WORKING paper

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Corporate Liquidity During the Covid-19 Crisis: the Trade Credit Channel

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Abstract

Using unique daily data on payment defaults to suppliers in France, we show how the trade credit channel amplified the Covid-19 shock, during the first months of the pandemic. It dramatically increased short-term liquidity needs in the most impacted downstream sectors: a one standard deviation increase in net trade credit position leads to a rise in the probability of default of up to a third. This effect is short-term and cyclical and is concentrated on financially constrained firms. We argue that taking into account the trade credit channel is critical to properly quantify liquidity shortfalls in crisis times.

Keywords: Firm, Corporate Finance, Trade Credit, Liquidity, Payment Default, Covid-19, Lockdown, Pandemic.

Classification JEL : E32, G32, G33, H12, H32

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NON-TECHNICAL SUMMARY

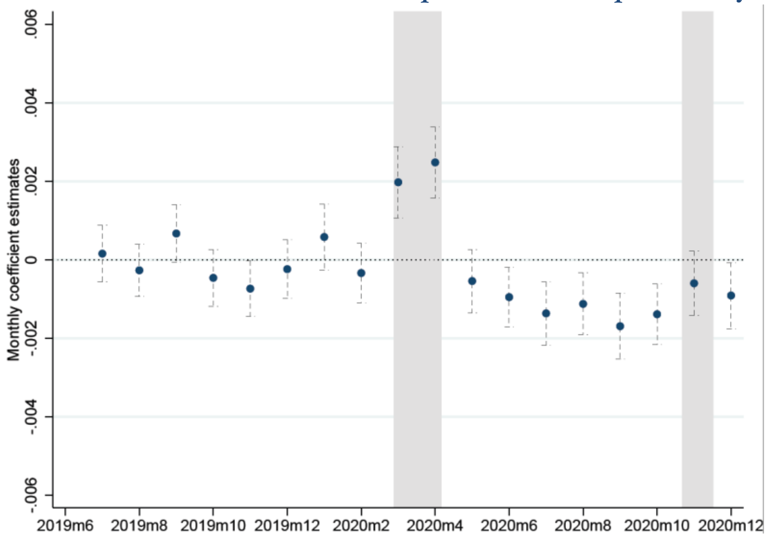
Short-term funding of non-financial firms essentially comes from suppliers. In 2019, trade payables of French firms exceeded EUR 520 billion, more than seven times higher than short-term bank funding. Such numbers highlight how critical the reliance on trade credit is for firms' liquidity in France, as in other countries. Despite its economic significance, trade credit has surprisingly received little attention in the growing volume of literature analysing the impact of the Covid-19 crisis on the economy. This paper fills the gap by shedding light on a trade credit channel of the Covid-19 crisis, which goes against the traditional role of trade credit as a countercyclical way of funding.

While trade credit has been shown to provide an alternative source of financing, as a substitute for bank finance in times of banking crises, we show how relying on trade credit finance (i.e., being a net trade credit borrower) turned into a source of liquidity stress during the early stage of the Covid crisis.

Firstly, we show that the existing net trade credit position of a firm amplifies the liquidity stress caused by the lockdown and significantly increases the probability that the firm defaults on its suppliers. This impact on payment default is stronger in, but not limited to, downstream sectors like retail trade, with structurally positive net trade credit position. This effect is short-term and cyclical. After reaching a peak in April, it fades out when the activity resumes after the lockdown, and even reverses in June, albeit to a lesser extent as the recovery is gradual. Secondly, we find that financially weaker firms are more exposed to defaults induced by the trade credit channel: smaller, riskier, capital constrained and less profitable firms that are net trade credit borrowers, default significantly more than financially stronger firms. Thirdly, we document that firms can offset the effect on payment defaults by hedging liquidity risk. As expected, firms with high cash buffers are able to counterbalance the liquidity stress induced by the trade credit channel during the lockdown. We also find evidence consistent with a default reduction effect of using accounts receivable financing, but only for the largest firms.

Our results enable readers to better understand one of the critical channels affecting the transmission of the shock along the supply chain. They shed light on the cyclical and short-term nature of trade credit. The inverted U-shape effect on default to suppliers we document throughout the paper is somewhat simple but critical to properly assess the intensity of the liquidity shock and to accurately quantify potential liquidity shortfalls at a given point in time. The liquidity "path" of the firm, i.e., this bounce-back effect, shall not be neglected to calibrate liquidity bridge schemes aiming at alleviating funding stress in crisis times and to avoid contagion along the supply chain.

Monthly coefficient estimates of the effect of trade credit position on the probability of firm payment default



Notes: The level of observation is a firm i in month t. The dependent variable is a dummy variable, which takes the value 1 if the firm defaults at least once on paying a trade bill to one of its suppliers in month t. The graph shows the results of the estimation of a linear probability model where firm's one-year-lag trade credit position seeks to explain firm's payment default in month t (for more details see equation (1) in the paper). Coefficients for each month, starting in 2019m7 are plotted, along with 95% confidence intervals. The sample period of estimation is 2019m1 to 2020m12.

Liquidité des entreprises pendant la crise du Covid-19 : le canal du crédit interentreprises

RÉSUMÉ

À partir de données journalières sur les incidents de paiement sur effets de commerce, nous montrons que le crédit interentreprises a amplifié le choc d'activité lié au confinement mis en place en mars 2020 pour répondre à la crise sanitaire. Ce canal du crédit interentreprises a fortement augmenté le besoin de liquidité à très court terme, en particulier pour les entreprises en aval de la chaine de valeur : pour les plus exposées, une hausse d'un écart type de leur position de crédit inter-entreprises avant le confinement s'est matérialisée par une probabilité de défaut un tiers plus élevée. Cet effet est de court terme, cyclique et concentré sur les entreprises vulnérables financièrement. Nous montrons ainsi que prendre en compte le canal du crédit inter-entreprises est essentiel pour quantifier correctement le besoin de liquidité des entreprises en période de chute de la demande.

Mots-clés : entreprise, finance d'entreprise, crédit interentreprises, liquidité, défaut de paiement, Covid-19, confinement, pandémie.

1 Introduction

Short-term funding of non-financial firms essentially comes from suppliers. In 2019, trade payables of French firms exceeded EUR 520 billion, more than seven times higher than short-term bank funding.[1] Such numbers highlight how critical the reliance on trade credit is for firms' liquidity. That importance has also been observed in other countries, such as in the United-States,[2] Germany, Spain, Italy,[3] China,[4] and Mexico,[5] and was particularly marked during periods of financial stress. Trade credit does indeed provide an alternative source of financing as a substitute for bank finance in times of banking crises (Cunat, 2006; Garcia-Appendini and Montoriol-Garriga, 2013; Carbo-Valverde et al., 2016).

Despite its economic significance, trade credit has received surprisingly little attention in the growing volume of literature analysing the impact of the Covid-19 crisis on the real economy. This paper fills the gap by shedding light on a trade credit channel of the Covid-19 crisis on firm liquidity.

Firstly, we seek to understand the role of trade credit for corporate liquidity in times of demand shocks associated with the Covid-19 pandemic: to what extent does the existing net trade credit position of a firm amplify the liquidity stress caused by the lockdown? Does it affect the probability that a firm defaults on its suppliers? Secondly, we examine whether financially weaker firms were more exposed to the trade credit channel of Covid-19 as well as whether, and how, some firms did manage to cope better with it by actively managing their liquidity risk.

[1]The total of accounts payable is as much as 90% of the amount of long-term bank debt of French firms and represents 7% of their total liabilities (Computation based on 2018 Banque de France FIBEN data).

[2]Barrot (2016) indicates that in the United States "nonfinancial firms are the main providers of short-term corporate financing to their customers. Accounts payable are three times as large as bank loans [...]."

[3]According to the BACH database (Bank for the Accounts of Companies Harmonized, `https://www.bach.banque-france.fr/?lang=en`), accounts payable represent 50% of bank loans for the average firm in Germany in 2019 (over a 35,500 firms sample), almost 80% for the average firm in Spain (531,000 firms) and more than 140% for the average firm in Italy (468,000 firms).

[4]According to Lin and Chou (2015) "the share of accounts payable to total liability in Chinese firms (not including financial industry) reached 20% in 2012 [...]".

[5]Cardoso-Lecourtois (2004) stresses that "in an economy like Mexico [...] 65% of firms claim their main source of financing to be other firms".

Thirdly, we examine how trade credit exposure acted as a key determinant of needs for refinancing and demand for State-guaranteed loans. Lastly, we provide a related policy-oriented discussion on the size of liquidity needs induced by trade credit and of their distribution in the economy. This question is of first-order importance as preventing disruptions in trade payments is key in avoiding the propagation of liquidity shocks along the supply chain that would aggravate a recession (Kiyotaki and Moore, 1997; Boissay and Gropp, 2013).

To pin down the trade credit channel of the crisis, we draw on unique Banque de France daily data for 2019 and 2020, which tracks payment defaults on trade bills for all businesses in France. We match those default data with financial statements of more than 175,000 firms, accounting for roughly two thirds of non-financial firms' added value in 2019.

We define a firm's trade credit balance as the difference between accounts payable and accounts receivable, scaled by sales. Hence, a positive balance means that the firm is a net borrower. This balance reflects payment terms negotiated between a firm and its suppliers and is largely explained by the industry in which the firm operates and its position in the supply chain. Typically firms operating in business-to-consumer activities are net borrowers (i.e., with a positive trade credit position) as they directly serve non-business customers paying cash, while payment delays increase from downstream to upstream (Gonzalez, 2020).

Our interest in the trade credit channel stems from the fact that :

(i) Assuming that a firm's activity level is constant between two dates, its trade credit position is unchanged (other things being equal), so there are no liquidity flows induced by the trade credit channel. This is just as if the debt to suppliers and the credit to customers were continuously rolled over. This is the "business as usual" case.

(ii) When demand brutally falls (during the lockdown), the firm still needs to meet the payment obligations towards its suppliers contracted before the shock. In addition, those payments have to be done within the legal payment terms of 60 days in

France. However cash flows decrease as demand dropped. If the firm is a net trade credit borrower (respectively a net creditor), this leads to cash outflows (respectively inflows) and to a liquidity stress (or a liquidity increase) potentially leading to payment default.
(iii) When activity bounces back, it goes the other way around as depressed demand lowered input needs, thus reducing the level of payables during the lockdown, while a rebound in sales boosts cash and receivables, leading to cash inflows for initially net borrowers (respectively outflows for net creditors).

We use the negative activity shock induced by the unexpected nationwide lockdown announced in France on 16 March 2020 to analyse the extent to which trade credit balances built up prior to the lockdown contributed to firms' liquidity stress. To do so, we examine whether the probability that a firm defaults on its suppliers once the lockdown has been imposed, varies depending on its reliance on trade credit financing. Firstly, we find no differential behavior across firms with higher or lower trade credit positions in the 14 months prior to the crisis. This is crucial to interpret our effect as the specific impact of the Covid-shock through the trade credit channel. While a firm's trade credit balance is not a significant determinant of default in "normal" time, we document, however, that it does significantly contribute to liquidity stress during the Spring 2020 lockdown. A one standard deviation increase in trade credit position (meaning that the firm becomes more of a net borrower) leads on average to a 3% higher probability of default compared with the pre-crisis period, and to up to a 10% higher probability of default in April at the peak of the crisis. In a word, relying on trade credit finance (i.e., being a net trade credit borrower) turned into a source of liquidity stress during the early stage of the Covid crisis. This effect is extremely robust to alternative specifications and definitions of our sample. While that effect is moderated on the overall economy, we show that the liquidity stress coming from the trade credit channel is strongly heterogeneous across business sectors, reflecting the combined effect of their exposure to the shock (i.e., their trade credit balance in March and April 2020) and of the intensity of the activity shock. We show that trade credit positions' impact on payment default is stronger in, but not limited to, downstream sectors like retail trade, with structurally positive net trade credit position. In the retail sector in particular, we quantify the impact of restrictions on activity on payment default. Firms that were legally mandated to shut down during the first two months of the pandemic, experienced by far the highest increase in default induced by trade credit payment obligations built up prior to the crisis. With the magnitude of the effect being up to five times higher in retail trade sub-sectors that had to close compared to the overall economy, in April more than 5% of the firms of these sub-sectors ended up defaulting at least once on one of their supplier.

