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Working Paper 17/04

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July 2017

Abstract

We investigate the impact of well-established trade credit theories on different parts of the distribution of trade credit taken by firms. Our results suggest that the trade credit - bank loans substitution increases at the higher trade credit quantiles and is stronger for larger firms (financing theory). Firms with high market shares operating in less concentrated industries have higher account payables to assets ratios (bargaining power theory). While the customer bargaining power motive strengthens up to the 70th quantile and prevails in industries independent on external finance, financing reasons play the main role especially at the higher trade credit quantiles.

Keywords: trade credit; bargaining power; panel quantile regression

JEL classification: G3, C2

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1. Introduction

Recent empirical studies have stressed the importance of trade credit relationships in the transmission of credit contagion among firms. Boissay and Gropp (2009), for instance, show that credit constrained firms that face negative liquidity shocks are more likely to default (i.e., delay or partially pay) their own suppliers. This may trigger a succession of defaults being transmitted further up the supply chain, which could potentially lead to aggregate economic decline unless unconstrained suppliers along the supply chain can absorb the liquidity shock. Their finding is consistent with the idea that trade credit provides an insurance mechanism (Cuñat, 2007) as liquidity is allocated from unconstrained suppliers to constrained buyers. Similarly, Jacobson and von Schedvin (2015) link customer bankruptcies with increased supplier losses and heightened supplier bankruptcy risk. Shenoy and Williams (2017) take a different approach and examine how relaxation of bank branching laws in the US allows suppliers to extend larger amounts of trade credit to their customers which lack access to a bank line of credit, thereby increasing the probability of survival of the supplier-customer relationship.

Given the risks faced by the granting suppliers, the large amounts of trade credit on firms' balance sheets are somewhat puzzling. Ellingsen et al. (2016) find support both for the financing view of trade credit, in that customers with stronger financial health have lower account payables, and for the bargaining power theory (Klapper et al., 2012, Dass et al., 2015, Fabbri and Klapper, 2016) since the customers' size and their relative share in their suppliers' sales influence the terms of trade credit. Overall, however, Ellingsen et al. (2016) conclude that trade credit transactions are more complex than the existing theories may account for.[1]

This paper contributes to this line of research. We examine whether the relative roles played by the financing and bargaining power motives, in particular, vary depending on the amount of trade credit taken by firms. Whether, for instance, financing reasons prevail over bargaining motives when customer firms already have *higher* rather than *lower* trade credit to assets ratios has important implications. Consider, for example, that a negative liquidity shock affects the suppliers' ability to extend trade credit. The transmission of this liquidity shock to their customers and through the economy depends on the strength of the financing and the bargaining power motives for trade credit. If the financing motive prevails at the high quantiles of the trade credit taken distribution, these customers relying heavily on supplier finance are

[1] The literature review sections mentions briefly the main trade credit theories. For a more detailed discussion see Klapper et al. (2012) and Giannetti et al. (2011).

likely to curtail their own activities and/or default on their current payables. In turn, this may lead to liquidity shocks being transmitted along the production chain as in Boissay and Gropp (2009), Jacobson and von Schedvin (2015), Lian (2017), and Shenoy and Williams (2017). The picture is different if the customers primarily use their bargaining power to demand supplier credit and they have a low usage of trade credit. Following the supplier liquidity shock, the customers may either revert to alternative funding or further constrain their suppliers. Importantly, the contagion effect is likely to be more limited in this case.

We aim, therefore, to establish the relative role played by the financing and the bargaining power reasons on different parts of the trade credit distribution. Methodologically, we depart from the ordinary least squares approach typically used in the trade credit literature exploiting either contract level (Klapper et al., 2012, Ellingsen et al., 2016), cross-sectional firm level (Fabbri and Klapper, 2016) or company panel data (Dass et al., 2015). Instead of analysing the average trade credit usage as in the previous studies, our empirical approach — panel quantile regression — allows us to establish whether different motives are relatively more important at different levels of trade credit taken.

The analysis is conducted on a dataset for French firms, which is perfectly suited for our purpose. While trade credit is used by firms around the world, there are cross country variations in the relative importance of its use with respect to alternative sources of funding (Demirguc-Kunt and Maksimovic, 2001). Trade credit is much more prominent as a source of external funding in France than in the US, as bonds and commercial paper represent a negligible fraction of French firms' total debt (Boissay and Gropp, 2013). Our analysis contributes to the trade credit literature which mainly employs databases such as Compustat (for large quoted) or NSSBF for (small) US firms. Our panel dataset (circa 190,000 observations) follows over time a large cross section of firms of various size, across manufacturing industries. As small unquoted firms are well represented in the sample, our analysis can therefore properly explore the financing motive of trade credit. Given the sample composition, our paper complements Klapper et al. (2012) who benefit from very detailed contract level information but pertaining to only 56 large customer firms. We relate also to Ellingsen et al. (2016), who exploit contract level information for 51 large Swedish suppliers and all their domestic customers over a period of nine years.

Even though our dataset does not allow matching customers with their suppliers, we make good use of the available accounting data jointly with information regarding the degree of concentration of the industry in which firms operate to construct a proxy of customer relative bargaining power. While previous studies have used the firm's sales market share to proxy bargaining power (Fabbri and Klapper, 2016, Shenoy and Williams, 2017), we suggest that this has to be used in conjunction with measures of industry concentration. The intuition is that the same market share gives a customer-firm a relatively stronger bargaining power if it operates in a less concentrated industry.

Our results shed light on the relevance of the financing theory of trade credit across firms: the substitution between trade credit and bank loans strengthens at higher quantiles and for larger firms. We also find that firms with a high market share operating in less concentrated industries have higher account payables to assets ratios, supporting the customer bargaining power theory. The relationship, however, disappears beyond the 70^{th} quantile of the trade credit distribution. Our results suggest that, while both theories can explain the uptake of trade credit, only the financing reason prevails at the higher quantiles.

To further investigate the relative strength of the financing and the bargaining power reasons, we adopt the approach in Rajan and Zingales (1998) and identify separate samples according to the (relative) external finance dependence of the industry in which the customer firm operates. Our results indicate that financing reasons influence the uptake of trade credit of all firms but become stronger, especially at the high trade credit quantiles, for firms in industries dependent on external funding. Interestingly, the customer bargaining power explanation is much stronger for firms operating in industries which do not rely on external funding. Even for these firms, however, the customer bargaining power significantly influences the uptake of trade credit only up to the 70^{th} quantile of the trade credit distribution. The financing reason alone appears to prevail at the highest quantiles of the trade credit distribution.

A series of sensitivity tests confirm robustness of our findings. Firstly, changing the cut-off to separate firms into size categories or the threshold to classify industries according to their degree of concentration produces qualitatively similar results. Secondly, we control for industry specific effects including the characteristics of the goods transacted. Finally, using an ordinary least squares approach - the correlated random effects estimator - confirms the robustness of our findings regarding the relative importance of the financing and bargaining power motives across industries' degree of dependence on external funding.

Our finding that financing reasons prevail at high values of trade credit uptake stresses the important role which interfirm credit relationships can play in the propagation of financial shocks in an economy. On the one hand, it provides further indirect evidence of an increased use of trade credit to ameliorate tight credit constraints, possibly associated with tight monetary policies (Meltzer, 1960), a central theme in earlier studies. On the other hand, it suggests that liquidity shocks affecting firms with high trade credit to assets ratios are likely to result in payment defaults being transmitted along the production chain, which supports the concern in recent research that trade credit relationships can transmit credit contagion among firms (Boissay and Gropp, 2009, Jacobson and von Schedvin, 2015, Shenoy and Williams, 2017).

The paper is structured as follows. The next section presents the related literature and develops the hypotheses tested in the empirical analysis. Section 3 introduces our empirical models and methodology. Section 4 describes the data. Section 5 presents our empirical results and the final section concludes.

2. Related literature and hypotheses development

A vast literature provides both theoretical explanations and empirical evidence on the reasons why firms use trade credit (delayed payment for the transfer of goods to downstream firms). Among the many theories, we focus on financing motives and on the customer's relative bargaining power.[2]

2.1 Customer financing

The financing theory of trade credit posits that suppliers accept delayed payment and are willing to fund the input purchase of their customers because they benefit from a relative financial advantage over banks, which may stem from several sources. Firstly, suppliers may have better information about their trading partners than banks do, especially if firms and their customers operate in related lines of business or have a long standing trading relationship.

Secondly, suppliers may have an advantage in monitoring and disciplining buyers because they can credibly threaten to cut off future supplies if customers do not pay on time. The threat is particularly credible if a customer accounts for a small proportion of a supplier's sales or if the buyer is dependent on that specific input (Cuñat, 2007). Burkart and Ellingsen (2004) point out that the advantage of trade credit relative to bank loans lies in its illiquid nature. Trade credit is limited to the value of the transacted good and is less easily diverted than cash inputs.

