The Effect of Stock Market Fluctuations On Corporate Cash Flows

by

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ABSTRACT

Fluctuations in stock prices affect corporate cash flows. When a firm's own stock price drops significantly, the firm's customers are less likely to delay payment on invoices. In effect, customers are providing insurance to the firm. This insurance effect does not exist for private firms. However, overall customers delay payment on invoices from publicly traded firms more than twice as often as they delay payment on invoices from private firms. As far as we can tell this is not driven by a difference in the average quality of the customers. Thus in terms of corporate cash flows there are both costs and benefits to being publicly traded.

(JEL:)

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I. Introduction

Day-to-day stock price fluctuations provide freely available information on the health of a publicly traded firm. Customers can condition their payment of invoices on this information. If they do so, then stock price fluctuations will affect corporate cash flows.

Suppose a firms' share price drops, as a reflection of difficult times for the firm. Will customers be more prompt in paying their bills (an "insurance effect")? Or, will customers be less prompt in paying their bills (a "taking advantage of the weak effect")? Or, will they simply ignore the stock price fluctuations ("oblivious")? A priory it is hard to be sure which effect would dominate. These alternative cases have quite different implications for how the stock market affects the real side of the economy.

In order to tell these effects apart we need good information not only about daily stock prices, but also about daily customer payments patterns. In order to control for overall changes in industry conditions it is helpful to have information about private firms as well as public firms. We have such data for a population of French firms from 1997-2003. We construct a data set with all French publicly traded firms and match a set of not traded firms drawing on the universe of French firms. Ultimately we use a data set containing more than 450,000 daily observations about customer delayed payment on invoices.

The first question is whether the publicly traded firms customers are more, or less likely to face payment delays on average? Stock price fluctuation information is not readily available for private firms. Customers can elect to treat publicly traded firms differently from private firms. However, for the private firms the customers cannot condition their bill payments on the firm's public stock price since it does not exist. Empirically, it is easy to reject the idea that the stock market is unimportant. Publicly listed firms face more than twice as many customer delays due to illiquidity on an invoice when compared to a private firm.

The second question is what happens to customer payments for the publicly traded firms when their stock price declines? The insurance effect would imply more prompt payments and few delays by customers. The taking advantage effect would imply lengthier delay and more customer delays. Among the publicly traded firms stock price declines do affect repayments and the effect is non-linear in the extent of the drop. Moderately large stock price drops significantly reduce the likelihood of customer delay. Over this range of parameters the evidence supports the insurance motive rather than the taking advantage motive. However, if the stock price drop is very large (beyond the negative 8 percentile of the distribution), the effect reverses and customer delays tend to increase again. It should be stressed that it is the firm's own stock price that matters. Declines in the CAC stock market index tend to increase customer delays for both listed and unlisted firms.

This paper adds to a growing literature examining the effects of stock price fluctuations on real activity. Dye and Sridhar (2002), Dow and Rahi (2003) and Chen et al. (2007) all provide evidence that the own stock price of a firm may provide information to the managers, which can guide their investment decisions. The underlying idea is that stock prices aggregate information from many different participants who do not have other means of communication with the management of firms. Our results suggest that this information can not only guide managers' investment decisions but may also guide payment decisions of the customers of the firm, which in turn may affect corporate cash flows. Hence, we provide further evidence that the stock market may affect the real economy and is not just a "sideshow" (Mork, Shleifer and Vishny, 1990). Related evidence is provided by Giammarino et al. (2004) who show that managers use the information contained in equity prices when deciding whether or not to go ahead with a seasoned equity offering and Luo (2005), who show that the positive correlation between announcement date return and the completion of a merger can be interpreted as insiders learning from outsiders about the likelihood of success of a merger.

The evidence in the paper further supports the notion that trade credit links among firms serve to insure firms against liquidity shocks (Wilner, 2000, Cunat, 2007, Boissay and Gropp, 2007). The evidence in this paper suggests, however, that this insurance function is not limited to small credit constrained firms, as in Boissay and Gropp, 2007 and Cunat, 2007, but that also large, listed firms may benefit from some insurance. This is further evidence that the puzzle of the prevalent use of trade credit among firms despite its high implicit interest rate may in part be explained by this insurance function that appears to be unavailable from other sources (Peterson and Rajan, 1997).

The paper is organized as follows. In the next section, we present a simple model of buyer/seller interaction that guides our empirical hypotheses. In section 3 we describe the data used in the paper and show our procedures for obtaining a matched sample of listed and private firms used in the empirical analysis. Section 4 contains the main results, section 5 presents some robustness checks and section 6 concludes the paper.

II. Theory

Consider the following simple, highly stylized, model of buyer seller interaction. In the model the buyer purchases one unit of some good at price *p* and the buyer and seller agree upon a payment due date. Some buyers experience adverse liquidity shocks after signing the contract, which are not observable to the seller and, hence, non-contractable. Given his state of liquidity at the time of the payment due date, the buyer has to decide whether to pay on time or not. If he does not pay on time, the seller decides whether to collect the bill or whether to accommodate the buyer by extending the due date. Collection is costly for example due to legal fees, foreclosure costs or other legal expenses If the seller collects, he will not receive the full amount of the bill due. Buyer payoffs are denoted as $\pi^B_{k,i}$ where $k \in \{E, L\}$ and $i \in \{d, c, l\}$. R denotes the buyer's cash on hand. Type E buyers have enough cash flow to satisfy their obligations to the seller. hence for these buyers $p \leq R$. In contrast, type L buyers received an adverse liquidity shock which caused a delay in the arrival of R until after the due date of the payment. These buyers have no cash to make the payment. For simplicity, we assume that $R = 0 < p$.

The buyer can pay the invoice when it is due, d and he can try to pay the invoice late. If the seller responds to late payment by collecting, the payoff to the buyer is denoted by subscript c. If the seller responds to late payment by accommodating the delay, the payoff to the buyer is denoted by the subscript l. Sellers are characterized by being either private firms and public firms and by being either "good" or "bad", which will be defined below. The state of the public firm is common knowledge, the state of the private firm is private information to the seller. We denote the risk free rate at which cash not needed immediately for the operations of the firm can be deposited with r. Both types of buyers also are endowed with some non-liquid wealth, W.

