

The Signalling Role of Trade Credit: Evidence from a Counterfactual Analysis*

Pasqualina Arca[†] Gianfranco Atzeni[‡] Luca Deidda[§]

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Abstract

We quantify the signaling effect of trade credit on bank credit in a sample of US firms. Our identification strategy relies on the signaling model by Biais and Gollier (1997) and accounts for the endogeneity due to the possibility of self-selection and the simultaneity between banks' and firms' credit decisions. We find that: i) firms' self-select into trade credit; ii) firms' decision to use trade credit results in a higher chance of obtaining bank credit and a lower cost than the counterfactual ones they would have faced if not using trade credit.

Keywords: Trade credit, Asymmetric Information, Counterfactual, Signalling, Bank Credit, Cost of credit, Endogenous Switching Regression.

JEL-Codes: C21, D82, G32.

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[†]Dipartimento di Giurisprudenza, Università di Sassari

[‡] DiSea, Università di Sassari and CRENoS

[§] DiSea, Università di Sassari and CRENoS

1 Introduction

Trade credit is the most important source of short-term external finance for many firms. Rajan and Zingales (1995) report that in 1991 trade credit (estimated using accounts payable) amounted to 15% of total assets for a large sample of non-financial US firms.¹ In Mian and Smith Jr (1994), trade credit comprised 26% of the total debts of non-financial firms listed on the NASDAQ at the end of 1992. In the sample used by Aktas, De Bodt, Lobež, and Statnik (2012), which contains non-financial, listed US firms between 1992 and 2007, trade credit represents an average of 8.22% of total assets. Trade credit is an important financing source also outside of the US. Marotta (2005) shows that trade credit finances, on average, 38.1% of the input purchases of non-rationed Italian firms and 37.5% of rationed ones. Using a survey that covers 48 countries, Beck, Demirgüç-Kunt, and Maksimovic (2008) find that, on average, trade credit accounts for 19.7% of all external finance used to finance investments. They also find that trade credit is the second most important source of external finance in most countries. Such large use of trade credit is surprising if we compare its cost with other short-term financial resources. For instance, the equivalent one-year interest rate of a “two-part” contract is about 44% (Cuñat, 2007; Ng, Smith, and Smith, 1999)².

In this paper, we focus on the strategic relationship between bank and trade credit due to the potential signaling role of trade credit. Specifically, our objective is to empirically identify the signaling effect of trade credit and how the information content of the decision to use trade credit affects firms’ access to credit and its cost, using firm-level data from the US.

We base our identification strategy on the theoretical model by Biais and Gollier (1997), hereafter BGM, according to which trade credit is used to reduce the information asymmetry between firms and banks. The BGM provides the theoretical foundations

¹Ellehausen and Wolken (1993) report that in 1987 trade credit accounted for about 15% of the liabilities of non-farm non-financial businesses in the United States (US), and for small businesses, this percentage was about 20% of their liabilities.

²A standard two-part contract offers the client a discount of 2 percent if they pay within ten days of delivery. Otherwise, they are expected to pay the total amount due by the 30th day, which, according to Ng, Smith, and Smith (1999) is the most typical deal used in the US. Other standard deals such as “8-30 net 50” imply even higher implicit interest rates (Cuñat, 2007).

necessary to pin down the endogeneity problems that might affect any empirical analysis of the relationship between trade credit and bank credit, thereby undermining its validity. Accordingly, the paper’s contribution is also to put forward an estimation strategy that, being grounded on the BGM signaling model, delivers consistent and efficient estimates of the informational content of the trade credit decision and its effects.

The BGM shows that trade credit constitutes a signaling device for creditworthy and yet informationally opaque firms in a credit market characterized by asymmetric information. Trade credit helps these firms to signal their creditworthiness to the banks. The intuition is that firms that extend trade credit to other firms, might have more information about the creditworthiness of these firms compared to banks, due to pre-existing commercial relationships. By obtaining trade credit, creditworthy and opaque firms can pass such information to the banks, thereby reducing the asymmetric information that would otherwise prevent them from accessing bank credit. Therefore, even though trade credit is the most expensive source of finance, opaque firms in need of financial resources, differently from transparent ones, can strategically decide to use trade credit to increase their chance to access bank credit and reduce its cost,

From an empirical perspective, such strategic interaction between firms and banks gives rise to two sources of endogeneity. First, since informationally opaque and creditworthy firms have a different incentive to self-select into the use of trade credit, and the creditworthiness of informationally opaque firms is, by definition, unobservable, there is a selection issue. Consequently, the causal effect of such unobservable characteristics must be considered when estimating the impact of trade credit on access and cost of bank credit. Second, the decision to use trade credit is strategically driven by the consequences in terms of access and cost of credit.³

In order to account for these sources of endogeneity, we use an endogenous switching regression approach. Specifically, the estimation strategy is the following. First, we explicitly model the process according to which, based on their private information, firms self-select into the use of trade credit or not. Namely, firms that suffer from asymmetric

³We use “cost of credit” and “interest rate” interchangeably.

information (opaque firms) self-select into the use of trade credit, while firms that do not suffer from asymmetric information (transparent firms) do not. Once we have accounted for self-selection, we estimate the bank loan interest rate and the probability of obtaining financing with and without trade credit. We also compute the expected actual and counterfactual outcomes and hence the treatment effects.

Our estimates confirm that firms self-select into the use of trade credit to convey information about their creditworthiness to the banks. Firms self-selecting into the use of trade credit face a lower cost of bank credit than the counterfactual one they would have faced not using it. Similarly, firms who do not self-select into trade credit face a higher cost of bank credit than the counterfactual one they would have faced if using it. Notably, the effect is stronger for firms self-selecting into the use of trade credit. In addition, we find that the counterfactual cost of bank credit that firms not using trade credit would have faced had they used it is lower than the cost of bank credit faced by firms that use trade credit. Similarly, the cost of bank credit faced by firms not using trade credit is smaller than the counterfactual cost of credit that firms using trade credit would have faced if not using it. These results corroborate the hypothesis based on the BGM that firms not using trade credit are less opaque to start with and, therefore, are perceived as less risky by the bank. Finally, concerning the probability of obtaining financing, we find a positive effect of the treatment on the treated. The probability of obtaining financing for firms that self-select into the use of trade credit is higher than the counterfactual probability of accessing credit that firms that do not use trade credit would have faced had they decided to use it. Our analysis complements the theoretical model of Biais and Gollier (1997) by adopting the model as an identification tool and providing a set of direct, reliable empirical tests of the key assumptions and equilibrium properties of the model, which we find to be strongly supported by the US data.