In Daripa and Nilsen (2011), both the customer and the supplier need to borrow to finance production, but one of them has more favourable borrowing terms. The firm with the higher borrowing rate has an incentive to delay production, generating a negative externality for its trading partner. As a result, the firm with the lowest borrowing rate has an incentive to subsidize its trading partner. The customer facing stochastic demand must decide whether to

[2] Other theories include price discrimination (Brennan et al., 1988), product quality (Smith, 1987, Lee and Stowe, 1993, Kim and Shin, 2012, Dass et al., 2014), redeployment of goods after default (Frank and Maksimovic, 2005), and inventory transaction costs (Ferris, 1981, Emery, 1987, Bougheas et al., 2009, Daripa and Nilsen, 2011).

hold inventory to meet sales or to order inputs only when final demand materialises. This decision is influenced by inventory financing costs. In such a setting, trade credit then arises whenever upstream firms find it optimal to offer their buyers an incentive to purchase inventories and continue production.

Finally, suppliers benefitting from an existing sales network may have an advantage relative to banks in repossessing their own goods sold on credit if the customer defaults (Longhofer and Santos, 2003). The supplier's advantage depends on the nature of the transacted goods, how much the customer transforms them (Petersen and Rajan, 1997; Mateut et al., 2015), and the prevailing bankruptcy law and legal system (Fabbri and Menichini, 2010).[3]

Even though the theories mentioned above focus on different aspects of trade credit (e.g., Bias and Golier, 1997, on signalling, Burkart and Ellingsen, 2004, on diversion, Daripa and Nilsen, 2011, on inventory costs), they all evolve around the relationship between trade credit and bank loans. Typically, studies in this area find that account payables and bank loans are negatively correlated. Using detailed contract level data, Ellingsen et al. (2016) confirm that payables are negatively related with customers' financial strength.

This paper departs from the existing literature focusing on deviations around the mean. Instead, we investigate whether the sensitivity of trade credit taken to bank funding availability varies along the trade credit distribution. Put differently, we want to find whether access to bank loans matters more when the firm's use of trade credit is already high relative to when it is low. The first hypothesis tested in our empirical analysis is:

Hypothesis 1 – Financing advantage: *The negative correlation between trade credit taken and bank loans varies at the different quantiles of the trade credit distribution.*

Consistent with the financing strand of the trade credit literature, financially constrained firms rely more on supplier delayed payment than financially stronger firms with better access to bank funding.[4] Our analysis will also investigate the strength of the substitution between trade credit taken and bank loans along the trade credit distribution separately for financially constrained and unconstrained firms (***Hypothesis 1b***).

2.2 Bargaining power

That a financially constrained customer is allowed to delay input payment by their supplier does not always support the financing theory of trade credit. Wilner (2000) argues that

[3] In Biais and Gollier (1997), the suppliers' willingness to extend trade credit to their customers reveals favourable information to other lenders. Consequently, banks become more willing to lend. The information embedded in the sellers' extension of trade credit can alleviate credit rationing due to adverse selection.

[4] Casey and O'Toole (2014) provide consistent evidence of trade credit substitutability for bank loans during the recent financial crisis for credit constrained firms in the euro area.

a dependent supplier may help a customer with temporary financial problems because of his desire to maintain an enduring product market relationship. In this case, trade credit is the result of customer market power. In a model in which trade credit serves as a commitment device for suppliers, Dass et al. (2014) argue that trade credit increases with the relative bargaining power (higher profit margins) of the downstream firms. A few empirical works have linked trade credit use and contract terms with customer bargaining power. Using cross-sectional survey data for Chinese firms, Fabbri and Klapper (2016) find that suppliers in a highly competitive output market (with a weaker bargaining power) are more likely to extend trade credit and offer better credit terms. Klapper et al. (2012) exploit contract level data for 56 large US and European buyers to show that a number of factors influence trade credit terms. Large and creditworthy buyers receive longer credit terms (consistent with the market power explanation) from smaller suppliers (who might need to guarantee the quality of their products). Ellingsen et al. (2016) confirm that customer market power helps explain variation in trade credit terms using detailed data on all trade credit arrangements between 51 large Swedish suppliers and all their domestic corporate customers over a nine year period.

Following the discussion above, we want to investigate whether the way firms exploit their bargaining power over their trading partners is related to the extent firms already use trade credit to finance their assets. The second hypothesis we test is:

Hypothesis 2 – Bargaining power*: *Customers with larger bargaining power have larger account payables and the effect differs at the different quantiles of trade credit taken.

The sample used in this paper covers all size categories of firms operating in different manufacturing industries, allowing us to test both the supplier financing and the bargaining power reasons. It is worth noting that firm size, on its own, has opposite implications for the two theories. Larger firms are likely to be financially stronger and would therefore likely need less supplier credit, i.e., the financial reason diminishes with firm size.[5] At the same time, larger firms may have stronger bargaining power and so could potentially demand larger account payables, i.e. firm bargaining power increases with its size. To measure customer-firm market power we instead build a proxy starting from the firm's market sales share in its total industry sales.[6] We argue that the firm's relative bargaining power can be gauged using the firm's market share in conjunction with the degree of concentration in the firm's own industry. A

[5] The weak evidence of a financing motive in Klapper et al. (2012) is probably due to the relative large size of the buyers in their sample.
[6] Ellingsen et al. (2016) use a similar sales-share measure defined as the ratio of the credit sales extended by a supplier to one of its customers relative to the total trade credit extended by that supplier to all its customers.

higher market share gives a customer-firm a relatively stronger bargaining power if it operates in a less concentrated industry. The lower concentration of the customer firm's industry magnifies the relative importance of that customer in the relationship with the industry's suppliers. Thus, although our dataset does not permit matching suppliers with their customers, we exploit the detailed accounting data and the information on industry characteristics to investigate the impact of the financing and the bargaining power motives along the trade credit distribution.

3. Empirical model and methodology

We use the following specification to explain trade credit taken by firms, where i indexes firms and t denotes time periods:

$$TC_{it} = \alpha_i + \beta_1 BankLoans_{it-1} + \beta_2 MktShare_{it} + \beta_3 MktShare_{it} * IndConce_{jt} + \boldsymbol{\beta}'_4 \boldsymbol{x}_{it} + d_t + u_{it} \quad (1)$$

TC is the amount of trade credit taken (account payables) scaled by assets. α_i and d_t denote firm- and time-specific effects, while u_{it} is the random error term. *BankLoans* (bank loans relative to assets) controls for other short-term sources of external finance. A negative coefficient β_1 implies that firms substitute trade credit and bank loans, consistent with the financing theory (*H1*). To mitigate the potential endogeneity problem caused by unobservable factors affecting both trade credit uptake and the use of bank loans, *BankLoans* is measured at the end of the year *t-1*.

As discussed above, we argue that a firm's bargaining power over suppliers increases with its relative market strength over competitors. We therefore measure firm bargaining power by combining each firm's market share with its industry's degree of concentration. Market share ($MktShare_{it}$) is the percentage of the firm's sales in its own two-digit industry sales. Similar to Fabbri and Klapper (2016), we set $IndConce_{jt}$ equal to 1 if the Herfindahl-Hirschler index (HHI) for the two-digit industry j is below the median value for all industries in year t, and 0 otherwise. The interaction term $MktShare_{it} * IndConce_{jt}$ gauges the fact that a given market share offers the customer a higher bargaining power if it operates in a less concentrated industry. We expect firms with a higher market share to obtain more credit sales (positive β_2) especially if they operate in a less concentrated industry (positive β_3) (*H2 customer bargaining power*).

The vector of controls — denoted by $\boldsymbol{x}$ in (1) — includes *Profitability* (profit for the period scaled by assets), *Liquidity* (the ratio of liquid assets to total assets), and firm *Age* (logarithm). The financial variables are lagged to control for their possible endogeneity. Notice that firm financial strength could capture both the financial advantage and the bargaining power theories but the two motives work in opposite directions. For instance, finding that younger, less liquid, unprofitable firms receive more trade credit would support the financing rationale and contradict the bargaining power theory.

To test how the financing motive is influenced by the firm's ability to access alternative external funding, we estimate model (2) below which includes the interaction of $BankLoans_{it}$ with a proxy for firm financial strength as an additional regressor. (*H1b*).

$$TC_{it} = \alpha_i + b_1 BankLoans_{it-1} + b_{12} BankLoans_{it-1} {*} Size_{it-1} + b_2 MktShare_{it} + \\ + b_3 MktShare_{it} {*} IndConce_{jt} + \boldsymbol{b}'_4 \boldsymbol{x}_{it} + d_t + u_{it} \qquad (2)$$

We use the categorical variable *Size* as a proxy for firm's access to alternative external finance. Firms are considered to be either large (*Size* =1) if their total assets in a given year are in the top third of the assets distribution of all firms in the same two-digit industry and year, or small (*Size* =0). Firms are thus ranked within their own industry and are allowed to change size category over time. All the other variables are defined as in model (1).

3.1. Methodology

We employ two techniques to estimate our models. Firstly, to facilitate comparison with the literature, we start from a linear estimator and employ the correlated random effects (CRE) approach for panel data proposed by Chamberlain (1984) to evaluate the impact of the regressors at the mean value of the trade credit taken. This technique is equivalent to the panel fixed-effects estimator. Secondly, for reasons discussed below, we use the correlated random effects quantile regression (CREQR) technique developed by Abrevaya and Dahl (2008) to quantify the effect of external funding (i.e., bank loans) and customer bargaining power at different values of the trade credit to assets ratio. The CREQR approach parallels the CRE approach but is applied in the context of the quantile regression to measure the impact of the covariates at different points along the distribution of the dependent variable. We briefly discuss both approaches in the following paragraphs.