If the buyer pays the invoice when it is due, the seller has nothing to decide and simply accepts payment. If the buyer does not pay the invoice when it is due, then the seller must decide whether to spend resources to collect the invoice, or to simply wait for the buyer to pay late. If the seller decides to collect, then the buyer pays right away and suffers a reputation cost denoted as h, with $h > 0$. The only uncertainty in the model is the unobservable state ("good" or "bad") of private sellers.

Consider the following sequence of events:

1. At time t, the buyer purchases a good from the seller at price p and both agree on a contract governing the terms of payment.

2. At time $t+1$, type E buyers receive cash flow R, which is private information to the buyer. The state of the seller is revealed to the seller only (if he is private) or to both buyers and seller (if he is public).

3. Time $t+2$ is the initially agreed upon due date of payment. The Buyer decides whether to pay on time or whether to delay payment. If the Buyer delays payment, the Seller decides whether to collect or not. If he collects he receives the payment from the seller immediately. If there is collection, the buyer suffers a reputation cost h.

4. At time $t+3$, the type L buyers receive cash flow R and pay the seller if they decided to pay late and the seller did not collect. All payoffs are realized.[1]

A. Buyer's Payoffs

A.1. For types E

At time $t+3$ the type E buyer receives the following payoffs:

[1] The assumption that the liquidity shock to the buyer is private information to the buyer and that the seller's state is only revealed after signing the contract are crucial for the model. This prevents the buyer and seller from agreeing on different maturity contracts, depending on the buyer's and seller's states, respectively. With uncertainty about the seller's state upon signing of the contract, all contracts will be short term (i.e. mature in period t+2, rather than t+3), as the seller has to take into account the possibility that he will be in the "bad" state.

$$
\begin{aligned}
\pi^B_{E,d} &= (1+r)(W+R-p) \\
\pi^B_{E,c} &= (1+r)(W+R-p)-h \\
\pi^B_{E,l} &= (1+r)(W+R)-p
\end{aligned}
$$

The type E buyer does not need to liquidate its wealth W in order to make the payment as they have sufficient cash flow R. However, he can still choose whether to pay late or not. If he pays late and the seller decides to collect, rather than accommodate late payment, he suffers a loss of reputation, h. His gain from paying late is the risk free return from depositing the purchase price p in a deposit account, rp.

Payoff ordering

The ordering of the type E buyer payoffs is given by:

$$
\pi^B_{E,l} \geq \pi^B_{E,d} > \pi^B_{E,c}
$$

The buyer prefers to pay late and not be collected. However, if he thinks the seller will collect, he will prefer to pay on time. In equilibrium, the type E buyer will always pay on time as long as the risk free rate, r is small and there is some non-zero probability that the seller will collect.

A.2. For types L

The payoff structure is different for a type L buyer, who is short of liquidity. In this case the buyer does not have the cash on hand to pay the seller. He is faced with the choice to liquidate assets at a liquidation cost γ, with $\gamma > 0$, and pay on time or to pay late. As before, if he pays late, he may face collection:

$$
\begin{aligned}
\pi^B_{L,d} &= (1+r)((1-\gamma)W-p)+R \\
\pi^B_{L,c} &= (1+r)((1-\gamma)W-p)+R-h \\
\pi^B_{L,l} &= (1+r)W+R-p
\end{aligned}
$$

When the buyer is late, either he pays on time and then has to liquidate his wealth; or he pays late.

Payoff ordering

The ordering of the type L buyer payoffs is given by:

$$\pi^B_{L,l} > \pi^B_{L,d} > \pi^B_{L,c}$$

No matter whether the buyer's has enough cash on hand (type E) or does not due to an adverse liquidity shock (type L), the buyer's profits are highest when he pays late and there is no collection. The buyer's profits are lowest when he does not pay on time and the seller decides to collect. The buyers profits are in between when he pays the invoice when it is due.

B. Seller's Payoffs

The seller's payoff is denoted as $\pi^S_{c,j}$, where $c \in \{C_G, C_B\}$ and $j \in \{d, c, l\}$. C_G denotes the amount of cash flow available to a "good" seller and C_B the amount of cash flow available to a "bad" seller. We assume $C_B < C_G$. The subscripts are as before, referring to prompt payment by the buyer, d, late collected payment by the buyer, c and late accommodated payment by the buyer, l.

We define m_o as cash that the seller spends on operations, m_b as "extra cash" beyond that needed for operations that generates the risk-free rate of return r. m_c is the expense the seller must incur when he decides to collect. The collection cost m_c is a fixed cost with $0 < m_c < p$. Sellers need cash to run their firm, i.e. they need to pay wages, their own suppliers etc. Cash is transformed into "operations" with $f(m_0)$, with $f'(.) > 0$ and $f'' < 0$.[2]

Sellers maximize the following programme:

[2] We need $f(.)$ to be twice differentiable and concave for the following to hold. We do not need $f(.)$ to have any particular functional form, however.

B.1. Type G

$$\begin{cases} \pi^{S}_{G,d} = f(m_o) + (1+r)m_b \\ m_o + m_b \leqslant C_G + p \\ m_b \geqslant 0 \end{cases}$$

$$\begin{cases} \pi^{S}_{G,c} = f(m_o) + (1+r)m_b \\ m_o + m_b + m_c \leqslant C_G + p \\ m_b \geqslant 0 \end{cases}$$

$$\begin{cases} \pi^{S}_{G,l} = f(m_o) + (1+r)m_b + p \\ m_o + m_b \leqslant C_G \\ m_b \geqslant 0 \end{cases}$$

Solution

We set the parameters of the model such that type G sellers always reach the first best solution:

$$f'(m_o) = 1 + r \Leftrightarrow m_o^* = f'^{-1}(1+r)$$

The marginal return to cash of the type G sellers is just the risk-free rate.[3]

This implies the following solution:

$$\begin{cases} \pi^{S*}_{G,d} = f(m_o^*) + (1+r)\left[C_G + p - m_o^*\right] \\ \pi^{S*}_{G,c} = f(m_o^*) + (1+r)\left[C_G + p - m_o^* - m_c\right] \\ \pi^{S*}_{G,l} = f(m_o^*) + (1+r)\left[C_G - m_o^*\right] + p \end{cases}$$

Payoff ordering

[3] This is equivalent to assuming that there is no wedge between borrowing and lending rates for type G sellers. They are not credit constrained (see e.g. Kaplan and Zingales, 1997).

