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# Trade Credit Defaults and Liquidity Provision by Firms

Frederic Boissay and Reint Gropp*

04 May 2007

**Abstract**

Using a unique data set on trade credit defaults among French firms, we investigate whether and how trade credit is used to relax financial constraints. We show that firms that face idiosyncratic liquidity shocks are more likely to default on trade credit, especially when the shocks are unexpected, firms have little liquidity, are likely to be credit constrained or are close to their debt capacity. We estimate that credit constrained firms pass more than one fourth of the liquidity shocks they face on to their suppliers down the trade credit chain. The evidence is consistent with the idea that firms provide liquidity insurance to each other and that this mechanism is able to alleviate the consequences of credit constraints. In addition, we show that the chain of defaults stops when it reaches firms that are large, liquid, and have access to financial markets. This suggests that liquidity is allocated from large firms with access to outside finance to small, credit constrained firms through trade credit chains.

**JEL classification:** G30, D92, G20

**Key words:** inter-firm liquidity provision, trade credit, credit constraints, credit chains.

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## Non-Technical Summary

Trade credit is the single most important source of external finance for firms. It appears on every balance sheet and represents more than one half of businesses' short term liabilities and a third of all firms' total liabilities in most OECD countries. Yet, trade credit tends to be very expensive with implicit annual interest rates of about 40%. This has sparked a large literature on why firms use trade credit despite its high cost. Many theories emphasize that firms use trade credit because they are unable to obtain funds from the financial sector. Much of the previous empirical literature, starting with Meltzer (1960) has examined whether firms increase their use of trade credit under adverse circumstances. In the same vein, subsequent empirical work has focused on the financing role of trade credit and the substitution effects between trade credit and bank loans at the aggregate level. Under the assumption that trade credit is substitutable to bank loans, the literature generally argues that simultaneous decreases in bank loans and increases in trade credit indicate that firms are unable to obtain financing from banks and that trade credit works to mitigate the effects of firms' financial constraints. This paper proposes a new empirical identification scheme for firms facing adverse shocks. Hence, it complements the literature showing that trade credit is counter-cyclical at an aggregate level.

In this paper we do not examine whether large and liquid firms extend new or more trade credit to other firms in the economy during bad times. Instead, we estimate the extent to which credit constrained firms pass on adverse liquidity shocks they face by defaulting on their suppliers. We use a French firm-level panel data set that contains quarterly information on inter-firm trade credit defaults. Our data provide a unique opportunity to investigate the allocation of liquidity among firms because they enable us to identify the *idiosyncratic* liquidity shocks faced by firms and to analyze firms' subsequent response to these shocks tracking them through the corporate sector along trade credit links of firms. Further, our data permit to ascertain whether the supplier/customer relationship continues even after defaults. Given the size of the data set (in excess of 1.8 million observations) we can control for an extensive set of firm characteristics, as well as sector and time specific shocks.

We find evidence in favour of the existence of trade credit default chains. Firms that face defaults are themselves more likely to default. The estimates suggest that firms more likely to be credit constrained are able to pass on more than one fourth of their unexpected liquidity shocks by defaulting on trade credit, while large, liquid firms with access to outside finance do not pass on trade credit defaults they face. Our findings are consistent with theories explaining the existence of trade credit as providing finance to credit constrained firms. The results particularly lend credence to Cuñat's (2006) liquidity insurance theory and the existence of shared rents between customers and suppliers, who accommodate defaults.

Our results suggest that (i) credit constraints are prevalent among small French firms; (ii) the option to default on trade credit permits credit constrained firms to cope with adverse liquidity shocks; (iii) we interpret the mechanism as liquidity insurance through trade credit, because we have evidence that firms continue to supply firms that have defaulted to them in the past; (iv) in addition to providing such insurance, large, liquid and non credit constrained firms inject fresh liquidity into the system. (v) This liquidity is allocated via trade credit default chains within the corporate sector.

# 1 Introduction

We use new data on French firms to investigate the role of trade credit links among firms. We find evidence that they result in chains of default, and argue that these chains may serve a useful role in allocating liquidity from large firms with access to outside finance to credit constrained firms. By defaulting on trade credit, credit constrained firms are able to alleviate the effects of idiosyncratic liquidity shocks. We show that a large portion of liquidity shocks are ultimately absorbed by firms with access to outside finance further down the trade credit chain. The evidence supports theories that view trade credit as an important source of financing for credit constrained firms.

Trade credit is the single most important source of external finance for firms. It appears on every balance sheet and represents more than one half of businesses' short term liabilities and a third of all firms' total liabilities in most OECD countries. Yet, trade credit tends to be very expensive with implicit annual interest rates of about 40%.[1] This has sparked a large literature on why firms use trade credit despite its high cost. Many recent theories emphasize that firms use trade credit because they are unable to obtain funds from the financial sector. A number of reasons have been offered why suppliers may still be willing to lend when banks are not, including that suppliers have more accurate information about their customers than banks (Biais and Gollier, 1997; Petersen and Rajan, 1997), that suppliers have advantages in liquidating collateral (Mian and Smith, 1992; Frank and Maksimovic, 1998; Longhofer and Santos, 2003), that moral hazard and cash diversion problems may be less important for interfirm relationships than for bank-firm relationships (Burkart and Ellingsen, 2004) and that suppliers and their customers may have a common interest in mutual survival due to shared rents from long standing business relationships (Wilner, 2000; Cuñat, 2006). This paper not only shows that there seems to be interfirm lending via trade credit links to credit constrained firms, but that trade credit serves two distinct functions. One, suppliers may insure their customers against liquidity shocks and second, liquidity is allocated within the corporate sector along trade credit chains to where it is needed most, i.e. where credit constrained firms experienced adverse shocks.

Much of the previous empirical literature, starting with Meltzer (1960) has examined whether firms increase their use of trade credit under adverse circumstances. Meltzer (1960) showed that in periods of monetary tightening, large liquid firms increase the amount of trade credit extended. In the same vein, subsequent empirical work has focused on the financing role of trade credit and the substitution effects between trade credit and bank loans at the aggregate level. Under the assumption that trade credit is substitutable to bank loans, the literature generally argues that simultaneous decreases in bank loans and increases in trade credit indicate that firms are unable to obtain financing from banks (Kashyap et al., 1993) and that trade credit works to mitigate the effects of firms' financial constraints (Calomiris et al., 1995). This paper proposes a new empirical identification scheme for firms facing adverse shocks. Hence, it complements the literature showing that trade credit is counter-cyclical at an aggregate level.[2]

[1] Tirole (2006) reports that about 80% of the US firms offer their products on terms called "2-10 net 30", which means that the buyer must pay within 30 days, but receives a 2% discount if payment occurs within 10 days. Similar terms can be observed in most European countries.

[2] The observation of counter-cyclical behaviour of trade credit at the aggregate level may not only be consistent with the idea that firms are credit constrained but also with other explanations. For example, even in the absence of credit constraints, firms may well demand more trade credit during economic downturns in order to attract the suppliers that supply the best quality products, or supply more trade credit to attract new customers.

In this paper we do not examine whether large and liquid firms extend new or more trade credit to other firms in the economy during bad times. Instead, we estimate the extent to which credit constrained firms pass on adverse liquidity shocks they face by defaulting on their suppliers. We use a firm-level panel data set that contains quarterly information on inter-firm trade credit defaults. Our data provide a unique opportunity to investigate the allocation of liquidity among firms because they enable us to identify the *idiosyncratic* liquidity shocks faced by firms and to analyze firms' subsequent response to these shocks tracking them through the corporate sector along trade credit links of firms. Further, our data permit to ascertain whether the supplier/customer relationship continues even after defaults. Given the size of the data set (in excess of 1.8 million observations) we can control for an extensive set of firm characteristics, as well as sector and time specific shocks.

We find evidence in favour of the existence of trade credit default chains. Firms that face defaults are themselves more likely to default. The estimates suggest that firms are able to pass on more than one fourth of their unexpected liquidity shocks by defaulting on trade credit. Large, liquid firms with access to outside finance do not pass on trade credit defaults they face, even though they face the bulk of the defaults in the data. Our findings are consistent with theories explaining the existence of trade credit as providing finance to credit constrained firms (e.g. Biais and Gollier, 1997; Petersen and Rajan, 1997; Frank and Maksimovic, 1998; Burkart and Ellingsen, 2004 and Cuñat, 2006). The results particularly lend credence to Cuñat's (2006) liquidity insurance theory and the existence of shared rents between customers and suppliers, who accommodate defaults. However, the interactions within the corporate sector documented in this paper are more complex than simple bilateral customer-supplier relationships. The results suggest that there is not only mutual but also multilateral insurance as well as liquidity provision among firms. All types of firms, including credit constrained firms, supply liquidity insurance to their customers. Credit constrained firms can afford to insure their customers because they are themselves insured by their suppliers. We show that liquidity shocks are transmitted down trade credit chains until they reach firms with access to outside finance ("deep pockets"), which ultimately absorb the shocks. By extending the maturity period of trade credit to their defaulting customers, deep pockets do not only relax the financial constraints faced by their direct customers but also of those faced by their customers' customers and other firms they do not have direct business relationships with. Hence, large firms with access to outside finance inject fresh liquidity into the corporate sector.

In a nutshell, our results suggest that (i) credit constraints are prevalent among small French firms; (ii) the option to default on trade credit permits credit constrained firms to cope with adverse liquidity shocks; (iii) we interpret the mechanism as liquidity insurance through trade credit, because we have evidence that firms continue to supply firms that have defaulted to them in the past; (iv) in addition to providing such insurance, large, liquid and non credit constrained firms inject fresh liquidity into the system. (v) this liquidity is allocated via trade credit default chains within the corporate sector.

The remainder of the paper is organized as follows. As the data have never been used for research, we document them in relatively great detail in section 2 and present extensive descriptive statistics.[3] The basic results are shown in section 3. Section 4 contains a number of extensions and robustness checks. Section 5 concludes.

[3] The only exception is Bardos and Stili (2006), who provide some interesting descriptive statistics on the transmission of shocks across sectors.

# 2 Data

The compilation of the data set starts with a combination of two data sources from the Banque de France: the CIPE ("Fichier Central des Incidents de Payment sur Effets") and a firm balance sheet database, the FIBEN ("FIchier Bancaire des ENtreprises") databank. CIPE contains information on *all* firms' defaults of payment related to trade bills. Defaults are recorded on a daily basis. In CIPE a "default" is defined as a trade bill between two firms which is not paid in full and/or on time.[4] FIBEN contains detailed information on essentially all French firms' annual balance sheets and profit and loss accounts. We describe both datasets and the procedure for merging the two in more detail in the appendix (see also Bardos and Stili, 2006).

The main difficulty in merging the two datasets is their different frequency. CIPE is a daily dataset and FIBEN contains annual balance sheet information. Ultimately, we decided to construct a quarterly data set. To construct it, we proceeded in three steps (for a detailed description, see the appendix). First, we excluded firms whose balance sheet was not available, firms in agriculture, forestry, fishing, real estate activities, and education, health and social work, as well as the public sector and financial and insurance firms. We also dropped all micro-firms, that is firms with less than EUR500,000 of assets or less than 10 employees, as well as all firm-quarter observations for which our main explanatory variables (i.e. assets, purchases, sales, accounts payable and receivable) were missing.

Second, we transformed the daily information on defaults in CIPE into quarterly data. We created dummies equal to one for firm $i$ in quarter $t$ if firm $i$ defaulted at least once during quarter $t$, and calculated the total amount and the number of defaults made by firm $i$ in quarter $t$. We generated equivalent variables for the defaults faced. Third, we matched the transformed CIPE data of every firm $i$ and quarter $t$ with the corresponding balance sheet data. When firm $i$ did not default in quarter $t$ (i.e. the firm is not present in CIPE in quarter $t$), we assigned the value 0 to its statistics on defaults and kept its balance sheet information in the database. We assigned to firm $i$ in quarter $t$ its most recent balance sheet available between quarters $t-5$ and $t$, and dropped the firm when its most recent balance sheet was more than five quarters old. Hence, the same balance sheet information is assigned to firm $i$ between quarters $t-j$ and $t$ when firm $i$ last released its balance sheet in quarter $t-j$ (for $j \leqslant 5$). As we will use the lags of the explanatory variables in our regressions, we also dropped, for every quarter, the firms that were not present in the panel in the previous quarter. Ultimately, our data set includes 1,8 million firm/quarter observations for a total of 121,060 firms over the period 1998-2003 (see table 2.1).

**[Insert table 2.1 about here]**

Table 2.2 shows that the average firm in our sample has total assets of almost EUR14 million. The size distribution is skewed: The median firm has only EUR2 million in total assets. Firms on average are 22 years old, but the data set contains the entire range from very young to very mature firms. Nevertheless, by deleting the firms smaller than EUR500,000, we have eliminated most upstarts.

[4] This definition is different from commonly used definitions of "default" in bank accounting (i.e. non-performing loans). Loans are generally only classifed as in "default" after the firm has missed interest payments for several months. This definition is closely in line with the idea of suppliers accepting late payments of already extended debts (Wilner, 2000; Cuñat, 2006).