Conversely, we show that, when the activity resumes after the lockdown, the trade credit effect reverses, albeit to a lesser extent as the recovery is gradual. Thus, trade credit induced payment defaults go down after the lockdown.

We also examine whether financially weaker firms are more sensitive to the trade credit channel. We show that the effects on payment default are stronger for constrained firms: smaller, riskier, capital constrained and less profitable firms that are net trade credit borrowers, default significantly more than financially stronger firms. We next examine whether firms can offset the effect on payment defaults by hedging the liquidity risk associated with trade credit. As expected, we find that firms with high cash buffers are able to counterbalance the liquidity stress induced by the trade credit channel during the lockdown. We also find evidence consistent with a default reduction effect of using accounts receivable financing, but only for the largest firms. Finally, we document that the trade credit channel was unique and that other operational or financial expenses such as wages, interest payments or rents did not generate a similar liquidity squeeze during the crisis. We interpret our findings as the combined result of a lower flexibility in debt payables management compared with financial debt (because of the possibility to renegotiate, extend maturity and to loan moratoria) and of a lower degree of public support specifically devoted to working capital at the initial stage of the crisis, while labor costs were swiftly and massively cut down through short-term work schemes in France.

Overall our empirical results shed light on the cyclical and short-term nature of trade credit. The inverted U-shape effect on default to suppliers we document throughout the paper is somewhat simple but critical to properly assess the intensity of the liquidity shock and to accurately quantify potential liquidity shortfalls at a given point in time. The liquidity "path" of the firm, i.e., this bounce-back effect, shall not be neglected to calibrate liquidity bridge schemes aiming at alleviating funding stress in crisis times and to avoid contagion along the supply chain.

Our paper is related to three strands of the literature. Firstly, we provide a new angle on trade credit. The literature on trade credit generally emphasizes the insurance-like role of trade credit in times of financial crisis or liquidity shock: credit-constrained buyers may be financed by their suppliers, when other forms of financing are not available (see, e.g., Boissay and Gropp (2013)). In this paper we highlight how, on the contrary, in the specific context of the Covid crisis, trade credit dependency generates a temporary and acute liquidity shock for trade credit users.

Secondly, this paper contributes to the rapidly expanding literature seeking to elucidate the impact of the Covid-19 pandemic on the economy. We add to the literature that seeks to estimate the implications of the crisis on firms' financing and liquidity needs. To the best of our knowledge, we are the first to highlight the significance of a trade credit channel in the context of the Covid-19 crisis. Most papers in that literature rely on models of cash flows projections, in which essentially sales, wages bills, input costs and taxes are used to estimate corporate cash flows (Schivardi and Romano, 2021; Carletti et al., 2020; Demmou et al., 2020). At the exception of Bureau et al. (2021), they do not take into account other significant cash flows like trade credit, investment or dividends. This leads potentially to underestimations of firms' liquidity needs, as we show in the case of trade credit.

Thirdly, our paper adds to the literature which analyses the propagation of shocks through production interdependencies (Baqaee and Farhi, 2020; Barrot et al., 2021). An important function of these models is to demonstrate how firms are primarily impacted in order to simulate the propagation. Our results enable readers to better understand one of the critical channels affecting the transmission of the shock along the supply chain. In particular, we highlight the cyclical effect of the lockdown shock on firms through the trade credit channel. This calls for the need of a dynamic approach to fully understand the effect of the trade credit channel on corporate liquidity.

The rest of the paper is organised as follows. Section 2 describes the lockdown and fiscal measures in France, Section 3 describes the data and the identification strategy, Section 4 presents our empirical results, Section 5 discusses policy implications, Section 6 presents robustness checks and additional results, and Section 7 concludes.

2 The Spring 2020 lockdown and fiscal responses to Covid-19

2.1 The Spring 2020 lockdown in France

The main source of identification in this paper is the first nationwide lockdown that comes into effect in France on 17 March 2020 in response to the Covid-19 outbreak. This event offers a unique opportunity to analyse the impact of a negative shock to corporate liquidity, which is totally unrelated to any financial supply shock. Moreover the event is large, sudden, unexpected and of unknown duration, with a direct effect on business activity.

The event is large: (i) it is a nationwide lockdown and (ii) all businesses have to shut down, with the exception of some specific activities (food stores, dry cleaners, computer repair shops, etc.).[6]

[6]These so-called "essential activities" (*activités essentielles*) are listed in the Decree 2020-293

The event is sudden and unexpected. Across the world, prior to March 2020, no country has applied nationwide lockdown yet. At that time, restrictions were implemented locally (e.g., at city or province level). Most European countries will actually decide on a nationwide lockdown at the exact same time as France (with the exception of Italy, which imposed its own lockdown in early March).

The first real nationwide restrictions are announced on 12 March 2020 in France and involve the closure of universities, schools and daycare centers. The decision to impose a nationwide lockdown is announced on 16 March[7] and comes into effect the following day.[8]

The duration of the lockdown is also unexpected. While it was initially planned to last for two weeks, it was extended several times. The exit from lockdown finally (and progressively) begins eight weeks later, on 11 May 2020.

2.2 A negative shock that hit businesses heterogeneously

The crisis has a heterogeneous effect across sectors. Some literally closed their doors, while some were only partially impacted. According to the French National Institute of Statistics (INSEE) the overall decrease in turnover during the last week of March is by one third (-35%) lower than in normal times, with falls of as much as 52% in manufacturing (excluding agrifood industries), 89% in construction and 36% in market services.[9]

A Banque de France's survey[10] of several thousand firms reveals the breakdown of the activity shock at a more granular level. According to that survey, activity in April was deemed by business leaders to be 1% of the normal activity in the ac-

of 23 March 2020. https://www.legifrance.gouv.fr/jorf/id/JORFTEXT000041746694

[7]Decree 2020-260 of 16 March 2020: https://www.legifrance.gouv.fr/loda/article_lc/LEGIARTI000041738805/2020-03-21/

[8]Compared to its neighbours, the nationwide lockdown started in Spain on 14 March 2020, in Belgium on 18 March 2020 in Portugal on 19 March 2020, in Germany and in United Kingdom on 23 March 2020.

[9]See https://www.insee.fr/en/statistiques/4473305?sommaire=4473307.

[10]See https://www.banque-france.fr/sites/default/files/media/2020/08/20/update_on_business_conditions_in_france_at_the_end_of_july_2020_0.pdf.

commodation services, 6% in food services, 11% in the automotive industry, 16% in automotive repair services, but 78% in the agrifood industry, 80% in the pharmaceutical industry and 81% in information services.

2.3 Fiscal support to corporate liquidity

The French government announced a set of measures at the very beginning of the lockdown to try to attenuate the impact of the health-related measures taken to limit the impact of the Covid-19 pandemic on the economy. The main measures implemented in France to help firms overcome their liquidity issues include (i) a State credit-guarantee scheme for new corporate loans up to EUR 300 billion, (ii) a deferral of tax payment and social security contributions, (iii) a job retention scheme.

More specifically, the State guarantee scheme was tailored as a public guarantee on new loans granted by financial institutions to non financial firms. The State guarantee covers 90% of the loan amount. The interest rate on those loans at cost price shall be equal to the refinancing cost of the relevant lender, with no repayment due during the first year and the option of repayment over five years. Eventually, the maximum amount a firm can borrow was capped at three months of 2019 sales. Around EUR 130 billion of guaranteed loans were distributed from March to December 2020, mainly to small and medium-sized firms. We will focus on the guarantee scheme in the policy discussion of this paper (Section 5).

3 Empirical strategy

3.1 Data

3.1.1 Payment defaults to suppliers

Data on firms' payment defaults comes from the CIPE database (*Centrale des incidents de Paiement sur effets*) of the Banque de France. That database collects all firms' payment default to suppliers information on a daily basis. When a customer misses a payment on a trade bill intermediated by commercial paper, the event is reported as a payment default to the Banque de France[11]. A payment default is defined as a trade bill that is not paid on time and/or in full.

Figure 1 and 2 plot the cumulative number of defaults within three consecutive years: 2018, 2019 and 2020. It first reveals a clear jump in defaults in Spring 2020, which illustrates the negative impact of the first lockdown. Payment defaults then increase at a much slower pace than in the previous two years. That trend is the result of several effects. Firstly, the economic crisis results in reduced trade between firms. Secondly, more firms may want their customers to pay cash. Thirdly, there was extensive public support to corporate liquidity at that time. Figure 1 and 2 suggest that, after the first lockdown, these effects offset the higher probability of default (*ceteris paribus*) of financially distressed firms. In the end, around 650,000 payments defaults were recorded in 2020, versus 870,000 on average in the previous two years (2018 and 2019).

3.1.2 Firms' balance sheet and fiscal statement

Data on firms' characteristics (i.e., balance sheet, financial statements, main activity and credit risk measured by the Banque de France's rating) come from the FIBEN database (*Fichier bancaire des entreprises*) of the Banque de France. Firms' information is collected as soon as their sales are above EUR 0.75 million. Data are collected yearly, so we use panel data covering two years: 2018 and 2019.

3.1.3 Sample composition and summary statistics

Our sample results from merging the FIBEN financial statement database and the CIPE database on payment defaults. We follow standard practice in the literature and drop firms in the agriculture, financial, utility and public sectors. Firms filing for bankruptcy in 2019 are also excluded. To prevent outliers from affecting the

[11]This rich dataset is also used in Boissay and Gropp (2013) and Barrot (2016)

results, we filter out observations with a fiscal year of more or less than 12 months and we winzorise all ratios at the 1% level. At the end, our sample contains 175,539 firms.

Table 1 presents descriptive statistics about payment defaults in 2019. On average, for a given month, 3% of firms in our sample exhibit at least one payment default. Considering the sole firms that make default, the median of the monthly amount under default is EUR 1,500 per firm. The average is EUR 12,000.

Panel A of Table 2 focuses on firm-level balance sheet characteristics. The median firm has a slightly negative trade credit to sales ratio (-2%) over the 2018-2019 period. Thus a bit more than half of the firms are net trade credit creditors, while a bit less than half of the firms are net trade credit borrowers. The average firm in our sample has EUR 17.7 million sales, 55 employees, and its cash holdings represent 19% of total assets while its leverage ratio is equal to 23%. Regarding the "other expenses" that we compare to trade credit in Section 4.6, the average firm has a wages to sales ratio of 31%, a rent to sales ratio of 21% and an apparent cost of debt of 6% prior to the crisis. Also, one firm out of five (22%) in our sample benefited from a State-guaranteed loan in the first half of 2020. Those loans are analysed in Section 4.7 and in Section 5.

Finally, panel B of Table 2 shows summary statistics related to financing constraints and hedging (that is, issues that will be explored in Sections 4.4 and 4.5). Over the 2018-2019 period, 79% of firms are standalone firms or belong to a SME-sized group. 69% of firms in our sample have a risky credit rating prior to the crisis[12] and 52% of firms did not pay dividends.

[12] Risky ratings are defined as ratings below the eligibility threshold of the General Collateral Framework of the Eurosystem. We use the internal credit ratings provided by Banque de France.

3.2 Payment term legislation

In France,[13] the law restricts contractual payment terms to a maximum of 60 days after the issuance of the invoice. Exceeding that payment deadline renders the debtor liable to a fine of up to EUR 2,000,000, with the requirement to publicise the penalty in a journal of legal notices or on the firm's website. Those restrictions are enforced by several mechanisms: (i) external auditors of firms have to notice the Ministry for the Economy and Finance in the event of repeated incidents of missed payment deadlines and (ii) the French administration carries out audits and imposes sanctions.

However, a specific legislation applies to (i) foodstuff (fresh, frozen or processed) for which the maximum payment terms are between 30 and 40 days (depending on the delivery date), and to (ii) some alcoholic beverage (rum, whisky, gin, vodka, etc.) for which the maximum payment delay is 30 days after the end of the month of delivery (so, in practice, between 30 and 60 days).

