

Corporate liquidity during the Covid-19 crisis: The trade credit channel

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Abstract

Using unique daily data of payment defaults on suppliers in France, we show how the trade credit channel amplified the demand shock that firms met during the COVID-19 crisis. That channel dramatically increased short-term liquidity needs during the first months of the pandemic. A one standard deviation higher ratio of net debt to suppliers over sales increases the probability of payment default by roughly a third in sectors that were forced to shut down. This effect is extremely heterogeneous across sectors as well as across firms, depending on financing constraints. Understanding the cyclical trade credit dynamics is central for policy makers seeking to enable illiquid but solvent companies to remain afloat until revenues recover.

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1 Introduction

Short-term funding of non-financial firms essentially comes from suppliers. In 2019, trade payables of French firms amounted to more than EUR 530 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 also prevails in other countries, such as in the U.S. (see [Barrot \(2016\)](#))² and has been shown to significantly matter during periods of financial stress. Trade credit indeed provides an alternative source of financing to substitute bank finance in times of banking crisis ([Cunat \(2006\)](#); [Garcia-Appendini and Montoriol-Garriga \(2013\)](#); [Carbo-Valverde et al. \(2016\)](#)).

However, the COVID-19 crisis turned this resilience factor into a vulnerability for trade credit users when, in spring 2020, a lockdown was imposed in France to contain the outbreak. As demand plummeted overnight, firms' operating cash flows froze abruptly, leaving a pile of trade payables to be paid within 60 days, straining businesses' cash and working capital. Even large firms turned out to be severely weakened (see for example the announcement made by one of the most famous large French retailer, Le Printemps group, to suspend payment of all outstanding supplier invoices on March 20, 2020).³

Despite its economic significance, trade credit has surprisingly received attention in the growing literature analyzing the impact of the COVID-19 crisis on the real economy. This paper fills the gap by shading lights on a trade credit channel of the COVID-19 crisis, which has exacerbated short-term liquidity needs faced by French firms during the course of 2020.

First, we seek to understand the role of trade credit for firms' liquidity in times of

¹Accounts payable total is as high as 85% of the amount of long-term bank debt of French firms and represent 7% of their total liabilities. Computation based on Banque de France Fiben data 2018, for a sample of 316 800 firms, which encompasses most of non-financial French firms with sales above 750 000 euros.

²Such economic significance of trade credit is also reported in [Cardoso-Lecourtois \(2004\)](#): *"in an economy like Mexico [...] 65% of firms claim their main source of financing to be other firms"*.

³See *Libération, Retards de paiement: Bercy interpelle les grandes entreprises et vole au secours des petites*, March 23, 2020.

demand shock: to what extent does firm liquidity stress comes from its trade credit balance? To what extent does firm trade credit balance affect the probability of payment default? Second, we document important heterogeneities across affected firms depending on the interaction between their trade credit balance and financing constraints. Third, we provide policy useful estimates of the size of liquidity needs induced by trade credit and of their distribution in the economy. Preventing disruptions in trade payments is indeed of first order to avoid propagating 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 take advantage of unique 2020 daily data from the Banque de France, which tracks payment defaults on trade bills for all businesses in France. 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 France⁴. We match default data with the 2019 financial statements of more than 250,000 French firms, that account for 72% of non-financial firms added value.

We define a firm's trade credit balance as the difference between debt payables and accounts receivables, scaled by sales. Hence, a positive balance means that the firm is a net borrower. This balance reflects negotiated payment terms 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 acting in business to consumers 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 \(2020\)](#)).

We use the negative activity shock induced by the unexpected nationwide lockdown announced in France on March 16, 2020 and implemented on March 17, to analyze the extent to which trade credit balances built up prior to the lockdown contributed

⁴This rich dataset is also used in [Boissay and Gropp \(2013\)](#) and [Barrot, \(2016\)](#).

to firm's liquidity stress. First, we show that, while firm's trade credit balance is not a significant determinant of its probability of payment default in "normal" times, it does significantly contribute to liquidity stress during the spring 2020 lockdown. A 10 p.p. higher trade credit balance position leads to a 0.2 p.p. higher default probability in March and April 2020, which is equivalent to a 6% increase in the average probability of default.