Extensive empirical literature focuses on the relationship between bank and trade credit.⁴ Within that literature, the evidence of complementarity between the two sources

⁴See, among many others, Cuñat and Garcia-Appendini (2012), Palacín-Sánchez, Canto-Cuevas, and Di-Pietro (2019), Bussoli, Giannotti, Marino, and Maruotti (2022) for an extensive review on the role of trade credit in entrepreneurial finance.

of finance is often interpreted as evidence of the signaling role of the latter. However, most of the existing contributions neither identify the informational content of trade credit directly nor fully account for the endogeneity due to the informative and strategic role of the decision to use trade credit.

Using NSSBF data, Giannetti, Burkart, and Ellingsen (2011) find that trade credit seems to facilitate access to bank credit by firms that have shorter lending relationships with banks, which is suggestive of the possibility that trade credit is acting as a signal.⁵ Similarly, Agostino and Trivieri (2014), using micro-data on Italian SMEs in the years 1998-2006, find that bank funding tends to increase more as trade credit increases for those firms that have a shorter lending relationship with the financing banks. However, both studies do not fully account for the fact that the decision to use trade credit might result from a self-selection process corresponding to the strategic behavior of opaque firms that seek better outcomes in terms of access and cost of bank credit.

On a related ground, Atanasova (2012) tests the relationship between trade credit and bank financing using GMM. She distinguishes between a level effect, i.e., the quantitative effect of trade credit on the ratio of bank debt to sales, and a time effect, finding that the importance of trade credit as a financing source declines with firm age. The use of GMM accounts for the simultaneity between trade credit and bank debt. However, the potential endogeneity due to self-selection in trade credit is still not directly addressed. Garcia-Appendini (2011) computes an increase in the probability of obtaining a bank loan for firms using trade credit that ranges between 6% and 24%. These results are consistent with the idea that sellers provide quality certification to finance firms. She compares an IV approach with sample selection and propensity score. However, the empirical model does not consider the possibility that trade credit is used strategically to obtain a lower cost of credit and a higher probability of accessing credit.

Del Gaudio, Sampagnaro, Porzio, and Verdoliva (2021), using confidential data at the

⁵Consistently with such signaling role of trade credit, Engemann, Eck, and Schnitzer (2014), in a sample of German manufacturing firms, find that while in general trade credit and bank credit are inversely related, such relationship is attenuated for financially constrained exporters. Elliehausen and Wolken (1993), using a different wave of the NSSBF dataset, find evidence of complementarity, as firms that use a relatively large amount of short-term bank credit are also the most significant users of trade credit.

firm-bank loan level of Italian SMEs, examine the role of trade credit in the loan approval process. They find that the probability of a borrower receiving a positive response to a loan request increases with the amount of trade credit, which is consistent with the hypothesis that trade credit is a positive signal. They consider the endogeneity arising from the reverse causality between bank and trade credit by employing an IV estimation, which relates to the strategic content of the trade credit decision. Nevertheless, their empirical model does not fully account for self-selection.

The above discussion highlights the need for an empirical model that correctly identifies the informative and strategic contents of the firms' decision to use trade credit. In this paper, we provide such a model, which enables us to quantify the significant signaling effect of trade credit on bank credit access and the cost of credit. Our results support the predictions of Biais and Gollier (1997) and fully rationalize the interpretation often put forward in the literature that the complementarity between bank and trade credit found in the data is due to the signaling effect of the latter.

The remainder of the paper is organized as follows. Section 2 discusses the signaling role hypothesis stemming from the BG model. In particular, in section 3 we present the empirical model and the testable hypotheses. In section 4, we discuss the data and the estimation results. Section 5 concludes the paper.

2 BGM: signalling role of trade credit

According to the BGM, trade credit facilitates firms' access to credit and reduces the cost of bank credit by providing banks with an informative signal about firms' creditworthiness. The BGM considers an adverse selection framework with three types of risk-neutral agents: banks, buyers, and sellers. Banks lend to both buyers and sellers. The buyers are firms endowed with an investment opportunity that requires one input unit and generates a random cash flow at the end of the period. They are of two types: creditworthy and not creditworthy.⁶ Buyers do not have cash, so in order to undertake the investment,

⁶Creditworthy buyers' investments have a positive NPV, while the NPV of the investments of the not creditworthy type is negative.

they either borrow financial resources from the banks or buy the required inputs through delayed payment (trade credit). The sellers are the firms that produce and supply the buyers with the inputs. Sellers are cashless and cover their liquidity needs associated with production costs by requiring buyers to pay cash or borrow from the banks. In the latter case, they are in the condition to offer buyers trade credit by accepting delayed payments on input supplies.⁷ Each seller is assumed to interact with only one buyer. Each buyer perfectly observes her type. Banks and sellers receive a private independent signal about each buyer's type. Suppose buyers can obtain financing only from banks, and the observable information about firm creditworthiness is not very informative. Then, if the proportion of not creditworthy buyers is sufficiently high, the credit market breaks down as the equilibrium cost of bank loans would be too high to sustain the exchange of financial resources. Under these circumstances, the BGM shows that delayed payments conceded by sellers to their buyers (trade credit) might restore the functioning of the credit market. The banks and the sellers simultaneously finance buyers. The bank finances a fraction of the buyer's financial needs conditional on receiving a positive signal and on the seller co-financing buyers through trade credit. Similarly, the seller supplies trade credit for a fraction of the buyer's purchase conditional on observing a positive signal about the creditworthiness of that buyer and on the bank co-financing the rest of the buyer's financial needs. Note that trade credit is more expensive than bank credit. Therefore, the buyer demands trade credit if and only if it is necessary to obtain credit.⁸

In this paper, we are interested in the empirical evidence of trade credit as a signaling device to reduce buyers' credit rationing. Therefore, in the next section, we discuss how we apply the BGM model to derive an identification strategy and some related testable hypotheses about (i) the decision to use trade credit; (ii) the probability of obtaining bank financing, and; (iii) the cost of bank credit.

⁷Note that, in this case, they could collateralize their bank debt by pledging an exogenous source of income to ensure banks against the losses they would experience if their buyers default on trade credit.

⁸The higher cost of trade credit compared to bank credit that emerges in the BGM is also documented in Cuñat (2007) and Ng, Smith, and Smith (1999).

3 Empirical model

In reality, there are firms that banks can easily rate and firms that banks cannot rate at all. Accordingly, in applying the BGM to obtain an identification strategy for our empirical analysis, we allow for transparent and opaque firms. Coherently with the original BGM, we assume that banks observe a very informative signal about the creditworthiness of transparent firms. In contrast, the signal they observe about opaque firms is not informative. Therefore, the BGM implies that trade credit is useless for transparent firms. Differently, opaque firms might be willing to engage in costly trade credit to inform banks, thereby increasing the chance to access bank credit and reducing the cost of bank credit. In other words, the BGM predicts that trade credit signals firms' creditworthiness to banks. Accordingly the bank decides whether to offer credit and at what interest rate also based on such information, and the firm anticipates such behavior of the bank. Based on this argument, we derive the following set of testable hypotheses.

Hypothesis 1. The firm's decision to use trade credit conveys otherwise unobservable information.