Table 3 presents descriptive statistics of *observed* trade credit positions by sector prior to the crisis. Trade credits positions are highly heterogeneous across sectors. The average firm is a net trade credit debtor within two sectors: retail trade (net trade credit to sales ratio of +5% on average), and accommodation and food (+6%). That is consistent with their downstream position on the supply chain. On average, all other sectors are net trade credit creditors. However the magnitude of their position varies substantially: for instance, the net trade credit to sales ratio is -2% in the agricultural or recreation sectors, -5% in manufacturing or real-estate, but up to -13% for corporate services and -11% for the information sector. Interestingly, accommodation and food, and retail trade exhibit the lowest payable to purchases ratios (15% and 12%, respectively). This is consistent with the fact that (i) they are more exposed to the more stringent legislation on foodstuff and alcoholic beverage, and (ii) firms belonging to those downstream sectors are paid more rapidly, so that

[13]Like in many countries: e.g., all countries of the European Union have to implement European directive on restrictions of payment terms (Directive 2011/7/UE).

they can allow paying their suppliers more quickly in turn.

3.3 Empirical strategy

The goal of this paper is to analyse the contribution of the trade credit channel to the liquidity shock associated with the lockdown.

In the absence of any fiscal measure, a firm suffering from a lower level of activity because of the lockdown still has to face some costs (e.g., monthly loan repayments, rent, at least part of the usual wage bill) together with supplier invoices from past deliveries (trade payables). To cope with those cash outflows, the firm can rely on sales (if any), liquidities (cash holdings, credit lines) and trade receivables. The difference between trade payables and trade receivables is referred to hereafter as the *net trade credit position* of a firm. When the trade credit position is positive, the firm is a net borrower with regard to its supplier-customer relationships. As the payment deadline law generally precludes the payment of invoice beyond 60 days, the question we address is: to what extent the net trade credit position of a firm prior to the lockdown amplified the liquidity stress caused by the lockdown?

The analysis focuses on the early stage of the pandemic crisis to identify the effect of the lockdown on corporate liquidity before public support fully kicks in: a massive liquidity support has indeed been provided by different public schemes (e.g., State-guaranteed loans or government subsidies called *"Fonds de solidarité"*, see Section 2.3) to rapidly alleviate corporate liquidity stress.

We use the default payment to suppliers (hereafter DS) as a measure of firm liquidity stress. A crucial advantage of this indicator is that a bank observing a client's inability to pay an invoice must report that situation to the Banque de France quite quickly, within four days after the event. Aside from DS, two other measures of liquidity stress could be considered: (i) firms that file for bankruptcy. Under provisions that are somewhat similar to those found in Chapter 11 in the United States, a firm that is unable to pay its creditors must self-declare that situation to the commercial court within 45 days.[14] However, this 45 days constraint did not apply from 12 March 2020 until 24 June 2020. In addition, commercial courts closed their doors during the lockdown, which implied much slower dematerialized procedures. At the end, despite the strength of the shock, the number of firms filing for bankruptcy dramatically decreased over the period under study.[15] (ii) The banking default could also be used as an indicator of a firm's liquidity stress. A banking default is defined as a delay of more than 90 days of payment on a loan or the probability of inability to repay a loan. All in all, (i) and (ii) are lagged information on firm situation compared to DS, which we then use in our analysis.

To carry out our analysis we need to consider a period prior to the lockdown, so we rely on DS information from 1 January 2019 to 30 June 2020. Following Boissay and Gropp (2013) and Barrot (2016), we aggregate DS data at monthly frequency and run the following OLS regression:

$$DS_{ft} = \alpha TC_{f,y-1} + \gamma \left[TC_{f,y-1} \times \text{Post}_t\right] + \beta_1 . X_{f,y-1} + \beta_2 . \left[\text{X}_{f,y-1} \times \text{Post}_t\right] + \kappa_f + \theta_{Industry,t} + \epsilon_{f,t} \quad (1)$$

where DS_{ft} is a dummy set to one if firm f defaults to a supplier in month t. The variable TC_{y-1} is the one fiscal year lagged trade credit position of a firm at time t. The trade credit position is defined as the difference between trade payables and trade receivables. The dummy *Post* is set to one starting in March 2020 and to zero prior to March 2020.

Firms with high or low trade credit positions could differ along a number of dimensions that might be correlated with the default outcome and hence bias our estimate. To address this issue, we control for firms' initial characteristics, as well as their interaction with our *Post* dummy.

The set of lagged firm controls which is added, X_{y-1}, include firm's cash level scaled by total assets, leverage defined as financial debt over assets as well as the size of

[14] In practice, the bankruptcy procedure can be initiated also at the request of firms' creditors or the public prosecutor. See, e.g., Plantin et al. (2013).

[15] For instance, the number of firms filing for bankruptcy halved in 2020 Q2 as compared to 2019 Q2 (See http://webstat.banque-france.fr/en/#/node/5385030).

the firm (log of total assets).

These controls ensure that the results are not driven by pre-crisis differences between low or high trade credit firms. They prevent the estimation from being biased if these firms vary in their sensitivity to economic fluctuations due to heterogeneous distributions of firm characteristics, such as size, cash holdings, or leverage.

For a given firm f with a net trade credit position TC, trade payables TP and trade receivables TR (with TC = TP - TR), all other things being equal, the liquidity stress of that firm depends on the ability of its customers to pay the firm. If its customers can pay TR, so the firm "only" has to manage the payment of TC. But if its customers are unable to pay TR or pay only a portion of TR (because it fails short of cash due to the negative activity shock), so the firm faces a liquidity stress that is higher than its net trade credit position. Put another way, the coefficient α and γ of equation 1 depend on the situation of firms' customers and can be considered as business sector dependent. Our main analysis relies on the net trade credit position of firms. In the robustness part of the paper, we deeper analyze the contribution of accounts payable and accounts receivable on firm's payment default during the lockdown.

Fixed effects are set at firm level to take into account unobservable features of firms and at "industry $\times$ month" level to take into account the economic situation at business sector level through time. Industries are defined at 2-digit level. In all specifications, standard errors are clustered at firm level to take into account serial correlation of data (Bertrand et al., 2004). The definition of each variable is detailed in Table 15.

4 Results

4.1 The trade credit channel of payment default

Table 4 presents the main results of our analysis. It shows how relying on trade credit finance (being a net trade credit borrower) turned into a source of liquidity stress during the early stage of the Covid crisis.

We estimate equation (1) from January 2019 to June 2020. Our dependent variable is a monthly firm-level indicator set to one if a firm misses a payment owed to at least one of its suppliers in a given month, and to zero otherwise.

The main variables of interest are (i) firm's net trade credit position and (ii) that same variable interacted with a *Post* dummy, which is set to one from March to June 2020. Our *Post* period thus encompasses 2 months of lockdown, from mid-March to mid-May, and roughly 2.5 months of post-lockdown period.

The trade credit position is the one-year-lagged trade credit position of the firm. We define it as the difference between accounts payable and accounts receivable scaled by sales, so that firms with positive trade credit positions are net borrowers while those with a negative trade credit position are net lenders. All continuous variables have been standardised to facilitate the interpretation of coefficients. All specifications include firm fixed effects and industry-month fixed effects defined at the NACE 4-digit level (555 industry categories in our final sample). As our identification is within-firm, the results are not coming from the comparison between firms with different trade credit intensity, that could be correlated with difference in financial strength.

4.1.1 The trade credit channel amplifies the probability of default

As reported in column (1) of Table 4 and in all subsequent specifications, the trade credit position is not a determinant of payment default in general which is crucial in our strategy to identify the specific effect of the crisis. During the crisis period on the contrary, the larger the initial trade credit position of the firm, the higher the default probability. As reported in column (2), the coefficient of the interaction between trade credit position (TC) and our *Post* dummy is highly significantly positive. As $TC \times Post$ captures the difference in the probability of default incurred by firms with higher net TC position vs. firms with lower TC position, our estimate in column (2) implies that a one standard deviation increase in the net trade credit position increases the monthly probability of payment default by 0.001 percentage point. This amounts to a significant 3% increase with respect to the pre-Covid period level. While this average impact on firm's payment default may seem moderate, we show in the next sections how strongly heterogeneous this effect is, firstly across time and secondly across sectors.

In columns (3), we supplement our analysis by controlling for other determinants of default: namely firm's cash holdings, leverage and size. Adding firm-level controls does not impact the coefficient which remains highly statistically significant. In column (4) we interact those control variables with the *Post* dummy. The coefficient on the $TC \times Post$ dummy remains unaffected. This makes it unlikely that systematic differences in crisis trends in firms' cash holdings, leverage or across firms of different size, might explain the results.

Not surprisingly while high cash holdings help reducing default probability in normal times, they reduce it to an even greater extent during the crisis. That finding is expected and in line with the literature. Importantly, the trade credit effect is unaffected by the inclusion of these other drivers and our effect remains as strong and significant.

4.1.2 The effect is dynamic and materialises straightaway

Next we split our post period into 4 month dummies to better understand the dynamic of the effect and how long it lasts. Mechanically, even in absence of policy support, the effect is not expected to last more than 2 months, as trade credit positions are capped by legislative requirements: French firms have been required by law to pay their suppliers within 60 days since the introduction of the 2008 Law on the Modernisation of the Economy (see (Barrot, 2016) for details).

As shown in column (5), the trade credit channel of payment default is strong in March and April while it becomes non significant in May and significantly negative in June. At its peak, in April 2020, a one standard deviation increase in trade credit position leads to a 0.27 p.p. higher probability of payment default, which translates in an economically significant 9% increase compared to the pre-Covid monthly probability of default.

Our estimates illustrate the cyclical dynamics of trade credit. The positive coefficients in March and April, when activity collapses, and the negative coefficient in June, when activity bounces back, are consistent with the short-term nature of trade credit. As French firms are legally required to pay accounts payable within 60 days, on the one hand, accounts payable registered in February had to be paid by the end of April. However, on the other hand firms forced to shut down had no or low sales at that time, and as a result no or low cash inflows to meet their payables. This explains the acute liquidity stress in March and April.

As the lockdown ended on 11 May 2020, the situation reverses for two reasons: (i) activity increases progressively so that cash comes in, (ii) there are no or few payables inherited from the past 60 days as sales were depressed during lockdown. So, in a context of low accounts payables, cash inflows significantly and rapidly improve firm's liquidity position. This explains why the coefficient of June is significantly negative.

Last, we take a closer look at the dynamics of the effect over time. Figure 3 shows the estimation results of a dynamic version of equation (1), where we increase our sample period towards the end of 2020 and interact the trade credit position with dummies for each month but the first six months of 2019. We find no differential behavior across firms with higher or lower trade credit positions prior to the crisis. This suggests that the parallel trend assumption is satisfied, which is crucial for the validity of our estimate.

The probability of default starts to increase right at the the time of the first lockdown and is amplified the month after. The effect fades away after the economy reopens in May and mechanically reverses over the summer for the reason explained above. Interestingly as we extended our estimation period, we can compare the effects of the first and second lockdown: in November as entire sectors are forced to shut down again we do not see any increase in payment default. Firms at that time have been provided a lot of liquidity support and can absorb stress on working capital financing. In addition the impact of the second lockdown on the economy was less negative than the first one.

All those results vary across sectors, depending on the upstream or downstream position of the industry, and its associated degree of reliance on trade credit. This is the focus of the next section.

4.2 Trade credit and payment default: an industry-level analysis

In Table 5, our baseline results are broken down by industry. Our variable of interest is an indicator variable set to one for the March-April 2020 period.

As expected the average effect of trade credit on liquidity stress is not the same across sectors. Trade credit positions' impact on payment default is stronger in, but not limited to downstream sectors like retail trade, with structurally positive net trade credit position (firms are net debtors and do not have lots of receivables as most of their clients pay cash).

The retail trade sector is by far the most impacted by the liquidity stress from trade credit positions, which is in line with its downstream position in the supply chain. The highly statistically and economically significant coefficient (0.0112) reported in column (2) implies a 28% increase in the pre-crisis average default probability.[16]

However, firms' trade credit positions also drive the probability of payment defaults

[16] The average probability of payment default in the retail trade sector in 2019 is 4%.

in wholesale trade, construction or manufacturing. The average effect we identify in these sectors is actually a reduction in payment default as the average firm has a negative net trade credit position. Finally we do not find any significant effect in other sectors, and surprisingly so, in the Accommodation and food industry[17]

Overall, the aggregated macro effect of the trade credit channel depend on the relative weight of each sector in the economy.