3.1.1 The Correlated Random Effects Model (CRE)

We start with the linear panel estimator. Unlike the random effects (RE) approach, which assumes that the unobserved firm-specific characteristics, denoted by α_i, are uncorrelated with the explanatory variables, the CRE approach explicitly models the correlation between α_i and the regressors. Formally, it assumes that

$$\alpha_i = \alpha + \boldsymbol{\gamma}'\boldsymbol{z}_i + r_i \tag{3}$$

where α is a constant, r_i is a time-constant unobservable uncorrelated with the regressors, and vector $\boldsymbol{z}_i$ collects the "endogenous" variables, each of which is uncorrelated with r_i. We will discuss the significance of vector $\boldsymbol{z}_i$ in more detail shortly.

Under the CRE framework, it is assumed that α_i partly affects the dependent variable, i.e., TC_{it} in equations (1) and (2), either directly, or indirectly through a subset of the explanatory variables — the "sufficient covariates" — which we denote by $\boldsymbol{s}_{it}$. The main idea behind the CRE approach is that by using repeated measurement of $\boldsymbol{s}_{it}$ we can "learn" enough to construct endogenous covariates, contained in $\boldsymbol{z}_i$, which explicitly model the relationship with the unobserved firm-specific characteristics. Our approach specifies $\boldsymbol{z}_i = \bar{\boldsymbol{s}}_i$ where $\bar{\boldsymbol{s}}_i$ is the t-mean (i.e., time average) of $\boldsymbol{s}_{it}$. Because α_i is, by definition, constant over time, allowing it to be correlated with $\bar{\boldsymbol{s}}_i$ captures the correlation between the unobserved heterogeneity and the endogenous variables. The left-over term, r_i, is uncorrelated with the regressors, and hence may be included in a composite error term. As shown by Wooldridge (2010, Chapter 10), CRE estimators and fixed-effects (FE) estimators are in fact identical.

3.1.2 The Correlated Random Effects Quantile Regression (CREQR) Model

We now turn to the CREQR technique. The quantile regression, pioneered by Koenker and Bassett (1978), has been extensively applied to cross-sectional data and—to a lesser extent— to time series data. Its applications to panel data, however, have been surprisingly limited so far. The most likely reason, as pointed out by Abrevaya and Dahl (2008), is the difficulty in extending differencing methods to quantiles because, unlike the expectation operator, the quantile operator is not linear.[7]

During the past decade, progress has been made in the area of quantile regression for panel data. Koenker (2004) introduces the penalised quantile regression model with fixed effects, involving estimating the model for different quantiles simultaneously while restricting the unobserved heterogeneity α_i to be the same. The procedure penalises estimates of the fixed effects by shrinking them towards zero. This approach, however, assumes that α_i is the only source of endogeneity without explicitly modelling its relationship with the regressors. It also

[7] As originally discussed by Koenker and Hallock (2001) and elaborated in Abrevaya and Dahl (2008), conditional quantiles are not linear operators and therefore preliminary strategies, such as differencing, which can be straightforwardly applied to Gaussian models have unanticipated effects on quantiles. This implies that models for each conditional quantile are required. However, as Angrist et al. (2006) point out, the reduced-form linear model can provide a useful approximation to the true conditional quantile function.

assumes that the effect of α_i is a pure location shift. Canay (2011) proposes a simple two-step procedure whereby the conditional mean of α_i is estimated and subtracted from the dependent variable before the model is estimated using the standard method for quantile regression. This approach has attracted much attention from applied researchers due to the simplicity of its implementation. A problem with this two-step technique, however, is that observations at the bottom of the conditional distribution of the transformed dependent variable (i.e., after differencing) may be near the top of the non-transformed conditional distribution of the dependent variable, thereby causing the structural quantile function to change and altering the interpretation of the estimated coefficients. Moreover, as acknowledged by Canay (2011), neither of these two estimators is suitable for panels with small *T*.

As our panel has a short time-series dimension (small *T*) and is also unbalanced, we opt instead for the CREQR technique. Originally developed by Abrevaya and Dahl (2008) and subsequently extended by Bache et al. (2013) to render it applicable for unbalanced panels, the CREQR estimator allows for correlated random effects in the spirit of Chamberlain (1984) in the context of quantile regression. In other words, as explained earlier and formally captured by equation (3), the estimation controls for the correlation between the unobserved heterogeneity and the covariates by including the time-means of the time varying endogenous regressors.[8]

Formally, the conditional quantile functions which we estimate take the following form:

$$Q_\tau(TC_{it}|.) = a_\tau + b_{1\tau}BankLoans_{it-1} + b_{2\tau}MktShare_{it} + b_{3\tau}MktShare_{it}*IndConce_{jt} + \\ + \boldsymbol{b}'_{4\tau}\boldsymbol{x}_{it} + \boldsymbol{\gamma}'_\tau\boldsymbol{z}_i + d_t$$

and

$$Q_\tau(TC_{it}|.) = a_\tau + b_{1\tau}BankLoans_{it-1} + b_{2\tau}BankLoans_{it-1}*Size_{it-1} + b_{3\tau}MktShare_{it} + \\ + b_{4\tau}MktShare_{it}*IndConce_{jt} + \boldsymbol{b}'_{5\tau}\boldsymbol{x}_{it} + \boldsymbol{\gamma}'_\tau\boldsymbol{z}_i + d_t$$

where the estimated parameters give us the impact of the control variables at the τ-th percentile ($0 < \tau < 1$) of the trade credit taken distribution.

4. Data and summary statistics

Our sample is drawn from the Diane database collected by Bureau van Dijk for French manufacturing firms. Most firms in our sample are not quoted on the stock exchange and rely on bank loans to finance production. This will allow us to test the financing motive of trade

[8] We use the R package rqpd developed by Koenker and Bache (2011), which is appropriate for our short time-period unbalanced panel.

credit. Firms are allowed to enter and exit the sample, which renders our panel unbalanced. The final sample includes 189,566 observations for 27,670 firms. Panel A of Table 1 reports the number of firms observed each year. As shown in Panel B, most firms provide complete information over the sample period and more than 75% of firms have at least 8 annual observations.

<Table 1 about here>

The database provides detailed industry information which allows us to link firm trade credit uptake with its relative bargaining power within its own industry. Table 2 presents the two-digit industry composition of the sample and details about the degree of concentration for each industry. To calculate the Herfindahl-Hirschler index (HHI) we sum up the squared terms of the firms' sales market share separately by each industry and year. The industry with the lowest concentration index (HHI = 0.002) is Fabricated metal products, while the most concentrated industry is Coke, refined petroleum products and nuclear fuel (HHI = 0.750). For each year, industries are separated into less and more concentrated relative to the median value of the HHI for all industries in that year. Thus, similar to Fabbri and Klapper (2016), $IndConce_{jt}$ is set equal to 1 if the concentration index for the two-digit industry j is below the median value for all industries in year t, 0 otherwise. Table 2 reveals that the less concentrated industries are Food and beverages (SIC 15), Fabricated metal products (SIC 28), Machinery and equipment (SIC 29), and Publishing, printing and reproduction of recorded media (SIC 22).

<Table 2 about here>

Table 3 reports summary statistics for all firm level variables. The one percentile tails of the financial variables are winsorised to limit the potential influence of outliers. Mean values and standard deviations are calculated for the whole sample and also separately for two size classes of firms. Firms are considered to be large if their total assets in a given year are in the top third of the assets distribution of all firms in the same two-digit industry and year, otherwise they are regarded as small. The classification criterion allows firms to change size category over time.

<Table 3 about here>

We first establish whether the trade credit usage in our sample is representative for the French economy and then make comparisons with the trade credit ratios reported for other countries. The average trade credit taken to assets ratio in our sample is around 25%, which compares well with the 23.6% ratio of payables to assets reported by Boissay and Gropp (2013) for French manufacturing, wholesale and retail firms over the period 1998-2003. Cuñat (2007) reports also a 25% trade credit to assets ratio for a sample of 250,000 UK firms of all sizes observed over the years 1993-2002. Our ratio is slightly higher than the 20% payables to assets ratio reported by Giannetti et al. (2011) for their 1998 NSSBF sample of US small firms.

Apart from the trade credit extended to assets ratio presented in Table 3, we calculate the receivables to sales ratio and compare it with the ratio reported by Shenoy and Williams (2016) for their sample of US listed firms observed over the period 1980-2008. The 21.5% receivables to sales ratio in our sample is slightly higher than their 17.3% ratio for the Compustat sample but consistent with the more prominent role of trade credit in the French bank-based system.

The manufacturing firms in our sample extend more trade credit to their customers down the production chain than they receive from their suppliers, which makes them net trade credit providers (on average). There are small but statistically significant differences for the trade credit ratios between size categories of firms (*p*-values for the *t* test are reported in the last column). That larger firms have slightly higher account payables ratios than smaller firms implies that they can use their bargaining power to receive better credit terms from suppliers. Consistent with this explanation, small firms extend more trade credit to their customers.

Use of bank funding seems to be affected by differences in firm size, where larger firms have lower bank loans to assets ratios than smaller firms. The market share of large firms seems to be several times larger than that of small firms. The other firm financial variables are the profit margin measured as profit / loss for the period over assets and the liquidity ratio defined as cash and bank deposits relative to assets. Large firms have lower profitability and liquidity ratios, and are (on average) older than their smaller counterparts. The *t* test results in the last column confirm that, in all cases, the mean differences across size categories are statistically significant.