Almost all firms have accounts payable and receivable in their balance sheet and therefore extend and receive trade credit. Receivables represent more than 25% of the median firm's total assets and payables about 20%. Payables are more than four times as large as bank debt (including overdrafts). This highlights the importance of trade credit as a source of financing for French firms.[5] The positive average net trade credit position (6% of assets) is due to trade credit to households, which are not part of the data set. Finally, liquid assets (defined as the sum of cash and short term marketable securities) represent almost 10% of firms' total assets on average. Overall, as is outlined in more detail in the appendix, the sample is near exhaustive of French manufacturing, wholesale and retail firms above our specified size requirement of EUR500,000 in total assets or 10 employees.

**[Insert table 2.2 about here]**

Using a standard classification of small, medium and large firms, we find that small firms form the majority of our data set in terms of number of firms. 74% of all firms have total assets below EUR5 million and only 11% of the firms more than EUR15 million (see table 2.3). However, large firms represent more than 80% of aggregate total assets in our database, and more than 70% of trade (sales and purchases), receivables and payables. The extensive coverage of small firms in our data set is a strength as we expect that credit constraints, trade credit defaults and trade credit chains to be particularly important in this segment of the corporate sector.

**[Insert table 2.3 about here]**

Let us now examine trade credit defaults in some more depth. Summary statistics are given in table 2.4. Consider the last column of the table first. Defaults are relatively common: on average 18.5% of the firms default at least once per quarter while 7.2% are defaulted upon at least once per quarter. The difference reflects that we do not identify all defaults faced, while the data are exhaustive in defaults made.[6] As we discuss below, it also reflects an asymmetry between defaults faced and made. In total, in our sample firms defaulted on EUR5.4 billion and faced default of EUR2.1 billion.

One of the crucial features of the data set is that it contains information on the reason for the default. There are four main reasons (see also section A2 in the appendix):

*Disagreement*: the firm rejected the claim because it disagreed on the terms of the bill as presented by its bank, or because it was not satisfied with the delivered goods;

*Omission*: the firm omitted to pay, i.e. it neither endorsed nor repudiated the bill;

*Illiquidity*: the firm did not have, momentarily, the sufficient provisions on its bank account to pay the bill on time and in totality;

*Insolvency*: the firm filed for bankruptcy or was in a liquidation process.

[5] Bonds and commercial paper represent a negligible fraction of French firms' total debt.

[6] Notably, we could identify only about 85% of the firms that faced defaults in CIPE. This is a consequence of having to match on name, rather than identification number with regards to defaults faced. More explanations are in the appendix, where we also show that the (non-)identification of the suppliers in CIPE is random.

Table 2.4 shows that the most prevalent reason for defaulting on trade credit is disagreement (16.2% of the firm/quarter observations), followed by illiquidity (2.1% of the firm/quarter observations). Omission and insolvency are relatively rare occurrences at 1% and 0.4%, respectively. Given a firm defaults, the size of the default is almost EUR16,000 on average in a quarter, but this hides considerable variation across reasons. If it the default is due to disagreement regarding the good delivered, average default is EUR11,600, while if the reason for default is illiquidity or insolvency, average defaults are much larger (around EUR40,000). For the defaults faced we observe the opposite pattern. Even though our summary statistics on defaults faced do not account for all defaults, defaults faced for disagreement are higher at EUR15,500 than the defaults made on average for the same reason. In contrast the amounts faced due to illiquidity and insolvency are considerably smaller than the defaults made.

**[Insert table 2.4 about here]**

Table 2.4 suggests that firms face individually more defaults than they make and that defaults are asymmetric across motives. Their magnitude appears to depend on which party (the customer or the supplier) is at the "origin" of the default. In case of disagreement, the origin of default is the supplier, who did not deliver the expected (or delivered poor quality) products. A firm that supplies poor products may therefore be defaulted upon by several customers and face large amounts of defaults due to disagreement. Data on the average number of defaults faced within a quarter support this interpretation as the firms that are defaulted upon due to disagreement face on average 3 defaults in the same quarter, against an average of around 2 when the defaults are due to financial distress (illiquidity or insolvency). In contrast, when defaults are due to financial distress, the "fault" lies with the customer, who does not have sufficient funds to pay. A financially distressed customer therefore defaults several (eight to nine) times in the same quarter. Firms defaulting due to disagreement do so only 2.5 times per quarter.

Are defaults large enough to be relevant for the firms? Table 2.5 shows how large trade credit defaults are relative to firms' size and operations. The mean amount of default is 0.5% of total assets. This seems small. However, note that we are comparing an end of year stock variable (total assets) with a quarterly flow variable (defaults). A more meaningful statistic may be to examine defaults relative to payables, which is 2% on average. The tails of the distribution may even be more informative than the mean and suggest that at least for some firms (top 1% tail, i.e. about 18,000 firms) they represent a sizeable share of their assets (above 8 percent) or payables (about 30%). From this perspective it may be even more interesting to examine defaults faced, as this represents a liquidity shock to the firm. Compared to total assets, defaults faced by firms are small: on average 0.2%; in terms of receivables it is just below 2%. When comparing flows to flows and to available cash, we find that firms' exposure to non-payments can be substantial. Quarterly defaults represent on average 4.8% of firms' annual gross operating surplus and 43.7% of current liquid assets. In the one percent tail of the distribution, defaults faced can amount to a multiple of liquid assets and more than 50% of the firms gross operating surplus.

**[Insert table 2.5 about here]**

The fact that firms may face defaults that represent a good deal of their annual operating profits and may exceed the available liquid assets suggests that being defaulted upon may in some cases be far from innocuous to firms' financial health.[7] If a firm faces liquidity constraints and therefore is unable to pay its trade bills on time through increases in short-term loans or a credit line, then it has two options. First, it can raise cash by reducing its inventories, its planned investment, or by liquidating assets, all of which solutions are potentially costly to the firm. Second the firm can default on its suppliers and create the starting point of a trade credit default chain. This is the focus of the paper.

**[Insert tables 2.6a and 2.6b about here]**

To get a first sense of whether trade credit default chains exist, we report in table 2.6a the unconditional probability to default in a given quarter against the probability to default conditional on being defaulted upon in the previous quarter for small firms and compare it to the same statistic for large firms, which are less likely to be credit constrained (table 2.6b). The figures support our basic ideas. While the unconditional probability that a small firm defaults at least once due to illiquidity in a given quarter is 2.5%, this probability increases to 2.7% when the firm faced a default the same quarter, irrespective of the reason. This difference is statistically significant at the 1% level. For large firms we find no such effect: large firms are equally (un-)likely (0.6%) to default irrespective of whether or not they experienced a liquidity shock. Note also that this is the case despite the fact that they are much more likely to face default (17.3% versus 4.8% of the firm/quarter observations). Of course, these figures are unconditional on firm characteristics. For example, the firm may be operating in a weak sector (where defaults are common) or the firm may be poorly managed. Poor management of the firm may result in a higher likelihood of facing defaults (due to a poor quality of goods or a poor selection of customers) and simultaneously in a higher likelihood of defaulting (due to poor cash management). We address these issues in the econometric analysis below.

# 3 Econometric Analysis

In order to examine whether firms provide financing to each other in times of distress we test a series of interrelated hypotheses.

*Hypothesis 1. [Trade credit default chains] A firm is more likely to default to a supplier due to illiquidity if it faces an adverse liquidity shock.*

We will measure a liquidity shock in the data as the case in which a firm faces default. Under hypothesis 1, we should expect idiosyncratic liquidity shocks to trigger chains of trade credit defaults. However, if defaulting on trade credit is costly, only firms that are more likely to be credit constrained should take this option, rather than raise fresh external funds. Hence, hypothesis 1 can be refined to state:

*Hypothesis 2. [Credit constraints] Firms that are ex ante more likely to be credit constrained are more likely to default once faced with an adverse liquidity shock. Firms with access to outside finance are not.*

[7] If these shocks are not innocuous, why don't firms insure against them using trade credit insurance or factoring? Our understanding of the practice of trade credit insurance contracts suggests that they tend to cover the case of insolvency of the customer, rather than the type of payment delay as in our data. Hence, trade credit insurance would only insure against defaults due to insolvency, which represent less than 0.5% of the observations. Dropping these observations does not affect the results (available from the authors upon request).

The evidence regarding hypothesis 2, if confirmed, would suggest that firms default due to the presence of credit constraints. Indeed it would be strong evidence of their existence. If firms unlikely to be credit constrained also are more likely to default if faced with a liquidity shock, this would suggest that defaulting is costless and unrelated to credit constraints. Further, if non-credit constrained firms do not default once faced with a liquidity shock, this suggests that they inject new liquidity into the corporate sector. Since firms are linked via trade credit default chains, this liquidity is ultimately allocated to credit constrained firms. This is the idea behind Hypothesis 3:

*Hypothesis 3. [Liquidity allocation] Firms with access to outside finance absorb a disproportionate number of liquidity shocks and do not default.*

Finally, we want to check whether the fact that credit constrained firms default and liquidity is allocated is a reflection of relationships among firms and liquidity insurance in the spirit of Cuñat (2006). We examine this question by checking whether we observe that customers default to the same supplier more than once.

*Hypothesis 4. [Interfirm relationships] Firms continue to supply trade credit to customers that defaulted in the past due to illiquidity.*

In order to examine these hypotheses, we focus on defaults due to illiquidity as the dependent variable. We estimate the probability that firm $i$ defaults at least once on its trade credit in quarter $t$ due to illiquidity; $dftmade\_dum3_{it}$, as a function of its characteristics and whether it experienced a liquidity shock in quarter $t-1$. A liquidity shock is measured as whether or not the firm faced a default (no matter what the reason) in quarter $t-1$, $dfltfaced\_dum1234_{it-1}$ and how large this shock was with respect to its total assets in quarter $t-1$, $dfltfaced\_amount1234_{it-1}$.[8]

In all models, we use an extensive set of sector-quarter dummies, based on the two-digit NES 16 classification, as well as regional dummies intended to control for sectoral, quarterly, and regional shocks. In addition, our basic specification includes a set of variables aimed at controlling for the firm characteristics that may also affect the probability of default. They are largely based on variables that have been used extensively in the trade credit literature (e.g. Peterson and Rajan, 1997) and the corporate finance literature (e.g. Frank and Goyal, 2005). Firms with a long track record should find it easier to raise external funds. Hence, we include the logarithm of the firm's age ($age_{it}$). We expect age to have a negative effect on the probability to default. Similarly, we use the logarithm of total assets in the previous quarter ($asset_{it-1}$) for firm size. Again, we expect large firms to have a lower probability to default due to liquidity problems than small firms, which are a priory more likely to be credit constrained.[9] We also include the logarithm of the purchases to total assets ratio ($purchase_{it-1}$), for a firm may have more payments coming due when it purchases more goods and the logarithm of the sales to total assets ($sales_{it-1}$), which we expect to have a negative effect on the probability of default as firms with higher sales generate more cash flow.

[8] Note our notation here: we have two dummy variables: dfltmade_dum and dfltfaced_dum. Continuous variables are denoted as dfltmade_amount and dfltfaced_amount. The numbering "1234" indicates the reason for default, i.e. reason 1 is disagreement, reason 2 is omission, reason 3 is illiquidity and reason 4 is insolvency (see the previous section).

[9] This is not the case for the other types of defaults, notably those due to disagreement. In our database large and old firms indeed default relatively more often because of disagreement than small firms do, simply because they purchase more supplies and also because they may be more assertive in enforcing quality standards with their suppliers.

Further, we include the logarithm of one plus the liquid asset to total asset ratio ($liquid\ asset_{it-1}$) and the logarithm of one plus the receivables to total asset ratio ($receivables_{it-1}$) as proxies for firms' repayment capacity. Receivables can be viewed as a type of liquid assets, insofar as firms may pledge them as collateral in order to raise cash from banks.[10] Hence, we would expect a negative relationship to the probability to default. Alternatively, receivables might be viewed as a variable related to the firm's quality. Ferris (1981) and Brennan et. al. (1988) have argued that firms that have a difficult time selling their products may be more likely to accept being paid on credit. In this case, receivables would then be positively related to the probability of default. On the liability side, we use the logarithm of one plus the accounts payables to total assets ratio ($payables_{it-1}$) to control for firms' exposure to defaults given size, for firms with more trade debt should be more likely to default.

The ability to raise external funds affects the probability of default. Hence, we include three variables measuring the degree to which firms can access external finance. First, we use the logarithm of one plus the total bank debt to total liabilities ratio to control for firms' leverage ($bank\ debt_{it-1}$). A priory, the relationship of the share of bank debt in total assets and the probability of defaulting on trade credit is ambiguous. If a higher share of bank debt reflects relatively easy access to external finance then firms with high shares of bank debt should be less likely to default. On the other hand, firms with high leverage may have a lot of fixed obligations related to the debt and may be close to their borrowing capacity. In addition, they may be dependent on the further goodwill of their bank and therefore prefer to default on their suppliers rather than on their bank. All of this would suggest that firms with a lot of bank debt may be more likely to default.