4.3 A focus on the effect of mandated business closures in the retail trade sector

We have shown that the retail trade sector suffered from a much more acute liquidity stress in March-April 2020 due to its trade credit position contracted prior to the lockdown. In this section we are interested in the heterogeneity that prevailed within this sector based on the relative exposure of firms to business restrictions during the lockdown. In other words heterogeneity here is not only coming from our *Trade Credit* variable but also from our *Post* variable. In particular, we exploit the fact that business restrictions were not uniform within the retail trade sector: some firms, whose activity was deemed as "essential" by the French government, were allowed to stay open while others had to shut down.

In Table 6 we estimate our baseline specification on two sub-samples: the sample of "non essential" retail traders that had to close their doors during the lockdown (column (1)) and the sample of "essential" retail traders that were allowed to carry on their activity during the lockdown (column (2)).

As shown in Table 6, only retail traders that were forced to shut down during the lockdown suffer a liquidity stress. A one standard deviation increase in net trade credit position leads to an increase of 1.4 p.p. in payment default in March 2020 and

[17] Note however that the coefficient for this last industry is positive, as expected. One potential explanation is that the sector somehow *benefited* from the more stringent legislation on payment terms for foodstuff and alcohol (see Section 3.2) so that, everything else equal, bars and restaurants (including hotels) entered the lockdown carrying a relatively smaller burden of trade payables. In addition the data collection threshold of EUR 0.75 million sales does not enable us to capture the smallest and more vulnerable firms, that account for the vast majority of firms in this sector.

even 1.6 p.p. in April 2020, meaning that the average probability of default increases by more than a third during those two months for a one standard deviation increase in net trade credit. The economic impact of restrictions on activity and in turn on payment default for these firms was thus very important. Note that we cannot compare both samples to interpret our effect as the causal effect of government-mandated closures on payment default of businesses that have been allowed to stay open (the pseudo control group) actually experienced strong positive changes in sales growth at the same exact time, driven by substitution effects.

4.4 Has the trade credit channel amplified financial vulnerabilities ?

Next we investigate the role of financial constraints on the probability of payment default. Firstly, we verify that our trade credit effect is not capturing other firm characteristics linked with financial vulnerabilities. Secondly, we measure how the effect of the trade credit channel vary with the intensity of liquidity constraints.

If trade credit position put firm liquidity under stress, we can expect ex ante financially weaker firms to be more sensitive to this channel and to have a harder time meeting payment to suppliers when the lockdown starts.

We consider five proxies for the intensity of financial constraints: size, credit risk, productive capital constraints, profitability and dividend payout.

We show in Table 7 that the trade credit channel interacts with each one of this five dimensions, leading to a large amplification of the effect on default, which is up to two times higher than in our baseline specification. This means that constrained firms, that are more likely to default absent the trade credit channel, are particularly exposed and that their vulnerabilities may be a critical source of contagion effects in supply chain networks.

Table 7 presents the triple difference estimates of the effect of the trade credit channel on payment defaults conditional on our five proxies for financial constraints.

Financially weaker firms experience a 0.0011 to 0.018 p.p. higher default probability relative to financially stronger firms, due to the trade credit channel, as shown by the significance of the estimate of our coefficient on $Post \times TC \times D$. In fact, smaller, riskier, capital constrained, less profitable and low-payout firms drive the increase in the probability of payment default.

Group size

We first use the size of the *parent* company of the firm as a proxy for being constrained or not. We already control for the size of the firm itself (total asset of the firm) and interpret the size of the group the firm belongs to as a proxy for the existence of internal capital markets. Indeed, small firms which are subsidiaries of larger entities can benefit from transfer of liquidity from the parent firm.

We set our "Small" dummy to one if the firm is a standalone firm or if it belongs to a SME-sized group in 2019, and to zero otherwise.

As reported in column (1), independent firms and firms belonging to small groups have a higher probability of payment default in the *Post* period ($D \times Post$), and do default significantly more when facing higher trade credit position ($D \times TC \times Post$ is positive and significant and equal to 0.0013).

Credit rating

Our next proxy is the Banque de France credit rating of the firm as of January 2020.[18] Then, our "Low rating" dummy is equal to 1 when a firm's rating is below the minimum credit rating required for a loan to be eligible as collateral for the ECB in the general collateral framework. This is approximately equivalent to having a long-term rating lower than BBB-/Baa3 from SP/Moody's, just below the investment grade threshold. In column 2, we show that low rated firms have a higher probability of defaulting on payment after the start of the Covid crisis ($D \times Post$),

[18] In this set up we estimate our effect of interest over the population of firms that are rated by Banque de France, i.e., the ones with a turnover above EUR 750,000. Firms without a rating do not enter the estimation.

and that this effect is magnified when the firm has a positive trade credit position prior to the crisis ($D \times TC \times Post$).

Capital constraints

Following Bau and Matray (2020), we compute the pre-Covid period within-industry marginal revenue products of capital (MRPK) as the sales to capital ratio or the added value to capital ratio (industry is defined at the 4 digit level). To determine whether firms have a high or low MRPK, we average each firm's measures of MRPK over 2018-2019. We then classify a firm as capital constrained (high MRPK) if its averaged measure is above the industry median. We document the fact that firms with relatively high sales to capital ratios default more in early 2020 when they had a higher trade credit position.

Profitability and payout

Finally, we rank firms based on their average return on assets in 2018-2019 and classify as "Low profitability" those with a ROA which is below the sample median. We also characterize firms that did not pay any dividends in 2018 and 2019 as "None payers". Along both dimensions, we show how the trade credit channel drives higher payment default for the weakest firms.

4.5 Hedging liquidity stress

In this section, we study whether firms can offset the effect of the trade credit channel on default, by hedging the liquidity risk associated with trade credit.

Firms have several means to manage liquidity risk. They can retain cash holdings, they can transfer the risk associated with their receivables through factoring or get bank finance against the pledge of their accounts receivable financing to overcome some liquidity mismatch.

Cash holdings

In column (1) of Table 8 we investigate how the effect of trade credit exposure on payment default varies conditional on the level of firm's cash holdings. We define cash-rich firms as firms with above-median level of cash in the preceding fiscal year. Our double interaction estimate ($HighCash \times TC \times Post$) shows that high-cash firms have a significantly lower probability to default on their suppliers relative to low-cash firms in the crisis period. In addition, the magnitude of the coefficient is twice as large as the one stemming from the direct trade credit effect. In other words, firms with a high level of cash were able to counterbalance the liquidity stress induced by the trade credit channel due to the lockdown.

Risk management of receivables

We now examine whether firms that rely on accounts receivable financing (ARF). Receivable financing can take various forms and we consider both accounts receivable loans and factoring in our set up.[19] To measure the intensity of the use of ARF we calculate the firm yearly average amount of receivable financing from the Credit register data, and report it to the face value of receivables in that same year. A firm is a high user of ARF if its one-year lagged ratio lies above the median of the sample of firms using receivable financing. This median ratio is slightly over 25%. However, while more than 10% of large and intermediate sized firms use receivable financing, this is only the case for 5% of smaller firms.

In columns (2) to (4) of Table 8 we run similar regressions as in column (1) conditional on firms having positive receivables, except that our dummy variable of interest now categorizes high users of accounts receivable financing. The idea is that firms with high ARF were in a better position to access cash than firm that did not rely on such financing.

[19] Accounts receivable loans implies that firms have managed to get a short-term loan tailored to meet their financing needs by pledging their receivables. In the case of factoring the borrower sells its receivables to a factoring institution, at a discount, and actually transfer the risk of non-payment to the factor. We pool the two sources of account receivables financing as their usage is scarce.

Note that while these regressions help understand the mechanism at play, they do not pin point a causal effect of receivables financing on (a reduction in) default to suppliers. The choice to use this type of short-term finance is endogenous to the firm. It is thus likely to be correlated with liquidity weak firms or firms with low quality customers, so that on average such firms may actually default more than firms not using ARF.

While receivable financing has a reduction effect on payment defaults induced by the trade credit channel, the effect is not significant for the average firms. However, within the sample of large firms, which also use ARF the most, high users with positive net trade credit exposure default less than low or non users (see column 4). We also investigate heterogeneity along the availability of undrawn lines of credit but did not find any significant effect on that side. The absence of effect may comes from the fact that credit line contracts contain covenants that allow banks to restrict drawdowns if covenants are violated, typically following a decline in firm profitability (Sufi, 2009). So that firms that most need it may not have actually been able to use them.

4.6 Comparison with other operational and financial expenses

In this section, we study whether the effect associated with trade credit is somewhat unique or whether others costs firms had to face at a time of liquidity squeeze generated similar effects on default. To check whether this is the case, we compare the impact of trade credit with the incidence of other operational or financial expenses. When faced with a demand shock, firms may adjust some variable costs rather easily (raw material, marketing expenses, etc.) but strive harder to manage others in presence of rigidities (typically labor costs in France).

However, some expenses proved easier to curb down than others during the Covid crisis, because of differential policy support treatment. For example, in Europe, one of the main measure to help workers and firms was the introduction or scaling up of job retention schemes (see, e.g., Blanchard et al. (2020)) allowing for significant labor cost reductions. Likewise, several countries, including France, decided to defer certain taxes and social security contributions.[20] Moreover, even within fixed costs, some expenses are owed to public institutions, with whom one may consider that it is easier to negotiate payment deferrals.[21]

On the contrary, accounts payable are particularly costly to manage. Firstly, the payment term legislation we mentioned above was maintained during the whole crisis. Secondly, it is legally forbidden for customers and suppliers to re-negotiate longer payment terms (the latter can even ask additional fees in the case of delayed payments). Thirdly, delayed payments or defaults may alter the relationship between a firm and its suppliers, which may be particularly detrimental for firms operating on markets without many options for alternative suppliers. In the end, firms wishing to avoid delayed payments or default have only two options: *informal* negotiation with their suppliers and asking banks for additional debt; the issue of both solutions being quite uncertain.[22]

However, as stated above, most papers addressing the impact of the Covid-19 lockdown on firm's liquidity did not consider the trade credit channel (see, e.g, Schivardi and Romano (2021); Carletti et al. (2020); Demmou et al. (2020)). They exclusively focus on the role of labour costs, property rental costs and debt interests as sources of liquidity stress. In Table 9, we estimate the impact of those three sources of liquidity stress on default to suppliers. To do so we augment our baseline regression with a control for the (one-year lagged) category of expenses of interest (wages and social benefits over sales in column (1), apparent cost of debt in column (2) and rents over sales in column (3)), as well as with an interaction term between this variable

[20] See, e.g., Bruegel's review of the fiscal response to the economic fallout from the coronavirus. https://www.bruegel.org/publications/datasets/covid-national-dataset/

[21] For example, as a proprietary owner, the Paris municipality decided temporary exemptions of rent payments for some firms.

[22] For instance, in France, State-guaranteed loans were not supposed to be used to rollover debt.

and *Post*. Not only our estimate of the trade channel is insensitive to the inclusion of these controls interacted with the *Post* dummy, but these other types of expenses do not have any significant additional effect on payment default to suppliers.

This does not mean that those expenses did not put firm's liquidity under stress. But the findings suggest that (i) either government support enabled to offset those effects (particularly in the case of labor costs), (ii) or that firms may have manage to defer or renegotiate payment (on corporate debt or rents) when needed, so that such expenses did not weight enough on firm liquidity so as to materialize in payment default to suppliers. In other words, contrary to the trade credit, other key expenses like wages, rents or interest expenses did not *amplify* the demand shock which firms encountered during the Covid-19 crisis.

4.7 Reliance on State-guaranteed loans

As shown in the previous sections, the trade credit channel has been a source of liquidity stress during the lockdown. As a result, firms entering the crisis with high net trade credit exposures should have been in deeper need for government support. To check whether this is the case, we test whether firms more exposed to the trade credit channel were more likely to ask for a State-guaranteed loan.

In Table 10, we seek to explain firm subscription to the State-guaranteed loan program. To this end we collapse the data at the firm level. We carry out a cross-sectional analysis in which we compare firms that get and did not get a State-guaranteed loan during the first six months of 2020, based on their one-year lagged observable characteristics. This evidence is arguably only suggestive of the main determinants of guaranteed loans demand as we cannot have firm fixed effects in such a set up and many unobservables are likely to drive the results. To limit such effects, we redefine our industry fixed effect at the finest grain possible (5-digits). Standard errors are clustered at the industry level.