Since type G sellers always achieve the first best solution, for $\forall j \in \{d, c, l\}$, we have:

$$\pi^S_{G,d} > \max\left\{\pi^S_{G,l}, \pi^S_{G,c}\right\} \tag{1}$$

which means that the good seller always prefers to be paid on time. If he is not paid on time, then the good seller faces a trade-off between collecting the money at a cost m_c and investing the extra money at the risk free rate r, or not to collect and wait for late payment. For good sellers the marginal gain of collecting is equal to the risk free rate. Good sellers will prefer to wait for the late payment (and not to collect) if:

$$\pi^S_{G,l} > \pi^S_{G,c} \Leftrightarrow m_c > \frac{r}{1+r}p \tag{2}$$

Hence, good sellers prefer to wait rather than to collect the money, if the collection cost is high enough. Note that if there is no opportunity cost of waiting ($r = 0$), then good sellers never collect the money. For simplicity and without loss of generality, we will assume that the risk-free rate is zero, i.e. $r = 0$. This implies that good sellers never collect, as long as $m_c > 0$. The main point here is that they never collect because they are not dependent on their cash flow to reach their first best level of production. Recall that if $r = 0$, type E buyers are indifferent between paying on time and paying late.

B.2. For types B

The maximization programme for type B sellers is equivalent to the one for Type G sellers:

$$\begin{cases} \pi^S_{B,d} = f(m_o) + (1+r)m_b \\ m_o + m_b \leqslant C_B + p \\ m_b \geqslant 0 \end{cases}$$

$$\begin{cases} \pi^S_{B,c} = f(m_o) + (1+r)m_b \\ m_o + m_b + m_c \leqslant C_B + p \\ m_b \geqslant 0 \end{cases}$$

$$\begin{cases} \pi^S_{B,l} = f(m_o) + (1+r)m_b + p \\ m_o + m_b \leqslant C_B \\ m_b \geqslant 0 \end{cases}$$

The only difference to type G sellers, is that for type B sellers the budget constraint is binding:

$$f'^{-1}(1) > C_B + p \Leftrightarrow f'(C_B + p) > 1 \tag{3}$$

which means that for type B sellers, the marginal gain from collecting is not the risk free rate but rather the return to using cash in operations. Type B sellers are cash constrained. This implies the following payoffs:

$$\begin{cases} \pi^{S*}_{B,d} = f(C_B + p) \\ \pi^{S*}_{B,c} = f(C_B + p - m_c) \\ \pi^{S*}_{B,l} = f(C_B) + p \end{cases}$$

The best type B sellers can do is use their entire cash on operations.

Payoff ordering

While type B sellers also prefer to be paid on time, we have for $\forall j \in \{d, c, l\}$:

$$\pi_{B,d}^{S*} > \max\left\{\pi_{B,l}^{S}, \pi_{B,c}^{S}\right\} \tag{4}$$

If he is not paid on time, the type B seller faces the trade-off between collecting the money at a cost m_c and spend the extra money on operations at a marginal gain of $f'(C_B + p) > 1$, or not to collect.[4] For bad sellers, the marginal gain of collecting is equal to the marginal productivity of money in the operations of the firm. Bad sellers will prefer to collect rather than wait for the late payment if:

$$\pi_{B,c}^{S} > \pi_{B,l}^{S} \Leftrightarrow f(C_B + p - m_c) > f(C_B) + p \tag{5}$$

Since we have assumed parameters (in (3)) such that $f(C_B + p) > f(C_B) + p$, we know that there exists $m_c > 0$ such that the above inequality holds. This is independent of the risk free rate. In contrast to type G sellers, type B sellers may collect if the collection cost is low relative to the marginal benefit of having additional cash to fund operations.

C. Equilibrium

The inequalities (2) and (5) are key. In order to obtain more easily interpretable results, suppose now further that while the buyer cannot observe the state of the seller in case of a private firm, he can assign probabilities to each state. The ex ante probability that the buyer assigns to the possibility that the seller's state is G is denoted as $\Pr(G)$, and the ex ante probability that the seller's state is B is denoted as $\Pr(B)$, with $\Pr(G) > 0, \Pr(B) > 0$, and $\Pr(B) + \Pr(G) = 1$. First recall that type E buyers are indifferent between paying on time and paying a type G seller late. Since they cannot observe the private seller's type they will always pay the private seller on time.

What about a type L buyer? Suppose first that the seller is a public firm and suppose further that observing the seller's share price reveals the seller's true state. If the seller state is G then because $\pi_{G,l}^{S} > \pi_{G,c}^{S}$ we know that the seller will not collect and wait for payment. If the seller

[4]Note that it is easy to see that $\pi_{B,d}^{S*} > \pi_{B,l}^{S}$, i.e. that $f(C_B + p) > f(C_B) + p$ under assumption (3).

state is B then because $\pi^S_{B,c} > \pi^S_{B,l}$ we know that the seller will collect. The buyer understands this. Type L buyers will thus choose to pay the type B seller when the invoice is due, and pay the type G seller late.

Suppose that the seller is a private firm. Now the buyer will use the ex ante probabilities $\Pr(G)$, and $\Pr(B)$ to guide his choice. Then type L buyers will pay the invoice when it is due, provided

$$\pi^B_{L,d} > \Pr(G)\pi^B_{L,l} + \Pr(B)\pi^B_{L,c} \tag{6}$$

If (6) holds, the buyer always prefers to pay early, whatever the type of the buyer. If these inequalities do not hold, then the buyer will pay late. This kind of buyer payment does not fluctuate with the seller's state.[5]

D. Empirical predictions

The model has a number of empirical predictions regarding the patterns of payments between buyers and sellers in the economy and the impact of stock price fluctuations on corporate cash flows, which we test below:

Hypothesis 1 [Signal availability]: Public firms face more payment delays than private firms.

Hypothesis 1 is based on the idea that for public firms a signal about their type is available. If buyers take this signal into account when deciding whether to pay late or on time, as our model postulates, hypothesis 1 follows. Support for hypothesis 1 would also imply a trade-off to being publicly listed: While the firm presumably will have more easy access to equity capital, it will also suffer an adverse effect on its cash flow.