Hypothesis 2. Banks' decision to extend credit and firms' decision to use trade credit are interdependent. Similarly, banks' interest rate decisions and firms' decisions about trade credit are interdependent.

Hypothesis 3. Firms that use trade credit face a lower interest rate on bank loans than the one they would have faced had they not used trade credit (counterfactual).

Hypothesis 4. Firms that use trade credit have a higher probability of being financed than the one they would have faced had they not used trade credit (counterfactual).

The strategic interaction between firms and banks gives rise to two sources of endogeneity, which must be taken into account to correctly identify the signaling role of trade credit in the empirical analysis. The first source of endogeneity originates from firms' unobserved heterogeneity in the incentive to use trade credit. Opaque and creditworthy firms have a

different incentive to use trade credit compared to transparent ones. Accordingly, a firm's self-selecting into trade credit informs the bank about its creditworthiness (Hypothesis 1). Indeed, it is crucial to distinguish between the causal effect of trade credit use on bank credit and the effect of firms' unobserved heterogeneity.

The second source of endogeneity arises from the interdependence between the decision of firms and banks. On the one end, a firm behaves strategically as it expects its choice to affect the bank's decision. On the other hand, the bank decides whether to extend credit and the interest rate based on the firm's choice (Hypothesis 2).

The above endogeneity problems imply an effect of the unobservable heterogeneity of firms associated with the decision to use trade credit on the cost of credit (Hypothesis 3) and access to it (Hypothesis 4).

The econometric strategy must consider two aspects based on the discussion mentioned above. First, the fact that firms self-select into trade credit also due to unobservable characteristics implies that the effect of trade credit cannot be correctly inferred by differences in access and cost of credit between firms that use it and those that do not. The self-selection process means that there are common unobservable characteristics determining the decision to use trade credit and the cost of bank credit and the access to it. Econometric models that do not account for this problem produce biased results.

Second, since a firm's use of trade credit and expected outcomes in terms of access and cost of bank credit are interdependent, the observable factors that determine trade credit cannot be considered exogenous, which is essentially a problem of simultaneity.

In principle, to take into account the interdependence of firms' and banks' decisions, a possibility would be to estimate two models consisting of two simultaneous equations each. The first model would consist of an equation for the decision of the firm to use trade credit as a function of the bank's loan interest rate and one of the loan interest rate decisions of the bank as a function of the firm's decision to use trade credit. The second model would consist of an equation for the decision of the firm to use trade credit as a function of the bank's decision to extend credit and one for the bank's decision to extend credit as a function of the firm's trade credit decision. However, we cannot implement

such models directly for the following reasons. First, while we observe the cost of bank credit for firms using trade credit (TC), we do not observe the interest rate they would have been charged had they chosen not to use trade credit (NTC). Second, while we observe the probability of accessing credit for firms using trade credit, we do not observe the probability they would have faced if not using trade credit. As a consequence, the errors of each of the two-equation models we just described would be correlated (Kai and Prabhala, 2007).

As described in the following subsections, our empirical strategy is to develop two switching models. One accounts for the role of unobservables in determining the use of trade credit and the cost of bank credit: The other accounts for the role of unobservables in determining the use of trade credit and the access to bank credit.

3.1 Trade credit and cost of credit

In this subsection, we describe the econometric framework that we use to test whether the trade credit choice conveys unobservable (private) information to the bank (Hypotheses 1), which the bank uses to determine the interest rate (Hypothesis 3). We develop a switching regression in two stages, which allows us to test the significance of the correlation between unobservable factors that drive the selection into trade credit and those that affect the bank's interest rate decision, which is the first source of endogeneity in our model. Second, we implement an endogenous switching regression that allows to consider also the second potential source of endogeneity, which lies in the interdependence between firms' and banks' decisions (Hypothesis 2). Notice that the endogenous switching model still allows us to test for Hypotheses 1 and 3 by looking at the significance of correlation coefficients between the error terms of the decision to use trade credit and the interest rate equations.

We model the decision to use trade credit as follows. The value to firm i of using trade credit is

$$TC_i^* = Z_i\gamma + v_i, \tag{1}$$

where Z is a set of trade credit determinants, γ is a vector of parameters, and v is the

error term. The latent variable TC^* is associated with the following index function:

$$TC_i = \begin{cases} 1 & \text{if } Z_i\gamma + v_i > 0 \\ 0 & \text{if } Z_i\gamma + v_i \leq 0. \end{cases} \quad (2)$$

Note that in the data, we do not observe directly TC_i^* , while we observe whether a firm uses trade credit, which can be informative about TC_i .

In modelling the cost of credit, we account for the fact that banks might charge different interest rates depending on whether a firm uses trade credit ($TC = 1$) or not ($TC = 0$), as follows

$$R_{TC,i} = X_i\beta_{TC} + u_{TC,i}, \quad (3)$$

$$R_{NTC,i} = X_i\beta_{NTC} + u_{NTC,i}, \quad (4)$$

where R_{TC} and R_{NTC} are the costs of credit for firms using and not using trade credit respectively, β_{TC} and β_{NTC} are vectors of parameters, X_i is a matrix of explanatory variables, and $u_{TC,i}$ and $u_{NTC,i}$ are the error terms. Note that we assume that $u_{k,i}$, and v_i are bivariate normal, where $k = \{TC, NTC\}$. If a firm uses trade credit, i.e. $TC = 1$, we only observe R_{TC} while R_{NTC} is unobservable (latent or missing). Similarly, if $TC = 0$, we only observe R_{NTC} while R_{TC} is unobservable.⁹

In order to estimate the determinants of the bank loan interest rate accounting for the fact that firms self-select into using trade credit, we use a switching regression approach based on equations (2), (3) and (4). Accordingly, the conditional expected cost of credit

⁹We assume that there is interchangeability across statuses, i.e. firms not using trade credit would be able to use it if they wish to do so.

for a firm who self-select into trade credit is

$$\begin{aligned}
E(R_{TC,i}|TC = 1) &= E(R_{TC,i}|TC^* > 0) \\
&= E(R_{TC,i}|v_i > -Z_i\gamma) \\
&= X_i\beta_{TC} + E(u_{TC}|v_i < Zi\gamma) \\
&= X_i\beta_{TC} + \sigma_{TC,v}\lambda_{TC,i},
\end{aligned} \tag{5}$$

where $\lambda_{TC,i} = \frac{\phi(Z_i\gamma)}{\Phi(Z_i\gamma)}$, ϕ is the pdf of the standard normal distribution and Φ is the cumulative density function.¹⁰ Similarly, the expected cost of credit for firms not using trade credit is:

$$\begin{aligned}
E(R_{NTC,i}|TC = 0) &= E(R_{NTC,i}|TC^* \leq 0) \\
&= E(R_{NTC,i}|v_i \leq -Z_i\gamma) \\
&= X_i\beta_{NTC} + E(u_{NTC}|v_i \geq Zi\gamma) \\
&= X_i\beta_{NTC} - \sigma_{NTC,v}\lambda_{NTC,i},
\end{aligned} \tag{6}$$

which follows from the truncation of R_{NTC} from above, with $\lambda_{NTC,i} = -\frac{\phi(Z_i\gamma)}{1-\Phi(Z_i\gamma)}$. Note that $\lambda_{TC,i}$ and $\lambda_{NTC,i}$ are the inverse Mills's ratios, which correspond to the expectation of v conditional on a firm i self-selecting into trade credit or not, respectively.