Given this ambiguity, we also include the logarithm of one plus the share of used credit lines in total liabilities ($overdraft_{t-1}$). Following the recent evidence by Sufi (2006) that access to credit lines is a good indicator for credit constraints, we would have liked to include a dummy variable measuring whether or not the firm has access to a credit line. However, we only observe whether or not the firm uses credit lines (and to which extent). Put differently, a zero in used credit lines may reflect that the firm does not have access to a credit line or it may reflect that it does not use its credit line. In any case, if firms resort to financing a high share of their liabilities with credit lines, which presumably are relatively expensive, this may suggest that they face difficulties with obtaining cheaper long term finance and that they are close to the limits on their debt capacity. Hence, we expect a positive relationship between used credit lines and the probability to default. Finally, we use a dummy equal to one if firm $i$ has been publicly listed over the sample period and to zero otherwise ($listed_i$). Listed firms are unlikely to be credit constrained and, therefore, are expected to be less likely to default on trade credit. The results are discussed in the next section.

## 3.1 Baseline Results

Our baseline results are reported in table 3.1. Model 1 shows that, given size, age is not significantly related to the probability to default. As expected, however, larger firms are less likely to default on trade credit due to illiquidity. Similarly, sales, receivables and liquid assets have a negative impact on the probability to default, while purchases and payables have a positive impact. This is consistent

[10] Receivables are the sum of the balance sheet item "receivables" and the receivables that have been pledged as collateral against a bank loan. These receivables exited the balance sheet but are still due to the firm.

with the idea that firms with large working capital requirements are more likely to default and firms purchasing more on credit are also more likely to default. A higher share of bank debt and a higher share of overdrafts increases the probability of default, in line with a trade-off between paying bank or trade debts. All coefficients are significant at the 1% level. Perhaps most surprising is the positive coefficient (significant at the 5% level) of the dummy related to whether or not the firm is publicly listed. We speculate that since there are only very few listed firms in the sample (just above 300) and they are also among the largest, we may be picking up some interaction with our size measure (the log of total assets). The dummy may be capturing second order effects related to the need, rather than the ability, to raise external funds, which is underlying the firm's decision to publicly list in the first place. To check this interpretation, we estimated the same model without total assets and, as initially expected, we found a strong negative effect of being publicly listed on the probability to default.

In model 2 we include a credit score variable calculated by the Banque de France, $score3years_{it-1}$, which is a synthetic indicator of firms' financial health. Its calculation is quite similar to Altman's Z score.[11] Score is increasing in poor financial health, suggesting a positive coefficient, which is what we find. As expected, it takes away explanatory power from the basic debt and financial ratios, whose coefficients remain however statistically significant with the same sign as in regression 1. The strong increase in the Wald statistic from regression 1 to regression 2 suggests that $score3years_{it-1}$ contains relevant additional information on firms' financial health in addition to the financial ratios. Hence all further models will include this variable.

**[Insert table 3.1 about here]**

In order to test hypothesis 1, we include in model 3 a dummy measuring whether or not the firm faced a default in the previous quarter ($dfltfaced\_dum1234_{it-1}$) as well as, in model 4, the amount of these defaults ($dfltfaced\_\ amount1234_{it-1}$). First we note that these two additional variables do not change the sign or magnitude of the control variables. This means that defaults faced capture additional information, possibly reflecting that these new variables are related to firms' customers (while the control variables are related to firms themselves). In this sense they seem to be exogenous liquidity shocks to the firm; nevertheless we explore the exogeneity of the variable further in section 4.1. Second, we find a positive and significant sign for the lagged default dummy in both models, which means that firms are more likely to default due to illiquidity when they themselves faced defaults last period. This result is confirmed in model 4, where in addition to the dummy of defaults faced, the amount of default faced also increases the probability of default. Firms are more likely to default due to liquidity problems if they themselves have been defaulted upon in the previous quarter and this probability is increasing in the amount of the defaults faced.

Hence, we find evidence in favour of hypothesis 1: Trade credit default chains appear to exist. Next, we turn to tests of hypotheses 2 and 3.

[11] The score variable of the Banque de France $score3years_{it}$ is the probability that firm $i$ either goes bankrupt (liquidation or reorganisation) or defaults on a large fraction of its bank debt at a 3 year horizon from quarter $t$ onward. This variable summarizes balance sheet ratios only and does not include any soft information or information about the defaults on trade credit faced or made by firm $i$. The methodology and main financial variables used by the Banque de France to construct this probability are described in Bardos et al. (2004).

## 3.2 Credit Constraints and Liquidity Provision by Firms

In the previous section we demonstrated that firms generally react to a liquidity shock by defaulting on their suppliers in a chain of trade credit defaults. In this section we examine the question of whether this chain ends once the shock is passed on to large and liquid firms (hypotheses 2 and 3). If it is the case that *only* small and illiquid firms pass on liquidity shocks, then this would be evidence (i) that these firms are credit constrained; (ii) that non-credit constrained firms supply liquidity to financially distressed firms through trade credit; and (iii) that liquidity is allocated in the corporate sector along trade credit chains.

We estimate the model separately for firms more likely and those firms less likely to face credit constraints. We use two standard candidate variables to distinguish the two groups of firms: liquid and illiquid firms; large and small firms, complemented by a third distinction related to the rating assigned by the Banque de France, which enables a bank to use a firm credit as collateral in refinancing operations (see below).

For the results consider table 3.2. First, in models 5a and 5b, we show that liquid firms, which are defined as firms with above median liquid asset to total asset ratios, are significantly less likely to default due to illiquidity. In the first instance, this is simply confirming the validity of the reasons for default given in our data set. Liquid firms are quite unlikely to default for illiquidity: the unconditional probability of default is 0.63% (reported at the bottom of the table). Illiquid firms, in contrast, show a probability of default of 3.58%. However, liquid firms are almost equally likely to face default: 6.19% for liquid firms versus 8.26% for illiquid firms.[12] Even though liquid firms face default with a similar probability as illiquid firms, this does not increase their own probability of default. Moreover, the coefficients on whether or not they faced default and on the amount they faced are both statistically insignificant, while they are statistically significant and positive in the case of illiquid firms. The insignificance of these coefficients could simply reflect the fact that in the sub-group of liquid firms we observe too few defaults to obtain statistically significant coefficients at all. This does not seem to be the explanation, however, as the coefficients on the control variables are still very precisely estimated.

Even though the finding that liquid firms do not default on trade credit due to illiquidity may seem somewhat of a tautology, we think the results are interesting for two reasons. One, they are evidence that illiquid firms are indeed credit constrained, because clearly even illiquid firms in the absence of credit constraints could have obtained short term financing from their bank. Second, the results show the absorption of liquidity shocks by liquid firms, raising the possibility that liquid firms offset the potential negative effects of the liquidity shocks they experience by injecting fresh cash into the trade credit chain. It follows that non-credit constrained firms not only provide their customers with insurance against liquidity shocks (liquidity insurance) but they also provide the whole system with liquidity (liquidity provision).

**[Insert table 3.2 about here]**

[12] One could have expected liquid firms to be more likely to face default, as this may be the reason to hold a high share of liquid assets in the first place.

In models 6a to 6c we report results separately for small, medium, and large firms. First we examine the probabilities of defaulting and facing default for firms in the different size categories, which are again reported at the bottom of the table. Small firms default on trade credit due to illiquidity more than four times as often as large firms (2.5% versus 0.6%). Medium size firms are also significantly less likely to default compared to small firms with an unconditional probability of 1.1%. In contrast, large firms face defaults with a probability of 17.3% in any given quarter while small firms face default with a probability of only 4.8%. Although large firms face a lot more defaults this does not increase their probability to default: Both $dfltfaced\_dum1234_{it-1}$ and $dfltfaced\_amount1234_{it-1}$ are insignificant. The opposite is true for small firms, where facing a default and facing a larger default significantly increases the probability of default. Hence, trade credit default chains exist, but only among small firms (hypothesis 2).[13]

The third way to classify firms that are likely or unlikely to be credit constrained relates to the ability of banks to pledge high quality corporate loans as collateral with the Banque de France in the context of participating in the bi-weekly liquidity auctions conducted by the Eurosystem. The Banque de France permits the pledging of loans to firms with a rating of higher than 3 as collateral,[14] which corresponds to a probability of default over a one year horizon of 0.1% (see European Central Bank, 2001 and Banque de France, 2005). Clearly, if the loans to firms below this threshold can be pledged as collateral with the central bank, banks have no incentive to deny credit to these firms. We do not have access to the rating itself and could therefore not precisely identify the firms whose loans are eligible as collateral or not. However, we had access to the ex ante probabilities to go bankrupt at a three year horizon, or score ($score3years_{it-1}$), computed by the Banque de France. This score is not used in Banque de France's rating process but Bardos (1998) and Bardos et al. (2004) showed that it is a good proxy for firm financial health. In addition, firms whose loans are eligible have been shown to have bankruptcy rates between 0.25% and 0.75% at a three year horizon (Banque de France, 2006b). Hence, as an approximation, we based our classification on the ex ante probability to go bankrupt at a three year horizon and took the probability of 0.5% as threshold. In models 7a and 7b we report the results for firms whose $score3years_{it-1}$ variable takes on values above ("low quality") and below ("high quality") 0.5% respectively. The results confirm the earlier findings: Firms without access to outside finance are more likely to default on trade credit when faced with a liquidity shock in the form of trade credit defaults, while firms with this access are not.

In summary:[15] When a credit constrained firm faces a liquidity shock, this shock is partly absorbed and partly passed to the firm's suppliers. In contrast, when a large, liquid firm with access to outside finance ("deep pocket") faces default, it fully absorbs the shock. These findings suggest that (i) liquidity is provided to defaulting customers through an extension of the maturity period of their trade credit; (ii) large firms use their access to outside finance to inject liquidity into the system by both paying their

[13] Due to the non-linearity of the model, the high coefficient of the defaults faced for medium size firms (38.57) does not reflect a larger sensibility of medium firms to defaults. Table 3.4 indeed shows that the economic effect of the amount of defaults faced on the probability to default decreases monotonously with firm size.

[14] The Banque de France rating ranges from 9 (for firms that do not provide any balance sheet information) to 3++ (for the best fims).

[15] An alternative way of testing the liquidity provision mechanism would be to constrain the coefficient of the control variables to be the same across the various types of firms, to dummy out each type of firm, and to test the significance of the coefficients for each type. We checked that this would not change our results. In addition, the finding that defaults have different effects (even when allowing differents effects of the control variables) across firms' types makes our results stronger.

trade credit on time and by extending the maturity period of their receivables, and (iii) trade credit default chains are the channels through which liquidity is reallocated from deep pockets to small, credit constrained firms. These findings strongly support hypotheses 2 and 3.

In addition, small and illiquid firms face defaults as well. Hence, *all* types of firms supply liquidity insurance to their customers, even small and credit constrained firms. Credit constrained firms can afford insuring their customers, because they are themselves insured by their suppliers: Firms that are defaulted upon may default on their suppliers, and so on. Hence, not only deep pockets insure their customers, but only deep pockets are able to inject fresh liquidity into the system. In addition, by extending the maturity period of their trade credit, suppliers do not only relax the financial constraints faced by their direct customers but also ultimately those faced by their customers' customers and other firms they may not have direct business relationships with.

Due to the non-linearity of the model the economic magnitude of the coefficients in table 3.2 is difficult to interpret. Hence in table 3.3, we present the marginal elasticities to the control variables. The marginal effects are computed for the median firm of each sub-group. A 1% increase in assets reduces the probability of defaulting by 0.29% for large firms and by 0.69% for small firms. Receivables and payables have symmetric effects, with elasticities around 0.5 for all categories of firms, except for firms that have easy access to outside finance.[16] The positive effects of bank debt and overdrafts on the probability to default is relatively small for all firms (although statistically significant); However, to the extent that firms can use bank debt to increase their cash holdings, bank debt might have a positive effect on the default probability through liquid assets. The impact of liquid assets is overall relatively strong but varies across firms. While a 1% rise in the liquid assets to total assets ratio reduces the probability to default of large firms by 0.12%, it decreases that of small firms by 0.7%. This is further evidence for the presence of liquidity constraints in the data.

**[Insert table 3.3 about here]**

In table 3.4 we evaluate the effect of facing default on the probability to default. We report the probabilities of default of the various types of firms separately, and for various amounts of defaults faced (median, 95th percentile, and 99th percentile of the sample considered). As expected, illiquid firms are the most sensitive to adverse shocks. For instance, when the median illiquid firm faces default of an amount that represents 0.03% of its total assets (which is the median default faced by illiquid firms) in a quarter, then its probability to default next quarter increases from 2.08% to 2.44%. When it faces a default equal to 2.59% of its total assets (99th percentile of the distribution of the defaults faced), then its probability to default increases to 2.75%. We obtain similar results for the breakdown using the size and score variables. Notably, small firms are more sensitive to shocks than medium firms, which are more sensitive to shocks than large firms. Overall, facing a median liquidity shock raises the default probability of credit constrained firms by around 15%. In contrast, facing default does not affect the probability of defaulting of large, liquid, or high quality firms.

[16] One explanation for this latter result is that firms with easy access to bank loans may not need to pledge their receivables as collateral to obtain short term credit, hence implying that, for these firms, receivables are not used as a way to raise cash.