Hypothesis 2 [Signal precision]: Public firms that are more actively traded (liquid stocks) face more payment delays than public firms not actively traded (illiquid stocks).

[5] Why is it worthwhile for the private seller not to truthfully reveal his type to the buyer? If the private seller would truthfully reveal his type to the buyer, then there would be no informational advantage to being public. To see why private sellers do not have this incentive, recall that both types of sellers prefer to be paid on time. If the seller G truthfully revealed his type, then the type L buyer would pay late for sure. As a consequence, private sellers of type G always want to mimic types B, because then they would be paid on time. Hence, private firms of type G do not have an incentive to reveal their type truthfully.

Hypothesis 2 states that the model would predict that for firms with a high signal to noise ratio in the stock price, i.e. firms in which stock price fluctuations accurately reflect all available information about the firm, should face more payment delays compared to firms that are listed, but not frequently traded. Firms with a liquid stock provide a more accurate signal to the buyer when deciding whether to delay payment or not.

Hypothesis 3a [Insurance]: Payment delays decline when the stock price of the seller declines (negative signal).

This is the centre of our investigation. If buyers take the stock price as a signal to decide on the timeliness of their payment, stock price fluctuations of a firm have implications for its cash flow. If our model of buyer/seller interaction is correct, buyers should take the decline of the seller's stock price as a negative signal of the seller's state and, therefore, his willingness to accommodate payment delays. Note that this hypothesis is complementary to the insurance effect documented in Boissay and Gropp (2007), who show that large liquid firms accommodate more payment delays. In that paper, the insurance was provided by the seller to the buyer. In Hypothesis 3a, the insurance would be provided by the buyer to the seller: If the seller is in bad shape, buyers make their payments more promptly. This also would suggest that while being publicly listed entails the costs of facing more payment delays on average (e.g. of acting as insurer more often), listed firms also enjoy insurance. Both effects do not exist for unlisted private firms.

Hypothesis 3b [Taking advantage]: Payment delays increase when the stock price of the seller declines.

The alternative to hypothesis 3a would be that buyers take advantage of a week seller by delaying payment more rather then less after they have received a negative signal about their state.

III. Data

The compilation of our data set starts with a combination of data from three sources: the CIPE database on trade credit delays, the FIBEN database on firm balance sheets (both from the Banque de France), and Datastream for firms' stock market prices. After excluding the public sector, agriculture, energy, health, education, and domestic services, the financial sector, and holding companies, FIBEN contains annual balance sheets for 140,000 non-listed and 355 listed firms. We built our data set in two steps. First, to obtain a meaningful control group for listed firms, we selected the non-listed companies that were similar to listed companies by using a propensity score technique (see Todd, 2006). We thus kept 1,128 public or private firms in the sample. Second, we merged together for these firms information about trade credit delays (CIPE), stock market prices (Datastream), and balance sheets (FIBEN).

A. The matching process

We identified the private companies similar to listed companies by estimating the probability of being listed as a function of a number of important firm characteristics, that is age, size (assets), financial health (summarized by the Z-scores computed by the Banque de France), as well as time, regional and 3-digit sector dummies.[6] Since these variables are only available at an annual frequency, we estimated the model using annual data. For the firms that went public during the sample period, we classified them as listed from the year they became listed onward. We used a Logit model, whose estimates are shown in Table 1.

[Table 1 about here]

As expected, firms are significantly more likely to be listed when they are older and larger. However, financial health does not seem to have an effect. We computed the propensity score for every firm i and every year t. We then we paired, for each year, each listed company i together with the non-listed company that had the propensity score the closest to firm i's (Todd, 2006). We kept the matches when the difference between the two probabilities was smaller than 0.01. With this method we obtained a total sample of 2,370 firm/year observations, one half of which related to listed firms and one other half related to non listed firms. Note that we paired some listed

[6]For detail on the computation of the credit score computed by the Banque de France see Banque de France (2006b) and Bardos et al., (2004).

companies with several different non listed companies over time; hence our sample includes 262 listed and 866 non listed individual companies.

B. The data set

In the second step, we merged the information on trade credit delays (CIPE), stock market prices (Datastream), and balance sheets (FIBEN) to generate a dataset of firm/day observations.[7] Detailed descriptive statistics for the CIPE database on payment delays are reported in Boissay and Gropp (2007) and further institutional information on the compilation of the dataset is given in Appendix A. CIPE contains daily data on payment delays by all French firms. The data are collected by the Banque de France. The data contain the identity of the buyer, the seller, the amount that remained unpaid, the day of the non-payment (e.g. when it was due but was not paid) and the reason for the payment delay. Three main reasons for payment delay are given:

1. [Disagreement] There was disagreement over the quality of the goods delivered.
2. [Illiquidity] There were insufficient funds in the buyers bank account to cover the payment.
3. [Insolvency] The buyer filed for bankruptcy or is in a liquidation process.

Payment delays are reported to the Banque de France by the buyer's bank. The reporting is obligatory and occurs in the context of the electronic payment system in France that covers almost all inter-firm transactions (see Boissay and Gropp, 2007, Bardos and Stili, 2006 and Appendix A). Boissay and Gropp (2007) show that the reason reported for the payment delay appears to be reported truthfully. While delays on trade credit and stock market prices are daily data, balance sheet data are annual. Hence following Boissay and Gropp (2007) we replicated balance sheets information in year t as many times as there were business days in that year (i.e. on average 250 times). In addition, we only kept the observations when balance sheets were available for the previous year. Our data set ultimately contains 455,723 firm/day observations over the period 1999-2003. To get a sense of how successful we were matching listed and private firms, we report in Table 2 the means and quartiles of the distribution of the main firm characteristics for each sub-sample.

[7] For more information on the FIBEN data base of firm balance sheets at the Banque de France, see Banque de France (2006a).