The procedure is to estimate in the first stage the following equation:

$$TC_i = Z_i\gamma + v_i. \tag{7}$$

From equation (7) we obtain the linear prediction, $Z_i\hat{\gamma}$ which is used to compute λ_{TC} and λ_{NTC} . The strength of this approach is that it allows for a clear interpretation of the sign of the inverse Mills's ratio, as it tells us the direction of the selection, and most importantly, we are able to verify Hypothesis 1 as follows

1. the variables λ_{TC} and λ_{NTC} are an estimate of the private (unobservable) information underlying the firm's decision to use trade credit, and

¹⁰In computing $E(R_{TC,i}|TC = 1)$, equation (5), we use the fact that the distribution of R_{TC} is truncated from below.

2. the test of the significance of the coefficients associated with the inverse Mills' ratios is a test of whether such private information, which is revealed by the decision to use trade credit, is passed to the bank and affects the cost of bank credit (Kai and Prabhala, 2007).

However, as we have already discussed, even though this approach allows to control for self-selection, it does not fully address the endogeneity issue potentially arising from the fact that, as the use of trade credit conveys private information about firms' credit-worthiness, firms' decision to use it credit strategically depends on the expected outcome in terms of cost of credit (Hypothesis 2). For that reason, we employ the endogenous switching approach (Lee and Trost, 1978; Maddala, 1986). The endogenous switching model can be fitted one equation at a time using the two steps estimation proposed by Maddala (1986), pp. 223-228, or by maximum likelihood. The endogenous switching consists of three equations estimated simultaneously using maximum likelihood, assuming trivariate normality between the error terms of the three equations. We rely on the full-information ML method proposed by Lokshin and Sajaia (2004) which yields consistent standard errors.

Consider the model represented by equations (5), (6) and (7). Assume that v_i , $u_{TC,i}$ and $u_{NTC,i}$ have a trivariate normal distribution, with mean vector zero and covariance matrix

$$\Omega = \begin{bmatrix} \sigma_v^2 & \sigma_{u_{TC},v} & \sigma_{u_{NTC},v} \\ \sigma_{u_{TC},v} & \sigma_{u_{TC}}^2 & \cdot \\ \sigma_{u_{NTC},v} & \cdot & \sigma_{u_{NTC}}^2 \end{bmatrix} \quad (8)$$

where σ_v^2 is the variance of the error term in the trade credit selection equation, and $\sigma_{u_{TC}}^2$ and $\sigma_{u_{NTC}}^2$ are the variances of the error terms in the cost of credit equations. $\sigma_{u_{TC},v}$ is the covariance of v_i and $u_{TC,i}$, and $\sigma_{u_{NTC},v}$ is the covariance of v_i and $u_{NTC,i}$. The model is identified through non linearities. Nevertheless, as explained in section 3.2, we include as exclusion restriction a variable that affects the decision to use trade credit but not the

cost of credit. The logarithmic likelihood function for the equations (5), (6) and (7), is

$$\begin{aligned} \ln L_i &= \sum_{i=1}^N \left\{ TC_i \left[\ln \phi \left(\frac{u_{TC,i}}{\sigma_{TC}} \right) - \ln \sigma_{TC} + \ln \Phi(\eta_{TC,i}) \right] + \right. \\ &\quad \left. + (1 + TC_i) \left[\ln \phi \left(\frac{u_{NTC,i}}{\sigma_{NTC}} \right) - \sigma_{NTC} + \ln (1 - \Phi(\eta_{NTC,i})) \right] \right\}, \end{aligned} \quad (9)$$

where

$$\eta_{j,i} = \frac{Z_i \gamma + \rho_j u_{j,i} / \sigma_j}{\sqrt{1 - \rho_j^2}} \frac{1}{2}, \quad (10)$$

with $j = \{TC, NTC\}$. The test of the significance of the estimated correlation coefficient corresponds to a test of the interdependence (Hypothesis 2) between firms' decision to use trade credit and banks' interest rate decision. Moreover, such a test also represents a robustness check about the conclusions we derive from the test of the significance of the inverse Mill's ratio of the switching regression model (Hypothesis 1).

The endogenous switching regression model is used to compute the observed cost of credit for TC and NTC users and the hypothetical counterfactual cost of credit, i.e. the cost of credit for trade credit users had they not used it, and the cost of credit for non-trade credit user had they used it. The conditional expectations for the cost of credit in the four cases are defined as follows

$$E(R_{TC,i} | TC = 1) = X_i \beta_{TC} + \sigma_{TC,v} \lambda_{TC,i}, \quad (11)$$

$$E(R_{NTC,i} | TC = 0) = X_i \beta_{NTC} + \sigma_{NTC,v} \lambda_{NTC,i}, \quad (12)$$

$$E(R_{NTC,i} | TC = 1) = X_i \beta_{NTC} + \sigma_{NTC,v} \lambda_{TC,i}, \quad (13)$$

$$E(R_{TC,i} | TC = 0) = X_i \beta_{TC} + \sigma_{TC,v} \lambda_{NTC,i}. \quad (14)$$

Equation (11) is the expected cost of bank credit for a firm that self-selects into the group of firms using trade credit (TC) conditional on the factual action of using trade credit. Conversely, equation (13) denotes the expected cost of bank credit for a firm self-selecting into the TC group conditional on the counterfactual action of not using trade credit, i.e. had it chosen not to use trade credit. Equation (12) is the expected cost of bank credit for

a firm that self-selects into the group of firms not using trade credit (NTC) conditional on the factual action of not using trade credit. Finally, equation (14) is the expected cost of bank credit for a firm that self-selects into the NTC group conditional on the counterfactual action of using trade credit, i.e. had it chosen to use trade credit.¹¹

The treatment effect for the treated group (TC), given by

$$TT_R = E(R_{TC,i}|TC = 1) - E(R_{NTC,i}|TC = 1) \quad (15)$$

allows us to test our Hypothesis 3. A negative value for TT_R , would rationalize that a reason why some firms use trade credit might be that they can get a significant gain in terms of cheaper bank loans. In principle, we are also interested in testing whether some other firms do not use trade credit because they would not get a significant reduction in the cost of bank credit. Such test can be conducted using the treatment effect for the untreated group (NTC)

$$TU_R = E(R_{TC,i}|TC = 0) - E(R_{NTC,i}|TC = 0). \quad (16)$$

Finally, the difference between TT_R and TU_R , known in the literature as the “transitional heterogeneity effect” (Carter and Milon, 2005), is informative about the difference in the expected net benefit of using trade credit for the TC and NTC groups.