The correlation coefficients reported in Panel B are relatively small and statistically significant at the 5% level. They also have the expected sign. For instance, in line with the financing theory, access to bank loans is negatively correlated with trade credit taken. The correlation between the firm's market share and trade credit uptake is positive. The positive relation is even stronger for firms in less concentrated industries, consistent with the bargaining power theory. We also find that younger, less profitable and less liquid firms are associated with more trade credit as all the correlation coefficients associated with the control variables are negative. These are, however, just simple pairwise correlation coefficients, evaluated at the mean values of the variables. The multivariate analysis in the next section includes relevant controls influencing the relation between trade credit taken, firm financial situation and its relative bargaining power towards its suppliers. Moreover, using the quantile regression approach allows us to consider the possibility of nonlinear relationships between trade credit uptake and the covariates.

To further explore characteristics of firms at the various percentiles of the trade credit distribution, we sort all the observations in our sample into six groups based on the value of the trade credit taken at the 10^{th}, 20^{th}, 40^{th}, 60^{th}, 80^{th}, and 90^{th} quantiles. Table 4 reports the values of the covariates at these quantiles. Several features stand out. Firstly, firms with lower outstanding trade credit appear to be those that are more profitable and liquid, while less profitable and illiquid firms tend to be those which are located at the higher percentiles of the trade credit distribution. This finding offers evidence of the use of trade credit by firms for financing purposes as the ratio of trade credit taken to assets increases. They are in line with Ellingsen et al. (2016) who find that a strengthening of the customer's financial position is associated with a reduction in account payables. The inverse relationship between trade credit uptake and profitability, however, comes at odds with Dass et al. (2014) who argue that downstream firms with high profit margins have relative bargaining power towards their suppliers and can claim more trade credit.

Firm size also appears to bear some relationship with the amount of trade credit taken with firms at the lower quantiles of the trade credit distribution having largest assets and vice versa. Also, firms at the higher quantiles of the distribution of trade credit appear to be those with higher market shares operating in less concentrated environments, as can be seen from the figures of 0.364 and 0.011 for variables *MktShare* and *MktShare*IndConce* for observations at the 90^{th} percentile of the trade credit distribution. The finding is consistent with the bargaining power hypothesis whereby firms' relative bargaining power allows them to enjoy advantageous credit terms offered by their suppliers.

<Table 4 about here>

5. Empirical results

First, we estimate equation (1) using the CREQR technique setting $\tau = 0.05$, 0.1, 0.3, 0.5. 0.7, 0.9, 0.95. Vector $\boldsymbol{z_i}$ in the model contains the time-averaged values of each of the explanatory variables, including the time dummies in unbalanced panels. Table 5 presents the estimated coefficients and bootstrapped standard errors (500 replications).

<Table 5 about here>

The CREQR estimates in Table 5 shed light on the financing theory (*H1*). The negative coefficient associated with $BankLoans_{it}$ is highly significant and increases monotonically in magnitude in absolute terms (i.e., becomes more negative) as we move from the lower quantiles towards the higher quantiles of the trade credit taken. This suggests that the trade credit - bank loans substitution becomes stronger at the higher trade credit values.

The sales market share of the customer firm appears to play a significant role at the low and the intermediate quantiles. The main variable of interest, however, is the interaction term $MktShare_{it}*IndConce_{jt}$ which accounts for the degree of industry concentration, i.e., given its market share, the customer's relative bargaining power is higher in a less concentrated industry (*H2*). The CREQR parameter on the interaction term suggests that firms with high bargaining power are able to obtain larger trade credit. The positive relationship holds at the lower and the intermediate quantiles, peaks at around the median of the trade credit distribution and remains strong until the 70th quantile after which its significance fades. The results suggest that while the financing motive and the bargaining power are both determinants of the trade credit at the lower and the intermediate quantiles, the former alone appears to influence trade credit uptake at the higher quantiles of the trade credit distribution. Since average firms with the amounts of account payables locating at the higher quantiles tend to be those that are illiquid and less profitable, our CREQR estimates on $BankLoans_{it}$ and $MktShare_{it}*IndConce_{jt}$ indicate that for the average firms at the 90th quantile of the trade credit distribution, the financing motive is stronger than the bargaining power.

Our results also indicate that profitable and liquid firms are associated with less trade credit taken, consistent with our earlier findings regarding the strength of the financial and bargain power motives as the ratio of trade credit taken to assets increases. They are in line with Ellingsen et al. (2016) who find that a strengthening of the customer's financial position is associated with a reduction in account payables. The negative correlations, however, come at odds with Dass et al. (2014) who argue that downstream firms with high profit margins have relative bargaining power towards their suppliers and can claim more trade credit. Firm age is found to be positively related with trade credit taken at the lower quantiles but the association becomes negative at the higher quantiles. In other words, older firms have larger account payables ratios when the ratio of trade credit taken to assets is relatively small. Older firms, however, are less likely to be associated with large ratios of trade credit taken to assets. This would imply that firm age captures the bargaining power rationale when trade credit is low and the financing motive when trade credit taken has reached high levels.

We now turn to the CREQR results for model (2) which includes also the interaction term *BankLoans*Size* in the set of regressors. The variable *Size* is a binary variable taking the value of 1 if the firm's assets are in the top third of the assets distribution of all firms in the same two-digit industry in a given year, and the value of 0 otherwise. The CREQR estimates for model (2) reported in Table 6 and the quantile regression process plots shown in Figure 1 suggest that, while our previous findings remain unaltered, the trade credit - bank loans substitution becomes stronger for large firms at the higher quantiles, which is consistent with the financing theory as larger firms have better access to external funding (*H1b*).

<Table 6 about here>

5.1. Additional tests

We subject our results to a series of sensitivity tests. Firstly, instead of using the median value, we set $IndConce_{jt}$ equal to 1 if the concentration index for the two-digit industry *j* is below the top quartile value for all industries in year *t*, 0 otherwise. As before, we expect firms with a higher market share to obtain more credit sales (positive β_2) especially if they operate in a less concentrated industry (positive β_3). We confirm that changing the industry concentration threshold leaves our (unreported) results qualitatively unchanged.

Secondly, we find that raising the firm size cut-off at the upper quartile of the assets distribution for all firms in the same industry and year produces similar results, confirming that the trade credit - bank loans substitution becomes stronger for large firms at higher quantiles. For brevity, these results are not reported but are available upon request.

Thirdly, to facilitate comparisons with the rest of the literature we employ a linear estimator. Table 7 presents the correlated random effects (CRE) estimates obtained with linear estimation. As explained in the methodology section, the CRE estimates control for firm heterogeneity by adding the time averages of all time-varying regressors (including time dummies in unbalanced panels). Practically, the CRE estimates collapse to the fixed-effects estimates and capture the marginal effects of the explanatory variables when the dependent variable is located at the mean. Additionally, this approach allows us to control for disaggregated two-digit industry specific effects (columns 3 and 4), as trade credit terms have been shown to vary significantly across industries (Ng, et al, 1999, Giannetti et al., 2011). Across columns, these OLS estimates confirm the significant negative relationship between trade credit taken and bank loans, and the substitution is stronger for larger firms. They also confirm the customer bargaining power theory as firms with a larger market share operating in a less concentrated industry have larger ratios of account payables to assets.

Finally, we investigate one more aspect of the financing view of trade credit, according to which suppliers have an advantage relative to banks in repossessing their own goods sold on credit, should the customer default. The nature of the transacted goods is one factor that impacts the suppliers' comparative advantage: it will be more pronounced for differentiated goods, tailored to the needs of fewer customers, for which it is harder to identify suitable alternative buyers, than for standardised (off-the-shelf) goods, with readily available reference prices (Fabbri and Menichini, 2010, Giannetti et al., 2011). This advantage is absent in the case of service suppliers as services have no liquidation value. Therefore, firms with larger proportions of differentiated goods inputs take more trade credit than firms with more standardised goods inputs. Conversely, as services have no liquidation value, firms with higher proportions of service inputs receive less trade credit.

To account for the transacted goods' characteristics, we calculate the proportion of inputs that comes from sectors producing differentiated products (*Pdiff*) and the proportion of service inputs (*Pserv*) over total inputs. These ratios are calculated at the three-digit SIC level using the input-output tables from INSEAD. The CRE results presented in columns 5 and 6 confirm that firms that purchase a higher proportion of differentiated inputs buy more on credit from their suppliers, whilst a higher proportion of service inputs relative to standardised inputs reduces the trade credit taken. Importantly, controlling for input characteristics does not alter our results regarding the relationship between trade credit and bank loans, and the importance of customer bargaining power.

<Table 7 about here>

We extend the analysis using the CREQR approach to estimate equations (1) and (2) with both *Pdiff* and *Pserv* added to the set of covariates. The results shown in Tables 8 and 9 suggest the following. Qualitatively, including *Pdiff* and *Pserv* to the models does not alter our previous CREQR estimates presented in Tables 5 and 6, which indicate that the financing motive is stronger for firms with accounts payable locating at the higher quantiles and that firms with stronger bargaining power tend to take on more trade credit. The positive sign of the estimated parameter on *Pdiff* suggests that larger proportions of differentiated product inputs are associated with larger accounts payable. The positive relation is observed across all the quantiles under investigation except at the 95^{th} quantile where the association is not statistically significant. The negative estimated parameter on *Pserv* observed across all the quantiles under examination is consistent with Fabbri and Menichini (2010) who suggest that firms buying services make fewer purchases on accounts payable than firms buying standardised goods. The magnitude of both parameters associated with our measures of input characteristics increases as we move from the left tail to the right tail, peaks at around the median, and then decreases slightly as we move towards the higher quantiles of the distribution.

