG, the maximization problem of supplier 1 with respect to buyer i: $\max_{t_{i1}}(t_{i1} - m_{i1})(1 - F(t_{i1}))$ subject to s.t. $t_{i1} \leq \max\{m_{i2}, m_{i1}\}$. The constraint comes from the fact that if $t_{i1} > m_{i2}$, then supplier 2 would find it optimal to undercut supplier 1 in order to serve buyer i. Obviously, if $m_{i2} < m_{i1}$ supplier 1 will set t_{i1} no scriptsizeer than m_{i1}.

Finally, the fact that in equilibrium the trade credit window is open follows trivially from the observation that if the trade credit window were closed, supplier profit would be zero since $c = 0$. □

Appendix B: Omitted Tables

Table 1: Descriptive Statistics

Variable	N	Mean	Std. Dev.	Min	Max
% goods sold on credit	598	46	41	0	100
# days of payment delay granted to customers	594	28	31	0	180
Employment	598	370	582	17	1800
# of competitors in subdistrict†	598	13	27	1	182
% goods exported	598	10	25	0	99
log(1 + sales)	598	14	2	0	20
log(1 + book value of fixed assets)	598	10	6	0	21
firm age (years)	598	12	11	0	80
interest expense on sales	568	0.02	0.06	0	0.94
% capacity usage	598	71	26	0	100
# of firms in subdistrict	598	92	111	1	398
log(sales in subdistrict)	598	19	2	10	23
Average % of goods exported in subdistrict	598	11	21	0	99
% production capacity usage in subdistrict	598	70	20	0	100
% firm turnover in subdistrict	598	0.11	0.14	0	2

† We include the actual firm; hence the minimum, obtained when the firm is a monopolist, is 1.

(a) All Firms

	Monopolists			Duopolists			
Variable	N	μ	σ	N	μ	σ	|t-stat|
% goods sold on credit	158	38.2	41.0	87	49.5	39.7	2.09**
[% sold on credit > 0]	158	0.53	0.50	87	0.70	0.46	2.68***
log(sales in subdistrict)	158	14.4	2.18	87	14.3	2.27	0.33
# of firms in subdistrict	158	33.1	47.3	87	61.6	85.8	3.36***
Ave. % of goods exported in s.d.	158	10.7	25.0	87	9.9	19.1	0.29
% production capacity usage in s.d.	158	64.8	29.3	87	71.2	18.7	1.83*
% firm turnover in subdistrict	158	0.12	0.21	87	0.13	0.15	0.11

*** p<0.01, ** p<0.05, * p<0.1

(b) Only Monopolist and Duopolist Firms

Table 2: Correlation Matrix

% goods sold on credit	1.000								
# days of payment delay granted to customers	0.688***	1.000							
Employment	-0.05	0.052	1.000						
# of competitors in subdistrict	-0.039	-0.019	0.007	1.000					
% goods exported	-0.073*	-0.018	0.198***	-0.064	1.000				
log(1 + sales)	0.082*	0.102**	0.385***	0.018	0.318***	1.000			
log(1 + book value of fixed assets)	0.096**	0.103**	0.128***	-0.081*	0.068	0.212***	1.000		
firm age (years)	-0.11***	-0.099**	0.072*	-0.059	-0.054	0.065	-0.039	1.000	
interest expense on sales	0.087**	0.218***	0.037	-0.032	-0.011	0.051	0.147***	-0.061	1.000
% capacity usage	0.175***	0.214***	-0.002	0.469***	-0.127***	0.115***	-0.095**	-0.049	-0.028
# of firms in subdistrict	0.227***	0.273***	0.103**	0.236***	-0.011	0.386***	0.075*	-0.082*	0.035
log(sales in subdistrict)	-0.049	-0.021	0.163***	-0.062	0.762***	0.315***	0.079*	-0.064	-0.004
Average % of goods exported in subdistrict	-0.032	0.014	0.058	0.109***	0.024	0.067	0.025	0.055	-0.034
% production capacity usage in subdistrict	-0.02	0.041	0.033	0.105**	0.046	0.052	0.036	0.078*	-0.03
% firm turnover in subdistrict	-0.06	-0.051	-0.05	0.028	-0.089**	-0.109***	-0.023	0.033	-0.05