**[Insert table 3.4 about here]**

Finally, we are interested in whether the evidence is consistent with a symbiotic relationship between supplier and customer as in Cuñat (2006) or an abusive one as in, say, Kiyotaki and Moore (2001) (hypothesis 4). In order to examine this we checked whether suppliers continue to supply trade credit to firms that defaulted in the past. Hence, we calculated the percentage of repeat defaulters on the same supplier, given the customer defaulted due to illiquidity in the past. In order to avoid counting the same default more than once, we imposed a time lag between the first default and any further default of one quarter.[17] A repeat default on the same supplier occurs about 15% of the time in the dataset. This means that suppliers, even after having faced a default due to illiquidity once in the past, again extended trade credit to this very customer. Note that the figure of 15% measures the likelihood of repeat defaults, not the likelihood of a continuing relationship after a default occurs per se. Hence, the statistic significantly understates the number of ongoing supplier customer relationships: We only observe an ongoing relationship if there was indeed a further default. But there may very well be many instances in which trade credit is continued to be supplied and no further default occurs. Overall, this seems strong evidence in favour of hypothesis 4 and in favour of a symbiotic relationship among firms.

# 4 Discussion, further results and robustness

The aim of this section is to discuss the robustness of our findings and address a number of selected issues.[18] First, we examine the endogeneity of defaults faced by distinguishing between expected and unexpected defaults faced. Second, we use a Tobit model to estimate the amount of default, rather than the probability, which also enables us to assess the extent to which shocks are either passed along or absorbed. Third, given the importance we assign to differentiating between different reasons to default, we present evidence that the reason for default appears to be truthful (i.e. neither "disagreements" nor "omissions" hide illiquidity).

## 4.1 Controlling for Potential Endogeneity

So far we performed the econometric analysis with the notion that the extent to which firms face default (and therefore face liquidity shocks) is exogenous. As shown in table 2.4, however, most of the defaults faced are due to disagreement over the quality of the products delivered, which may have its origin with the firm facing the default. For instance firms that experience problems in the production process, resulting in poor quality goods, are more likely to face defaults due to disagreements. By the same token, problems in the production process may be evidence that the firm is poorly managed overall and therefore also more likely to default on its own trade credit. It follows that defaulting and facing default may be the result of the same unobserved characteristic or inherent quality. If so, then the baseline

[17] This is necessary, because the data do not permit a unique identification of specific bills. This implies that potentially the same bill is defaulted upon repeatedly. In our data, 12% of the firms that default in a given quarter continue defaulting on the same supplier for liquidity reasons in the next quarter. Of course this in itself shows some leniency on part of the supplier as any default where the supplier takes the customer to court disappears from our dataset.

[18] Although we do not report the results, we also checked that all our results hold when one drops the extreme values (i.e. the last percentile of the distribution) of the explanatory variables of the model as well as when one breaks down the sample according to whether firms are listed or not.

suffers from omitted variable bias.[19] We examine two modifications to our baseline specification, which address the problem in complementary ways. The results are reported in table 4.1.

**[Insert table 4.1 about here]**

In model 8 we add to the baseline regression the logarithm of one plus the average amount of default (divided by total assets) faced by the firm over the past year ($dfltfaced\_\ amount1234_{it-2,3,4}$). In this way we attempt to control for unobservable characteristics of the firm that would result in a higher likelihood of simultaneously facing default and defaulting.[20] We find that facing higher past defaults on average has a positive and significant impact on firms' probability of default. In addition, however, the coefficient on defaults faced in the last quarter remains significantly positive. Hence, while firm specific effects do in part seem to be at the root of seeing a higher probability of default if firms face higher default, we continue to find evidence that even controlling for this effect adverse liquidity shocks are passed along the trade credit chain through defaults.

Our second modification to address the potential endogeneity problem consists of disentangling the various motives of default by including the amount of defaults due to disagreement separately ($dfltfaced\_\ amount1_{it-1}$) into the specification (see model 9). Hence, we test whether the estimated trade credit default chains exist also if the defaults faced are due to other reasons besides disagreement. The rationale for this modification is that while defaults due to disagreements might be endogenous, this seems unlikely for defaults due to financial distress, especially controlling, as we do, for sector/quarter effects. We find that even when controlling for defaults faced due to disagreement, the coefficient on defaults faced due to reasons other than disagreement continues to be positive and significant at the 1% level.

The two modifications to the baseline model share the feature that they can both be viewed as distinguishing expected liquidity shocks from unexpected shocks. While imperfect, the average of past defaults faced is a proxy for the defaults firms can reasonably expect to face. Similarly, defaults faced due to disagreements over product quality are a proxy for expected defaults, to the extent that firms presumably know when they delivered poor quality products and, therefore, when to expect a higher rate of complaints. The fact that in model 8 the coefficient on the proxy for expected liquidity shocks is significantly positive confirms that intrinsically poor quality firms are indeed more likely to default. In addition the finding that expected defaults have a significantly weaker impact than unexpected defaults is consistent with the idea that firms may take precautionary steps to mitigate the negative effects of defaults when they anticipate them.[21]

[19] We already showed in table 3.2 that there exists a relationship between defaults faced and made for a priori credit constrained firms only, which can be taken as evidence against the endogeneity of defaults faced.

[20] While estimating model 8 we dropped 215,231 observations in the calculation of the average defaults over the past year.

[21] For instance, the firms that expect to be hit by liquidity shocks may (to the extent feasible) retain more earnings and accumulate more cash to deal with future shocks. This seems to be particularly the case as far as defaults due to disagreements are concerned, as the latter do not have any effect at all in model 9. This finding is in line with Wilner (2000), who shows that suppliers may be less inclined to concessions when shocks are systematic.

## 4.2 Tobit Model

In the previous section we modelled the probability to default. We now turn to the continuous version of our econometric model and estimate a Tobit model with the amount of default (divided by total assets) $dftmade\_amount3_{it}$ due to illiquidity in quarter $t$ as the dependent variable. We use a Tobit model because the dependent variable is truncated at zero. We include the same explanatory variables as in our previous specifications. Table 4.2 shows that results are robust: Small and illiquid firms, or those that have less access to outside finance, pass adverse liquidity shocks to their suppliers through trade credit chains. The control variables reveal the exact same patterns as in the discrete choice model, both in sign and econometric significance. Liquid, large firms with easy access to outside finance absorb the shocks and provide liquidity to credit constrained firms.

The continuous dependent variable permits some further insights into the relative magnitude of the proportion of the shocks passed on or absorbed by different types of firms. While small firms face 18.3% of the aggregate amount of defaults in a quarter (reported at the bottom of table 4.2) and hold 13.8% of aggregate payables (see table 2.3), they are responsible for 69.1% of the total amount of default. In contrast, while large firms face most of the defaults (67.9% of the total) and hold 74.5% of payables they are responsible of only 14.5% of the total amount of default. By the same token, the defaults made by low quality firms are more than four times as large in terms of assets than those made by high quality firms (2.1% of their assets against 0.5%), while both type of firms face similar amounts of defaults relative to their assets.

**[Insert table 4.2 about here]**

Combining this information with the coefficients from the Tobit model, we can calculate how much of an initial shock is passed on in the form of defaults, how much is absorbed by the firm and the amount that is passed on to different types of firms. The estimates from model 6a' suggest that small firms pass 19.4% of their liquidity shocks to their suppliers.[22] The suppliers are small 18.3% of the time and medium or large 81.7% of the time. As a consequence, small firms pass 15.8% of their liquidity shocks on to firms unlikely to be credit constrained (which will not default) and 3.5% on to firms, which again may default on their suppliers. Taking the sum of the infinite series, and assuming for the sake of argument that all small firms have the same size, we would obtain that EUR80.6 of a EUR100 liquidity shock that hits a small firm would be absorbed by the firm, EUR2.8 would be absorbed by other small firms down the trade credit chain, and EUR16.6 by large firms.

We also re-estimated the models in which we attempt to disentangle expected from unexpected defaults faced using the continuous dependent variable (table 4.3). We find that small firms pass along a larger proportion of unexpected adverse liquidity shocks than expected liquidity shocks, namely up to 28.3% of the shock.

**[Insert table 4.3 about here]**

[22] As in the binary model, the fact that the coefficient of the default dummy is not significant in model 6b' makes the high pass-through coefficient (0.656) for medium firms difficult to interpret economically.

These results stand in contrast to Kiyotaki and Moore's (2001) contention that trade credit default chains amplify the effects of liquidity shocks in the economy. In their model, credit constrained firms default on trade credit in order to avoid the liquidation of assets, which is assumed to be costly. Hence, part of the initial liquidity shock is passed on to suppliers, who in turn have to liquidate some assets and pass the remaining of the shocks onto their own suppliers and so on. As a consequence, the negative effect of the initial shock amplifies as liquidation costs accumulate along the trade credit default chain. Hence, the larger the share of the initial shock that firms absorb, the smaller the negative externality they impose on to their suppliers, and the weaker the amplification mechanism. The results presented in this paper emphasize that the conclusions of Kiyotaki and Moore (2001) hold only in the absence of firms with access to outside finance in the economy ("deep pockets"). We show that while trade credit default chains exist, they tend to reduce the likelihood of firms having to liquidate assets. Instead, they constitute a channel to allocate liquidity from deep pockets to credit constrained firms. Overall, our results would suggest that the impact of Kiyotaki and Moore's amplification mechanism, while it may exist, is relatively limited.[23]

## 4.3 Do "Disagreements" and "Omissions" Hide Financial Distress?

In the previous sections we assumed that the reason for default reported in our data set is in fact the "true" reason. Of course, one could imagine that, for instance to maintain a good reputation with other suppliers, firms may be inclined to claim that there was a disagreement on the product quality or simply omit to endorse the bill, rather than acknowledge liquidity problems. In this section we examine this question in more detail.

First recall that the reason for default is reported by the bank of the customer and not by the customer himself. In our view, this makes truthful reporting of the reason more likely compared to the case in which the firm itself would report the reason for default. In addition, the clear asymmetry of the defaults across motives that we show in section 2 is a further piece of evidence that defaults due to disagreement, omission, and financial distress are delineated from one another.[24]

**[Insert table 4.4 about here]**

We further investigate the truthfulness of the reason for default by re-estimating our baseline model, but instead of using the probability of default due to illiquidity as the dependent variable, we use the probability of default due to disagreement (model 12) and the probability of default due to omission (model 13). Comparing the results, which are reported in table 4.4, to model 2 (see table 3.1), we find significant differences. Older and larger firms are more likely to default due to disagreement or omission while they are less likely to default due to illiquidity. Firms with high shares of used credit lines in their liabilities are less likely to default due to disagreement, while they are more likely to default due to illiquidity. And finally, firms with poor credit quality as measured by the Banque de France's credit

[23] Rough calculations (available from the authors upon request) would suggest that dead weight asset liquidation costs of 20% could be offset by the injection of new liquidity. This implies that as long as liquidation costs do not exceed 20% of assets liquidated, trade credit default chains tend to dampen, rather than amplify shocks.

[24] In section 2 we showed that defaults faced due to disagreement are very concentrated while defaults made due to disagreement are dispersed across firms. In contrast, defaults faced due to illiquidity are dispersed while defaults made are concentrated. This could be taken as evidence that the reason is indeed reported truthfully.

scoring variable are less likely to default due to disagreement and more likely to default due to illiquidity. All of this is in line with the notion that mature firms are more likely to assert their rights with their suppliers, resulting in a higher probability of default due to disagreement, but these firms are less likely to face liquidity problems. Nevertheless, firms with little liquidity are also more likely to default for reasons unrelated to financial distress, which suggests that there may indeed exist a correlation between poor product quality, overall poor (liquidity) management, and the probability of default. All of the above supports our assumption that the reason for default is indeed reported truthfully.

# 5 Conclusion

Trade credit tends to be very expensive with implicit annual interest rates in excess of 40%. This has sparked a large literature on why firms use trade credit despite its high cost. This paper provides strong evidence in favour of the idea that trade credit is used to alleviate credit constraints (Petersen and Rajan, 1997; Burkart and Ellingsen, 2004 and others).[25] Specifically, our results are strongly supportive of Cuñat's (2006) idea of firms insuring each other against liquidity shocks, especially since we are able to document that suppliers continue to extend trade credit to firms that already defaulted on a payment in the past. Although in our test we focus on trade credit defaults, we would argue that our results are quite general and extend to any type of adverse shock to cash flows (e.g. demand, price, production shocks).

Specifically, using a unique data set for French firms we show that small, illiquid firms with little access to outside finance pass liquidity shocks on to their suppliers by defaulting on trade credit. If the supplier is also small and illiquid and cannot raise fresh funds on short notice, a substantial portion of the shock is likely to be passed on further down the trade credit chain. Large liquid firms ("deep pockets") with access to outside finance ultimately tend to absorb at least some of these shocks and hence inject new liquidity into the system. In this way credit constrained firms avoid having to liquidate assets as in Kiyotaki and Moore (2001). Trade credit default chains can serve a useful role in allocating liquidity to credit constrained firms.