[Table 2 about here]

The matching process appears to have successfully yielded very similar distributions of main firm characteristics (size, age and quality, as measured by the z-score) for listed and non-listed firms. We find that private firms are two years older on average and also have a higher median age, while they are on average slightly smaller. The higher mean size for listed firms appears to be driven by the presence of some very large listed firms, as the median private firm is larger than the median public firm. The distribution of the z-score shows even smaller differences. Both distributions have identical means; the median score of private firms is somewhat higher (meaning they are lower quality) compared to listed firms. A high degree of congruence across the two sub-samples is also found when considering the distribution across sectors, which is reported in Table 3.

[Table 3 about here]

While Table 2 shows that the distributions of age, assets, and financial health indicators are essentially identical across listed and non listed firms in our sample, Table 4 shows significant differences in delays faced due to illiquidity. Listed companies are paid late almost twice as often than non listed firms and face larger annual delays on average. Depending on the point in the distribution, the difference can be as large as 30 percent. Similarly, when scaled by annual receivables, we find that in the 75th percentile, listed firms face more than 40% more delays compared to private firms. Nevertheless, the difference in frequency of delay faced seems to be significantly large than the difference in amount of delay faced. This suggests that listed firms face many delays from small firms on relatively small invoices. In order to avoid biasing our results upward through many extremely small delays, we estimate the amount of delay faced, rather than the number of delays faced.[8]

[Table 4 about here]

[8]Note that the firms in our sample do not, or hardly ever (<0.01 percent of the time), themselves delay payment on their trade credit.

IV. Empirical implementation and results

We estimate the amount of payment delays faced by a seller on a given day as a function of the seller's balance sheet characteristics, whether or not the seller is publicly traded and stock price fluctuations of the seller's stock price. The dependent variable is the amount of delays faced by firm i in period t due to illiquidity divided by annual receivables. We use payment delays in which the reason reported is illiquidity only, as this corresponds closely to the main idea of the theoretical model that buyers tend to only default if they are short of cash to fund the operations of the firm. We estimate the model in daily frequency (we check alternative frequencies below) using a tobit model as the dependent variable is censored at zero (no delays faced). The baseline model is therefore:

$$Def_{it} = \alpha_0 + AX_{it} + \beta_1 Listed_i + \beta_2 Decline_{it-1} + \beta_3 \Delta Index_{t-1} + \beta_4 \Delta Own_{it-1} + \beta_5 Active + u_t + u_s + \epsilon$$

X_{it}represents a set of control variables of firm *i*. The variables include firm age, the log of total assets, the log of firm sales and the score calculated by the Banque de France[9] In addition we include bank debt divided by total assets and overdrafts used divided by total assets to proxy for the debt capacity of the firm. We use the last available balance sheet information as described above. Based on the insurance hypothesis, we would expect larger and older firms to face more delays and firms with higher scores (higher probability of default) to face fewer delays. If firms take advance of weakness in their suppliers, we should see the opposite: higher quality firms face fewer delays. If firms delay payment randomly to different suppliers without systematically taking their characteristics into account, we would expect none of the supplier characteristics to matter, as long as liquidity shocks are random across customers (see below). If the suppliers insure their customers and they actively seek out strong firms to delay payment to, we would expect firms with more debt and more used overdrafts to face fewer delays. We also include day of the week dummies, monthly dummies, annual dummies, as well as dummies indicating the day of the month

[9] The score variable is missing in some observations in the original data set. We imputed by using the mean score for the entire sample and added a dummy variable set equal to one if the score was missing. We also include the propensity score from the matching model as suggested by [reference] and a dummy variable whether during the five days when the stock price is measured, the firm published a new balance sheet. This is included to control for contamination arising from the news effect of the new balance sheet information.

and the day of the week, as due dates may be clustered around certain dates ($u_t.$), as well as 24 sectoral dummies (at the two digit level). We do not report the coefficients of the dummies below; the results are available from the authors upon request. The sectoral dummies serve the role of controlling for shocks that may affect the seller and the buyer simultaneously.[10]

The main variables of interest are *"Listed", "Decline", "Own", "Active"* and *"Index". "Listed"* represents a dummy variable equal to one if the firm was listed at the French stock exchange. Based on the model, we would expect listed firms to face more delays. *"Decline"* represents a dummy variable equal to one if the firm's stock price declined substantially during the previous five business days, measured relative to period t. "Substantially" is defined as the lower 10% tail of the sample distribution of stock price variations across all firms during the past five days. We report results based on alternative definitions below. *"Own"* represents the first difference in stock returns during the past five business days. This variable is included to control for the effect of "normal" fluctuations in the firms' stock price. *"Active"* is a dummy variable equal to one if the firm is regularly traded, given it is listed. We define "regularly traded" in line with Datastream as being actively traded on more than 50% of all business days during the sample period. The variable measures the quality of the signal that can be obtained by customers about the quality of the supplier from the stock price. Hence, it serves as a proxy for the signal to noise ratio of the stock price of the firm. Based on the model, we would expect firms that are listed and actively traded to face more delays than firms that are listed but not actively traded. For actively traded firms the information content of stock prices is higher. Finally to control for overall market effects we also include the returns of the CAC40, *Index,* (the most important stock market index in France) during the past five business days. We would expect that if the overall stock market declines, delays faced of all firms (listed and non-listed) increase, as the stock market represents an indicator of overall economic conditions. For detailed definitions of all variables see Appendix 2.

The results based on the benchmark model are given in Table 5. The control variables tend to support the insurance hypothesis. Larger and older firms face more delays and the coefficients are significant at least at the five percent level. Higher quality firms (with lower scores) face more delays, which supports our notion of the existence of insurance that is taken advantage off only if

[10] Note that this problem would be particularly severe if we found that delays faced *increase* with stock price declines. This is not what we find, however (see below).

the insuring firm has easy access to outside finance. Firms already close to their debt capacity face fewer delays; again in line with the notion of customers selecting firms to delay payment to based on their capacity to absorb the delays.

Now turn to the variables of interest. We find that listed firms face significantly more payment delay. The coefficient is significant at the 1 percent level. If the firm is not only listed, but actively traded, this effect becomes even stronger as "*Active*" is also significant at the one percent level and positive. We interpret this as evidence that a more precise signal helps the customer delineate good firms (that will accommodate delays) and bad firms (that will not). Both are in line with the model. The results also show that the effect of a decline of the own stock price has a different effect from a decline in the overall stock market. If the CAC 40 increases ("*Index*") all firms face significantly fewer delays, which we interpret as a business cycle effect: if the economy is performing poorly, the propensity of all firms to delay payment increases. Finally the insignificant coefficient of "*Own*", which measures the stock price return of firm *i,* is further evidence that only large movements in the stock price of a supplier are viewed as an informative signal by customers.