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% capacity usage	1.000					
# of firms in subdistrict	0.666***	1.000				
log(sales in subdistrict)	-0.063	0.057	1.000			
Average % of goods exported in subdistrict	0.189***	0.135***	-0.009	1.000		
% production capacity usage in subdistrict	0.135***	0.111***	0.041	0.767***	1.000	
% firm turnover in subdistrict	-0.078*	-0.191***	-0.103**	-0.033	-0.016	1.000

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Tobit Percent of Goods Sold on Trade Credit in Early 1997 (Log-Quadratic Specification)

	(1)	(2)	(3)	(4)	(5)
log(# of competitors in subdistrict)	13.020 [3.560]***	11.531 [3.151]***	12.138 [3.112]***	7.718 [2.543]**	11.180 [2.928]***
log(# of competitors in subdistrict)^2	-3.491 [4.658]***	-3.450 [4.691]***	-3.769 [4.519]***	-2.499 [3.964]***	-3.130 [4.026]***
% goods exported	-0.143 [1.930]*	-0.223 [2.271]**	-0.198 [1.874]*	-0.132 [1.757]*	-0.129 [1.742]*
log(1 + sales)	0.769 [0.929]	0.752 [0.860]	1.217 [1.359]	-0.736 [0.924]	-0.737 [0.942]
log(1 + book value of fixed assets)	0.530 [1.887]*	0.546 [1.997]**	0.558 [1.825]*	0.217 [0.897]	0.193 [0.790]
log(# of firms in subdistrict)		5.391 [1.728]*	7.361 [2.294]**	6.382 [2.526]**	6.559 [2.584]**
log(sales in subdistrict)		-2.256 [1.319]	-3.883 [2.238]**	-2.478 [1.769]*	-2.571 [1.822]*
Average % of goods exported in subdistrict		0.174 [1.236]	0.156 [1.020]	0.078 [0.725]	0.070 [0.650]
% turnover in subdistrict		-29.332 [1.700]*	-25.505 [1.515]	-13.431 [0.964]	-11.863 [0.834]
firm age (years)			-0.396 [2.342]**	-0.266 [1.969]**	-0.255 [1.881]*
% production capacity usage			-0.063 [0.600]	-0.129 [1.395]	-0.130 [1.429]
interest expense on sales			70.197 [2.799]***	36.970 [1.662]*	41.911 [1.862]*
% production capacity usage in subdistrict			-0.071 [0.483]	0.004 [0.0333]	0.001 [0.0112]
% of inputs bought on credit				0.447 [11.16]***	0.417 [9.430]***
Monopoly × (% of inputs bought on credit)					0.145 [2.128]**
Constant	51.960 [1.817]*	107.300 [2.173]**	197.300 [3.560]***	189.600 [4.278]***	184.000 [4.118]***
Observations	598	598	568	566	566
Log Likelihood	-1711	-1705	-1640	-1554	1552

Dependent variable: % of goods sold on credit; estimation procedure: double-censored Tobit

Marginal effects at the unconditional expected value of the dependent variable

3-digit ISIC sector dummies and district dummies included in all specifications

Absolute value of robust t statistics in brackets (clustering at subdistrict level).