The rich data set we use allows us to identify both the supplier, who extends the trade credit and the customer who receives it. For both we have a detailed set of balance sheet information. Further, the data set is representative of the non-financial corporate sector in France. The high number of firms permits extensive controls for sector, time and regional shocks. The data used in the paper also permit a clean identification of idiosyncratic liquidity shocks and allow us to estimate a direct link between the liquidity shock faced by a firm and its probability of default on trade credit. In our econometric

[25] Do our results provide evidence in connection with other theories of trade credit? The answer is yes. We find strong evidence that trade credit may be an incentive mechanism that ensures that customers are delivered high quality products (Lee and Stowe, 1993, Long et al., 1993, Deloof and Jegers, 1996). The prevalence of defaults due to disagreement in our database amounting to more than 80 percent of total defaults, is consistent with the theory that suggests that firms frequently use trade credit as a means to verify the quality of the goods that were delivered to them. Re-examining model 12 in table 4.4 presented in the previous section reveals patterns that further support his idea, as older, larger firms, which can be expected to possess more bargaining power with respect to their suppliers, are significantly more likely to default on trade credit due to disagreement. Finally, the negative effect of receivables on the default probability in table 3.1 could also be interpreted to provide some evidence against the notion that bad firms use the extension of trade credit as a marketing strategy for their goods (Summers and Wilson, 2003, Blazenko and Vandezande, 2003). In addition, if this were the case then young and small firms would presumably accommodate more defaults than large or well established firms. However, the results suggest the opposite.

analysis we are able to take great care identifying trade credit default chains (a higher likelihood of defaulting if facing defaults), and control for firms' unobserved characteristics that would cause firms to both face more defaults (due to e.g. poor product quality) and default more frequently (due to e.g. poor cash management). We also view our paper as providing some fresh evidence on the existence of credit constraints in the corporate sector.

Overall the paper points to the existence of symbiotic relationships between suppliers and their customers, as described in Cuñat (2006) and similar to those between banks and firms first described in Petersen and Rajan (1995). Petersen and Rajan (1995), however, rely on the assumption of a monopolistic banking system, which enables banks to collect rents from their customers. In this paper, the benefit appears to be mutual. Customers are willing to buy on credit even though the implicit interest rate that is charged is higher than the credit market rate because they do not have access to the credit market. Suppliers are willing to lend because they can threaten to stop the supply of customized goods. They also have an incentive to ensure the survival of their customers and therefore are willing to permit trade credit defaults. In our data, a significant proportion of firms continue to extend trade credit to a customer even after facing default due to illiquidity from the customer. A striking implication of our results goes beyond this bilateral relationship, however. The presence of trade credit default chains suggests that the supplier ultimately providing credit may not have any direct business relationship with the firm that was initially hit by the shock. Instead the allocation of liquidity operates indirectly through a chain of such relationships.

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# Tables

**Table 2.1: Number of observations**

| | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 1998-2003 |
|---|---|---|---|---|---|---|---|
| N | 53,329 | 326,709 | 348,278 | 360,350 | 368,516 | 373,483 | 1,830,665 |
| Number of firms | 28,355 | 84,614 | 92,506 | 97,163 | 99,492 | 100,763 | 121,060 |

**Table 2.2: Summary statistics - balance sheets**

| | mean | median | 1% | 99% | % strictly positive obs. [1] |
|---|---|---|---|---|---|
| Total assets (millions of euros) | 13.9 | 2.2 | 0.5 | 165.8 | 100 |
| Age (years) | 22.4 | 17 | 2 | 91 | 100 |
| Ratios in % of total assets | | | | | |
| Bank debt | 9.0 | 5.5 | 0.0 | 46.6 | 86.2 |
| of which: overdrafts | 2.9 | 0.0 | 0.0 | 28.5 | 53.9 |
| Payables | 23.6 | 21.0 | 1.7 | 67.0 | 99.98 |
| Receivables | 29.59 | 27.98 | 0.0 | 79.5 | 98.8 |
| Net receivables | 6.0 | 7.0 | -46.1 | 53.2 | 98.7 |
| Liquid assets | 9.9 | 5.5 | 0.0 | 51.3 | 95.7 |

N=1,830,665. [1] Number of firm-quarter observations where the ratios are strictly positive, in percentage of the total number of quarter-firm observations.

**Table 2.3: Proportion of small, medium, and large firms**

| | % share in aggregate | | | | | |
|---|---|---|---|---|---|---|
| | assets | trade [1] | receivables | payables | N | % of N |
| small [2] | 10.2 | 15.3 | 15.0 | 13.8 | 1,348,206 | 73.7 |
| medium [3] | 8.9 | 12.0 | 12.5 | 11.8 | 284,130 | 15.5 |
| large [4] | 80.8 | 72.9 | 72.5 | 74.5 | 198,329 | 10.8 |

Table 2.3 shows the share in totals aggregated over the full sample. [1] Trade is the sum of purchases and sales. [2] Small firms defined as total assets below EUR5 million. [3] Medium firms: between EUR5 and EUR15 million of total assets. [4] Large firms: more than EUR15 million of total assets.

**Table 2.4: Summary statistics - defaults**

| | disagreement | omission | illiquidity | insolvency | any motive [1] |
|---|---|---|---|---|---|
| Avge amount of defaults made per firm/quarter | 11,626 | 6,787 | 40,742 | 39,352 | 15,868 |
| (in euros, given default) | | | | | |
| N. obs with default | 295,767 | 18,568 | 37,669 | 6,751 | 338,098 |
| % obs with default | 16.2 | 1.0 | 2.1 | 0.4 | 18.47 |
| N. of defaults per firm/quarter (given default) | 2.5 | 2.1 | 8.5 | 9.7 | 3.5 |
| Total amount of default made (in billions euros) | 3.44 | 0.13 | 1.53 | 0.27 | 5.36 |
| Avge amount of defaults faced per firm/quarter | 15,524 | 4,308 | 9,621 | 5,970 | 15,734 |
| (in euros, given default) | | | | | |
| N. obs with default | 89,662 | 9,840 | 56,606 | 15,512 | 131,660 |
| % obs with default | 4.90 | 0.54 | 3.09 | 0.85 | 7.19 |
| N. of defaults per firm/quarter (given default) | 2.9 | 1.5 | 2.1 | 1.7 | 3.2 |
| Total amount of default faced (in billions euros) | 1.39 | 0.04 | 0.54 | 0.09 | 2.07 |

The average amounts of defaults are calculated over the full sample, conditional on observing defaults. [1] The column any motive is not the sum of the other four columns, because firms default or are defaulted upon several times and for several reasons in a given quarter.

**Table 2.5: Default ratios** [1], [2]

| Ratios in % | mean | med | 1% | 99% | Nb. obs | % obs |
|---|---|---|---|---|---|---|
| Defaults made/total assets | 0.47 | 0.04 | 0.00 | 7.86 | 338,098 | 18.47 |
| due to illiquidity | 2.12 | 0.97 | 0.00 | 15.00 | 37,669 | 2.06 |
| Defaults made/payables | 2.02 | 0.19 | 0.00 | 29.35 | 338,098 | 18.47 |
| due to illiquidity | 8.64 | 4.01 | 0.00 | 59.02 | 37,669 | 2.06 |
| Defaults faced/total assets | 0.19 | 0.03 | 0.00 | 2.59 | 131,660 | 7.19 |
| Defaults faced/receivables | 1.81 | 0.11 | 0.00 | 13.76 | 131,660 | 7.19 |
| Defaults faced/liquid assets | 43.66 | 0.95 | 0.00 | 762.25 | 127,544 | 6.97 |
| Default faced/GOS | 4.79 | 0.43 | 0.00 | 53.67 | 118,782 | 6.49 |

[1] We report quarterly amounts of default divided by annual balance sheet items in order to avoid double-counting the successive defaults that may occur between a given firm and its supplier during the year. [2] Ratios are conditional on observing defaults.

**Table 2.6a: Distribution of defaults - Small firms**

| | No default | Default | Total |
|---|---|---|---|
| | due to illiquidity | | |
| Not defaulted upon | 1,252,222 | 31,672 | 1,283,894 |
| (no matter the reason) | (97.5) | (2.5) | (95.2) |
| Defaulted upon | 62,602 | 1,710 | 64,312 |
| (no matter the reason) | (97.3) | (2.7) | (4.8) |
| Total | 1,314,824 | 33,382 | 1,348,206 |
| (no matter the reason) | (97.5) | (2.5) | (100) |

**Table 2.6b: Distribution of defaults - Large firms**

| | No default | Default due to illiquidity | Total |
|---|---|---|---|
| Not defaulted upon (no matter the reason) | 163,058 (99.4) | 987 (0.6) | 164,045 (82.7) |
| Defaulted upon (no matter the reason) | 34,072 (99.4) | 212 (0.6) | 34,284 (17.3) |
| Total (no matter the reason) | 197,130 (99.4) | 1,199 (0.6) | 198,329 (100) |

**Table 3.1: Logit estimation of the probability of default**

| Dependent variable | Default due to illiquidity ($dfltmade\_dum3_{it}$) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Independent variables | | | | |
| *Constant* | 1.86** (0.279) | 0.99** (0.281) | 1.02** (0.282) | 1.02** (0.282) |
| $age_{it}$ | -0.02 (0.015) | -0.03* (0.015) | -0.03 (0.015) | -0.02 (0.015) |
| $asset_{it-1}$ | -0.68** (0.013) | -0.61** (0.013) | -0.62** (0.013) | -0.62** (0.013) |
| $purchase_{it-1}$ | 0.05** (0.015) | 0.12** (0.015) | 0.12** (0.015) | 0.12** (0.015) |
| $sales_{it-1}$ | -0.78** (0.032) | -0.55** (0.031) | -0.55** (0.031) | -0.55** (0.031) |
| $liquid\ asset_{it-1}$ | -12.79** (0.238) | -11.18** (0.233) | -11.18** (0.233) | -11.17** (0.233) |
| $receivables_{it-1}$ | -2.34** (0.099) | -2.10** (0.097) | -2.14** (0.097) | -2.14** (0.097) |
| $payables_{it-1}$ | 4.96** (0.105) | 3.00** (0.108) | 3.00** (0.108) | 3.00** (0.109) |
| $bank\ debt_{it-1}$ | 0.98** (0.145) | 0.64** (0.140) | 0.65** (0.139) | 0.65** (0.139) |
| $overdraft_{it-1}$ | 6.76** (0.170) | 3.74** (0.177) | 3.74** (0.177) | 3.74** (0.177) |
| $listed_i$ | 0.43* (0.177) | 0.39* (0.170) | 0.39* (0.170) | 0.39* (0.170) |
| $score3years_{it-1}$ | - | 0.05** (0.000) | 0.05** (0.000) | 0.05** (0.000) |
| $dfltfaced\_dum1234_{it-1}$ | - | - | 0.15** (0.033) | 0.13** (0.033) |
| $dfltfaced\_amount1234_{it-1}$ | - | - | - | 5.76** (1.463) |
| Pseudo $R^2$ | 0.16 | 0.19 | 0.19 | 0.19 |
| Wald Statistic | 16,536 | 22,789 | 22,819 | 22,837 |
| Defaults made, % of obs | 2.1 | 2.1 | 2.1 | 2.1 |
| Defaults faced, % of obs | 7.2 | 7.2 | 7.2 | 7.2 |
| N | 1,830,665 | 1,830,665 | 1,830,665 | 1,830,665 |

The endogenous variable is the dummy $dfltfaced\_dum3_{it}$, which is equal to one if firm $i$ defaults at least once due to illiquidity in quarter $t$ and zero otherwise. The explanatory variables are the logarithm of the age (in number of years) of firm $i$ in quarter $t$ ($age_{it}$), the logarithm of the assets of firm $i$ in quarter $t-1$ ($asset_{it-1}$), the logarithm of the ratio purchases/assets of firm $i$ in quarter $t-1$ ($purchase_{it-1}$), the logarithm of the ratio sales/assets of firm $i$ in quarter $t-1$ ($sales_{it-1}$), the logarithm of one plus the ratio payables/assets of firm $i$ in quarter $t-1$ ($payables_{it-1}$), the logarithm of the ratio receivables/assets of firm $i$ in quarter $t-1$ ($receivables_{it-1}$), the logarithm of one plus the ratio total bank debt (including used credit lines)/assets of firm $i$ in quarter $t-1$ ($bank\ debt_{it-1}$), the logarithm of one plus the ratio used credit lines/assets of firm $i$

in quarter $t-1$ ($overdraft_{it-1}$), the logarithm of one plus the ratio liquid assets (i.e. stock of cash + short term marketable securities)/assets of firm $i$ in quarter $t-1$ ($liquid\ asset_{it-1}$), a dummy that is equal to one if firm $i$ has been listed on the French stock market once over the period 1998-2003 ($listed_i$), the probability that firm $i$ goes bankrupt or defaults on a large fraction of its bank debt within the next three years after quarter $t-1$ ($score3years_{it-1}$), a dummy equal to one if firm $i$ faced default at least once in quarter $t-1$ ($dfltfaced\_dum1234_{it-1}$) irrespective of the reason, and the logarithm of one plus the ratio total amount of the defaults faced by firm $i$ in quarter $t-1$ (irrespective of the motive)/total assets of firm $i$ in quarter $t-1$ ($dfltfaced\_amount1234_{it-1}$). All models also include 275 sector*quarter dummies and 22 regional dummies (not reported). Robust standard errors (in parentheses) are adjusted for clustering using the generalised method based on Huber-White. **, * : significant at the 1% and 5% level, respectively.