Next, we show that the liquidity stress coming from the trade credit channel is 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 demand shock. Manufacturing, construction, trade, accommodation and food services have been significantly impacted by the trade credit channel, while other business sectors have not. We show that the trade credit channel of the Covid crisis - i.e. the liquidity shock induced by trade credit positions built up prior to the crisis - has impacted the retail trade sector the most. The effect on payment default is more than five times larger for retail traders that were forced to shut down during the lockdown than for other firms.

Conversely, we show that, when the activity restarts after the lockdown, the effect reverses albeit to a lesser extent as the recovery is gradual. A 10 p.p. higher trade credit balance before the lockdown leads to a 0.004 p.p. lower default probability after the lockdown when receivables start to grow again. This dynamics comes from the fact that (i) when firm's activity level is constant between two dates t and $t + 1$, its trade credit position is unchanged (other things being equal), just like if the debt to suppliers and the credit to customers was rolled over, so there is no induced liquidity needs. (ii) When demand falls, the firm still needs to meet its payment to suppliers within 60 days due to the French legal constraint on payment delay; however receivables and cash flows are now lower as sales dropped. If the firm is a net trade credit debtor (respectively net creditor), this leads to cash outflows (respectively inflows) and to a liquidity stress (resp. increase). (iii) When activity bounces back, it goes the other way around as depressed demand had lowered input needs

that need to be paid over a two-month window, while rebound in sales boosts cash and receivables, leading to cash inflows for net debtors (respectively outflows for net creditors). The empirical results based on our population of firms show that on average we observe the debtor situation with the dynamic of liquidity for the average firm following case (ii) during lockdown and case (iii) when the economy reopens.

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 (see, e.g., [Boissay and Gropp \(2013\)](#)). In this paper on the contrary, we highlight how 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 understand the impact of the COVID-19 pandemic on the real 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 a trade credit channel of the COVID-19 crisis. Most papers in that literature rely on models of cash flows projections, in which essentially sales, wage bill, input costs and taxes are used to estimate corporate cash flows ([Bank of England \(2020\)](#); [Schivardi and Romano \(2020\)](#); [Carletti et al. \(2020\)](#); [Demmou et al. \(2020\)](#)). These papers do not take into account other significant cash flows (e.g. trade credit, investment, dividends), leading potentially to underestimations of firms' liquidity needs, as we show in the case of trade credit. We quantify the potential liquidity needs of firms from this sole channel. Based on 2019 data, account payables represent on their own between 11% to 16% of firm's sales.

Thirdly, our paper adds to the literature which analyses the propagation of the shocks through production interdependencies based on input-output-matrixes ([Baqae and Farhi \(2020\)](#); [Barrot et al. \(2020\)](#)). An important feature of these models is to

understand how firms are primarily impacted in order to simulate the propagation. Our results precisely enable to better understand one of the critical channels affecting the transmission of the shock along the supply chain. In particular, we highlight the cyclical shock of the lockdown on firms through the trade credit channel: the average French firm behaves like a trade credit debtor that (i) suffers from a liquidity stress during the lockdown and (ii) benefits from a liquidity release when restrictions ease. 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 organized as follows. Section 2 describes the lockdown and fiscal measures in France, section 3 describes the data and the identification strategy, section 4 the empirical results, section 5 discusses policy implications and section 6 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 March 17, 2020 to answer the COVID-19 outbreak. This event offers a unique opportunity to analyze 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 firm activity.

The event is large: (i) it is a nationwide lockdown and (ii) almost all businesses have to shutdown but for some specific activities (food stores, dry cleaners, computer repair shops, etc.). ⁵

⁵These so-called “essential activities” (*activités essentielles*) are listed in the decree 2020-293 of March 23, 2020. <https://www.legifrance.gouv.fr/jorf/id/JORFTEXT000041746694>

The event is sudden and unexpected. Across the world, prior to March 2020, no country has applied nationwide lockdown yet. At that time, restrictions used to be 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 (but for Italy which started it early March).