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Tobit Percent of Goods Sold on Trade Credit in Early 1997 (Piecewise Linear Specification)

	(1)	(2)	(3)	(4)	(5)
# of competitors in subdistrict	4.103 [2.616]***	3.268 [2.016]**	3.246 [1.933]*	2.189 [1.624]	3.327 [2.066]**
(# of comp − 4)×[# comp ≥ 4]	-4.331 [2.747]***	-3.521 [2.180]**	-3.540 [2.108]**	-2.396 [1.771]*	-3.542 [2.185]**
% goods exported	-0.143 [1.922]*	-0.220 [2.218]**	-0.196 [1.844]*	-0.130 [1.728]*	-0.123 [1.664]*
log(1 + sales)	0.785 [0.942]	0.782 [0.892]	1.201 [1.333]	-0.747 [0.935]	-0.752 [0.958]
log(1 + book value of fixed assets)	0.536 [1.914]*	0.554 [2.033]**	0.561 [1.827]*	0.218 [0.900]	0.194 [0.792]
log(# of firms in subdistrict)		5.032 [1.589]	7.074 [2.189]**	6.094 [2.409]**	6.247 [2.455]**
log(sales in subdistrict)		-2.202 [1.262]	-3.869 [2.205]**	-2.460 [1.739]*	-2.504 [1.759]*
Average % of goods exported in subdistrict		0.164 [1.148]	0.015 [0.938]	0.068 [0.627]	0.057 [0.526]
% turnover in subdistrict		-29.200 [1.716]*	-25.129 [1.526]	-13.140 [0.964]	-11.674 [1.867]*
firm age (years)			-0.393 [2.335]**	-0.262 [1.941]*	-0.253 [1.867]*
% production capacity usage			-0.064 [0.617]	-0.132 [1.427]	-0.132 [1.459]
interest expense on sales			71.589 [2.843]***	37.285 [1.689]*	41.900 [1.873]*
% production capacity usage in subdistrict			-0.065 [0.446]	0.010 [0.0832]	0.008 [0.0619]
% of inputs bought on credit				0.450 [11.20]***	0.424 [9.656]***
Monopoly × (% of inputs bought on credit)					0.127 [1.928]*
Constant	46.900 [1.594]	102.900 [2.018]**	194.200 [3.431]***	186.100 [4.088]***	179.2 [3.898]***
Observations	598	598	568	566	566
Log Likelihood	-1712	-1707	-1642	-1555	-1553

Dependent variable: % of goods sold on credit; estimation procedure: double-censored Tobit

Marginal effects at the unconditional expected value of the dependent variable

3-digit ISIC sector dummies and district dummies included in all specifications

Absolute value of robust t statistics in brackets (clustering at subdistrict level).

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Analysis of the Big Jump: A Closer Look at the Binary Decision to Grant Trade Credit

	(Logit) (1)	(Tobit) (2)	(Logit) (3)	(Tobit) (4)
log(# of competitors in subdistrict)	1.019 [3.110]***	1.464 [0.357]		
log(# of competitors in subdistrict)^2	-0.282 [4.016]***	-0.984 [1.303]		
Monopoly			-1.027 [2.785]***	1.25 [0.247]
% goods exported	-0.00227 [0.224]	-0.168 [2.372]**	-0.00235 [0.243]	-0.152 [2.079]**
log(1 + sales)	-0.166 [1.783]*	0.843 [1.227]	-0.169 [1.777]*	0.695 [1.020]
log(1 + book value of fixed assets)	0.0199 [0.649]	-0.307 [1.414]	0.0243 [0.818]	-0.319 [1.493]
log(# of firms in subdistrict)	0.468 [1.809]*	2.97 [1.175]	0.297 [1.196]	1.14 [0.466]
log(sales in subdistrict)	-0.121 [0.866]	-1.855 [1.329]	-0.0915 [0.660]	-1.285 [0.931]
Average % of goods exported in subdistrict	-0.00923 [0.681]	0.174 [1.821]*	-0.00864 [0.666]	0.16 [1.673]*
firm age (years)	-0.0306 [2.186]**	-0.023 [0.203]	-0.0268 [1.942]*	-0.007 [0.0633]
interest expense on sales	12.18 [2.467]**	-0.684 [0.0429]	13.17 [2.729]***	-1.138 [0.0703]
% production capacity usage	-0.00489 [0.610]	-0.065 [0.774]	-0.00534 [0.655]	-0.066 [0.817]
% of inputs bought on credit	0.048 [6.176]***	0.208 [6.050]***	0.0474 [6.183]***	0.216 [6.413]***
Monopoly ×(% of inputs bought on credit)	0.0268 [1.776]*	0.018 [0.289]	0.0292 [1.867]*	-0.002 [0.0342]
Constant	23.83 [8.208]***	104.7 [4.000]***	24.82 [8.843]***	100.9 [3.926]***
Observations	497	358	497	358
Log Likelihood	-180.4	-1251	-183.2	-1253