The dependent variable is a dummy set to one if a firm benefits from a State-guaranteed loan over the period March-June 2020 and to zero otherwise. Note that this variable is not exactly capturing demand of State-guaranteed loans as some firms may have seen their application rejected. However rejection rates were below 3%[23] and primarily for very small firms not entering our sample.[24] As reported in column (1), the higher the trade credit position of a firm prior to the crisis, the higher the probability to rely on a State-guaranteed loan.

Adding additional firm-level controls modifies slightly the coefficient estimate but it remains strongly significantly positive. As expected we find that cash-rich, low-leverage and larger firms have a lower probability to ask for a State-guaranteed loan.

Finally we control for firm's wage bill, interest expenses, and property rent expenses (column (3)), and for firm's credit risk based on its Banque de France rating (column (4)). Our main result remains unchanged, meaning that firm's trade credit position prior to the crisis was a strong driver of State-guaranteed loan demand during the crisis. And this was even more the case in sectors with high exposure to the trade credit channel as shown by the two times larger magnitude of our last estimate for the retail trade sector in column (5).

5 Discussion on liquidity needs and fiscal measures

Understanding the trade credit dynamics is central for policy makers seeking (i) to enable illiquid but solvent companies to remain afloat until revenues recover and (ii) to provide firms with sufficient liquidity to absorb temporary cash flow deficits and

[23] As of 24 July 2020, the rejection rate was 2.7% according to the Ministry of Economy and Finance.

[24] After a rejection, firms were able to apply to the French mediation program in order to have their case settled. In 2020, 84% of firms applying to this program had no more than 10 employees. The mediator reports also that "solutions" were found for around half of the cases. See https://www.banque-france.fr/sites/default/files/medias/documents/communique-de-presse_2021-01-26_bilan-mediation-2020.pdf.

avoid the propagation of liquidity shocks along the supply chain.

5.1 On the structural fragilities of downstream sectors

One the main instruments used by governments to protect firms from the negative effects of the Covid-19 crisis has been public guarantee on bank loans. Such guarantees have often been allocated with limited eligibility criteria, in particular irrespective of a firm's business sector, size or cash holding level.[25] However, some of these features have shaped firms' liquidity needs during the lockdown and may be taken into consideration. As shown in this paper, retail traders are particularly impacted when a demand shock hits, as depressed sales comes hand-in-hand with payment obligations to suppliers inherited from the previous period, creating high short-term pressure on liquidity. This comes from a *structural* feature of this sector: retail traders pay suppliers with a delay (of at most 60 days in France) but always get paid cash by customers. This makes those firms particularly exposed to a cash shortfall in the event of any unexpected negative demand, even if they are solvent. That fragility is reflected in firms' trade credit positions.

Our goal here is not to provide a socially optimal allocation rule of fiscal measures. This is out of the scope of this paper. But our work highlights that providing liquidity bridges in downstream sectors is essential to prevent bankruptcy of illiquid but solvent firms over the short term.

Retail traders may theoretically benefit from their structural trade credit position after the lockdown is removed. Our empirical estimates suggest, however, that the post-lockdown benefits are smaller than the lockdown costs. This is expected as recovery was gradual and the activity had not fully bounced back to its normal level over the summer 2020.

[25] See, e.g., https://www.bruegel.org/publications/datasets/covid-national-dataset/ for a synthesis of the national measures applied worldwide.

5.2 On the size of State-guaranteed bank loans

An important feature of a credit guarantee scheme is the maximum size of the guaranteed loan a firm can request. In France, State-guaranteed loans are limited to 25% of the sales reported in the year prior to the crisis (i.e. 3 months of sales). As stated above, firms' accounts payable have to be paid within 2 months in France. So, for a retail trader without activity seasonality, accounts payable can represent two-thirds of the maximum amount of the guaranteed loan. Taking into account (i) business seasonality and (ii) fixed charges (e.g. rent, loan repayment), firms can be short of liquidity when facing a two-month lockdown despite the use of a State-guaranteed loan. Indeed, as shown in section 4.7, beyond the trade credit channel, firm's indebtedness was an other driver to sign up for a State-guaranteed loan.

6 Robustness checks and additional results

6.1 Receivables and payables

In the paper the firm's exposure to the trade credit channel is measured through the net trade credit position, computed as the difference between firm's accounts payable and receivable. Other measures of the trade credit channel could have been the gross exposures like firm's accounts receivable or accounts payable. In Table 11, we challenge the use of the net exposure with gross exposures.

Column (1) reports the main regression except the net trade credit position is substituted with the level of firm's accounts receivable scaled by sales. Just like in the main regression that information is one-year-lagged. We expect a negative coefficient as accounts receivables are a source of liquidity. As reported in column (1), the coefficient is significant and negative. The higher the level of firm's accounts receivable prior to the lockdown, the lower probability of a payment default. In the column (2), firm's net trade credit position is added. The coefficient related to firm's accounts receivable is not anymore significant, only the net trade credit position prior to the crisis explain firm's payment default during the crisis.

In column (3) and (4), we carry out the same regressions, i.e., we carry out the main regression with firm's accounts payable as main variable of interest in column (3) and add firm's net trade credit position in column (4). We expect a positive coefficient related to accounts payable as they drop liquidity. As reported in column (3), the coefficient is positive but not significant. And in column (4), only the net trade credit position prior to the crisis is significant to explain firm's payment default during the crisis.

In column (5), we carry out the main regression with firm's accounts payable and receivable as main variables of interest. Only the coefficient related to firm's accounts receivable is significant.

Eventually, in column (6), we set all three variables: firm's accounts payable, receivable and firm's net trade credit position. Firm's net trade credit position comes close to be significant but is not, in this saturated specification.

6.2 Intensity of payment default

In the Table 12, we carry out a set of robustness tests by substituting the main dependent variable with variables describing the intensity of payment defaults: in column (1) the dependent is the number of payment defaults of a given firm in a given month; in column (2) the dependent variable is a dummy set to one if a firm made several payment defaults in a given month, zero if the firm made zero or one default in a given month; in column (3) the dependent variable is the total default amount of a given firm in a given month scaled by the lag of firm sales, and in column (4) the dependent variable is the logarithm of the total default amount of a given firm in a given month plus one euro.

As reported in Table 12, whatever the dependent variable describing firm's payment default, the main results remain: the higher the trade credit position of a firm prior to the crisis, the higher the probability of multiple payment default (columns (1) and (2)) and the higher the amount in default (columns (3) and (4)).

6.3 Robustness to empirical specification and sample definition

In Table 13, we use alternative sample definitions. Firstly, we run our baseline regression on a sample of independent firms. The idea is that for firms belonging to a group, trade credit positions partly reflect intra-group transactions and those may offer more flexibility and potentially be renegotiated in some cases. This possibility does not exist for independent firms and indeed we find a stronger negative effect of trade credit position on payment default for this subset of firms when the crisis hits. Secondly, we restrict the sample to all firms with fiscal year end in December, so as to measure the ratio of end-of-year accounts at the same exact time for all firms. The effect goes through. Finally, we estimate our baseline regression on an unbalanced panel (note that in this case firms that enter the regression only contribute to the estimation of industry level fixed effects). The effect is unchanged and slightly stronger than in our main sample.

Lastly, we test the robustness of our baseline effect to alternative clustering of standard errors (at the industry level), as well as to the inclusion of a finer set of fixed-effects to control for size effects and geographical effects (based on the location of the firm when this information is available). The results are reported in Table 14, they are unchanged and even stronger in these tests.

7 Conclusion

This paper examines how trade credit amplified the demand shock that French firms encountered during the Covid-19 crisis. More specifically, it sheds light (i) on the time-varying effects of trade credit on corporate liquidity and (ii) on the heterogeneous effect of the trade credit channel depending on firms' position in the supply chain, and on their financing constraints.

The unique feature of our setup is that we can observe the monthly dynamics of default on trade bills, which provides us an infra-annual view on liquidity stress induced by trade credit positions. As this phenomenon is short lasting by construction - because French firms have to pay their suppliers within 60 days and because widespread policy support has rapidly alleviated corporate liquidity needs - no study using aggregate data[26] or taking the picture at the end of the year 2020 can really pin it down. Yet it is critical to assess in-time liquidity needs and understand which forces are driving them as they may prevent the firm from surviving until the next period. Understanding the cyclical trade credit dynamics is then central for policymakers seeking to enable illiquid but solvent companies to remain afloat until revenues recover.

Finally, we hope that our results provide some motivation for the researchers who estimate the impact of the crisis on firms' liquidity needs to carefully model the trade credit channel.

[26]Aggregate data do not report the network of customer/supplier relationships which is at the core of the trade credit channel that we highlight here.

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8 Figures

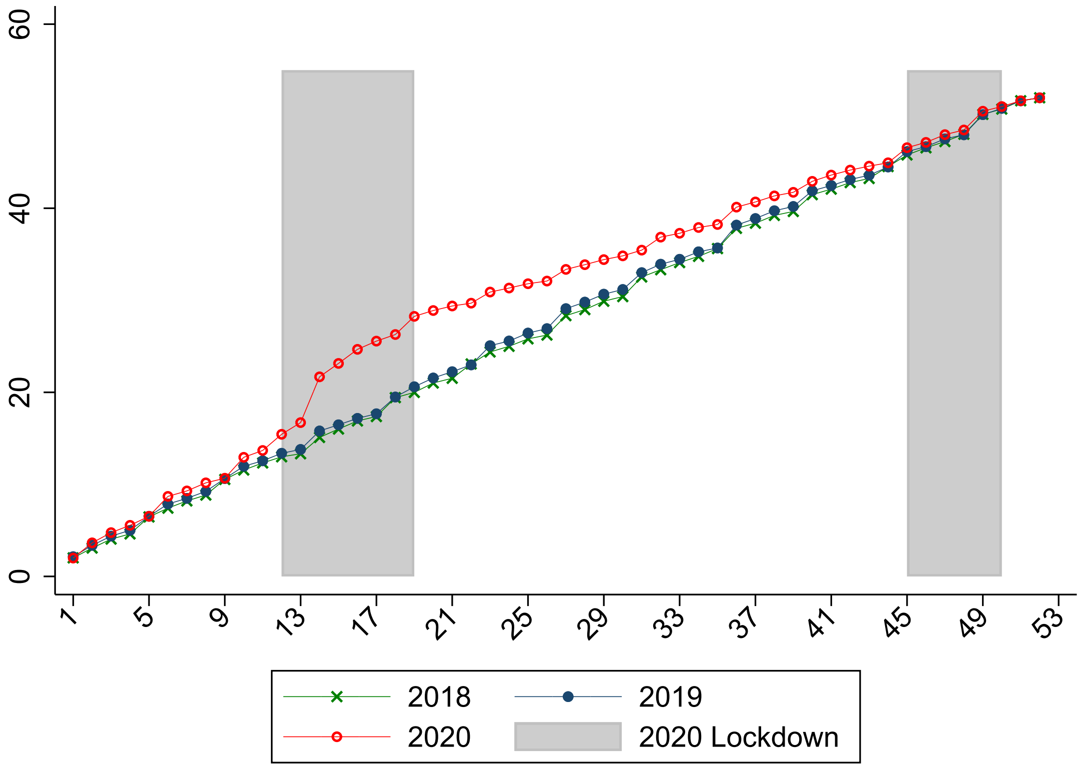

Figure 1 – Cumulated number of payment defaults on trade bills, scaled by the average weekly number of payment default events over the year

The level of observation is the relationship between a firm i and its supplier j in week t. Time 1 is the first week of a given year. The graph plots the cumulated number of default payment events in 2018, 2019 and 2020 scaled by the average weekly number of payment default events over the year. The shaded areas represent lockdown periods in 2020.