Next, we check whether for some unobserved reason, listed firms' customers are different from the customers of unlisted firms. There are two main reasons why sector controls might be important. One, our results may be driven by the (somewhat unlikely) possibility that listed firms simply have poorer customers than unlisted firms. Note that the fact that we find that the firms that are *of higher quality* face more delays is a first indication that this does not seem to drive our results. Nevertheless, we include the average score of the firm's customers to control for this possibility. Second, and this might be more important, our story about mutual liquidity insurance is correct, but listed firms face more delays not because of an observable signal about their quality, but because they have longer term relationships with their customers.[11] We attempt to control for this effect by including the average age of the customers. We also included the average assets of the firms' customers, with the idea that smaller firms are more likely to be liquidity constrained. If listed firms customers are significantly smaller than the customers of unlisted firms, this could result in a positive coefficient on *"listed"* in the absence of any signalling effect of the stock price.

[11]Note that in Table 2 we show that unlisted firms tend to be slightly older than listed firms, which is evidence against the idea that listed firms have longer relationships with their customers compared to unlisted firms.

However, we do not observe a full set of customers for the firms in our sample, as CIPE records the customer supplier link only if there is a payment delay, not if the payment was made at the due date. Hence, we were forced to construct the customer variables by relying on the information obtained from the payment delays only. We calculated the mean of all firms belonging to a sector where at least one firm delayed payment at least once during the sample period to any of the firms in the same sector as the supplier *i*. Hence, the customer variables are sector, rather than firm specific variables. For more details on the calculation of the customer control variables see Appendix 2. The results are reported in column 2 of Table 5 ("Model 2: Customer controls"). The model includes the same set of supplier control variables as model 1 The results suggest that including customer controls the main results remain unchanged. If a firm is listed and actively traded it faces significantly more delays. If its stock price declines, the amount of delays it faced also declines. All control variables retain their significance and economic magnitude. Turning to the coefficients of the customer control variables themselves, we find that if suppliers have older and poorer quality firms, they face more delays. This makes sense: if firms are older, the length of the relationship may be longer, suggesting a stronger insurance motive or possibly a stronger negotiating position of the buyer. If firms operate in sectors with on average poorer quality firms, they face more delays, but listed firms are not more likely to operate in these sectors than unlisted firms. We do not find a significant effect of size. As we find that model fit is improved by including the customer control variable, we retain them in all further specifications.

So far we have used the stock price decline during the past week as our measure of an adverse signal about the supplier. Are our findings robust if we use longer term declines? This is explored in model 3 (third column of Table 5). All variables are defined as before, except "*decline"* is now equal to one if the supplier's stock price decline was in the negative 10 percent tail during the 20 days, rather than five days. The control variables are unaffected by this change. All retain their sign, significance and economic magnitude. The coefficients on the main variables of interest are also the same as for the weekly stock price declines. Listed, actively traded firms face more delays and if their stock price declines substantially, the amount of delays they face decreases. However ,the coefficient on "decline" is much smaller than for the weekly return. This suggests that customers seem to adjust their payment behavior relatively quickly in response to stock market fluctuations and could be interpreted as further evidence of customers interpreting large stock price declines as a signal Overall, our central results are robust to considering monthly stock price declines.

Our model is concerned with liquidity shocks. Do listed firms face also more delays due to other reasons and do these delays vary with stock price fluctuations in a similar manner? If this were so, we would view this as evidence against the main hypotheses from our model. As discussed above, the data set permits a distinction of the reason for the delay of payment. In particular, we also observe delays due to a disagreement over the quality of the goods delivered.[12] Hence, we re-estimate the model with the amount of delay due to disagreement faced by firm i as the dependent variable (column 4 in Table 5). We use the same control variables as before. Most of the control variables also have the same sign and significance as before. There are a few notable exceptions. One, a larger share of bank debt is unrelated to payment delays faced if they are due to disagreement. Second, higher quality firms do not face more delays due to disagreement, while they do face more delays due to illiquidity. Hence, when firms do not pay because they are unhappy about the quality of the goods delivered to them, they do not take the quality of their supplier into account.

With regards to the variables of particular interest, we find that listed firms are less likely to face delay due to disagreement, while they are more likely to face delay due to illiquidity. This lends further credence to the presence of a liquidity insurance effect. The reason listed firms may face fewer delays due to disagreement may relate to their relatively strong position in the market: they may have strong bargaining power in this regard. We also do not find an effect of stock price declines on the amount of payment delay faced However, we do find that firms that are actively traded face more delays due to disagreement. We checked wether the sum of the coefficients "*Active*" and *"Listed"* are significantly different from zero and they are not. This suggests that listed, but not actively traded firms face fewer payment delays due to disagreement than both unlisted and actively traded firms.

[12] Boissay and Gropp (2007) show that the characteristics of firms defaulting due to disagreement and those defaulting due to illiquidity are vastly different. In particular, larger, older firms are much less likely to default due to illiquidity and much more likely to default due to disagreement. Further, they argue that since the reason for the default is reported by the bank conducting the transaction it seems less likely that the reason is misreported.

Fluctuations in the CAC40 index also have no relationship with the amount of delays faced due to disagreement, further supporting the idea that delays due to disagreement are unrelated to liquidity or solvency problems of firms (see Boissay and Gropp, 2007). Finally, if firms' customers are larger, older and poorer quality, they face more payment delays due to disagreement over the quality of goods delivered.

V. Robustness

We explore the robustness of our results in two main dimensions. One, we vary the frequency of the data set. Whereas in the baseline results, the amount of delays faced were measured on a daily basis, we now explore what happens if we consider weekly or monthly amounts of payment delay faced as a function of weekly or monthly stock price declines, respectively. Second we vary the size of the tails used to compute the stock price decline. In the baseline model we used the 10 percent negative tail of returns and we explore the sensitivity of the results to using 5 percent or 20 percent tails.