(1) & (3) Dependent variable: 1 iff trade credit > 0.

(1) & (3) Estimated coefficients reported.

(2) & (4) Dependent variable: % of goods sold on credit if trade credit > 0.

(2) & (4) Marginal effects at the unconditional expected value of the dependent variable

3-digit ISIC sector dummies and district dummies included in all specifications

Absolute value of robust t statistics in brackets (clustering at subdistrict level).

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Random and Fixed Effects Estimates (Percent of Goods Sold on Trade Credit; Log-Quadratic and Piecewise Linear Spline)

	Subdistrict Fixed Effects (Logit) (1)	Subdistrict Random Effects (Logit) (2)	Subdistrict Fixed Effects (OLS) (3)	Subdistrict Fixed Effects (Logit) (4)	Subdistrict Random Effects (Logit) (5)	Subdistrict Fixed Effects (OLS) (6)
log(# of comp in subdistrict)	0.732 [1.783]*	0.745 [2.796]***	13.38 [2.141]**			
log(# of comp in subdistrict)^2	-0.223 [1.963]**	-0.22 [3.792]***	-3.323 [2.367]**			
# of comp in subdistrict				0.124 [0.847]	0.213 [1.871]*	4.258 [1.632]
(# of comp $-$ 4)$\times$[# comp $\geq$ 4]				-0.14 [0.908]	-0.227 [1.992]**	-4.394 [1.674]*
% goods exported	-0.00182 [0.266]	-0.00688 [0.992]	0.107 [0.790]	-0.00192 [0.274]	-0.00658 [0.950]	0.113 [0.835]
log(1 + sales)	0.00807 [0.112]	-0.0158 [0.243]	1.138 [0.945]	0.0112 [0.156]	-0.0115 [0.178]	1.209 [1.003]
log(1 + book value of fixed assets)	0.0219 [0.766]	0.0488 [2.403]**	0.515 [1.240]	0.0225 [0.793]	0.0492 [2.439]**	0.514 [1.237]
log(# of firms in subdistrict)		0.341 [1.671]*			0.304 [1.520]	
log(sales in subdistrict)		-0.031 [0.276]			-0.026 [0.233]	
Ave. % of goods exported in subdistrict		0.00431 [0.500]			0.00372 [0.431]	
% production capacity usage		-0.00446 [0.769]			-0.00377 [0.654]	
Constant		20.44 []	87.78 [4.359]***		20.12 []	82.32 [4.064]***
Observations	276	598	598	276	598	598
Log Likelihood	-105.5	-281	—	-107.3	-282.8	—
R^2	—	—	0.264	—	—	0.259

Absolute value of robust z statistics in brackets (clustering at subdistrict level).