**Table 3.2: Logit estimation of the probability of default**
**Breakdown by liquid assets, asset size, and access to external finance**

| Dependent variable | Default due to illiquidity: $dfltmade\_dum3_{it}$ | | | | | | |
|---|---|---|---|---|---|---|---|
| | (5a) | (5b) | (6a) | (6b) | (6c) | (7a) | (7b) |
| Independent variables | illiquid | liquid | small | medium | large | low quality | high quality |
| $Constant$ | 1.33** (0.295) | -3.16** (1.029) | 1.65** (0.317) | -1.02 (1.414) | -6.65** (1.270) | 1.05** (0.282) | -8.84** (1.483) |
| $age_{it}$ | -0.01 (0.016) | -0.10** (0.030) | -0.03 (0.016) | -0.01 (0.041) | 0.03 (0.054) | -0.03* (0.015) | 0.12 (0.122) |
| $asset_{it-1}$ | -0.64** (0.014) | -0.50** (0.030) | -0.70** (0.021) | -0.66** (0.113) | -0.29** (0.073) | -0.62** (0.013) | -0.24** (0.098) |
| $purchase_{it-1}$ | 0.13** (0.017) | 0.09** (0.032) | 0.14** (0.017) | 0.00 (0.039) | 0.11* (0.050) | 0.12** (0.015) | 0.33* (0.152) |
| $sales_{it-1}$ | -0.58** (0.034) | -0.33** (0.064) | -0.61** (0.036) | -0.28** (0.081) | -0.44** (0.093) | -0.56** (0.031) | -0.84** (0.277) |
| $liquid\ asset_{it-1}$ | -15.99** (0.771) | -6.04** (0.320) | -11.53** (0.250) | -9.42** (0.830) | -4.76** (0.915) | -11.26** (0.242) | -3.31** (0.798) |
| $receivables_{it-1}$ | -2.09** (0.106) | -2.12** (0.196) | -2.09** (0.103) | -2.40** (0.365) | -2.45** (0.522) | -2.14** (0.097) | -0.11 (1.113) |
| $payables_{it-1}$ | 2.82** (0.123) | 3.58** (0.202) | 3.05** (0.117) | 2.98** (0.378) | 3.20** (0.554) | 2.95** (0.109) | 2.84* (1.168) |
| $bank\ debt_{it-1}$ | 0.70** (0.153) | 0.45 (0.278) | 0.52** (0.150) | 1.60** (0.477) | 1.48** (0.505) | 0.59** (0.141) | 1.03 (0.850) |
| $overdraft_{it-1}$ | 3.21** (0.194) | 5.02** (0.372) | 3.97** (0.195) | 2.59** (0.544) | 2.61** (0.679) | 3.74** (0.178) | 9.88** (2.510) |
| $listed_i$ | 0.34 (0.194) | 0.64* (0.325) | -0.18 (0.448) | 0.17 (0.376) | 0.29 (0.22) | 0.36* (0.174) | 0.94 (0.808) |
| $score3years_{it-1}$ | 0.05** (0.000) | 0.06** (0.002) | 0.05** (0.000) | 0.05** (0.002) | 0.04** (0.003) | 0.05** (0.000) | 0.52 (1.129) |
| $dfltfaced\_dum1234_{it-1}$ | 0.16** (0.036) | -0.02 (0.075) | 0.12** (0.038) | 0.14 (0.083) | 0.18 (0.105) | 0.13** (0.033) | -0.25 (0.345) |
| $dfltfaced\_amount1234_{it-1}$ | 6.09** (1.853) | 2.98 (3.597) | 5.02** (1.404) | 38.57* (18.050) | 4.72 (4.367) | 5.76** (1.463) | 23.87 (22.848) |
| Pseudo $R^2$ | 0.15 | 0.13 | 0.19 | 0.15 | 0.10 | 0.19 | 0.13 |
| Wald Statistic | 14,572 | 6,320 | 19,626 | 3,743 | 1,627 | 21,967 | 551 |
| Defaults made, % of obs | 3.58 | 0.63 | 2.48 | 1.09 | 0.60 | 2.21 | 0.22 |
| Defaults faced, % of obs | 8.26 | 6.19 | 4.77 | 11.68 | 17.26 | 7.35 | 5.28 |
| N | 885,800 | 944,865 | 1,348,206 | 284,130 | 198,329 | 1,692,773 | 137,892 |

The endogenous variable is $dfltfaced\_dum3_{it}$, which is equal to one if firm $i$ defaults at least once due to illiquidity in quarter $t$ and zero otherwise. The explanatory variables are defined as in 3.1 Models 5a,b are estimated on the subsamples of firms whose liquid assets to total assets ratio is below ("illiquid") and above ("liquid") the median of the sample, see table 2.2). Models 6a,b,c are estimated on the subsamples of small, medium, and large firms, as defined in table 2.3. Model 7a,b are estimated on the subsamples firms whose probability to go bankrupt within the next three years in quarter $t-1$ ($score3years_{it-1}$) are above ("low quality") or below ("high quality") 0.5%, respectively. Models 5a, 6a, and 7a also include 275 sector*quarter dummies and 22 regional dummies (not reported). Model 5b includes 269 sector*quarter dummies and 22 regional dummies (not reported). Model 6b includes 265 sector*quarter dummies and 22 regional dummies (not reported). Model 6c includes 225 sector*quarter dummies and 22 regional dummies (not reported). Model 7b includes 113 sector*quarter dummies and 22 regional dummies (not reported). Standard errors adjusted for clustering using the generalized method based on Huber-White in parenthesis. The statistics on the defaults made/faced (in % of obs) at the bottom of the table corresponds to the number of firm/quarter observations where a default is observed in percentage of the total number of observations in the considered subsample. **, * : significant at 1% and 5% respectively.

**Table 3.3: Marginal elasticities (models 5a,b, 6a,b,c and 7a,b)**

| in % | illiquid | liquid | small | medium | large | low quality | high quality |
|---|---|---|---|---|---|---|---|
| $age_{it}$ | -0.01<br>(2.89) | -0.10**<br>(2.89) | -0.03<br>(2.83) | -0.01<br>(3.13) | 0.03<br>(3.25) | -0.03*<br>(2.89) | 0.12<br>(3.09) |
| $asset_{it-1}$ | -0.62**<br>(7.82) | -0.50**<br>(7.60) | -0.69**<br>(7.36) | -0.66**<br>(8.89) | -0.29**<br>(10.26) | -0.61**<br>(7.67) | -0.24**<br>(7.95) |
| $purchase_{it-1}$ | 0.13**<br>(-0.59) | 0.09**<br>(-0.57) | 0.14**<br>(-0.55) | 0.00<br>(-0.60) | 0.11*<br>(-0.76) | 0.12**<br>(-0.53) | 0.39*<br>(-1.30) |
| $sales_{it-1}$ | -0.57**<br>(0.38) | -0.33**<br>(0.44) | -0.61**<br>(0.47) | -0.29**<br>(0.26) | -0.44**<br>(0.06) | -0.56**<br>(0.44) | -0.85**<br>(-0.02) |
| $liquid\ asset_{it-1}$ | -0.18**<br>(0.01) | -0.79**<br>(0.13) | -0.70**<br>(0.06) | -0.42**<br>(0.04) | -0.12**<br>(0.02) | -0.53**<br>(0.05) | -0.58**<br>(0.17) |
| $receivables_{it-1}$ | -0.53**<br>(0.25) | -0.50**<br>(0.23) | -0.53**<br>(0.25) | -0.56**<br>(0.23) | -0.51**<br>(0.21) | -0.55**<br>(0.26) | -0.01<br>(0.13) |
| $payables_{it-1}$ | 0.55**<br>(0.19) | 0.65**<br>(0.18) | 0.59**<br>(0.19) | 0.57**<br>(0.19) | 0.50**<br>(0.15) | 0.58**<br>(0.20) | 0.22*<br>(0.08) |
| $bank\ debt_{it-1}$ | 0.05**<br>(0.08) | 0.01<br>(0.03) | 0.02**<br>(0.05) | 0.08**<br>(0.05) | 0.05**<br>(0.03) | 0.03**<br>(0.05) | 0.01<br>(0.01) |
| $overdraft_{it-1}$ | 0.05**<br>(0.01) | 0.05**<br>(0.00) | 0.00**<br>(0.00) | 0.00**<br>(0.00) | 0.01**<br>(0.00) | 0.00**<br>(0.00) | 0.00**<br>(0.00) |
| $listed_i$ | -0.008<br>(0) | 0.000*<br>(0) | -0.002<br>(0) | 0.000<br>(0) | 0.000<br>(0) | 0.000*<br>(0) | 0.000<br>(0) |

Table 3.3 shows the elasticities of the probability to default of firm $i$ in quarter $t$ to the control variables in the models in table 3.2. Estimated at median values (in parenthesis) of the considered subsamples.

**Table 3.4: Economic size of trade credit default chains: default probabilities**

| in %, median firm | illiquid | liquid | small | medium | large | low quality | high quality |
|---|---|---|---|---|---|---|---|
| No default faced | 2.08 | 0.03 | 1.10 | 0.07 | 0.00 | 1.14 | 0.00 |
| Default faced - median | 2.44**<br>(0.03) | 0.03<br>(0.03) | 1.28**<br>(0.02) | 0.09<br>(0.02) | 0.00<br>(0.01) | 1.30**<br>(0.03) | 0.00<br>(0.03) |
| Default faced - 95th pctile | 2.53**<br>(0.76) | 0.03<br>(0.79) | 1.31**<br>(1.27) | 0.09*<br>(0.43) | 0.00<br>(0.20) | 1.35**<br>(0.79) | 0.00<br>(0.60) |
| Default faced - 99th pctile | 2.75**<br>(2.59) | 0.03<br>(2.60) | 1.45**<br>(3.81) | 0.11*<br>(1.26) | 0.00<br>(0.61) | 1.47**<br>(2.63) | 0.00<br>(2.05) |

The probabilities of default when the median firm does not face default in quarter $t-1$ are reported in the first line for each subsample. Calculated using the estimates of models 5a,b, 6a,b,c, and 7a,b at the median of the subsamples. The next three lines show the default probabilities of the median firm when it faces defaults in quarter $t-1$ and when these defaults are median, high (95th percentile), and very high (99th percentile). The median, 95th percentile and 99th percentile of the defaults faced (in percentage of total assets), respectively, are reported into parentheses.

**Table 4.1: Logit - Controlling for endogeneity**

| Dependent variable | Default due to illiquidity: $dfltmade\_dum3_{it}$ | |
|---|---|---|
| | (8) | (9) |
| Independent variables | (average past defaults) | (defaults breakdown) |
| *Constant* | 0.68* (0.343) | 1.02** (0.282) |
| $age_{it}$ | -0.03** (0.016) | -0.02* (0.015) |
| $asset_{it-1}$ | -0.61** (0.014) | -0.62** (0.013) |
| $purchase_{it-1}$ | 0.13** (0.018) | 0.12** (0.015) |
| $sales_{it-1}$ | -0.59** (0.035) | -0.55** (0.031) |
| $liquid\ asset_{it-1}$ | -11.18** (0.250) | -11.17** (0.233) |
| $receivables_{it-1}$ | -2.22** (0.105) | -2.14** (0.097) |
| $payables_{it-1}$ | 3.08** (0.117) | 3.00** (0.108) |
| $bank\ debt_{it-1}$ | 0.81** (0.153) | 0.65** (0.139) |
| $overdraft_{it-1}$ | 3.73** (0.193) | 3.74** (0.177) |
| $listed_{i}$ | 0.41* (0.174) | 0.39* (0.170) |
| $score3years_{it-1}$ | 0.05** (0.000) | 0.05** (0.000) |
| $dfltfaced\_dum1234_{it-1}$ | 0.14** (0.034) | 0.12** (0.033) |
| $dfltfaced\_amount1234_{it-1}$ | 6.49** (1.739) | 10.65** (3.038) |
| $dfltfaced\_amount1234_{it-2,3,4}$ | 4.29** (1.464) | - |
| $dfltfaced\_amount1_{it-1}$ | - | -5.99 (3.350) |
| Pseudo $R^2$ | 0.19 | 0.19 |
| Wald Statistic | 20,341 | 22,843 |
| Defaults made, % of obs | 1.95 | 2.06 |
| Defaults faced, % of obs | 3.31 | 7.19 |
| N | 1,615,434 | 1,830,665 |

The dependent and explanatory variables are defined as before, except: Model 8 includes the average of the logarithm of one plus the ratio total amount of the defaults faced by firm $i$ (irrespective of the motive)/total assets of firm $i$ over quarters $t-2$, $t-3$ and $t-4$ ($dfltfaced\_amount1234_{it-2,3,4}$). Model 9 includes the logarithm of one plus the ratio total amount of the defaults faced by firm $i$ in quarter $t-1$ (when the default is due to disagreement only)/total assets of firm $i$ in quarter $t-1$ ($dfltfaced\_amount1_{it-1}$). Models 8 also includes 239 sector*quarter dummies and 22 regional dummies and model 9 275 sector*quarter dummies and 22 regional dummies (not reported). Standard errors adjusted for clustering using the generalized method based on Huber-White reported in parentheses. The statistics on the defaults made/faced (in % of obs) at the bottom of the table corresponds to the number of firm/quarter observations where a default is observed in percentage of the total number of observations. **, * : significant at 1% and 5% respectively.