The results are presented in Table 6. In column 1 ("Model 5") we report the results for the weekly model. All control variables retain their significance and sign relative to the baseline model with customer controls (model 2 in Table 5). The exceptions are bank debt and score, which are no longer significant. The main results are as before. Note that due to moving to a weekly data set, the number of observations is substantially reduced to a quarter, from more than 450,000 to less than 90,000 observations. We obtain the same results, when considering the monthly dataset (Model 6 in Table 6), although *"listed"* while continuing to be positive, is only significant at the 10 percent level in this model. *"Active",* however, continues to be positive and significant at the one percent level. When moving to longer term horizons, the precision of the signal that buyers receive from the stock market appears to matter more. Again note the reduction in sample size due to the monthly nature of the data (to 21,500 observations).

Finally consider what happens if we define the stock price decline dummy based the 5 percent or 20 percent tails of the distribution (Models 7 and 8 in Table 6). We find that for very large declines in the stock price the results no longer hold: While the coefficient on *"decline"* remains negative, it is no longer significant. This stands in contrast to a wider definition of the stock price drop: If we consider the 20 percent tail the results not only go through but tend to become stronger. This seems to suggest that there are substantial non-linearities in the relationship between the stock market and the behavior of customers. For a wide range of stock price fluctuations there is no reaction. If customers observe sufficiently large declines, they tend to pay in a more timely fashion (helping their supplier). But if the declines become very large, this effect disappears: One interpretation would be that once the customers doubt that their supplier will survive or ever be able to provide them with liquidity insurance again, they resume a relatively poor payment record.

We wanted to explore these non-linearities further and show in Chart 2 the results for a series of regressions that vary the tail in the calculation of *"decline"*. The horizontal axis shows the coefficients of the baseline model (Model 2 in Table 5) as we move from using the one percent tail to the distribution up to the median. We find that the effect of stock price declines on the payment behavior of customers has a U-shape with the minimum around the 15th percentile of the distribution. This confirms the notion given above: Customers condition payment on the stock price of their supplier. For small changes in the stock price there is no adjustment in the payment behavior. For moderately large changes (stock price declines between the negative 6th and 25th percentile of the distribution of returns), customers pay more timely. This has a positive effect on the cash flows of those firms suffering adverse shocks reflected in their stock price. However, if stock price declines become very large, customers resume their normal payment patterns. Our interpretation is that if stock prices of firms show very large downward adjustments, the survival of the supplier may be called into question. This makes these suppliers less valuable as potential future insurers, which in turn suggests they may find it no longer advantageous to "help out" their supplier.

VI. Conclusions

This paper documents that customers condition their decision to pay on time on the stock prices of their suppliers. Hence, stock price fluctuations affect the cash flows of firms. Specifically, buyers tend to insure listed firms: If the stock price of a listed firm declines substantially, buyers tend to increase the timeliness of their payments. This is a benefit of being listed. However, listing also has a cost in terms of cash flow: Listed firms overall are about twice as likely to face payment delays from their customers as comparable unlisted firms. This effect is even stronger for actively traded firms, which we interpret as evidence that buyers prefer to rely on a more accurate signal about the quality of the seller to take the decision on prompt versus late payment. All of these findings are in line with a simple model of buyer seller interaction presented in this paper.

Interestingly, the insurance effect operates only for moderately large declines in the stock price of the seller. For very large declines, the effect disappears. This may be evidence that buyers assign a low probability to these sellers to survive and therefore do not expect much liquidity insurance from these sellers in the future. The results may also have a bearing on the effects of stock price fluctuations on investment. While the insurance effect documented in this paper may dampen adverse effect of stock price fluctuations on investment of the listed firm, it may amplify investment effects for the customers of these firms. This is so, because listed firms are no longer willing to insure their customers against adverse liquidity shocks. Hence, such shocks, combined with a larger investment sensitivity of cash flow, may result in relatively large reductions in investment among small firms.

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Table 1: Propensity score

Logit	dummy of whether
Dependent variable	firm was listed in year t
	$listed_{it}$
Independent variables	
$Constant$	-30.38** (0.00)
lnage_{it}	-0.42* (0.01)
lnage_{it}^2	0.11** (0.00)
ln$asset_{it-1}$	3.65** (0.00)
ln$asset_{it-1}^2$	-0.13** (0.00)
Z-$score_{it-1}$	-0.004 (0.20)
Pseudo R^2	0.31
N	354,024

Estimated using annual data for all firms in FIBEN.

Table 2: Comparison of firm characteristics - listed/private

	listed	not listed
Age (years)		
mean	30.4	32.9
first quartile	11	11
median	17	24
third quartile	36	45
Assets (million euros)		
mean	240.3	225.6
first quartile	131.2	124.5
median	320.0	396.6
third quartile	1023.3	1274.8
Z-score		
mean	5.2	5.2
first quartile	0.65	0.86
median	1.95	2.64
third quartile	5.56	5.56
N	231,142	224,581

Table 3: Sectoral distribution

	listed	not listed
Consulting, service to businesses	16.71	15.60
Wholesale trade	14.39	13.91
Electrical equipment	9.86	8.83
Steel and metallurgical industry	6.14	4.87
Mechanical equipment	5.86	6.54
Chemicals, rubber	4.71	5.09
Retail trade	4.45	4.35
Pharmacy, cleaning materials	4.20	4.67
other	28.29	29.90
Total	100	100

Table 4: Comparison of delays faced - listed / non-listed

	listed	not listed
delay faced due to illiquidity		
in % of firm/day observations	2.1	1.2
total annual amount, in thousands euros		
mean	351.0	305.8
first quartile	57.6	32.2
median	160.2	126.8
third quartile	304.9	451.7
total annual amount, in % of receivables		
mean	1.76	1.74
first quartile	0.50	0.20
median	0.99	0.73
third quartile	2.81	1.62
N	231,142	224,581