*** p<0.01, ** p<0.05, * p<0.1

Table 7: Random and Fixed Effects Estimates (Percent of Goods Sold on Trade Credit; Step Function)

	Subdistrict Fixed Effects (Logit) (7)	Subdistrict Random Effects (Logit) (8)	Subdistrict Fixed Effects (OLS) (9)
# comp in subdistrict ≥ 2	2.051 [3.154]***	0.825 [2.203]**	23.61 [2.481]**
# comp in subdistrict ≥ 3	-0.712 [0.832]	0.119 [0.237]	-4.771 [0.513]
# comp in subdistrict ≥ 4	-0.803 [1.024]	-0.000488 [0.000871]	-1.639 [0.154]
# comp in subdistrict ≥ 5	0.222 [0.227]	-0.248 [0.369]	8.039 [0.434]
# comp in subdistrict ≥ 6	0.477 [0.414]	-0.412 [0.499]	-3.514 [0.199]
# comp in subdistrict ≥ 7	-0.98 [0.823]	0.339 [0.370]	9.125 [0.557]
# comp in subdistrict ≥ 8	0.488 [0.607]	-0.0739 [0.102]	-19.07 [1.611]
(# of comp in subdistrict)×[# comp ≥ 9]	-0.0104 [0.703]	-0.0124 [2.515]**	-0.047 [0.302]
% goods exported	-0.000735 [0.106]	-0.0074 [1.056]	0.11 [0.811]
log(1 + sales)	0.00951 [0.119]	-0.0146 [0.220]	1.284 [1.048]
log(1 + book value of fixed assets)	0.0269 [0.804]	0.0522 [2.538]**	0.531 [1.283]
log(# of firms in subdistrict)		0.343 [1.667]*	
log(sales in subdistrict)		-0.0337 [0.297]	
Average % of goods exported in subdistrict		0.00559 [0.636]	
% production capacity usage		-0.00471 [0.810]	
Constant		25.58 [11.94]***	86.18 [4.063]***
Observations	276	598	598
Log Likelihood	-101	-280.1	—
R^2	—	—	0.278

Absolute value of robust z statistics in brackets (clustering at subdistrict level).

*** p<0.01, ** p<0.05, * p<0.1

TABLE 8: The Big Jump (Fixed Effects Estimates): A Closer Look at the Binary Decision to Grant Trade Credit

	Subdistrict Fixed Effects (Logit) (1)	Subdistrict Fixed Effects (OLS) (2)	Subdistrict Fixed Effects (OLS) (3)
Monopoly	-0.885	-12.14	-12.78
	[1.797]*	[1.816]*	[1.648]
% goods exported	0.00289	0.0231	-0.0824
	[0.357]	[0.226]	[0.629]
log(1 + sales)	-0.0852	-0.856	0.201
	[0.889]	[0.661]	[0.186]
log(1 + book value of fixed assets)	0.0144	0.263	-0.0299
	[0.463]	[0.755]	[0.0767]
% of inputs bought on credit	0.0428	0.475	0.181
	[4.953]***	[8.399]***	[3.481]***
Monopoly × (% of inputs bought on credit)	0.00929	0.103	0.0944
	[0.548]	[0.844]	[0.811]
Constant		74.31	83.57
		[3.161]***	[4.338]***
Observations	275	596	369
Log Likelihood	-69.52	—	—
R^2	—	0.463	0.34

Dependent Variable: (1) 1 iff trade credit > 0.

Dependent Variable: (2) % of goods sold on credit.

Dependent Variable: (3) % of goods sold on credit if credit > 0.

Absolute value of robust z statistics in brackets (clustering at subdistrict level).

*** p<0.01, ** p<0.05, * p<0.1

Table 9: Estimates at District Level (Percent of Goods Sold on Trade Credit)

	(Tobit) (1)	(Tobit) (2)	District Fixed Effects (OLS) (3)	District Fixed Effects (OLS) (4)
log(# of competitors in district)	9.657 [2.708]***		12.22 [2.386]**	
log(# of competitors in district)^2	-1.439 [1.771]*		-2.049 [1.858]*	
# of competitors in district		7.315 [3.301]***		8.861 [2.198]**
(# of competitors-4)×[# comp ≥ 4]		-7.329 [3.305]***		-8.898 [2.204]**
% goods exported	-0.141 [1.406]	-0.135 [1.322]	-0.125 [1.355]	-0.116 [1.250]
log(1 + sales)	1.680 [1.947]*	1.608 [1.928]*	0.902 [1.018]	0.822 [0.942]
log(1 + book value of fixed assets)	0.574 [1.407]	0.584 [1.415]	0.611 [1.716]*	0.62 [1.791]*
population in district	8.700 [2.538]**	7.984 [2.280]**		
Constant	-98.57 [2.882]***	-114.7 [3.109]***	5.114 [0.377]	-3.889 [0.236]
Observations	598	598	598	598
Log Likelihood	-1787	-1788	—	—
R^2	—	—	0.107	0.105