<Tables 8 and 9 about here>

5.2. External finance dependence

This section aims to further disentangle the financing and the bargaining power motives for trade credit. Following Rajan and Zingales (1998), we assume that the reliance on external financing varies across industries.[9] The implication for our study is that the strength of the trade credit - bank loans relationship varies with the severity of an industry's need for external funding. Our conjecture is that the financing reason is stronger in industries dependent on external finance, while the bargain power explanation prevails in industries less dependent on external funding.

To determine an industry's dependence on external finance, we first use a profitability-based measure at the firm level. A firm *i* is classified as dependent on external finance if its return on assets in year *t* is negative. We then construct the mean value of the external finance needs of all firms in the same two-digit SIC code industry. An industry with a higher mean value of external finance dependence relies more on external finance. We classify an industry as dependent on external finance (*EFD* =1) if its percentile ranking is above the median for all industries during the sample period.

Tables 10 and 11 report our CREQR estimates for two samples separated by industry external finance dependence for models (1) and (2). The parameters on *BankLoans* for both samples (*EFD = 1* and *EFD = 0*) and models are negative and statistically significant across all the quantiles. The size of the parameters increases monotonically in absolute terms as we move from the left tail towards the right tail of the distribution, suggesting that the trade credit – bank loans substitution effect is more pronounced at the higher values of the trade credit distribution. Compared to the estimates for the sample independent on external finance (Panel B), the parameter estimates on *BankLoans* for firms which are dependent on external finance (Panel A) are smaller in absolute terms at the lower quantiles of the trade credit distribution. The discrepancy disappears as we move towards the middle quantiles and the relative higher magnitude reverses at the higher quantiles of the trade credit distribution. Looking at the results in Table 11, while there seems to be no statistically significant difference between small and large firms dependent on external funding (Panel A), there is a stronger bank loans - trade credit substitution for large firms than for small firms in industries independent of external finance at high quantiles of the trade credit distribution (Panel B). Both results still point to firms' reliance

[9] Rajan and Zingales (1998) argue that there is a technological reason why some industries depend on external finance more than others. There is, for instance, cross-industry variation in the initial project scale, the length of the production cycle, the cash harvest period, and the requirement for continuing investment.

on trade credit as a source of financing — regardless of the industry degree of dependence on external sources of funding.

<Tables 10 and 11 about here>

Our most important result, however, presented in Tables 10-11, is the striking different impact exerted by our customer bargaining power proxy across samples separated by external finance dependence. We notice that, in both tables, the magnitude of the estimated coefficients associated with our bargaining power measure $MktShare_{it}*IndConce_{jt}$ is roughly five times larger in Panel B relative to Panel A. This means that customer bargaining power plays a much more important role for firms in industries that do not depend on external funding relative to their counterparts in industries dependent of external finance. The larger magnitude of the parameter across all the quantiles can be seen in Figure 2 which plots the quantile process of the parameter for the separate samples. The results reported in Table 12 are obtained with the linear estimator and confirm that customer bargaining power is relatively more important in the sample independent of external finance ($EFD = 0$) when the dependent variable is located at the mean. The additional detail provided in Tables 10 and 11 is that customer bargaining power gains strength until the 70th quantile at which point its significance disappears. Irrespective of industry external finance dependence, the financial motive alone appears to influence trade credit uptake at the higher quantiles of the trade credit distribution.

<Table 12 about here>

6. Conclusions

This paper adopts a quantile regression technique to test the customer financing and the bargaining power hypotheses of trade credit uptake at various locations along the trade credit distribution. The results confirm that firms use trade credit as a substitute for bank loans and that firms with more bargaining power are able to obtain larger trade credit. The CREQR results also indicate that the substitution effect between trade credit and bank loans is nonlinear, conditional on the location on the trade credit distribution where the effect is evaluated. We find that the trade-off is larger at the higher quantiles where the average firms locating at these points tend to be those with weaker balance sheets. Our results suggest that firms' financial strength is negatively related to account payables. In other words, financially weak firms see trade credit as an important source of finance.

We also find that customer bargaining power plays an important role as we observe a positive relation between trade credit taken and the measure of customer bargaining power. The positive relation is present and statistically significant for most part of the trade credit distribution up to around the 70th quantile. At the higher quantiles of trade credit, however, the role of firm's bargaining power disappears, leaving trade credit to be determined solely by the financing motive. This finding suggests that the role played by customer bargaining power is limited: as the amount of trade credit gets very large, it becomes increasingly more difficult for firms to use their bargaining power to obtain even more trade credit.

We check for the robustness of our results in several ways. For instance, in line with the view that suppliers have a collateral liquidation advantage relative to banks, we control for the characteristics of the inputs used in production by customer firms. The idea is that firms buying a large proportion of inputs with unique characteristics are more likely to obtain trade credit. As services have no collateral value, firms purchasing a large proportion of service inputs are offered less trade credit by their suppliers. Our CREQR results confirm these conjectures. We find that the amount of trade credit taken increases with the proportion of differentiated goods inputs and decreases with the proportion of services inputs. The relations vary slightly across quantiles of the trade credit distribution.

To further investigate the extent to which the financing and the customer bargaining power motives influence the uptake of trade credit, we estimate the models on separate samples according to an industry's need for external funding. Our findings show that the degree of trade credit-bank loans substitution increases as we move along towards the higher quantiles of the trade credit distribution irrespective of an industry's dependence on external funding. There appears to be a stronger substitution for large vs. small firms at the higher quantiles of trade credit for industries which are not dependent on external funding. The most important result, however, is the finding that the customer bargaining power explanation is driven by the sample of firms in industries independent of external funding. Moreover, the financing motive of trade credit prevails, especially, when the level of trade credit uptake is high. This finding supports the view that trade credit relationships can transmit credit contagion among firms (Boissay and Gropp, 2009, Jacobson and von Schedvin, 2015, Shenoy and Williams, 2017).

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Table 1
Panel A. Structure of the panel data

Year	Freq.	Percent	Cum.
2000	21,099	11.13	11.13
2001	22,611	11.93	23.06
2002	23,274	12.28	35.34
2003	24,007	12.66	48.00
2004	24,536	12.94	60.94
2005	24,957	13.17	74.11
2006	25,211	13.30	87.41
2007	23,871	12.59	100.00
Total	189,566	100.00	

Panel B. Distribution of time observations (T_i) per firm

	min	1%	5%	25%	50%	75%	95%	max
Distribution of T_i :	2	3	5	8	9	9	9	9

Table 2. Industry structure and concentration ratios

SIC code	Industry	N	*HHI* Mean	*HHI* SD	*IndConce* Mean	*IndConce* SD
15	Food products and beverages	28399	0.005	0.000	1	0
17	Tobacco products	6250	0.007	0.000	0.115	0.319
18	Wearing apparel; dressing and dyeing of fur	4574	0.011	0.001	0	0
19	Tanning and dressing of leather; luggage, handbags, saddler harness and footwear	1843	0.081	0.008	0	0
20	Wood and products of wood and cork, except furniture; articles of straw and plaiting materials	8962	0.017	0.002	0	0
21	Pulp, paper and paper products; publishing and printing	4166	0.016	0.001	0	0
22	Publishing, printing and reproduction of recorded media	10018	0.006	0.001	0.886	0.318
23	Coke, refined petroleum products and nuclear fuel	306	0.750	0.015	0	0
24	Chemicals and chemical products	8094	0.013	0.002	0	0
25	Rubber and plastic products	11529	0.029	0.002	0	0
26	Other non-metallic mineral products	7757	0.015	0.002	0	0
27	Basic metals	2930	0.029	0.003	0	0
28	Fabricated metal products, except machinery and equipment	36856	0.002	0.000	1	0
29	Machinery and equipment not elsewhere classified	27243	0.005	0.000	1	0
30	Office machinery and computers	482	0.105	0.015	0	0
31	Electrical machinery and apparatus not elsewhere classified	5967	0.033	0.004	0	0
32	Radio, television and communication equipment and apparatus	3388	0.076	0.011	0	0
33	Medical, precision and optical instruments, watches and clocks	6011	0.031	0.003	0	0
34	Motor vehicles, trailers and semi-trailers	4323	0.221	0.007	0	0
35	Other transport equipment	2350	0.076	0.010	0	0
36	Furniture, manufacturing not elsewhere classified	8118	0.009	0.000	0	0
Total		189566	0.019	0.046	0.539	0.499

Note: *IndConce* equals 1 if the Herfindahl-Hirschler index (*HHI*) of industry j is below the median value for all industries in year t, 0 otherwise.