3.2 Trade credit and probability to obtain financing

In this subsection, we develop the econometric model that we use to test whether the trade credit choice conveys unobservable (private) information to the bank (Hypotheses 1), which the bank uses to decide whether to extend credit or not (Hypothesis 4). The estimation framework that we adopt accounts for the simultaneity issue arising from the fact that the firm’s strategic decision to use trade credit is affected by the expected outcome associated with banks’ decision to extend credit (Hypothesis 2).

¹¹The estimation of (11)-(14) is carried out employing the Stata command `movestay` (Lokshin and Sajaia, 2004).

We model the firm’s decision to use trade credit and the decision of the bank to extend a loan as a system of two simultaneous equations. Let π_i^* the bank’s value of extending credit to firm i

$$\pi_i^* = W_i\theta + TC_i\alpha + \epsilon_i. \quad (17)$$

We do not observe the latent variable, π_i^* . The variable we observe is the bank’s decision to extend credit, which we model as the index function

$$\pi_i = \begin{cases} 1 & \text{if } W_i\theta + TC_i\alpha + \epsilon_i > 0 \\ 0 & \text{otherwise,} \end{cases} \quad (18)$$

where W_i is a set of determinants of bank credit, θ and α are vectors of parameters, and ϵ is the error term. The model (17)-(18) is often referred as “multivariate probit model with a structural shift” (Heckman, 1978) or “dummy endogenous variable model” (Maddala, 1986).¹² The firm’s decision to use trade credit is modeled according to equation (7), which we discussed in subsection 4.1.

In order to estimate the simultaneous equation model given by equations (7) and (18), we use the procedure proposed by Lokshin and Sajaia (2011), which employs an ML estimator of the binary choice model with endogenous regressors. Although non-linearities identify the model, we also include an exclusion restriction variable. This procedure allows us to test for Hypotheses 1 and 4, taking into account the interdependence between trade credit and probability of being financed (Hypothesis 2).¹³

The effect of the use of trade credit on the probability of obtaining a bank loan is correctly estimated by the following equation

$$TT_\pi = Pr(\pi_{TC} = 1|TC = 1) - Pr(\pi_{NTC} = 1|TC = 1), \quad (19)$$

where $Pr(\pi_{TC} = 1|TC = 1)$ is the factual probability to be financed for a firm that

¹²If $\epsilon_i|W_i, TC_i \sim N(0, 1)$ it would be possible to estimate model (18) by standard probit. However, since the firm’s decision to use trade credit and the bank decision to supply loans are simultaneously determined, and given that the variable is a binary indicator its distribution is not normal, and hence such nonlinear models cannot be estimated using a two-stage method (Carrasco, 2001).

¹³The estimation is carried out employing the Stata command `switch_probit`.

chooses to use trade credit and $Pr(\pi_{NTC} = 1|TC = 1)$ is the counterfactual probability to be financed of a firm in the TC group had it decided not to use trade credit. Technically, TT_π measures the treatment effect on the treated.

4 Data and results

We use the 2003 NSSBF (National Survey of Small Businesses Finances) dataset conducted by the Board of Governors of the Federal Reserve System. The dataset provides information on a sample of 4240 firms selected from the target population of all for-profit, non-financial, non-farm, non-subsidiary business enterprises that had fewer than 500 employees and were in operation as of year-end 2003 and on the date of the interview. Information on the availability and use of credit and other financial services, demographic characteristics for up to three individual owners, and other firm characteristics such as the number of workers, organizational form, location, credit history, income statement, and balance sheet are available.

The survey contains a section about the use of trade credit by firms. We use this information together with that on bank financing to study the relationship between trade credit and bank credit. In particular, we use the information on firms' use of trade credit or not (during the last year), bank loans (in the last three years), and the interest rate charged by the bank.

In the following sub-sections, we present the estimation of the switching models introduced in sections 4.1 and 4.2. We first discuss the empirical results of estimating the cost of bank credit, and then we turn to the probability of obtaining bank credit.

4.1 Use of trade credit and cost of bank credit

We first discuss the results of the standard switching model, and then we analyze the estimates of the endogenous one.

4.1.1 Switching regression model

We estimate the two-equation switching regression model given by equations (7), (5) and (6) as follows. First, we estimate the firm decision to use trade credit, i.e., equation (7) and we obtain the inverse Mill's ratios. Then, we plug the inverse Mill's ratios into equations (5) and (6). In the estimation of the decision to use trade credit, equation (7), the dependent variable would take value equal to one if the firm made purchases of goods and services on account rather than paying at the time of delivery and takes value zero otherwise. The set of explanatory variables, Z , includes *liquidity on total asset* and the *growth of sales* as measures that account for the transaction use of trade credit. We expect that the higher is the share of liquid assets, the less likely the firm uses trade credit. Conversely, when sales are growing, we expect the likelihood of observing trade credit to increase. Moreover, we control for the firm's age. As argued by Petersen and Rajan (1997), for small firms *firm age* is a proxy for experience in the business. Some projects may be feasible after an adequate level of experience is achieved. However, for larger firms, investment opportunities may decline in firm age (Petersen and Rajan, 1997). Therefore, we do not have a clear *a priori* guess about how firm's age affects the decision to use trade credit. We also include a proxy of working capital needs, *Inventories*, which we expect to influence positively the decision to use trade credit. Furthermore, we control for capital structure by including the *ratio of loans to total asset* and for the quality of firm-bank relationships, captured by the *Length of relationship* between the firm and its major supplier of bank loans, which could be correlated negatively with the degree of informational opacity. Another observable measure of firm informational opacity we account for is the dummy *financial statement for internal use only*. Longer distances between the firm and its principal financing institution are proxies of the application cost of obtaining a loan. We expect a positive correlation between the variable measuring the *distance* in miles from the bank and the use of trade credit. Finally, we include the *amount of unused credit lines* as an exclusion restriction. This variable affects the firm decision to use trade credit, but it should not influence the cost of bank credit. The choice of this variable as an exclusion restriction is appropriate because a firm that has almost

exhausted its credit line limits is likely to need additional short-term funds, which affects the decision on the use of trade credit. Conversely, the amount of unused resources of lines of credit should not affect the interest rate charged by the bank on the most recent loan.