Table.5: Payment delays faced and the stock market

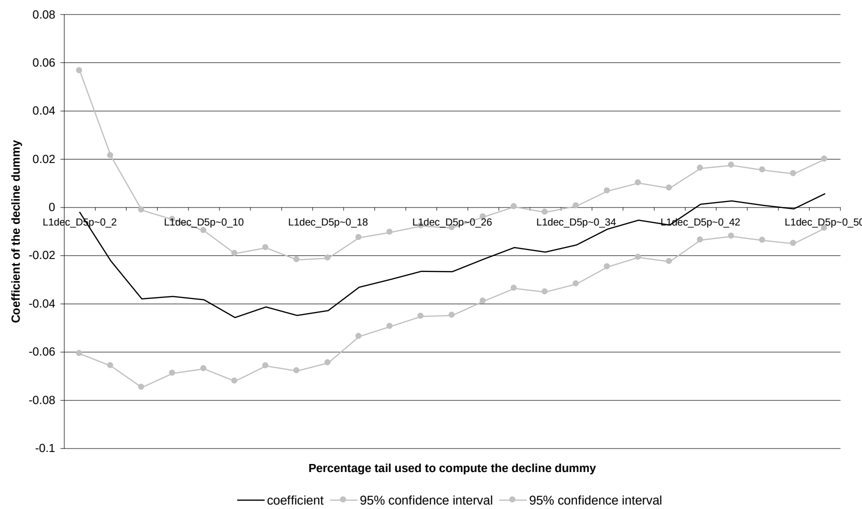
Independent variables	Model (1) Baseline	Model (2) Customer controls	Model (3) Monthly declines	Model (4) Disagreement
constant	−0.016*** (0.000)	−0.370*** (0.024)	−0.369*** (0.025)	-0.130*** (0.012)
age	0.007** (0.003)	0.009*** (0.003)	0.009*** (0.003)	0.012*** (0.002)
assets	0.068*** (0.002)	0.069*** (0.002)	0.069*** (0.002)	0.029*** (0.001)
sales	0.105*** (0.005)	0.107*** (0.005)	0.107*** (0.005)	0.037*** (0.002)
bank debt	−0.119*** (0.034)	−0.084*** (0.034)	−0.086*** (0.034)	−0.019 (0.019)
overdraft	−0.176*** (0.034)	−0.167*** (0.034)	−0.165*** (0.034)	-0.046*** (0.017)
score	-0.002*** (0.000)	-0.003*** (0.000)	-0.003*** (0.000)	0.000 (0.000)
score missing	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.000*** (0.000)
listed	0.090*** (0.009)	0.090*** (0.009)	0.092*** (0.009)	-0.011** (0.006)
decline	-4.32*** (1.46)	-3.83*** (1.46)	-0.001*** (0.000)	-1.19 (0.779)
own	0.008 (0.045)	0.014 (0.045)	0.022 (0.026)	−0.023 (0.025)
active	0.059*** (0.009)	0.054*** (0.009)	0.054*** (0.009)	0.068*** (0.006)
index	-0.201*** (0.067)	-0.200*** (0.067)	-0.108*** (0.039)	-0.037 (0.036)
propensity	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.000* (0.000)
new balance sheet	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)	-0.000 (0.000)
customer assets		0.000 (0.000)	0.000 (0.000)	0.002*** (0.000)
customer age		0.114*** (0.008)	0.113*** (0.008)	0.033*** (0.004)
customer score		0.003*** (0.001)	0.003*** (0.001)	0.001*** (0.000)
Chi^2	11121	11392	11402	7646
N	455,723	455,723	455,723	455,723

The dependent variable is the amount of defaults faced due to illiquidity except in model 5, where it is delays faced due to disagreement. All regressions include 24 sector dummies (2 digit level) and year dummies. Models 1 and 2 also include day of the week dummies (Friday is the omitted category), months dummies and 31 day of the months dummies. Model 3 includes months dummies.

Table.6: Robustness

Independent variables	Model (5) Weekly delays	Model (6) Monthly delays	Model (7) 5 percent tails	Model (8) 20 percent tails
constant	−0.190***	-0.272***	−0.371***	−0.369***
	(0.017)	(0.036)	(0.025)	(0.025)
age	0.023***	0.045***	0.009***	0.009***
	(0.005)	(0.011)	(0.003)	(0.003)
assets	0.073***	0.072***	0.069***	0.069***
	(0.004)	(0.008)	(0.002)	(0.002)
sales	0.123***	0.156***	0.107***	0.107***
	(0.008)	(0.017)	(0.005)	(0.005)
bank debt	−0.073	−0.164	−0.084***	−0.085***
	(0.059)	(0.125)	(0.034)	(0.034)
overdraft	−0.205***	−0.263**	−0.167***	−0.167***
	(0.059)	(0.125)	(0.034)	(0.034)
score	-0.001	0.014	-0.003***	-0.003***
	(0.001)	(0.014)	(0.000)	(0.000)
score missing	0.00	-0.000	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
listed	0.078***	0.001*	0.088***	0.091***
	(0.016)	(0.0003)	(0.009)	(0.009)
decline	-0.066***	-0.002***	-0.000	-0.033***
	(0.021)	(0.001)	(0.000)	(0.010)
own	0.003	-0.000	0.053	−0.001
	(0.065)	(0.001)	(0.043)	(0.047)
active	0.109***	0.002***	0.055***	0.056***
	(0.016)	(0.000)	(0.009)	(0.009)
index	-0.332***	-0.002	-0.198***	-0.204***
	(0.108)	(0.001)	(0.067)	(0.067)
propensity	0.004***	0.006***	0.002***	0.002***
	(0.001)	(0.002)	(0.001)	(0.000)
new balance sheet	0.001**	−0.001	-0.002***	-0.002***
	(0.000)	(0.001)	(0.001)	(0.001)
customer assets	0.001**	0.014	0.000	0.000
	(0.000)	(0.011)	(0.000)	(0.000)
customer age	0.049***	0.749***	0.114***	0.113***
	(0.005)	(0.108)	(0.008)	(0.008)
customer score	0.003***	0.023***	0.003***	0.003***
	(0.000)	(0.007)	(0.001)	(0.001)
Chi^2	4954	2015	11386	11395
N	89,945	21,581	455,723	455,723

Chart 2. Sensitivity of defaults faced to declines in stock prices



Appendix 1

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.[13]

[13] 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.

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 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.[14] 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.[15] In the case a customer cannot pay on time, or repudiates, its trade bill, then its bank is obliged, by law, to notify the non-payment 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.[16]

[14]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.

[15]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.

[16]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.

Appendix 2

[Variable definitions, to be completed]