**Table 4.2: Tobit on the amount of default due to illiquidity**

| Dependent variable | Log amount of defaults made: $dftmade\_amount3_{it}$ | | | | | | |
|---|---|---|---|---|---|---|---|
| | (5a′) | (5b′) | (6a′) | (6b′) | (6c′) | (7a′) | (7b′) |
| Independent variables | illiquid | liquid | small | medium | large | low quality | high quality |
| *Constant* | 0.01 | -0.10** | 0.03** | -0.02 | -0.07** | 0.002 | -0.08** |
| | (0.01) | (0.02) | (0.008) | (0.01) | (0.01) | (0.01) | (0.01) |
| $age_{it}$ | -0.001** | -0.003** | -0.001** | -0.00 | 0.000 | -0.001** | -0.002** |
| | (0.00) | (0.00) | (0.000) | (0.00) | (0.00) | (0.00) | (0.000) |
| $asset_{it-1}$ | -0.02** | -0.01** | -0.019** | -0.01** | -0.002** | -0.02** | -0.002** |
| | (0.00) | (0.00) | (0.000) | (0.00) | (0.000) | (0.00) | (0.000) |
| $purchase_{it-1}$ | 0.003** | 0.002** | 0.004** | 0.00 | 0.001** | 0.003** | 0.002** |
| | (0.000 | (0.001) | (0.000) | (0.00) | (0.00) | (0.00) | (0.001) |
| $sales_{it-1}$ | -0.01** | -0.01** | -0.02** | -0.004** | -0.004** | -0.01** | -0.01** |
| | (0.01) | (0.00) | (0.000) | (0.00) | (0.00) | (0.00) | (0.001) |
| $liquid\ asset_{it-1}$ | -0.38** | -0.12** | -0.24** | -0.10** | -0.04** | -0.23** | -0.02** |
| | (0.01) | (0.004) | (0.003) | (0.01) | (0.004) | (0.003) | (0.01) |
| $receivables_{it-1}$ | -0.05** | -0.05** | -0.06** | -0.03** | -0.02** | -0.05** | -0.002 |
| | (0.001) | (0.002) | (0.001) | (0.002) | (0.003) | (0.001) | (0.01) |
| $payables_{it-1}$ | 0.08** | 0.09** | 0.09** | 0.04** | 0.03** | 0.08** | 0.02* |
| | (0.001) | (0.20) | (0.001) | (0.002) | (0.003) | (0.001) | (0.01) |
| $bank\ debt_{it-1}$ | 0.02** | 0.01 | 0.01** | 0.02** | 0.01** | 0.01** | 0.01 |
| | (0.002) | (0.004) | (0.002) | (0.003) | (0.004) | (0.001) | (0.01) |
| $overdraft_{it-1}$ | 0.09** | 0.13** | 0.12** | 0.04** | 0.03** | 0.11** | 0.11** |
| | (0.002) | (0.01) | (0.003) | (0.004) | (0.01) | (0.002) | (0.02) |
| $listed_i$ | 0.01* | 0.02** | -0.003 | 0.001 | 0.002 | 0.01** | 0.007 |
| | (0.003) | (0.005) | (0.01) | (0.003) | (0.001) | (0.001) | (0.004) |
| $score3years_{it-1}$ | 0.001** | 0.001** | 0.001** | 0.00** | 0.00** | 0.001** | 0.003 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.000) | (0.01) |
| $dfltfaced\_dum1234_{it-1}$ | 0.003** | -0.001 | 0.002** | 0.001 | 0.001* | 0.002** | -0.002 |
| | (0.00) | (0.001) | (0.00) | (0.00) | (0.00) | (0.000) | (0.003) |
| $dfltfaced\_amount1234_{it-1}$ | 0.23** | 0.09 | 0.19** | 0.66** | 0.06 | 0.21** | 0.22 |
| | (0.04) | (0.11) | (0.04) | (0.11) | (0.10) | (0.04) | (0.26) |
| Pseudo $R^2$ | 0.43 | 0.28 | 0.46 | 0.42 | 0.30 | 0.45 | 0.32 |
| Wald Statistic | 42,619 | 10,578 | 61,210 | 5,509 | 1,631 | 68,701 | 576 |
| Defaults made | | | | | | | |
| in % of aggregate amounts | 86.3 | 13.7 | 69.1 | 16.4 | 14.5 | 99.7 | 0.3 |
| in % of assets (given default) | 2.2 | 1.9 | 2.3 | 1.1 | 0.6 | 2.1 | 0.5 |
| Defaults faced | | | | | | | |
| in % of aggregate amounts | 67.7 | 32.3 | 18.3 | 13.8 | 67.9 | 96.89 | 3.1 |
| in % of assets (given default) | 0.2 | 0.2 | 0.3 | 0.1 | 0.1 | 0.2 | 0.1 |
| N | 885,800 | 944,865 | 1,348,206 | 284,130 | 198,329 | 1692,773 | 137,892 |

The endogenous variable is the logarithm of one plus the ratio total amount of the defaults made by firm $i$ in quarter $t$ when the default is due to illiquidity divided by total assets of firm $i$ in quarter $t$ ($dftmade\_amount3_{it}$). All models include sectoral and regional dummies, as before. The statistics on the defaults made/faced (in % of amounts) at the bottom of the table corresponds to the share of the total amount of defaults made/faced by firms in each subsample with respect to the total amount of defaults made/faced in our whole data set (in %). Standard errors corrected for clustering using Huber/White are in parentheses. **, * : significant at 1% and 5% respectively.

**Table 4.3: Tobit on the amount of default due to illiquidity**

| Dependent variable | Log amount of defaults made: $dftmade\_amount3_{it}$ | |
|---|---|---|
| | Small firms | |
| | (10) | (11) |
| Independent variables | (average past defaults) | (defaults breakdown) |
| $Constant$ | 0.010 (0.009) | 0.025** (0.008) |
| $age_{it}$ | -0.001** (0.000) | -0.001** (0.000) |
| $asset_{it-1}$ | -0.018** (0.000) | -0.019** (0.000) |
| $purchase_{it-1}$ | 0.004** (0.000 | 0.004** (0.000 |
| $sales_{it-1}$ | -0.015** (0.000) | -0.015** (0.000) |
| $liquid\ asset_{it-1}$ | -0.236** (0.003) | 0.244** (0.003) |
| $receivables_{it-1}$ | -0.057** (0.001) | -0.056** (0.001) |
| $payables_{it-1}$ | 0.087** (0.001) | 0.089** (0.001) |
| $bank\ debt_{it-1}$ | 0.015** (0.002) | 0.012** (0.002) |
| $overdraft_{it-1}$ | 0.118** (0.003) | 0.122** (0.003) |
| $listed_i$ | -0.000 (0.007) | -0.003 (0.007) |
| $score3years_{it-1}$ | 0.001** (0.000) | 0.001** (0.007) |
| $dfltfaced\_dum1234_{it-1}$ | 0.002** (0.000) | 0.002** (0.000) |
| $dfltfaced\_amount1234_{it-1}$ | 0.215** (0.047) | 0.283** (0.086) |
| $dfltfaced\_amount1234_{it-2,3,4}$ | 0.109** (0.037) | - |
| $dfltfaced\_amount1_{it-1}$ | - | -0.116 (0.099) |
| Pseudo $R^2$ | 0.47 | 0.46 |
| Wald Statistic | 51,573 | 61,212 |
| N | 1,166,189 | 1,348,206 |

The endogenous variable is the logarithm of one plus the ratio total amount of the defaults made by firm $i$ in quarter $t$ when the default is due to illiquidity only divided by total assets of firm $i$ in quarter $t$ ($dftmade\_amount3_{it}$). The explanatory variables are defined as before. In addition, model 10 includes the average of the logarithm of one plus the ratio total amount of the defaults faced by firm $i$ (irrespective of the motive) divided by total assets of firm $i$ over quarters $t-2$, $t-3$ and $t-4$ ($dfltfaced\_amount1234_{it-2,3,4}$). Model 10 includes the logarithm of one plus the ratio total amount of the defaults faced by firm $i$ in quarter $t-1$ (when the default is due to disagreement only) divided by total assets of firm $i$ in quarter $t-1$ ($dfltfaced\_amount1_{it-1}$). Sector*quarter and regional dummies are included (not reported). Robust standard errors are in parentheses. **, * : significant at 1% and 5% respectively.

**Table 4.4: Logit - Does disagreement hide financial distress?**

| | Defaults due to: | |
|---|---|---|
| Dependent variables | disagreement | omission |
| | $dftmade\_dum1_{it}$ | $dftmade\_dum2_{it}$ |
| Independent variables | (12) | (13) |
| $Constant$ | -6.09** (0.158) | -6.76** (0.514) |
| $age_{it}$ | 0.15** (0.007) | -0.02 (0.015) |
| $asset_{it-1}$ | 0.31** (0.004) | 0.18** (0.012) |
| $purchase_{it-1}$ | 0.12** (0.007) | 0.01 (0.015) |
| $sales_{it-1}$ | -0.14** (0.014) | -0.05 (0.032) |
| $liquid\ asset_{it-1}$ | -0.53** (0.054) | -1.39** (0.139) |
| $receivables_{it-1}$ | -0.29** (0.045) | -0.64** (0.105) |
| $payables_{it-1}$ | 1.49** (0.051) | 0.98** (0.114) |
| $bank\ debt_{it-1}$ | 0.45** (0.066) | 0.13 (0.151) |
| $overdraft_{it-1}$ | -0.56** (0.102) | 0.72** (0.211) |
| $listed_i$ | 0.03 (0.069) | 0.18 (0.138) |
| $score3years_{it-1}$ | -0.00** (0.000) | 0.03** (0.001) |
| Pseudo $R^2$ | 0.07 | 0.04 |
| Wald Statistic | 23,934 | 5,407 |
| N | 1,830,665 | 1,830,665 |

In model 12, the endogenous variable is the dummy $dfltfaced\_dum1_{it}$, which is equal to one if firm $i$ defaults at least once due to disagreement in quarter $t$ and zero otherwise. In model 13, the endogenous variable is the dummy $dfltfaced\_dum2_{it}$, which is equal to one if firm $i$ defaults at least once due to an omission in quarter $t$ and zero otherwise. The explanatory variables are the defined as before. Both models also include sector*quarter and regional dummies (not reported). Robust standard errors (in parentheses) are adjusted for clustering using the generalised method based on Huber-White. **, * : significant at 1% and 5% respectively.

# Appendix

This appendix describes the initial datasets that we use to compile the working data and provides more detailed information on the merger process.

## *A1. Balance Sheet Data*

The balance sheet database "FIBEN" contains *unconsolidated* balance sheet information about closely-held and incorporated businesses that operated in France over the period 1998-2003. The FIBEN database includes firms whose turnover exceeds EUR750,000 or with bank loans above EUR38,000. It covers about 300,000 firms over the period 1998-2003, with an average of 200,000 businesses per year (see tables A1.1), which represents more than 80% of all firms with more than 20 employees (see also Banque de France, 2006a). For firms with less than 20 employees the coverage is about 50%. The quality of the data is high because the Banque de France uses them to rate French firms and checks, for medium and large firms, whether these data tally with information gathered in the field.[26]

**Table A1.1: Balance Sheet Data**

| | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | all |
|---|---|---|---|---|---|---|---|
| Nb. of firms (thds) | 187.5 | 191.9 | 195.0 | 201.4 | 205.5 | 208.9 | 299.3 |

## *A2. CIPE Data*

### *A2.1. The Data Collection Process of Trade Credit Defaults*

*The Typical Trade Deal.* Consider a firm A (the "customer") that buys on credit some goods from a firm B (the "supplier"), with terms of 2-10 net 30. This means that A has to pay within 30 days. In addition, a cash discount of 2% from the stated sales price is to be given if payment is made within 10 days. In effect, supplier B draws a bill of exchange on its customer A, stipulating the names of A and B's banks, A and B's bank account numbers, and the terms of the sale. In order to be paid, firm B is obliged, by law, to send to its bank the information related to this claim at least one week before the due date of payment. Once B's bank has received the information, the latter is instantaneously transmitted to A's bank through the French interbank clearing system (the so-called SIT system). A's bank thereby continuously gathers all information related to the bills of exchange that A issues. In order for A to check the features of the bills of exchange, A's bank sends to A, on a regular (usually weekly) basis, statements that take stock of all trade debts falling due. Following such statements, A must endorse or repudiate the bills. Typically, a bill is repudiated when there is a disagreement about the terms (e.g. on the price, the due date of payment, etc.); The bill will not be paid at the due date of payment, implying that firms A and B will have to either settle a new deal (B will then draw a new bill on A), or go to Court. On the contrary, if firm A endorses the bill, then the payment will in general be processed at the due date of payment, unless firm A has financial problems and is unable to pay. In such case, the two firms reach a new agreement and B draws a new bill on A with a later date of payment and possibly penalties, or firm B takes legal action. In some cases, it may also happen that a trade debtor simply omits to endorse/repudiate a bill. In the absence of payment order, his bank will not proceed to the payment at the due date and the trade creditor will have to send a reminder. In practice, reminders are

[26] Staff from Banque de France's subsidiaries may meet medium and large firms' managers to check balance sheets and gather soft information about the firms.

sent during the subsequent 2-3 weeks after the payment has become late. Although in France suppliers usually do not charge for reminders, they may however in few cases (about 15% of the cases) charge additional interest on late payments (Intrum Justitia, 2004a). The penalty rate is usually 1.5 times the European Central Bank's main refinancing rate.[27] When amicable collection is not possible, suppliers may sue their customers. According to World Bank (2004) estimates it takes on average 7 months to have the contract enforced through the legal system and costs about 7.6% of the amount of the trade bill. In the case where customers file for bankruptcy, suppliers have to wait longer, that is about 2.4 years in order to get on average 36% of their money back.[28] In the case a customer cannot pay on time, or repudiates, its trade bill, then its bank is obliged, by law, to notify the default to the Banque de France at the latest four working days after the due date of payment. These data are collected by the Banque de France via the SIT system and then recorded into the CIPE database.