The set X of the explanatory variables that we use when estimating the bank loan interest rate equations (5) and (6), contains the following information. We control for the characteristics of the firm's most recent successful loan application, including the *loan amount granted on the total amount applied*, the *amount of the loan on total firm asset* and a dummy equal one if firm post *collateral*. Since a loan with a fixed interest rate is likely associated with a higher cost of credit than a loan with a variable one, we also include a dummy that is equal to one for *fixed interest rate*, which we expect to affect the cost of credit positively. We also add a dummy that takes value one if the loan is a *mortgage*. To account for differences in the monitoring costs of the bank, we include the *distance* in miles of the firm from the bank. Furthermore, we control for the impact of a firm financial structure on the cost of credit by using the ratio of *debt on total asset*. Also, we control for the quality of the firm as observed by the bank by means of the variable *credit score*, which may affect the interest rate. To measure this effect, we include a dummy equal one if the firm credit score is in the top 25% of the distribution. Market characteristics may also affect the loan rate. To consider possible bank local market power, we include a dummy equal one if the *Herfindahl-Hirschman bank deposit index* of local banking market concentration is greater than 1800 (i.e. highly concentrated). Finally, we consider variables that account for borrowers' heterogeneity. As documented in the literature, entrepreneur experience contributes positively to a firm's profit. To catch the managing experience effect, we include the number of *years of the principal owner's managing experience*. We expect the interest rate to be decreasing in the years of managing experience as a more significant experience is positively correlated to higher profit. Hence, it generates a higher probability of success for the firm. The literature reports evidence that entrepreneurs that belong to a minority group rely more heavily on their funds to finance a start-up. We account for such effects with two dummies. The

first is equal one if the *principal owner is black*. In contrast, the second is equal one if the owner belongs to *other minority groups* (Asian, Hispanic, Asian Pacific, Native American). A firm’s proprietorship characteristics may affect credit availability and loan contract as family and non-family owned firms may exhibit different agency costs. We control for proprietorship effects using a dummy that takes value one if the firm is *family owned*.

From the estimation of equation (7) we obtain the inverse Mills’ ratio λ_{TC} and λ_{NTC} . Then we estimate the two equations of the cost of credit (3) and (4) augmented by the inverse Mills’ ratios. Results are reported in tables 1-3. In both loan rate equations (tables 2 and 3) the inverse Mills’ ratios are positive and statistically significant. In the switching model, a positive sign of the coefficient of λ_{TC} means that there is a positive correlation between the unexplained factors that affect the cost of credit and those that affect the decision to use trade credit. Therefore, we can confirm Hypothesis 1 about the role of trade credit in conveying private information from the buyer-seller relationship to the loan market. In addition, the significance of the inverse Mill’s ratios confirms that there is a selection effect in the use of trade credit. Among the various regressors that explain the loan rate equation, notice that the coefficient estimate of the dummy *collateral* is not significant for firms in the NTC group. At the same time, it is positive and statistically significant for firms in the TC group. This result is in line with the conclusions of Bellucci, Borisov, Giombini, and Zazzaro (2021) according to which the effect of collateral on the cost of credit is positive whenever one does not account for the endogeneity between the two contractual terms.¹⁴

4.1.2 Endogenous switching model

The estimates of the endogenous switching model discussed in section 3.1 are obtained as follows. To estimate the trade credit decision we use the same sets of X and Z variables described in the previous section. Results are displayed in table 4. The coefficient of the

¹⁴Bellucci, Borisov, Giombini, and Zazzaro (2021) show that when accounting for the endogeneity the effect of collateral on the interest rate appears to be weaker or not significant. Notice that we obtain a result similar to theirs when we run the endogenous switching regression in section 4.1.2; we find that the effect of collateral on the interest rate differs from what we obtain in the standard switching regression.

amount of unused credit lines, our exclusion restriction, is negative and significant. Our proxy for firm information opacity, *financial or accounting statements only for internal use*, is positive and highly significant. This finding supports the assumption that opaque firms rely more on trade credit. With regard to the dummy *collateral*, the coefficient of this regressor is positive and significant in the switching equation, and it is negative and significant in the cost of credit equation in both subsamples. A positive correlation between the decision to use trade credit and the dummy collateral can be explained by the fact that firms that use trade credit are generally more opaque, and as such these are also the ones most likely to be asked to provide collateral by the bank. However, once we account for the endogeneity of the decision to use trade credit, posting collateral always reduces the cost of credit. The effect of posting collateral is stronger for firm in the NTC group: cost of credit is reduced by 0.77 percentage points versus a reduction of 0.47 percentage points for firms in the TC group. The correlation coefficients, ρ_{TC} , and, ρ_{NTC} , are both positive and significant, confirming both Hypothesis 1 that firm self-selecting into one of the two groups conveys private unobservable information, and that firms and banks decisions are interdependent (Hypothesis 2).

The estimation in table 4 is used to compute the conditional expected cost of bank credit and the effect of the use of trade credit (the treatment) in the two groups, which are reported in table 5. The treatment effect on the treated is -2.4 , meaning that the predicted cost of bank credit for a firm in the TC group currently using trade credit (column 2) is lower than its counterfactual cost of credit had it not used trade credit (column 3). This results confirm our Hypothesis 3.

Moreover, by comparing the second column with the third column of table 5, we find that conditional on the same decision on the use of trade credit, firms in the NTC group get an interest rate always lower than firms in the TC group.¹⁵ This result supports the assumption that firms in the NTC group are the transparent ones and therefore, anything else equal, they carry on less uncertainty at the eyes of the bank.

¹⁵The differences between (11) and (14) and between (12) and (13) are known in the literature as “base heterogeneity effect” according to which those choosing to use trade credit could inherently be charged higher (or lower) loan rates regardless of the fact that they decided to use trade credit or not. (Carter and Milon, 2005).

4.2 Trade credit and access to credit

In order to estimate the two simultaneous equation model described in section 4.2 we proceed as follows. The SSBF dataset provides information about the firm application to bank credit and whether a firm is always rationed, sometimes rationed or always financed by the bank. Accordingly, in estimating the probability of a firm being financed by a bank, equation (18), we use as a dependent variable a dummy that takes value one if a firm is always financed and zero otherwise. The set of explanatory variables, W , is structured as follows. According to the consolidated literature on access to credit (see for example Steijvers and Voordeckers (2009) for a survey), we include the dummy equal one for firm posting *collateral*, the *distance between the firm and the bank* in miles, the dummy equal one if the firm has a *mortgage*. Creditworthiness is measured by firm *credit score*, and by a set of proxies among which we include a dummy equal one if *firm is turned down by other banks*, the *number of credit applications*, a dummy equal one if *firm has delinquency records*. We also include a dummy equal one for firms with *limited liability*. The quality of firm-bank relationships is measured by the *length of firm-bank relationship* (months). Local bank market power is measured by the dummy equal one for high *Herfindahl-Hirschman bank deposit index*. Finally, given that loan application outcomes are also affected by firm age and experience, we control for it by using the variable *firm age*.