Dependent variable: % of goods sold on credit; estimation procedure: double-censored Tobit

(1) & (2) report marginal effects at the unconditional expected value of the dependent variable

3-digit ISIC sector dummies in all specification; province dummies included in (1) & (2)

Absolute value of robust t statistics in brackets (clustering at district level).

*** p<0.01, ** p<0.05, * p<0.1

TABLE 10: Alternative Geographical Areas (Percent of Goods Sold on Trade Credit)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(# of competitors in country)	17.548 [1.050]	17.337 [1.039]	17.199 [1.025]	17.811 [1.077]	17.733 [1.087]	17.201 [1.123]	16.869 [1.108]	2.294 [0.944]	
log(# of competitors in country)^2	-1.340 [0.868]	-1.333 [0.865]	-1.326 [0.857]	-1.389 [0.913]	-1.377 [0.919]	-1.326 [0.937]	-1.386 [0.983]		
log(# of competitors in province)	-5.034 [0.708]	-4.793 [0.676]	-4.559 [0.645]	-2.887 [0.465]	-1.604 [0.257]	-1.147 [0.386]			
log(# of competitors in province)^2	0.271 [0.325]	0.266 [0.317]	0.239 [0.287]	0.033 [0.0463]	0.061 [0.0852]				
log(# of competitors in district)	5.318 [0.941]	5.498 [0.921]	5.096 [0.904]	2.764 [0.954]					
log(# of competitors in district)^2	-0.487 [0.535]	-0.473 [0.522]	-0.439 [0.490]						
log(# of competitors in village)	-3.532 [0.368]	2.553 [0.615]							
log(# of competitors in village)^2	1.608 [0.568]								
log(# of competitors in subdistrict)	10.524 [2.141]**	9.272 [2.049]**	9.74 [2.211]**	10.446 [2.464]**	12.117 [3.252]***	12.092 [3.249]***	11.867 [3.162]***	12.102 [3.228]***	13.02 [3.560]***
log(# of competitors in subdistrict)^2	-3.401 [3.118]***	-3.129 [3.576]***	-2.967 [3.528]***	-3.175 [4.075]***	-3.307 [4.373]***	-3.296 [4.433]***	-3.299 [4.395]***	-3.404 [4.565]***	-3.491 [4.658]***
% goods exported	-0.145 [1.963]*	-0.148 [2.022]**	-0.146 [1.986]**	-0.146 [1.980]**	-0.148 [2.000]**	-0.148 [2.001]**	-0.150 [2.039]**	-0.146 [1.984]**	-0.143 [1.930]*
log(1 + sales)	0.770 [0.947]	0.804 [0.975]	0.781 [0.954]	0.801 [0.976]	0.813 [0.995]	0.810 [0.993]	0.801 [0.978]	0.818 [0.996]	0.769 [0.929]
log(1 + book value of fixed assets)	0.540 [1.905]*	0.549 [1.947]*	0.549 [1.932]*	0.550 [1.936]*	0.552 [1.939]*	0.552 [1.941]*	0.560 [1.977]**	0.541 [1.923]*	0.530 [1.887]*
Constant	-52.19 [0.528]	-61.5 [0.626]	-56.75 [0.573]	-61.38 [0.629]	-67.5 [0.698]	-66.84 [0.694]	-62.44 [0.659]	20.69 [0.494]	51.96 [1.817]*
Observations	598	598	598	598	598	598	598	598	598
Log Likelihood	-1709	-1709	-1709	-1709	-1710	-1710	-1710	-1710	-1711

Dependent variable: % of goods sold on credit; estimation procedure: double-censored Tobit

Marginal effects at the unconditional expected value of the dependent variable

3-digit ISIC sector dummies and district dummies included in all specifications

Absolute value of robust t statistics in brackets (clustering at subdistrict level).