Table 3. Summary statistics and correlation coefficients

Panel A. Summary statistics

Variable	Total		Small		Large		*t* test
	Mean	SD	Mean	SD	Mean	SD	*p* value
TC	0.246	0.141	0.243	0.143	0.251	0.136	0.000
TD	0.352	0.187	0.362	0.198	0.332	0.162	0.000
NTC	-0.106	0.188	-0.119	0.199	-0.081	0.161	0.000
BankLoans	0.106	0.126	0.112	0.130	0.095	0.116	0.000
MktShare	0.084	0.796	0.012	0.019	0.223	1.349	0.000
Profitability	0.048	0.089	0.052	0.093	0.040	0.082	0.000
Liquidity	0.205	0.159	0.210	0.161	0.195	0.155	0.000
Age	2.871	0.783	2.743	0.754	3.118	0.778	0.000
Observations	189566		124663		64903		

Note: *TC* is trade credit taken (account payables) scaled by assets, *TD* is trade credit extended (account receivables) scaled by assets, and *NTC* is net trade credit calculated as *NTC = TC - TD*. *BankLoans* is the ratio of short-term bank loans to assets; *MktShare* is the ratio of the firm's sales in its own two-digit industry sales; *IndConce* equals 1 if the Herfindahl-Hirschler index (HHI) of industry *j* is below the median value for all industries in year *t*, 0 otherwise. *Profitability* is firm's profit (or loss) for the period relative to assets; *Liquidity* is the ratio of the firm's liquid assets (cash, bank deposits, and other current assets) in total assets; *Age* is the logarithm of firm age. Firms are considered to be large if their total assets are in the top third of the assets distribution for all firms in the same industry and year, and small otherwise. The last column reports the *t* test (*p* value) for the equality of mean values for small v large firms.

Panel B. Correlation coefficients

	TC	*BankLoans*	*MktShare*	*MktShare* IndConce*	*Profitability*	*Liquidity*
BankLoans	-0.083*					
MktShare	0.007*	-0.030*				
*MktShare*IndConce*	0.041*	-0.0276*	0.093*			
Profitability	-0.186*	-0.177*	-0.011*	-0.018*		
Liquidity	-0.204*	-0.278*	-0.011*	-0.017*	0.249*	
Age	-0.084*	-0.120*	0.051*	0.070*	-0.054*	0.007*

Note: * indicates significance at 5% level

Table 4. Summary statistics at various trade credit percentiles

TC percentile	10	20	40	60	80	90
Variable						
TC	0.083	0.124	0.191	0.260	0.353	0.437
BankLoans	0.097	0.083	0.104	0.103	0.110	0.084
MktShare	0.265	0.184	0.191	0.185	0.306	0.364
*MktShare*IndConce*	0.003	0.021	0.005	0.006	0.010	0.011
Profitability	0.076	0.065	0.077	0.041	0.037	0.033
Liquidity	0.278	0.238	0.203	0.162	0.153	0.182
Age	2.963	3.028	3.000	2.917	2.881	2.772
Assets	674.795	521.977	189.545	190.649	143.914	102.657

Note: *TC* is trade credit taken (account payables) scaled by assets, *BankLoans* is the ratio of short-term bank loans to assets; *MktShare* is the ratio of the firm's sales in its own two-digit industry sales; *IndConce* equals 1 if the Herfindahl-Hirschler index (HHI) of industry *j* is below the median value for all industries in year *t*, 0 otherwise. *Profitability* is firm's profit (or loss) for the period relative to assets; *Liquidity* is the ratio of the firm's liquid assets (cash, bank deposits, and other current assets) in total assets; *Age* is the logarithm of firm age; *Assets* is real value of total assets.

Table 5. Quantile regression estimates (500 bootstrap replications)

Variable	0.05	0.1	0.3	0.5	0.7	0.9	0.95
BankLoans	-0.016***	-0.03***	-0.064***	-0.092***	-0.13***	-0.172***	-0.184***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.009)	(0.013)
MktShare	0.029***	0.026***	0.025***	0.025***	0.027***	0.019*	0.014
	(0.005)	(0.006)	(0.005)	(0.004)	(0.007)	(0.011)	(0.009)
*MktShare*IndConce*	0.026**	0.032**	0.031	0.067***	0.062**	0.062	0.037
	(0.013)	(0.014)	(0.02)	(0.015)	(0.027)	(0.039)	(0.027)
Profitability	-0.018***	-0.038***	-0.076***	-0.11***	-0.16***	-0.253***	-0.283***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.007)	(0.011)	(0.014)
Liquidity	-0.019***	-0.027***	-0.046***	-0.06***	-0.057***	-0.046***	-0.049***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.007)	(0.01)
Age	0.015***	0.014***	-0.001	-0.011***	-0.018***	-0.039***	-0.046***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)	(0.008)

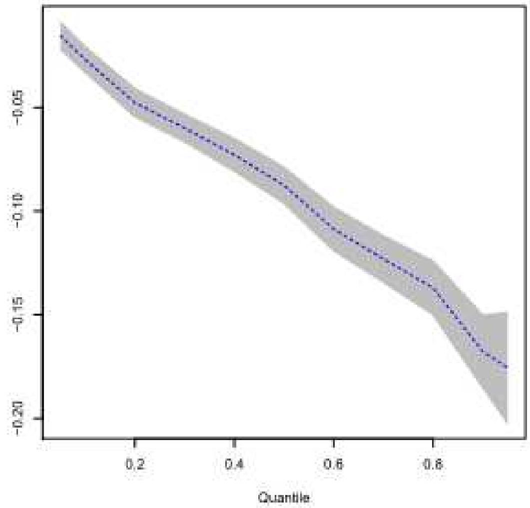
Note: The dependent variable is trade credit taken (account payables) scaled by assets. Covariates include the ratios to assets of short-term bank loans (*BankLoans*); firm's profit (or loss) for the period (*Profits*); firm's liquid assets (cash, bank deposits, and other current assets) *(Liquidity*). *Age* is the logarithm of firm age; *MktShare* is the ratio of the firm's sales in its own two-digit industry sales; *IndConce* equals 1 if the Herfindahl-Hirschler index (HHI) of industry *j* is below the median value for all industries in year *t*, 0 otherwise. The columns report the correlated random-effects estimates using the Bache and Koenker (2011) estimator. We set τ = 0.05, 0.1, …, 0.09, 0.95. All estimations control for time-specific effects. *** p<0.01, ** p<0.05, * p<0.10

Table 6. Quantile regression estimates (500 bootstrap replications)

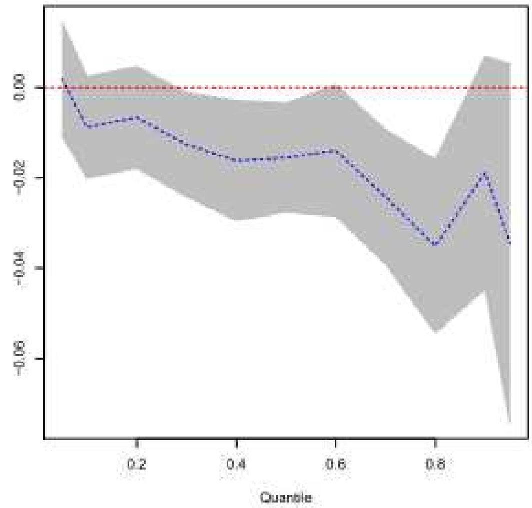
Variable	**0.05**	**0.1**	**0.3**	**0.5**	**0.7**	**0.9**	**0.95**
BankLoans	-0.015***	-0.027***	-0.06***	-0.087***	-0.123***	-0.168***	-0.175***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.007)	(0.011)	(0.016)
*BankLoans*Size*	0.002	-0.009	-0.013*	-0.016**	-0.024***	-0.019	-0.035
	(0.008)	(0.007)	(0.007)	(0.007)	(0.009)	(0.016)	(0.024)
MktShare	0.03***	0.028***	0.024***	0.023***	0.027***	0.019**	0.014**
	(0.006)	(0.007)	(0.005)	(0.004)	(0.008)	(0.01)	(0.007)
*MktShare*IndConce*	0.027**	0.032***	0.029*	0.066***	0.055**	0.048	0.033
	(0.013)	(0.011)	(0.016)	(0.015)	(0.026)	(0.042)	(0.024)
Profitability	-0.021***	-0.037***	-0.073***	-0.11***	-0.159***	-0.253***	-0.284***
	(0.005)	(0.004)	(0.004)	(0.005)	(0.007)	(0.012)	(0.015)
Liquidity	-0.019***	-0.027***	-0.046***	-0.058***	-0.056***	-0.044***	-0.049***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.005)	(0.007)	(0.009)
Age	0.017***	0.013***	-0.001	-0.012***	-0.017***	-0.039***	-0.046***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)	(0.008)

Note: See note to Table 5. *Size* equals 1 if firm's assets are in the top third of the assets distribution for all firms in the same industry and year, 0 otherwise.

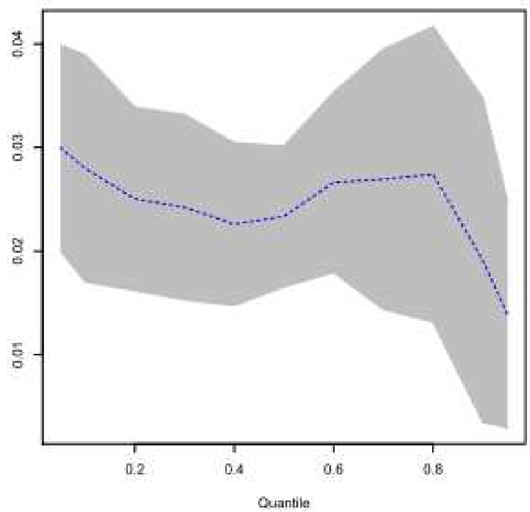
Figure 1. Plots of the quantile process estimates of the parameters on *BankLoans*, *BankLoans*Size*, *MktShare* and *MktShare*IndConce*. The 90% confidence intervals are depicted by the shaded areas.