*The French Interbank Teleclearing System (SIT).* In France, bills of exchange have been computerized since in 1994 in order to accelerate and secure trade debt payments. The former paper bills have all been replaced by electronic bills, whose payments are now operated through banks by using the automatized clearing system SIT. All resident credit institutions that manage retail payment transactions are required to participate in the SIT, which processes the transactions between participants. The exchange of payments is continuous and operated directly between banks' IT centres. At the bank level, multilateral netting takes place via an accounting centre and net balances are settled through the Banque de France's gross settlement system. The SIT system is the largest retail payment system in Europe. With 106 million of transactions in 2004 worth a total of EUR430 billions (i.e. 26% of GDP), bills of exchange represent 1% of the volume (9% in value) of the transactions processed by the SIT.[29]

### *A2.2. The Data*

The CIPE database contains information related to **all** defaults on trade credit of **all** private non-financial businesses that operated in France over the period 1998-2003. CIPE includes five variables: the SIREN number of the defaulter (which is the firm's identification number), the due date of payment, the amount of default, the name of the supplier that has been defaulted upon, and the motive for the default (disagreement, omission, illiquidity, or insolvency).

[27] On 8 August 2000, the Directive 2000/35/EC of the European Parliament and of the Council on combating late payment in commercial transactions was published. The Directive entered into force on 8 August 2002 and is now applicable in all EU25 member States (with the exception of Spain). It imposes a fixed payment term of 30 days unless otherwise contractually agreed, the legal interest rate on overdue payments (which amounts to the European Central Bank rate plus 7% per year), as well as the recovery costs. As the Directive has been transposed in France only recently, companies still use different interest rates.

[28] The 2004 survey by Intrum Justitia (2004b) also reveals that the average maturity of trade debts in France is about 52.3 days, while late payments are of about 14.1 days.

[29] The bulk of the transactions processed by the SIT are related to the other mass payment instruments, namely, cheques, credit transfers, direct debit, ATM withdrawals, credit and debit card payments. Note that about 23 other millions of bills of exchange were also processed outside the SIT in 2004, which corresponded to situations where both the issuers and the receivers of the claims had their bank account in the same bank, which then in general directly processed the payment at its level ("intrabank" clearing). In these cases, defaults are however also reported to the Banque de France and recorded into CIPE.

**Table A2.1: Defaults in CIPE**

| | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | all |
|---|---|---|---|---|---|---|---|
| Nb. of defaults (millions) | 1.90 | 1.79 | 1.71 | 1.72 | 1.63 | 1.54 | 10.3 |
| Avg. amount of default (euros) | 2,082 | 2,261 | 2,534 | 2,712 | 2,690 | 2,877 | 2,509 |
| Nb of defaulting firms (thds) | 306.6 | 303.9 | 305.8 | 310.7 | 304.3 | 301.2 | 805.9 |
| Nb of suppliers defaulted upon (thds) [1] | 175.1 | 165.1 | 154.1 | 154.6 | 144.0 | 137.1 | 454.8 |
| Nb. of defaults with identified suppliers (millions) | 0.83 | 0.82 | 0.82 | 0.83 | 0.80 | 0.76 | 4.85 |
| Avg. amount of default with identified suppliers (euros) | 2,032 | 2,306 | 2,643 | 2,614 | 2,556 | 2,652 | 2,464 |
| Nb of identified suppliers defaulted upon (thds) | 42.7 | 43.1 | 43.3 | 44.5 | 42.2 | 41.0 | 82.0 |

[1] The number of suppliers defaulted upon is approximated by the number of different suppliers' names in CIPE. This is an approximation for we counted several times the same supplier when its name was misspelled several times, while we counted homonym firms only once.

There are about 10.3 million defaults recorded in CIPE, with an average amount of EUR2,509 (see table A2.1). While 805,900 firms defaulted at least once over the period, 454,800 faced default.[30] The quality of the data is very high regarding all variables (in particular, we know the identity of all defaulters) except for the identity of suppliers. For the firms defaulted upon, only names are available. To identify the suppliers, we matched their names as reported in CIPE with the names and SIREN numbers of the firms present in the balance sheet database. In about 53% of the cases, the name of the firm defaulted upon in CIPE did not correspond to any SIREN number in the balance sheet database, either because it was mispelled or because the firm was not present in the balance sheet database – especially as far as micro firms are concerned. In 44% of the cases, we could match the name of the supplier in CIPE with one unique firm (or SIREN number) in the balance sheet database. Finally, suppliers' names corresponded to several different homonym firms in the balance sheet database for 3% of the defaults. In thoses cases, we assumed that the supplier defaulted upon was the largest of the homonym firms (i.e. with the largest total assets).[31] This way we could identify 82 thousand suppliers for a total of 4.85 million defaults. We checked whether the identified defaults faced differed from those not identified in some observable manner, but we found no evidence of this. In particular, the average amount of defaults faced by the identified suppliers over the sample period is almost the same as the average amount of default (EUR2,464 against EUR2,509). Hence we assumed the missing supplier identification to be random. For further evidence of this, we checked that we are as likely to identify the suppliers for any of the four main reasons: The distribution of the reasons given for defaults is the same for the defaults where we identify the suppliers as for the defaults where we do not.

## *A3. Matching of CIPE and balance sheet data*

Our data set is a quarterly panel built from the CIPE and the balance sheet data. To construct this panel, we proceeded in three steps. First, we excluded from our data set firms without balance sheet, firms in agriculture, forestry, fishing, real estate activities, and education, health and social work, as well as the public sector and financial and insurance firms. We also dropped all micro-firms with less than EUR500,000 of assets or less than 10 employees as well as all firm-quarter observations for which

[30] We explain the gap between these two figures in section 2 in the text, by the fact that most defaults are due to disagreement and that this type of default hits customers and suppliers in an asymmetric manner.

[31] Since large firms with large receivables are the most likely to face defaults, this assumption is the least likely to introduce measurement errors on defaults faced.

our main explanatory variables (i.e. assets, purchases, sales, accounts payable and receivable) were missing or inconsistent (e.g. total debt larger than total assets). Second, we summarized for each firm and each quarter the information in CIPE by transforming daily into quarterly data. For the defaults made, we created dummies equal to one for firm $i$ in quarter $t$ if firm $i$ defaulted at least once during quarter $t$, and calculated the total amount and the total number of defaults made by firm $i$ in quarter $t$, broken down by the reason for default. Note that to compute these statistics we used all the defaults made to all firms, including those made to non-identified suppliers or more generally to firms out of our sample. We generated equivalent variables for the defaults faced by the firms in our sample. In this case, however, we computed the statistics by using the defaults faced that originated from the firms present in our sample only. In particular, we excluded defaults made by micro-firms, which tend to be extremely small.

In a third step, we matched the transformed CIPE data of every firm $i$ and quarter $t$ with the corresponding balance sheet data. When firm $i$ did not default in quarter $t$ (i.e. the firm is not present in CIPE in quarter $t$), we assigned the value 0 to the CIPE variables (e.g. for the amount of default) and kept its balance sheet information in the database. Since balance sheet data are available at annual frequency only, we assigned to firm $i$ in quarter $t$ its most recent balance sheet available between quarters $t-5$ and $t$, and dropped the information from CIPE when the most recent balance sheet was more than five quarters old. Note that this matching strategy implies that the same balance sheet information is assigned to firm $i$ between quarters $t-j$ and $t$ when firm $i$ last released its balance sheet in quarter $t-j$ (for $j \leqslant 5$). As we will use the lags of the explanatory variables in our regressions, we also dropped, for every quarter, the firms that were not present in the panel in the previous quarter. For the number of firms present in our data set at each step of its construction consider table A3.1. Ultimately, our data set includes 121,060 firms over the period 1998-2003. More than 75% of the firms defaulted at least once over the period 1998-2003, while almost 25% of the firms have been defaulted upon at least once.

**Table A3.1: Number of firms in the data set (period 1998-2003)**

| thousands of firms with... | default made | no default made | default faced | no default faced | Total |
|---|---|---|---|---|---|
| in the whole economy | 805.9 | 1,656.1 | 454.8 [2] | 2,007.2 | 2,462 [1] |
| in CIPE | 805.9 | 0 | 454.8 [2] | 0 | - |
| in CIPE with available SIREN | 805.9 | 0 | 82.0 | 0 | 829.6 |
| in the balance sheet database [2] | 169.4 | 134.9 | 82.0<br>[95.6] | 217.3<br>[203.7] | 299.3 |
| ... non-micro firms and sectors of interest | 111.0 | 46.1 | 54.8 | 102.3 | 157.1 |
| ... with consistent balance sheets [3] | 100.4 | 32.0 | 49.6 | 82.8 | 132.4 |
| ... present in 2 consecutive quarters | 94.0 | 27.0 | 46.7 | 74.3 | 121.0 |
| in our data set | 94.0 | 27.0 | 29.0 [4] | 92.0 [4] | 121.0 |

[1] Total number of businesses in the French economy over the period 1998-2003. (Source: INSEE, www.insee.fr). There are about 2.4 million businesses in France, out of which 805.9 thousand defaulted at least once and 1.6 million never defaulted over the period 1998-2003. Initially we observe balance sheets for 169.4 thousand defaulting firms and for 82 thousand firm facing defaults. After dropping micro firms, firms with inconsistent balance sheets, and firms that are not present in our data set in two consecutive quarters, we are left with 121 thousand firms. [2] The number of suppliers defaulted upon in the whole economy and in CIPE is approximated by the number of different suppliers' names in CIPE. This is an approximation for we counted several times the same supplier when its name was misspelled several times, while we counted homonym firms only once. [2] The

figures into brackets refer to the numbers of firms once we account for the fact that we did not identify all the firms that faced defaults. We corrected the initial figures by using the ratio of the number of firms that defaulted and the number of firms that faced defaults in the whole economy (where there are 454,800 firms facing default for 805,900 firms defaulting). Under the assumption that this ratio is the same for firms with balance sheets as for all firms in the economy, there should be 1.77 times less firms facing defaults than firms defaulting in the balance sheet database, that is to say about 95,600 firms defaulted upon. [4] In our final data set we do not consider as liquidity shocks the defaults faced that originated from firms that do not belong to our data set. While 46,700 firms faced at least one default over the period 1998-2003, only 29,000 were defaulted upon by firms present in our data set. [3] As mentioned in the text, the quality of the balance sheet data is very high and in most cases the "inconsistencies" were due to missing values.

Our data set finally includes 94,000 firms that defaulted at least once over the period 1998-2003 (see table A3.1), and 1,8 million firm/quarter observations (see table 2.1), among which 338,098 with defaults made (see table 2.4). Each firm defaults on average 3.5 times per quarter (given default) for an amount almost twice as large as in the whole population (i.e. EUR4,500 against EUR2,500, compare tables 2.4 and A2.1), which reflects the trimming of micro-firms. Importantly, the fact that CIPE is exhaustive for the population of French firms ensures that a firm that is not present in our data set as a defaulter in a given quarter did indeed not default at all during this quarter. On the side of the defaults faced, however, we could only identify 85% of the firms with balance sheets that faced defaults.[32] In addition, since we calculated the quarterly default variables with the defaults that originated from the firms present in our sample only, our data set is not exhaustive in this dimension. It finally includes 29,007 firms that faced defaults at least once over the period 1998-2003 (see table A3.1) and contains 131,660 firm/quarter observations with at least one default faced (see table 2.4). Each firm is defaulted upon on average 3.2 times per quarter (given default) for an average amount of EUR4,900, which is slightly larger than the average amount of default made, reflecting the fact that we do not take into account the smaller defaults that originate from the firms out of our sample.

We show in table A3.2 that the sectoral distribution of assets is similar to that in the original balance sheet database, even though we dropped relatively more firms from the services-to-business and transport sectors than from the manufacturing sectors. Overall, our data set accounts for 62% of total assets in the original balance sheet database.

[32] We could identify 82,000 firms with balance sheets that were defaulted upon, out of approximatively 95,600 (see table A3.1).

**Table A3.2: Sectoral Distribution of Assets and Coverage**

| % share in total assets | balance sheet database (1) | our data set (2) | % of total assets in (1) which are also in (2) |
|---|---|---|---|
| Manufacturing sector | 38 | 56 | 93 |
| Manufacture of intermediate goods | 13 | 21 | 97 |
| Manufacture of food products, beverages and tobacco | 5 | 8 | 95 |
| Manufacture of capital goods | 8 | 12 | 90 |
| Manufacture of consumers goods | 6 | 9 | 90 |
| Manufacture of motor vehicles | 5 | 7 | 87 |
| Retail trade, repair of personal and household goods | 5 | 8 | 90 |
| Sale, maintenance and repair of motor vehicles | 2 | 3 | 85 |
| Wholesale trade and commission trade | 12 | 14 | 72 |
| Construction | 4 | 3 | 56 |
| Transports | 12 | 8 | 44 |
| Personal and domestic services | 4 | 2 | 33 |
| Services to businesses | 24 | 6 | 17 |
| Total | 100 | 100 | 62 |

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