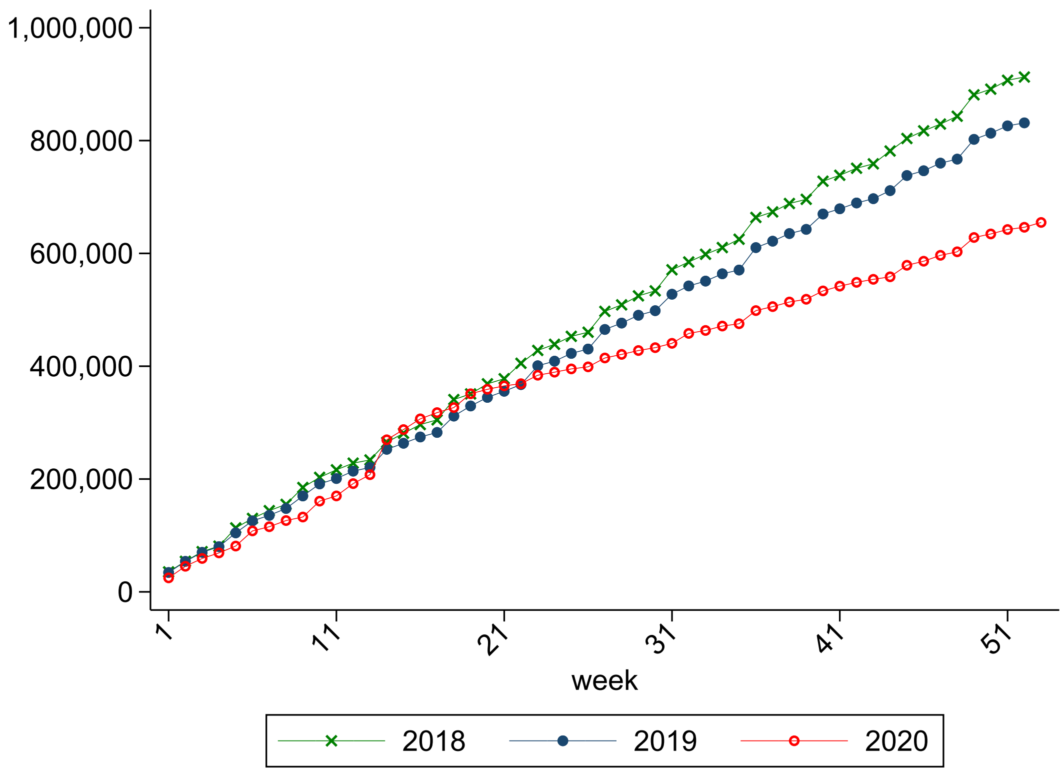

Figure 2 – Cumulated number of payment defaults on trade bills

The level of observation is the relationship between a firm i and its supplier j in week t. Time 1 is the first week of a given year. The graph plots the absolute number of cumulated default payment events in 2018, 2019 and 2020.

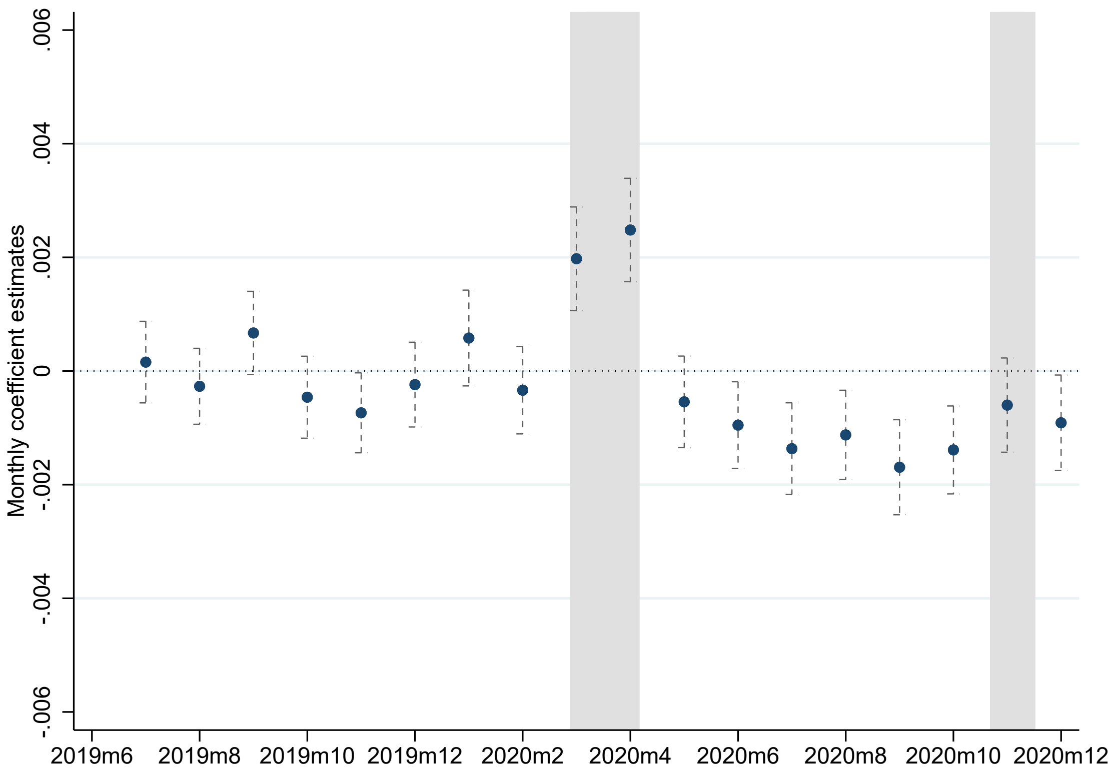

Figure 3 – Monthly coefficient estimates of the effect of trade credit position on the probability of firm payment default

The level of observation is a firm i in month t. The dependent variable is a dummy variable which takes the value 1 if the firm defaults at least once on paying a trade bill to one of its suppliers in month t. The graph shows the results of the estimation of equation (1). Coefficients for each month, starting in 2019m7 are plotted, along with 95% confidence intervals. The sample period of estimation is 2019m1 to 2020m12.

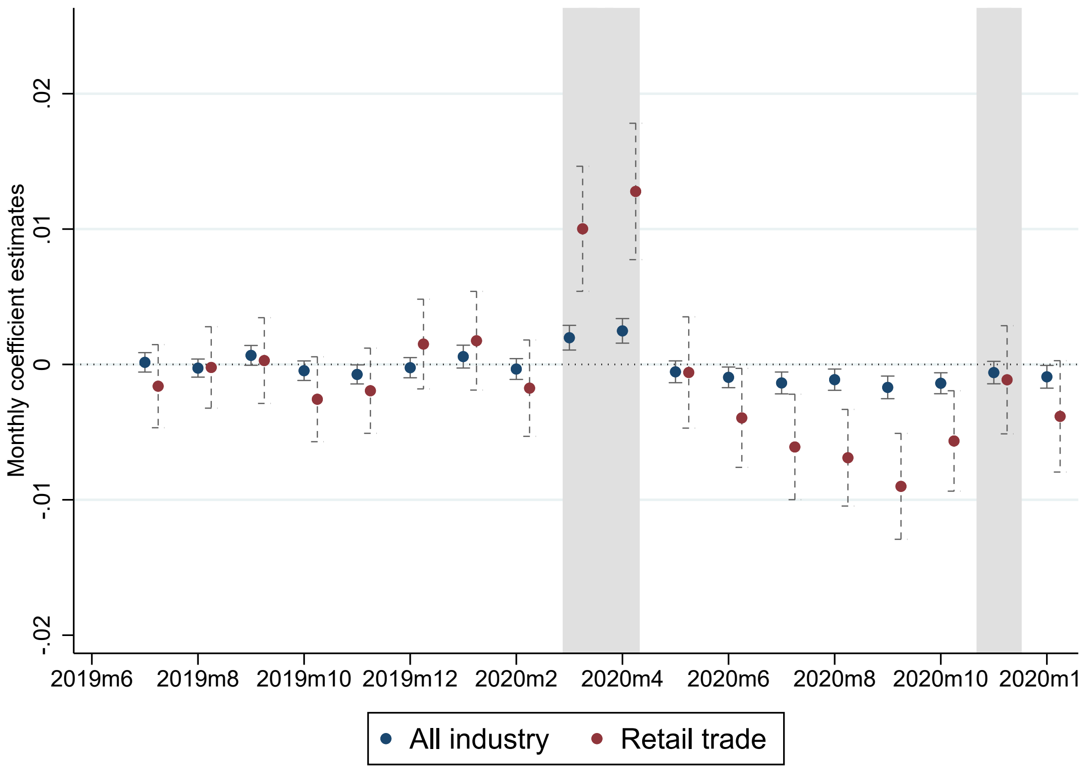

Figure 4 – Monthly coefficient estimates of the effect of trade credit position on the probability of firm payment default : retail trade industry vs. all industries

The level of observation is a firm i in month t. The dependent variable is a dummy variable which takes the value 1 if the firm defaults at least once on paying a trade bill to one of its suppliers in month t. The graph shows the results of the estimation of equation (1) as in graph 3 as well as the results of the same estimation from the retail trade sector only. Coefficients for each month, starting in 2019m7 are plotted, along with 95% confidence intervals. The sample period of estimation is 2019m1 to 2020m12.

9 Tables

Table 1 – Monthly-level payment default statistics (2019)

	Mean	Median	p95	p99	Std. dev.	No. obs.
Payment default dummy	0.03	0	0	1	0.17	2,106,468
Amount under default, in Keuros	12	1.5	43	128	218	64,372

Table 2 – Firm-level characteristics (2018-2019)

Panel A. Main balance-sheet characteristics	Mean	p5	p25	Median	p75	p95	Std. dev.	No. firms
Net trade credit to sales	-0.04	-0.26	-0.10	-0.02	0.04	0.15	0.14	175,539
Receivables to sales	0.14	0.00	0.03	0.12	0.20	0.39	0.14	175,539
Payables to purchases	0.17	0.04	0.09	0.13	0.20	0.44	0.14	175,539
Total assets in million euros	25.03	0.37	0.79	1.58	4.25	32.64	829.82	175,539
Sales in million euros	17.70	0.86	1.35	2.44	6.03	39.50	336.62	175,539
No. employees	55.37	1.00	6.00	12.00	29.50	148.00	845.11	175,539
Cash holdings to assets	0.19	0.00	0.04	0.13	0.29	0.60	0.19	175,539
Debt in million euros	9.62	0.00	0.07	0.25	0.89	9.09	401.45	175,539
Leverage (Debt to assets)	0.23	0.00	0.04	0.15	0.34	0.75	0.25	175,539
Apparent cost of debt	0.06	0.00	0.01	0.02	0.04	0.23	0.17	175,539
Wages and benefits to sales	0.31	0.03	0.15	0.27	0.43	0.75	0.22	175,539
Rents to sales	0.21	0.00	0.01	0.03	0.06	0.15	53.28	175,539
State-guaranteed loan dummy	0.22	0	0	0	0	1	0.41	175,539
Panel B. Financing constraints and hedging								
	Mean	p5	p25	Median	p75	p95	Std. dev.	No. firms
Return on assets	0.08	-0.09	0.02	0.06	0.13	0.32	0.13	175,539
Risky credit rating dummy	0.69	0	0	1	1	1	0.46	175,539
Non dividend payer dummy	0.52	0	0	1	1	1	0.50	175,539
Small firm dummy	0.79	0	1	1	1	1	0.41	175,539
Value added to capital (MRPK)	1.57	0.00	0.33	0.69	1.45	6.07	3.05	175,539

Table 3 – Firm-level statistics by sector (1/2)