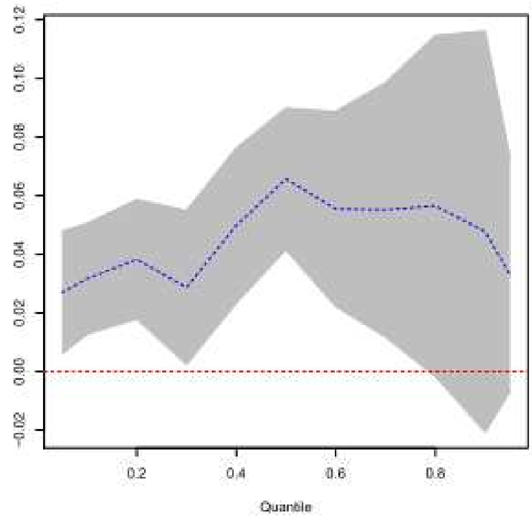
(a) *BankLoans*



(b) *BankLoans* × *Size*



(c) *MktShare*



(d) *MktShare* × *IndConce*

Table 7. Correlated random effects estimates

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
BankLoans	-0.088***	-0.083***	-0.088***	-0.083***	-0.088***	-0.085***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
*BankLoans*Size*		-0.018***		-0.018***		-0.008**
		(0.004)		(0.004)		(0.004)
MktShare	0.023***	0.023***	0.023***	0.023***	0.023***	0.023***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
*MktShare*IndConce*	0.034***	0.034***	0.034***	0.034***	0.034***	0.034***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Profitability	-0.121***	-0.121***	-0.121***	-0.121***	-0.121***	-0.121***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Liquidity	-0.044***	-0.044***	-0.044***	-0.044***	-0.044***	-0.044***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Pdiff					0.062***	0.062***
					(0.005)	(0.005)
Pserv					-0.196***	-0.196***
					(0.010)	(0.010)
Industry dummies			yes	yes		
Observations	189,566	189,527	189,566	189,527	189,566	189,527
Number of firms	27,670	27,670	27,670	27,670	27,670	27,670
R2	0.125	0.126	0.150	0.151	0.138	0.138

Note: See note to Table 5. The estimates are obtained with the correlated random effects linear estimator. All models include the time-average of all time-varying variables including the time dummies. *Size* equals 1 if the firm's total assets are in the top third of the assets distribution for all firms in the same industry and year, 0 otherwise. Columns 3 and 4 include controls for two-digit industry-specific effects. Columns 5 and 6 control for the proportion of differentiated products inputs (*Pdiff*) and the proportion of service inputs (*Pserv*) over total inputs. *** p<0.01, ** p<0.05, * p<0.01

Table 8. Quantile regression estimates (500 bootstrap replications) – controlling for input characteristics

Variable	0.05	0.1	0.3	0.5	0.7	0.9	0.95
BankLoans	-0.016***	-0.028***	-0.066***	-0.093***	-0.13***	-0.173***	-0.184***
	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)	(0.01)	(0.014)
MktShare	0.027***	0.025***	0.026***	0.024***	0.029***	0.02*	0.012
	(0.006)	(0.007)	(0.004)	(0.004)	(0.007)	(0.011)	(0.008)
*MktShare*IndConce*	0.032**	0.037***	0.027	0.052***	0.061**	0.052	0.037
	(0.014)	(0.011)	(0.018)	(0.016)	(0.028)	(0.044)	(0.027)
Profitability	-0.021***	-0.031***	-0.076***	-0.108***	-0.158***	-0.247***	-0.28***
	(0.006)	(0.004)	(0.004)	(0.005)	(0.007)	(0.012)	(0.015)
Liquidity	-0.022***	-0.028***	-0.048***	-0.057***	-0.055***	-0.048***	-0.046***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.005)	(0.008)	(0.011)
Age	0.016***	0.015***	-0.001	-0.011***	-0.019***	-0.037***	-0.047***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.006)	(0.008)
Pdiff	0.061***	0.075***	0.082***	0.071***	0.053***	0.016*	-0.001
	(0.005)	(0.004)	(0.004)	(0.005)	(0.006)	(0.009)	(0.01)
Pserv	-0.187***	-0.213***	-0.217***	-0.21***	-0.178***	-0.12***	-0.092***
	(0.011)	(0.01)	(0.01)	(0.01)	(0.012)	(0.016)	(0.02)

Note: See note to Table 5. *Pdiff* and *Pserv* are, respectively, the proportion of differentiated products inputs and the proportion of service inputs over total inputs.

Table 9. Quantile regression estimates (500 bootstrap replications) – controlling for input characteristics

Variable	0.05	0.1	0.3	0.5	0.7	0.9	0.95
BankLoans	-0.016***	-0.025***	-0.062***	-0.085***	-0.121***	-0.163***	-0.177***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.007)	(0.011)	(0.014)
*BankLoans*Size*	0.001	-0.012*	-0.015**	-0.018**	-0.03***	-0.022	-0.036
	(0.008)	(0.007)	(0.007)	(0.007)	(0.009)	(0.017)	(0.022)
MktShare	0.026***	0.026***	0.024***	0.024***	0.028***	0.018*	0.012
	(0.006)	(0.007)	(0.004)	(0.004)	(0.007)	(0.01)	(0.008)
*MktShare*IndConce*	0.033***	0.034***	0.027	0.06***	0.048*	0.062	0.033
	(0.012)	(0.013)	(0.018)	(0.017)	(0.025)	(0.045)	(0.03)
Profitability	-0.02***	-0.029***	-0.073***	-0.109***	-0.157***	-0.253***	-0.279***
	(0.005)	(0.004)	(0.004)	(0.006)	(0.007)	(0.012)	(0.014)
Liquidity	-0.02***	-0.029***	-0.047***	-0.057***	-0.054***	-0.046***	-0.047***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.008)	(0.01)
Age	0.017***	0.015***	-0.001	-0.012***	-0.017***	-0.038***	-0.046***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.006)	(0.007)
Pdiff	0.061***	0.075***	0.081***	0.071***	0.054***	0.017*	-0.001
	(0.004)	(0.004)	(0.005)	(0.005)	(0.007)	(0.009)	(0.01)
Pserv	-0.186***	-0.211***	-0.219***	-0.209***	-0.179***	-0.118***	-0.092***
	(0.01)	(0.01)	(0.01)	(0.011)	(0.012)	(0.017)	(0.022)

Note: See note to Table 5. *Size* equals 1 if firm's assets are in the top third of the assets distribution for all firms in the same industry and year, 0 otherwise. *Pdiff* and *Pserv* are, respectively, the proportion of differentiated products inputs and the proportion of service inputs over total inputs.

Table 10. Quantile regression estimates (500 bootstrap replications) – separate samples

Panel A. External finance dependent (*EFD = 1*) sample

Variable	**0.05**	**0.1**	**0.3**	**0.5**	**0.7**	**0.9**	**0.95**
BankLoans	-0.01***	-0.022***	-0.061***	-0.092***	-0.134***	-0.176***	-0.185***
	(0.004)	(0.004)	(0.005)	(0.006)	(0.009)	(0.013)	(0.018)
MktShare	0.018***	0.019***	0.024***	0.027***	0.031***	0.014	0.012
	(0.004)	(0.005)	(0.005)	(0.005)	(0.009)	(0.011)	(0.01)
*MktShare*IndConce*	0.022*	0.023**	0.018	0.035*	0.007	0.047	0.018
	(0.011)	(0.011)	(0.015)	(0.018)	(0.03)	(0.034)	(0.043)
Profitability	-0.014**	-0.027***	-0.075***	-0.113***	-0.164***	-0.27***	-0.3***
	(0.006)	(0.005)	(0.007)	(0.007)	(0.009)	(0.016)	(0.022)
Liquidity	-0.015***	-0.025***	-0.041***	-0.052***	-0.061***	-0.049***	-0.052***
	(0.004)	(0.004)	(0.006)	(0.006)	(0.007)	(0.011)	(0.016)
Age	0.013***	0.01***	0.003	-0.009*	-0.016***	-0.045***	-0.049***
	(0.003)	(0.003)	(0.004)	(0.005)	(0.006)	(0.009)	(0.011)

Panel B. External finance independent (*EFD = 0*) sample

Variable	0.05	0.1	0.3	0.5	0.7	0.9	0.95
BankLoans	-0.033***	-0.042***	-0.066***	-0.095***	-0.129***	-0.164***	-0.19***
	(0.006)	(0.007)	(0.006)	(0.007)	(0.008)	(0.014)	(0.021)
MktShare	0.037***	0.04***	0.019	0.024***	0.011*	0.014	-0.016
	(0.007)	(0.015)	(0.013)	(0.008)	(0.006)	(0.02)	(0.025)
*MktShare*IndConce*	0.117**	0.088*	0.147***	0.132***	0.158**	0.127	0.09
	(0.05)	(0.049)	(0.056)	(0.031)	(0.069)	(0.1)	(0.137)
Profitability	-0.029***	-0.04***	-0.075***	-0.105***	-0.158***	-0.237***	-0.262***
	(0.007)	(0.008)	(0.007)	(0.007)	(0.009)	(0.015)	(0.023)
Liquidity	-0.025***	-0.033***	-0.055***	-0.062***	-0.052***	-0.043***	-0.055***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.008)	(0.012)
Age	0.024***	0.018***	-0.005	-0.015***	-0.022***	-0.037***	-0.044***
	(0.004)	(0.005)	(0.003)	(0.005)	(0.006)	(0.007)	(0.01)

Note: See note to Table 5. We calculate the mean value of the external finance needs of all firms in the same two-digit SIC code industry, where a firm *i* is classified as dependent on external finance if its return on assets in year *t* is negative. We then sort industries into external finance dependent (EFD =1) and independent (EFD =0) based on the median external finance dependence of all industries during the sample period.