With regard to the decision to use trade credit, equation (7), we use the set of Z variables already discussed in the previous section. Yet, we add a dummy indicating a firm using the owner's credit card for business expenses whose extended credit is fully paid at the end of the month, which works as an exclusion restriction. Specifically, the survey reports an indicator equal one if the firm fully pays the debt on the revolving card at the end of the month, thus not taking advantage of alternative sources of short-term financing. We expect that this variable correlates positively with trade credit, but it should not affect the decision of the bank to extend credit. Results are reported in table 6. The coefficient of the exclusion restriction is positive and significant. Hypothesis 4 is confirmed by the computation of the treatment effect on the treated, which is $TT_{\pi} = 0.17$,

meaning that firms in the TC group have 17% higher probability of being financed than the one they would have had if not using trade credit. Moreover, the significance of the correlation coefficients confirms Hypothesis 2 about the endogeneity between the decision to use trade credit and the probability of obtaining credit.

Finally, consider two variables that the literature typically claims to have significant informative content, the dummy *collateral* and the *length of firm-bank relationship*. In the equation for firms not using trade credit, the collateral dummy is negative and significant, and the firm-bank relationship duration is positive and significant. Conversely, for firms using trade credit, the opaque ones according to the BGM, the same variables do not significantly affect the probability of accessing credit. This finding supports the hypothesis that trade credit choice has an informative role. In particular, when firms do not use trade credit, is collateral and length of the firm-bank relationship that privately inform the bank about the firm's creditworthiness. Differently, if firms use trade credit, such a decision informs the bank, which offsets the informative role of collateral and length firm-bank relationship.

5 Conclusions

The existing empirical literature often relates the complementarity relationship between trade and bank credit found in the data to the possibility that trade credit plays a signaling role. In this paper, we contributed to this literature by identifying and quantifying the signaling effect of trade credit on access to bank credit and on its cost in a sample of US firms. We based our identification strategy on the signaling model by Biais and Gollier (1997) according to which the decision to use trade credit conveys private information of borrowing firms to the banks that supply credit, thereby alleviating credit rationing due to asymmetric information. We employ an endogenous switching regression approach that enables us to account for the endogeneity arising from firms' self-selection into trade credit and from the simultaneity between the decisions of the banks to extend credit and of the firms to use trade credit. Our estimation results on a sample of US firms

provide strong evidence of the signaling role of trade credit in improving a firm's access to and cost of credit, supporting and confirming the empirical predictions of the BGM. Firms' decision to use trade credit is associated with a self-selection mechanism. Firms self-selecting into trade credit are found to face a higher probability of accessing bank credit and a lower cost of bank credit than the counterfactual ones they would have faced if not using trade credit. Finally, we found such an effect to be comparatively stronger than the estimated counterfactual effects of using trade credit for those firms that are not using it.

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Table 1: Probit estimation of the decision to use trade credit. Dep = Dummy=1 if firms uses trade credit

Variable	Coefficient	(Std. Err.)
liquidity on total asset	-0.9111***	(0.1832)
dummy =1 if firms increased sales wrt three years before	0.0203	(0.0570)
inventories on total asset	0.9472***	(0.1538)
loans on capital asset	0.0012	(0.0011)
dummy=1 if financial statement for internal use only	0.5262***	(0.1167)
distance between firm and bank (miles)	0.0096***	(0.0028)
years of firm-bank relationship on firm age	0.2639	(0.3656)
firm age (years)	0.0134***	(0.0034)
length of firm-bank relationship (months)	-0.0021	(0.0039)
amount of unused credit lines on total asset	-0.0564*	(0.0330)
Sector dummies		
mining	0.7069**	(0.2957)
construction	1.4076***	(0.1268)
manufacturing	1.0268***	(0.1038)
transport	1.7143***	(0.2143)
wholesale	0.5414***	(0.1189)
retail	0.7977***	(0.1076)
services	0.4606***	(0.0831)
N		804
Log-likelihood		-1275.8479
$\chi^2_{(17)}$		1809.9203
Significance levels : * : 10% ** : 5% *** : 1%		

Table 2: Cost of credit: firm using trade credit

Variable	Coefficient	(Std. Err.)
inverse Mills ratio (λ_{TC})	4.570143***	(0.238082)
dummy=1 equal one if firm post collateral	0.279549***	(0.083687)
loan amount granted on total amount applied	0.470580***	(0.046983)
loan amount applied on total asset	-0.184229***	(0.049951)
dummy=1 if fixed interest rate	1.762007***	(0.087575)
dummy=1 if firm has a mortgage	0.074491	(0.197433)
dummy=1 if Herfindahl-Hirschman bank deposit ind. > 1800	0.573883***	(0.083531)
dummy=1 if firm credit score is in the top 25%	0.433314***	(0.087261)
years of managing experience of firm owner	0.046736***	(0.003527)
dummy=1 if owner is black	0.022552	(0.540130)
dummy=1 if owner belongs to other minorities	0.820344***	(0.182058)
distance between firm and bank (miles)	0.003126***	(0.000532)
debt on total asset	0.187014***	(0.030431)
dummy=1 if firm is family owned	1.478009***	(0.092655)
N		720
R ²		0.820943
F _(14,3587)		1174.698118
Significance levels : * : 10% ** : 5% *** : 1%		

Table 3: Cost of credit: firm not using trade credit

Variable	Coefficient	(Std. Err.)
inverse Mills ratio (λ_{NTC})	1.758146***	(0.316523)
dummy=1 equal one if firm post collateral	-0.280575	(0.304418)
loan amount granted on total amount applied	1.115290***	(0.172601)
loan amount applied on total asset	0.048696	(0.078593)
dummy=1 if fixed interest rate	2.288044***	(0.288711)
dummy=1 if firm has a mortgage	0.135876	(0.431777)
dummy=1 if Herfindahl-Hirschman bank deposit ind. > 1800	0.442467	(0.283586)
dummy=1 if firm credit score is in the top 25%	-0.465334	(0.314356)
years of managing experience of firm owner	-0.024392*	(0.013700)
dummy=1 if owner is black	2.067928**	(0.853331)
dummy=1 if owner belongs to other minorities	3.391578***	(0.659520)
distance between firm and bank (miles)	-0.027340***	(0.006252)
debt on total asset	0.071537	(0.093145)
dummy=1 if firm is family owned	1.683876***	(0.329185)
N		110
R ²		0.79504
F _(14,535)		148.232996
Significance levels : * : 10% ** : 5% *** : 1%		