	Mean	p5	p25	Median	p75	p95	Std. dev.	No.firms
Accomodation and Food								
Net trade credit to sales	0.06	-0.02	0.03	0.05	0.09	0.20	0.08	10,366
Payables to purchases	0.15	0.04	0.08	0.12	0.18	0.37	0.13	10,366
Receivables to sales	0.02	-0.02	0.00	0.01	0.02	0.10	0.06	10,366
Agriculture								
Net trade credit to sales	-0.02	-0.33	-0.10	-0.01	0.06	0.32	0.18	2,118
Payables to purchases	0.22	0.04	0.10	0.17	0.27	0.57	0.17	2,118
Receivables to sales	0.16	-0.02	0.06	0.13	0.22	0.49	0.16	2,118
Construction								
Net trade credit to sales	-0.08	-0.27	-0.14	-0.08	-0.02	0.09	0.13	22,217
Payables to purchases	0.17	0.06	0.11	0.15	0.20	0.34	0.11	22,217
Receivables to sales	0.20	0.02	0.12	0.19	0.26	0.42	0.13	22,217
Corporate services								
Net trade credit to sales	-0.13	-0.44	-0.21	-0.13	-0.04	0.11	0.17	25,497
Payables to purchases	0.23	0.03	0.10	0.17	0.29	0.68	0.20	25,497
Receivables to sales	0.23	0.00	0.13	0.20	0.30	0.60	0.17	25,497
Health								
Net trade credit to sales	-0.04	-0.26	-0.08	-0.02	0.03	0.12	0.13	5,921
Payables to purchases	0.17	0.03	0.08	0.13	0.21	0.42	0.15	5,921
Receivables to sales	0.11	0.00	0.02	0.07	0.14	0.39	0.14	5,921
Information								
Net trade credit to sales	-0.11	-0.42	-0.20	-0.11	-0.02	0.15	0.17	5,611
Payables to purchases	0.25	0.05	0.12	0.19	0.29	0.71	0.20	5,611
Receivables to sales	0.24	0.02	0.13	0.21	0.31	0.61	0.17	5,611
Manufacturing								
Net trade credit to sales	-0.05	-0.22	-0.11	-0.05	0.01	0.12	0.11	28,993
Payables to purchases	0.18	0.06	0.11	0.15	0.21	0.40	0.12	28,993
Receivables to sales	0.17	0.01	0.10	0.15	0.21	0.36	0.11	28,993
Real-estate								
Net trade credit to sales	-0.05	-0.37	-0.11	-0.02	0.03	0.20	0.17	4,657
Payables to purchases	0.24	0.02	0.08	0.16	0.30	0.85	0.24	4,657
Receivables to sales	0.14	0.00	0.02	0.08	0.19	0.50	0.17	4,657
Recreation								
Net trade credit to sales	-0.02	-0.23	-0.08	0.00	0.05	0.18	0.14	2,435
Payables to purchases	0.18	0.03	0.09	0.14	0.22	0.48	0.16	2,435
Receivables to sales	0.11	-0.00	0.01	0.08	0.17	0.36	0.14	2,435
Retail trade								
Net trade credit to sales	0.05	-0.06	0.02	0.05	0.08	0.18	0.08	36,948
Payables to purchases	0.12	0.03	0.06	0.10	0.14	0.27	0.09	36,948
Receivables to sales	0.04	0.00	0.00	0.02	0.05	0.16	0.07	36,948

Table 3 – Continued (2/2)

Transportation								
Net trade credit to sales	-0.07	-0.22	-0.11	-0.07	-0.02	0.07	0.11	8,765
Payables to purchases	0.16	0.04	0.08	0.12	0.18	0.38	0.14	8,765
Receivables to sales	0.17	0.04	0.11	0.14	0.19	0.36	0.12	8,765
Wholesale trade								
Net trade credit to sales	-0.03	-0.19	-0.08	-0.02	0.02	0.13	0.11	22,011
Payables to purchases	0.15	0.03	0.09	0.13	0.18	0.35	0.12	22,011
Receivables to sales	0.15	0.02	0.08	0.13	0.19	0.33	0.11	22,011

Table 4 – Does trade credit position explain firms' payment default during the Covid-19 crisis?

Dependent	Payment default				
	(1)	(2)	(3)	(4)	(5)
Trade credit (TC)	0.0001	-0.0002	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TC × Post		0.0009***	0.0009***	0.0009***	
		(0.000)	(0.000)	(0.000)	
TC × March 2020					0.0022***
					(0.000)
TC × April 2020					0.0027***
					(0.000)
TC × May 2020					-0.0003
					(0.000)
TC × June 2020					-0.0008**
					(0.000)
Cash holdings			-0.0009***	-0.0009***	-0.0009***
			(0.000)	(0.000)	(0.000)
Leverage			0.0006**	0.0003	0.0003
			(0.000)	(0.000)	(0.000)
Size			0.0000	-0.0001	-0.0001
			(0.000)	(0.000)	(0.000)
Cash × Post				-0.0010***	-0.0010***
				(0.000)	(0.000)
Leverage × Post				0.0004*	0.0004*
				(0.000)	(0.000)
Size × Post				-0.0047***	-0.0047***
				(0.000)	(0.000)
Firm FE	Y	Y	Y	Y	Y
Industry-month FE	Y	Y	Y	Y	Y
No. firm clusters	175,539	175,539	175,539	175,539	175,539
No. observations	3,159,702	3,159,702	3,159,702	3,159,702	3,159,702
Adj-R^2	0.26	0.26	0.26	0.26	0.26

The regressions examine to what extent firm's trade credit position prior to the Covid-19 crisis explains its probability of payment default to suppliers during the Covid-19 crisis. We run a linear probability model over the period 2019m1-2020m6. The level of observation is firm-month. The dependent variable is a dummy equal to 1 if the firm defaults on at least one trade bill payment to its suppliers in month t, and 0 if not. The main variables of interest are firm's net trade credit position prior to the crisis, computed as the difference between firm's accounts payable less accounts receivable scaled by firm's sales, and that same variable interacted with a dummy *Post* set to one from March 2020, zero before. The control variables are firm's cash holdings, leverage and size and those same variables interacted with the dummy *Post*. All independent variables are one year lagged. All continuous independent variables have been standardised to facilitate the interpretation of coefficients. The operational definition of variables is detailed in Table 15. Standard errors, reported in parentheses, are clustered at firm level. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

Table 5 – Sectoral analysis: does trade credit position explain firms' payment default during the Covid-19 crisis?

Dependent	Payment default											
Industry	Retail trade	Wholesale trade	Construction	Manufacturing	Recreation	Accommod. & food	Corporate Services	Health	Information	Real estate	Agriculture	Transport, storage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TC × March-April 2020	0.0112***	0.0040***	0.0026**	0.0023**	0.0048*	0.0023	0.0003	-0.0004	-0.0007	-0.0003	0.0020	-0.0014
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
TC × May-June 2020	-0.0025*	-0.0018*	-0.0022*	-0.0007	0.0053**	-0.0037**	0.0001	0.0012	-0.0000	-0.0006*	0.0002	0.0005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.000)	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)
Trade credit (TC)	0.0018	0.0008	-0.0011	-0.0001	-0.0020	0.0001	0.0002	-0.0013	-0.0002	0.0005	-0.0020	0.0030*
	(0.002)	(0.001)	(0.001)	(0.001)	(0.004)	(0.002)	(0.000)	(0.001)	(0.001)	(0.000)	(0.002)	(0.002)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls × post	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
No. firm clusters	36,948	22,011	22,217	28,993	2,435	10,366	25,497	5,921	5,611	4,657	2,118	8,765
No. observations	665,064	396,198	399,906	521,874	43,830	186,588	458,946	106,578	100,998	83,826	38,124	157,770
Adj-R^2	0.23	0.25	0.21	0.17	0.17	0.14	0.17	0.17	0.15	0.17	0.15	0.17

The main results of Table 4 (i.e., the link between firm's trade credit position contracted prior to the Covid-19 crisis and firm's payment default to suppliers during the Covid-19 crisis) is now analyzed at industry level. The regressions reported here are similar to the one reported in column (5) of Table 4, except that (i) the analysis is now broken down by business sector and (ii) the crisis period is broken down into two sub-periods: March-April 2020 and May-June 2020. The same set of control variables is implemented as in column (5) of Table 4. Standard errors, reported in parentheses, are clustered at firm level. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

Table 6 – Focus on the retail trade sector: does trade credit position explain firms' payment default during the Covid-19 crisis?

Dependent	Payment default	
Firms situation during the lockdown?	**Shutdown** (1)	**Open** (2)
Trade credit × March 2020	0.013***	-0.001
	(0.003)	(0.004)
Trade credit × April 2020	0.015***	0.005
	(0.003)	(0.004)
Trade credit × May 2020	0.001	-0.006*
	(0.002)	(0.004)
Trade credit × June 2020	-0.004*	-0.005
	(0.002)	(0.003)
Trade credit (TC)	0.000	0.006*
	(0.002)	(0.003)
Controls	Y	Y
Controls × Post	Y	Y
Firm FE	Y	Y
Industry-month FE	Y	Y
No. firm clusters	18,931	18,017
No. obs.	340,758	324,306
Adj-R^2	0.21	0.26

The regressions reported here are the same as to the one reported in column (5) of Table 4, except that the analysis now focuses on the subsample of firms operating in the retail trade industry. Indeed the retail trade sector was particularly hit by the trade credit channel during the Covid-19 crisis (see Table 5). The present Table focuses on that industry and breaks down the analysis between firms forced to close their door during the lockdown (column (1)) and those that could keep on their activity during the lockdown because they were deemed as "essential" by the French government (column (2)). Standard errors, reported in parentheses, are clustered at firm level. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

Table 7 – Effect of firms' trade credit position on their payment default conditional on financial vulnerabilities

Dependent	Payment default				
	Size	**Credit risk**	**Capital constraints**	**Profitability**	**Dividend payout**
	D=1 if SME (1)	D=1 if High (2)	D=1 if High (3)	D=1 if Low (4)	D=1 if None (5)
D × TC × Post	0.0013**	0.0017**	0.0014***	0.0018***	0.0011**
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
TC × Post	0.0001	0.0001	0.0005	-0.0002	0.0002
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
D × Post	0.0070***	0.0027***	0.0011*	0.0010*	0.0005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
TC × D	0.0004	0.0002	0.0006	0.0006	-0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Trade credit (TC)	-0.0003	-0.0005	-0.0004	-0.0003	0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Covariates	Y	Y	Y	Y	Y
Covariates x Post	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Industry-month FE	Y	Y	Y	Y	Y
No. firm clusters	175,539	124,557	175,539	175,539	175,539
No. observations	3,159,702	2,242,026	2,962,038	3,159,702	3,159,702
Adj-R^2	0.22	0.27	0.22	0.22	0.22

In this Table, we analyse how the effect of the trade credit channel varies with the intensity of liquidity constraints. We run similar regressions as the main regression (column (5) of Table 4) except we add a dummy D tagging financially constraint firms and interact that dummy D with firm's trade credit position and the *Post* dummy identifying the onset of the Covid-19 crisis (i.e., from March 2020). We consider five proxies for the intensity of financial constraints: firm's size (column (1)), credit risk (column (2)), capital constraints (column (3)), profitability (column (4)) and dividend payout (column (5)). In column (1), the dummy D is set to one if a firm is a standalone firm or if it belongs to a SME-sized group in 2019, otherwise the dummy is set to zero. In column (2) the dummy D is equal to one when firm's rating prior to the Covid-19 crisis is below the minimum credit rating required for a loan to be eligible as collateral for the ECB. In column (3) the dummy D is equal to one when a firm has an industry marginal revenue products of capital (MRPK) above the industry median in the pre-Covid period (see Bau and Matray (2020)). In column (4), the dummy D is equal to one when a firm has an return on assets below the 2018-2019 industry median. And in column (5), the dummy D is equal to one when a firm did not pay any dividends in 2018 and 2019. Standard errors, reported in parentheses, are clustered at firm level. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

Table 8 – Effect of firms' trade credit position on their payment default conditional on hedging liquidity risk

Dependent	Payment default			
	Liquidity	Risk management of receivables		
	D=1 if High cash	D=1 if Accounts receivable financing		
	(1)	(2)	(3) Small firms	(4) Large firms
D × TC × Post	-0.0030***	-0.0180	-0.0157	-0.0777**
	(0.001)	(0.014)	(0.014)	(0.038)
TC × Post	0.0015***	0.0007**	0.0009***	-0.0013
	(0.000)	(0.000)	(0.000)	(0.001)
D × Post	-0.0027***	0.0027*	0.0025	0.0017
	(0.001)	(0.002)	(0.002)	(0.007)
TC × D	0.0002	0.0403***	0.0400***	0.0610*
	(0.000)	(0.014)	(0.015)	(0.032)
Trade credit (TC)	-0.0000	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.001)
D	0.0005	-0.0002	-0.0005	0.0118
	(0.001)	(0.002)	(0.002)	(0.010)
Covariates	Y	Y	Y	Y
Covariates x Post	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Industry-month FE	Y	Y	Y	Y
No. firm clusters	175,539	165,907	155,909	9,912
No. observations	3,159,702	2,930,724	2,754,582	174,612
Adj-R^2	0.22	0.22	0.21	0.35

In this Table, we analyse whether firms can offset the effect of the trade credit channel by hedging the liquidity risk associated with trade credit. Firms have several means to manage liquidity risk. They can rely on cash holdings (column (1)), they can transfer the risk associated with their receivables through factoring or accounts receivable financing (columns (2) to (4)). We run similar regressions as the main regression (column (5) of Table 4) except we add a dummy D tagging firms having access to means to manage liquidity risk during the Covid-19 crisis. In column (1), the dummy D is set to one for cash-rich firms defined as firms with above-median level of cash prior to the Covid-19 crisis. In columns (2) to (4), the dummy D is set to one for firms that strongly relied on factoring or account receivables financing prior to the Covid-19 crisis based on the French credit register. Those regressions in columns (2) to (4) are carried out on firms having positive account receivable prior to the crisis. In column (3) the analysis is run on all those firms, in column (4) and (5), the analysis is broken down between small firms (column(4)) and large firms (column (5)). Standard errors, reported in parentheses, are clustered at firm level. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

Table 9 – To what extent do labor, interest or rent expenses explain payment default during the Covid-19 crisis?