Table 11. Quantile regression estimates (500 bootstrap replications) – separate samples

Panel A. External finance dependent (*EFD = 1*) sample

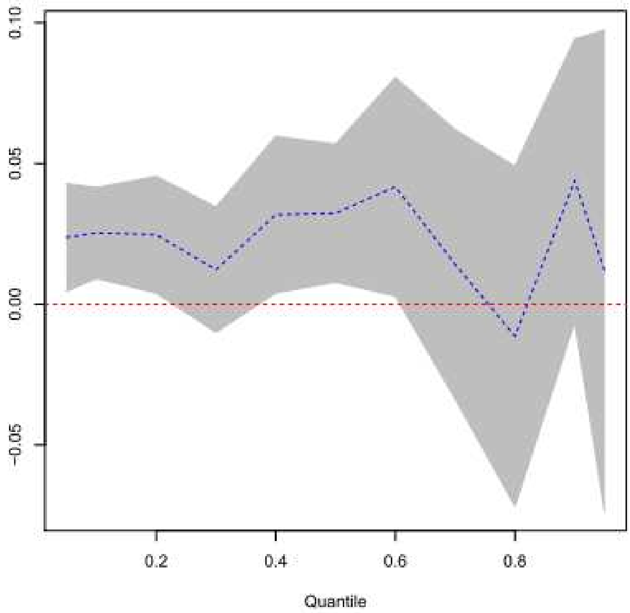
Variable	**0.05**	**0.1**	**0.3**	**0.5**	**0.7**	**0.9**	**0.95**
BankLoans	-0.009**	-0.022***	-0.057***	-0.09***	-0.124***	-0.177***	-0.182***
	(0.004)	(0.005)	(0.005)	(0.007)	(0.009)	(0.014)	(0.018)
*BankLoans*Size*	0.006	0.00	-0.015	-0.008	-0.023*	0.004	-0.015
	(0.01)	(0.009)	(0.011)	(0.01)	(0.013)	(0.021)	(0.027)
MktShare	0.019***	0.02***	0.023***	0.025***	0.032***	0.014	0.009
	(0.005)	(0.005)	(0.005)	(0.005)	(0.009)	(0.012)	(0.009)
*MktShare*IndConce*	0.024**	0.025***	0.012	0.032**	0.014	0.044	0.012
	(0.012)	(0.01)	(0.014)	(0.015)	(0.029)	(0.03)	(0.052)
Profitability	-0.01*	-0.027***	-0.072***	-0.11***	-0.166***	-0.271***	-0.302***
	(0.006)	(0.006)	(0.007)	(0.008)	(0.009)	(0.015)	(0.022)
Liquidity	-0.015***	-0.024***	-0.039***	-0.052***	-0.06***	-0.051***	-0.049***
	(0.004)	(0.005)	(0.005)	(0.006)	(0.007)	(0.011)	(0.015)
Age	0.014***	0.009***	0.001	-0.011**	-0.012**	-0.044***	-0.05***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.009)	(0.012)

Panel B. External finance independent (*EFD = 0*) sample

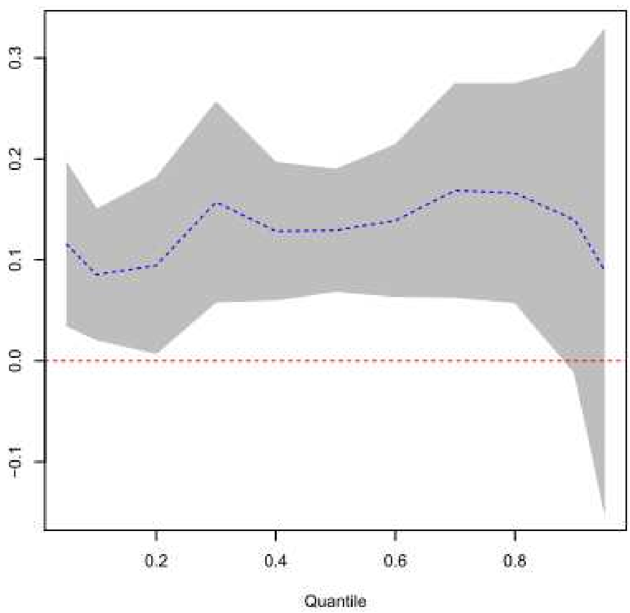
Variable	0.05	0.1	0.3	0.5	0.7	0.9	0.95
BankLoans	-0.033***	-0.041***	-0.061***	-0.085***	-0.12***	-0.154***	-0.172***
	(0.007)	(0.008)	(0.006)	(0.007)	(0.01)	(0.014)	(0.025)
*BankLoans*Size*	-0.001	-0.01	-0.017	-0.016	-0.03**	-0.033**	-0.05
	(0.013)	(0.012)	(0.011)	(0.01)	(0.012)	(0.017)	(0.032)
MktShare	0.039***	0.044***	0.017	0.024***	0.011**	0.015	-0.016
	(0.009)	(0.013)	(0.013)	(0.009)	(0.006)	(0.019)	(0.029)
*MktShare*IndConce*	0.115**	0.085**	0.157***	0.129***	0.169***	0.139	0.089
	(0.049)	(0.039)	(0.06)	(0.037)	(0.064)	(0.092)	(0.145)
Profitability	-0.033***	-0.04***	-0.075***	-0.108***	-0.154***	-0.234***	-0.262***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.01)	(0.014)	(0.024)
Liquidity	-0.023***	-0.034***	-0.054***	-0.06***	-0.054***	-0.041***	-0.051***
	(0.006)	(0.005)	(0.004)	(0.005)	(0.006)	(0.009)	(0.013)
Age	0.025***	0.019***	-0.006	-0.015***	-0.022***	-0.035***	-0.044***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.007)	(0.01)

Note: See note to Table 10. *Size* equals 1 if firm's assets are in the top third of the assets distribution for all firms in the same industry and year, 0 otherwise.

Figure 2: Plots of the quantile processes of the parameter on *MktShare*IndConce* estimated for equation (2) on separate samples (*EFD* = 1 and 0). The 90% confidence intervals are depicted by the shaded areas.



*MktShare*IndConce (EFD = 1)*



*MktShare*IndConce (EFD = 0)*

Table 12. Correlated random effects estimates and external finance dependence

VARIABLES	(1) *EFD* = 1	(2) *EFD* = 0	(3) *EFD* = 1	(4) *EFD* = 0
BankLoans	-0.086***	-0.091***	-0.085***	-0.086***
	(0.003)	(0.004)	(0.003)	(0.004)
*BankLoans*Size*			-0.002	-0.015***
			(0.005)	(0.006)
MktShare	0.022***	0.022***	0.022***	0.022***
	(0.002)	(0.004)	(0.002)	(0.004)
*MktShare*IndConce*	0.017***	0.111***	0.017***	0.111***
	(0.006)	(0.012)	(0.006)	(0.012)
Profitability	-0.125***	-0.117***	-0.125***	-0.117***
	(0.003)	(0.004)	(0.003)	(0.004)
Liquidity	-0.043***	-0.045***	-0.043***	-0.045***
	(0.003)	(0.003)	(0.003)	(0.003)
Age	-0.009***	-0.012***	-0.009***	-0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
Pdiff	0.067***	0.086***	0.067***	0.086***
	(0.006)	(0.008)	(0.006)	(0.008)
Pserv	-0.163***	-0.305***	-0.164***	-0.305***
	(0.013)	(0.016)	(0.013)	(0.016)
Observations	96,464	93,102	96,448	93,079
Number of firms	14,310	13,360	14,310	13,360
R2	0.132	0.151	0.132	0.151

Note: All models are estimated with the correlated random effects linear estimator and include the time-average of all time-varying variables. *Size* equals 1 if firm's assets are in the top third of the assets distribution for all firms in the same industry and year, 0 otherwise. *Pdiff* and *Pserv* are, respectively, the proportion of differentiated products inputs and the proportion of service inputs over total inputs. We calculate the mean value of the external finance needs of all firms in the same two-digit SIC code industry, where a firm i is classified as dependent on external finance if its return on assets in year t is negative. We then sort industries into external finance dependent (EFD =1) and independent (EFD =0) based on the median external finance dependence of all industries during the sample period. *** p<0.01, ** p<0.05, * p<0.01