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

TABLE 11: Market Shares (Percent of Goods Sold on Trade Credit)

	(1)	(2)
Market share in subdistrict	39.525 [1.968]**	39.049 [1.985]**
(Market share in subdistrict)^2	-47.524 [2.546]**	-42.378 [2.288]**
Market share in district		-8.609 [0.982]
Market share in country		-26.822 [0.475]
Market share in province		-5.526 [0.326]
% goods exported	-0.217 [1.947]*	-0.220 [1.981]**
log(1 + sales)	0.632 [0.638]	1.144 [1.202]
log(1 + book value of fixed assets)	0.696 [2.441]**	0.726 [2.537]**
log(# of firms in subdistrict)	2.583 [0.825]	3.093 [0.983]
log(sales in subdistrict)	-0.966 [0.556]	-0.964 [0.559]
Average % of goods exported in subdistrict	0.196 [1.281]	0.198 [1.264]
Constant	105.5 [2.183]**	87.99 [1.794]*
Observations	594	594
Log Likelihood	-1705	-1704

Dependent variable: % of goods sold on credit; estimation procedure: double-censored Tobit

Marginal effects at the unconditional expected value of the dependent variable

3-digit ISIC sector dummies and district dummies included in all specifications

Absolute value of robust t statistics in brackets (clustering at subdistrict level).

*** p<0.01, ** p<0.05, * p<0.1

TABLE 12: Industry Analysis (Percent of Goods Sold on Trade Credit)

	All Sectors	w/o metal product & machines	Food	Textile	Chemical & plastic prods	Metal product & machines
	(1)	(2)	(3)	(4)	(5)	(6)
log(# of competitors in subdistrict)	11.607	7.636	10.658	3.227	-0.842	50.672
	[3.125]***	[2.013]**	[1.287]	[0.462]	[0.0983]	[2.806]***
log(# of competitors in subdistrict)^2	-3.480	-2.951	-4.291	-1.975	-1.482	-13.878
	[4.723]***	[3.992]***	[0.977]	[1.564]	[0.907]	[2.570]**
log(1 + sales)	0.539	0.191	-1.137	2.466	1.096	0.998
	[0.643]	[0.211]	[0.819]	[1.182]	[0.661]	[0.414]
log(1 + book value of fixed assets)	0.517	0.497	0.607	-0.621	-0.27	1.482
	[1.849]*	[1.677]*	[1.243]	[0.810]	[0.540]	[1.666]
log(# of firms in subdistrict)	3.195	3.514	5.568	-1.375	10.265	5.252
	[1.604]	[1.751]*	[1.957]*	[0.343]	[3.572]***	[0.618]
% goods exported	-0.126	-0.131	-0.148	-0.059	0.003	-0.120
	[1.739]*	[1.786]*	[1.154]	[0.501]	[0.0237]	[0.142]
Constant	44.33	65.37	33.55	94.24	-8.028	-325.9
	[1.533]	[2.210]**	[0.855]	[1.470]	[0.104]	[2.122]**
Observations	598	549	209	154	186	49
Log Likelihood	-1709	-1581	-609.3	-404.9	-540.2	-115.9

Dependent variable: % of goods sold on credit; estimation procedure: double-censored Tobit

Marginal effects at the unconditional expected value of the dependent variable

3-digit ISIC sector dummies and district dummies included in all specifications, except [6] where province dummies used.

Absolute value of robust t statistics in brackets (clustering at subdistrict level).

*** $p<0.01$, ** $p<0.05$, * $p<0.1$