Dependent	Payment default		
	(1)	(2)	(3)
TC × Post	0.0010***	0.0009***	0.0010***
	(0.000)	(0.000)	(0.000)
Wages/Sales × Post	0.0002		
	(0.000)		
Apparent cost of debt × Post		-0.0002	
		(0.000)	
Rents/Sales × Post			-0.0003
			(0.000)
Wages/Sales	0.0004		
	(0.000)		
Apparent cost of debt		0.0000	
		(0.000)	
Rents/Sales			0.0001
			(0.000)
Trade credit (TC)	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)
Controls	Y	Y	Y
Controls X Post	Y	Y	Y
Firm FE	Y	Y	Y
Industry-month FE	Y	Y	Y
No. firm clusters	175,539	175,539	175,539
No. observations	3,159,702	3,159,702	3,159,702
Adj-R^2	0.26	0.26	0.26

Most papers addressing the impact of the Covid-19 lockdown on firm's liquidity did not consider the trade credit channel (e.g., Schivardi and Romano (2021); Carletti et al. (2020); Demmou et al. (2020)). They focused on the role of labour costs, property rental costs and debt interests as sources of liquidity stress. In this Table, we challenge those three sources of liquidity stress. We run similar regressions as the main regression (column (5) of Table 4) except we add firm's payroll in column (1). The payroll is measured as the wage bill scaled by sales. That information is one year-lagged. We interact that information with the dummy *Post* indicating the onset of the crisis. As for all specifications the dummy *Post* is set to one over the period from March 2020 to June 2020, zero before. In column (2), we add firm's interest expenses scaled by firm total debt in column (2) and the firm's rents scaled by sales in column (3). All those variables are one-year-lagged. Standard errors, reported in parentheses, are clustered at firm level. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

Table 10 – Determinants of the subscription to State-guaranteed loan

Dependent	Subscription to the State-guaranteed loan				
	(1)	(2)	(3)	(4)	(5)
Trade credit	0.007***	0.011***	0.011***	0.006***	0.020***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)
Cash holdings		-0.053***	-0.053***	-0.037***	-0.047***
		(0.003)	(0.003)	(0.003)	(0.004)
Leverage		0.013***	0.013***	0.000	-0.002
		(0.002)	(0.002)	(0.002)	(0.003)
Size		-0.032***	-0.032***	-0.025***	-0.028***
		(0.003)	(0.003)	(0.003)	(0.007)
Wages & benefits/Sales			-0.041***	-0.038**	-13.693
			(0.012)	(0.016)	(14.883)
Cost of debt			-0.000	-0.002**	-0.005***
			(0.001)	(0.001)	(0.002)
Rents/Sales			0.025***	0.024**	2.427
			(0.008)	(0.010)	(4.161)
Risky rating				0.132***	0.126***
				(0.006)	(0.012)
Industry FE	Y	Y	Y	Y	Y
No. industry clusters	668	668	668	668	116
No. observations	175,538	175,538	175,538	175,538	58,959
Adj-R^2	0.066	0.089	0.089	0.109	0.127
Industry	All	All	All	All	Retail Trade

We seek to explain firm subscription to the State-guaranteed loan. The dependent variable is a dummy set to one if a firm benefits from a State-guaranteed loan in the period March-June 2020, zero otherwise. In column (1), we seek to explain firm's subscription to the State-guaranteed loan with firm's trade credit position prior to the crisis. In column (2) we add firm's cash holdings, leverage and size, computed prior to the crisis. In column (3) we add the size of firm's wage bill, interest expenses, firm's property rent, and, in column (4), firm's credit risk as computed by the Banque de France. All those variables are calculated prior to the crisis. In column (5) we focus on the retail trade sector. Standard errors, reported in parentheses, are clustered at firm level. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

Table 11 – Robustness: Does firm's gross accounts receivable and/or payable explain firms' payment default during the Covid-19 crisis?

Dependent	Payment default					
	(1)	(2)	(3)	(4)	(5)	(6)
Trade credit × Post		0.0007*		0.0010***		0.0008
		(0.000)		(0.000)		(0.000)
Receivables × Post	-0.0009***	-0.0004			-0.0010***	-0.0003
	(0.000)	(0.000)			(0.000)	(0.000)
Payables × Post			0.0001	-0.0002	0.0003	-0.0001
			(0.000)	(0.000)	(0.000)	(0.000)
Trade credit		0.0006		-0.0001		0.0004
		(0.000)		(0.000)		(0.001)
Receivables	0.0005	0.0009*			0.0004	0.0007
	(0.000)	(0.001)			(0.000)	(0.001)
Payables			0.0005*	0.0005*	0.0004	0.0002
			(0.000)	(0.000)	(0.000)	(0.000)
Controls	Y	Y	Y	Y	Y	Y
Controls X Post	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Industry-month FE	Y	Y	Y	Y	Y	Y
No. firm clusters	175,539	175,539	175,539	175,539	175,539	175,539
No. observations	3,159,702	3,159,702	3,159,702	3,159,702	3,159,702	3,159,702
Adj-R^2	0.26	0.26	0.26	0.26	0.26	0.26

In this Table, we challenge the use of the net exposure to the trade credit channel with gross exposures: firm's accounts receivable and payable. In column (1), we run the same regression as the main regression (column (5) of Table 4) except we substitute the net trade credit position with the level of firm's accounts receivable scaled by sales. Just like in the main regression that information is one-year-lagged. In column (2), we add firm's net trade credit position to challenge both measures of the exposure to the trade credit channel. In column (3), we run the same regression as the main regression (column (5) of Table 4) except we substitute the net trade credit position with the level of firm's accounts payable scaled by sales. Like in the main regression that information is one-year-lagged. In column (4), we add firm's net trade credit position to challenge both measures of firm's exposure to the trade credit channel. In column (5) we set together the two alternative measures of firm's exposure to the trade credit channel: firm's accounts payable and accounts receivable. In column (6), we set all together the three alternative measures of firm's exposure to the trade credit channel: firm's accounts payable, accounts receivable and firm's net trade credit position. Standard errors, reported in parentheses, are clustered at firm level. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

Table 12 – Robustness tests to the dependent variable: Does firm's trade credit position explain the intensity of firms' payment default during the Covid-19 crisis?

	Number of defaults (1)	Multiple defaults (2)	AuD/Sales (3)	Amount under default (4)
TC × Post	0.00160***	0.00073***	0.00010***	0.00982***
	(0.000)	(0.000)	(0.000)	(0.002)
Trade credit (TC)	0.00042	0.00019	0.00007	0.00367
	(0.000)	(0.000)	(0.000)	(0.003)
Controls	Y	Y	Y	Y
Controls × post	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Industry-month FE	Y	Y	Y	Y
No. firm clusters	175,539	175,539	175,539	175,539
No. observations	2,962,038	2,962,038	2,962,038	2,962,038
Adj-R^2	0.28	0.21	0.18	0.23

In this Table, we carry out a set of robustness tests by substituting the main dependent variable with variables describing the intensity of payment defaults. In column (1) the dependent is the number of payment defaults of a given firm in a given month. In column (2) the dependent variable is a dummy set to one if a firm made several payment defaults in a given month, zero if the firm made zero or one default in a given month. In column (3) the dependent variable is the total default amount of a given firm in a given month scaled by the lag of firm sales, and in column (4) the dependent variable is the logarithm of the total default amount of a given firm in a given month plus one euro. Standard errors, reported in parentheses, are clustered at firm level. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

Table 13 – Robustness tests to the sample composition: does trade credit position explain firms' payment default during the Covid-19 crisis?

Dependent	Payment default		
	(1) Independent firms	(2) Fiscal year end December	(3) Unbalanced panel
TC × Post	0.0014*	0.0006*	0.0010***
	(0.001)	(0.000)	(0.000)
Trade credit (TC)	0.0002	0.0003	0.0003
	(0.001)	(0.000)	(0.000)
Covariates	Y	Y	Y
Covariates x Post	Y	Y	Y
Firm FE	Y	Y	Y
Industry-month FE	Y	Y	Y
No. firm clusters	59,982	130,858	249,921
No. observations	997,212	2,354,130	3,855,000
Adj-R^2	0.26	0.27	0.28

In this Table, we challenge our results by running the main regression (column (5) of Table 4 on different sub-samples. In column (1), the regression is carried out on independent (i.e., standalone) firms only. In column (2), the regression is carried out on firms with an account closing date in December. In column (3), the regression is carried out using an unbalanced panel where firms that appear only one year in our data (e.g., because their sales level decreased below the data collection threshold) are also taken into account. Standard errors, reported in parentheses, are clustered at firm level. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

Table 14 – Robustness tests to the specification: does trade credit position explain firms' payment default during the Covid-19 crisis?

Dependent	Payment default			
	Industry-level clusters	Finer set of fixed effects		
	(1)	(2)	(3)	(4)
TC × Post	0.0009***	0.0010***	0.0013***	0.0014***
	(0.000)	(0.000)	(0.000)	(0.000)
Trade credit (TC)	0.0000	-0.0000	-0.0001	-0.0001
	(0.000)	(0.000)	(0.001)	(0.001)
Covariates	Y	Y	Y	Y
Covariates x Post	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Industry-month FE	Y	Y	Y	Y
Size category-month FE		Y		Y
County-month FE			Y	Y
No. firm clusters		175,539	135,676	135,676
No. industry clusters	555			
No. observations	3,159,702	3,159,702	2,317,398	2,317,398
Adj-R^2	0.26	0.26	0.27	0.27

In this Table, we further challenge the main regression (column (5) of Table 4) by changing the clustering level (column (1)), or adding finer fixed effects: size-month fixed effects (column (2)), county-month fixed effect (column (3)), or both (column (4)). Standard errors, reported in parentheses, are clustered at firm level. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

Table 15 – Definition of variables

Dependent variable	Definition
Payment default	A monthly firm-level indicator set to one if a firm misses at least one payment owed to its suppliers in a given month, zero otherwise
Multiple payment default	A monthly firm-level indicator set to one if a firm misses at least two payment owed to its suppliers in a given month, zero otherwise
Number of defaults	A monthly firm-level indicator reporting the number of missed payments by a firm in given month
AuD/Sales	The amount under default in month m scaled by sales in year $t-1$
Amount under default	Logarithm of (1 + amount under default in month m)

Explanatory variable	Definition
Trade credit	Accounts payable in year t minus accounts receivables in year t scaled by sales in year t
Cash holdings	Cash and cash equivalents in year t scaled by total assets in year $t-1$
Leverage	Financial debt (=loans + bonds) in year t scaled by total assets in year $t-1$
Size	Logarithm of (1 + total assets in year t)
Wages/Sales	Wages in year t scaled by sales in year $t-1$
Apparent cost of debt	Interest expenses in year t scaled by financial debt in year t
Rents/Sales	Rents in year t scaled by sales in year $t-1$
Risky rating	Rating below the minimum credit rating required for a loan to be eligible as collateral for the ECB
Receivables	Accounts receivable in year t scaled by sales in year t
Payables	Accounts payable in year t scaled by sales in year t