Table 4: Endogenous switching: trade credit decision and cost of credit

Variable	Coefficient	(Rob. Std. Err.)
Outcome equation 1 : R_{TC}		
dummy=1 equal one if firm post collateral	-0.473063***	(0.084529)
loan amount granted on total amount applied	0.143027***	(0.049968)
loan amount applied on total asset	-0.051696	(0.046175)
dummy=1 if fixed interest rate	1.183193***	(0.080713)
dummy=1 if firm has a mortgage	0.202815	(0.188362)
dummy=1 if Herfindahl-Hirschman bank deposit ind > 1800	0.032523	(0.077727)
dummy=1 if firm credit score is in the top 25%	0.153419*	(0.080414)
years of managing experience of firm owner	-0.016326***	(0.003904)
dummy=1 if owner is black	-0.383795	(0.477908)
dummy=1 if owner belongs to other minorities	0.129929	(0.164786)
debt on total asset	0.028495	(0.027614)
Intercept	5.285500***	(0.157680)
Outcome equation 2 : R_{NTC}		
dummy=1 equal one if firm post collateral	-0.771444***	(0.276307)
loan amount granted on total amount applied	0.553505***	(0.157203)
loan amount applied on total asset	0.143076	(0.216793)
dummy=1 if fixed interest rate	2.192810***	(0.268327)
dummy=1 if firm has a mortgage	-0.033295	(0.463657)
dummy=1 if Herfindahl-Hirschman bank deposit ind. > 1800	0.190631	(0.260927)
dummy=1 if firm credit score is in the top 25%	-0.412132	(0.288063)
years of managing experience of firm owner	-0.024019*	(0.012889)
dummy=1 if owner is black	-1.443919	(0.958925)
dummy=1 if owner belongs to other minorities	3.571031***	(0.568365)
debt on total asset	0.080127	(0.135042)
Intercept	6.975768***	(0.551460)
Switching equation : TC		
dummy=1 equal one if firm post collateral	0.191085***	(0.061568)
loan amount granted on total amount applied	-0.013229	(0.032631)
loan amount applied on total asset	0.148358***	(0.052371)
dummy=1 if fixed interest rate	-0.107774*	(0.059780)
dummy=1 if firm has a mortgage	-0.727106***	(0.107829)
dummy=1 if Herfindahl-Hirschman bank deposit ind. > 1800	-0.028651	(0.058593)
dummy=1 if firm credit score is in the top 25%	0.117101*	(0.061860)
years of managing experience of firm owner	0.001434	(0.003618)
dummy=1 if owner is black	-0.400077	(0.258958)
dummy=1 if owner belongs to other minorities	0.078061	(0.125284)
debt on total asset	-0.040857	(0.026201)
liquidity on total asset	-1.090778***	(0.202924)
dummy =1 if firms increased sales wrt three years before	0.078483	(0.058557)
inventories on total asset	0.865151***	(0.153442)
loans on capital asset	0.001682	(0.001464)
amount of unused credit lines on total asset	-0.127742**	(0.055906)
dummy=1 if financial statement for internal use only	0.353969***	(0.117792)
distance between firm and bank (miles)	0.008202***	(0.002692)
years of firm-bank relationship on firm age	0.571624	(0.398891)
length of firm-bank relationship (months)	-0.004748	(0.003926)
firm age (years)	0.012294***	(0.004092)
intercept	0.711382**	(0.303378)
ρ_{TC}	0.39***	(0.1069)
ρ_{NTC}	0.48***	(0.0965)
Sector dummies		yes
N		783
Log-likelihood		-9941.529887
$\chi^2_{(11)}$		307.237948
Significance levels : * : 10% ** : 5% *** : 1%		

Table 5: Cost of credit: conditional Expectations and treatment effects

subsample	trade credit choice		treatment effects
	TC	NTC	
TC users (N=738)	(a) $E(R_{TC,i} TC = 1) = 5.45$	(c) $E(R_{NTC,i} TC = 1) = 7.85$	$TT_R = -2.4^{***}$
NTC users (N=114)	(d) $E(R_{TC,i} TC = 0) = 4.14$	(b) $E(R_{NTC,i} TC = 0) = 5.92$	$TU_R = -1.78^{***}$

Note: (a) and (b) are the observed expected cost of credit; (c) and (d) are the counterfactual expected cost of credit.

R_{TC} is the cost of credit if firm uses trade credit; R_{NTC} is the cost of credit if firm does not use trade credit

TT_R is the effect of the treatment (use of TC) on the treated (users of TC) ($a - c$);

TU_R is the effect of the treatment (use of TC) on the untreated (non users of TC) ($d - b$).

**Significant at the 1% level

Table 6: Endogenous switching: trade credit decision and probability of access to credit

Variable	Coefficient	(Std. Err.)
Switching equation : TC		
liquidity on total asset	-0.5832***	(0.1202)
dummy =1 if firms increased sales wrt three years before	0.1195***	(0.0427)
inventories on total asset	0.8642***	(0.1425)
dummy=1 if financial statement for internal use only	0.3077***	(0.0684)
dummy=1 if business expenses on owners credit card fully payed	0.0996**	(0.0410)
distance between firm and bank (miles)	0.0028***	(0.0009)
length of firm-bank relationship (months)	-0.0033	(0.0024)
years of firm-bank relationship on firm age	0.0803***	(0.0157)
firm age (years)	0.0121***	(0.0021)
Intercept	1.2554***	(0.0739)
Outcome equation 1 : π_{TC}		
dummy=1 equal one if firm post collateral	0.0029	(0.0713)
distance between firm and bank (miles)	-0.0006*	(0.0003)
dummy=1 if firm has a mortgage	-0.4809***	(0.0821)
dummy=1 if firm turned down by other banks	-1.1863***	(0.2663)
number of credit applications	-0.0859***	(0.0100)
dummy=1 if Herfindahl-Hirschman bank deposit ind. > 1800	0.0336	(0.0675)
dummy=1 if firm has limited liability	0.0072	(0.0795)
dummy=1 if firm has delinquency records	-0.1237***	(0.0260)
length of firm-bank relationship (months)	0.0007	(0.0032)
credit score	0.1641***	(0.0231)
firm age (years)	0.0204***	(0.0037)
Intercept	1.4992***	(0.1420)
Outcome equation 2 : π_{NTC}		
dummy=1 equal one if firm post collateral	-0.4202***	(0.1539)
distance between firm and bank (miles)	0.0111	(0.0099)
dummy=1 if firm has a mortgage	0.0781	(0.2092)
dummy=1 if firm turned down by other banks	-7.2234***	(0.7905)
number of credit applications	-0.5053***	(0.1027)
dummy=1 if Herfindahl-Hirschman bank deposit ind. > 1800	-0.2619*	(0.1433)
dummy=1 if firm has limited liability	0.6597***	(0.2284)
dummy=1 if firm has delinquency records	-0.3568***	(0.1104)
length of firm-bank relationship (months)	0.0512***	(0.0165)
credit score	0.1359**	(0.0616)
firm age (years)	0.0103	(0.0086)
Intercept	0.8820	(0.7190)
ρ_{TC}	-0.47***	(0.0983)
ρ_{NTC}	-0.60*	(0.3636)
Sector dummies		yes
N		1595
Log-likelihood		-3932.2033
$\chi^2_{(15)}$		591.1943
Wald test of indep. eqns. ($\rho_{TC} = \rho_{NTC} = 0$): $\chi^2(2) = 42.6$		$prob > \chi^2 = 0.000$
Significance levels : * : 10% ** : 5% *** : 1%		