The real first nationwide restrictions are announced on March 12, 2020 in France and involve the closure of universities, schools and day-cares. The decision of a nationwide lockdown is announced on March 16⁶ and come into effect on March 17.⁷

The duration of the lockdown is also unexpected. While it was initially planned to last for 15 days, it got extended several times. The exit from lockdown finally (and progressively) starts on May 11, eight weeks after its beginning.

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 expected, with a drop up to -52% in manufacturing (excluding agrifood industries), to -89% in building and -36% in services.⁸ A Banque de France's survey⁹ on several thousands firms enables to breakdown the activity shock at a more granular level. According to that survey, in services, *"the activity in April was deemed by business leaders to be"* 1% of the normal activity in the accommodation services, 5% in food services, 16% in automotive repair services, but

⁶Decree 2020-260: https://www.legifrance.gouv.fr/loda/article_lc/LEGIARTI000041738805/2020-03-21/

⁷Compared to its neighbors, the nationwide lockdown started in Spain on March 14, 2020, in Belgium on March 18, 2020 in Portugal on March 19, 2020, in Germany and in United Kingdom on March 23, 2020.

⁸See <https://www.insee.fr/en/statistiques/4473305?sommaire=4473307> and <https://www.insee.fr/en/statistiques/4479775?sommaire=4473307>.

⁹<https://www.banque-france.fr/en/statistics/business-surveys/business-surveys/update-business-conditions-france-end-july-2020>

81% in information services. According to that same survey, in the industry area, the activity in April was deemed to be 11% of the normal activity in automotive industry, but 78% in agrifood industry and 80% in pharmaceutical industry.

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 sanitary restrictions taken to limit 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 300 bn EUR, (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 while the bank granting the loan takes in charge the remaining 10%. 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 possibility to repay over five years. Eventually, the maximum amount a firm can borrow has been capped to three months of 2019 sales. Around EUR 130 billion of guaranteed loans have been distributed from March to December 2020, mainly to small and medium-size 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 default to suppliers

Data on firms' payment default comes from the CIPE database (Fichier Central des Incidents de Payment sur Effets) of Banque de France. That database collects all

firm's payment default to supplier at a daily frequency over the 2019-2020 period. A payment default is defined as a trade bill 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 exhibits a clear jump of defaults in Spring 2020, which illustrates the negative impact of the first lockdown. Payment defaults then increase at a much slower pace than in previous two years. That tendency is the result of several contradictory effects. Firstly, the economic crisis implies less trade between firms. Secondly, more firms want their customers to pay cash. Both effects imply less payment defaults. Thirdly, public support to corporate liquidity has been widely provided 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 Firm's 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 are collected as soon as firm's sales are above EUR 0.75 million. Data are yearly collected, so we use panel data over two years: 2018 and 2019.

3.1.3 Sample composition

Our sample results from merging the FIBEN financial statement database and the CIPE database. BdF assigns a credit rating to all firms in FIBEN. In case of payment default the firm will be downgraded to one of the bottom three rating categories. When firms have such rating they cannot use trade bills anymore to pay their suppliers. As a result, mechanically, we cannot observe payment default for this population. We thus restrict our sample to firms that have not experienced any payment default as of December 2019. We follow standard practice in the literature

and drop firms in the agriculture, financial, utility and public sectors. Table 1 presents the main descriptive statistics of our sample.

As reported in table 1, our sample contains 136,021 firms. The average firm has 19.3 million sales, its net trade credit position is creditor, cash holdings represent on average 19% of total assets and the average leverage is 30%.

3.2 Payment term legislation

In France,¹⁰ the law restricts contractual payment terms to 60 days after the issuance of the invoice. Exceeding that payment term limit is liable to a fine that can reach up to EUR 2,000,000 for a legal entity with the announcement of the penalty in a journal of legal notices or on the firm 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 case of repeated excess payment terms of a firm, (ii) the French administration carries out controls and imposes sanctions.

3.3 Empirical strategy

The goal of this paper is to analyze the contribution of the trade credit channel to the liquidity shock due to the lockdown.

In the absence of any fiscal measure, a firm suffering from a lower activity because of the lockdown still has to face some charges (e.g. monthly repayment of loans, rent, at least part of the usual wage bill), but also supplier invoices from past deliveries (trade payables). To face those cash outflows, the firm can rely on sales (if any), liquidities (cash, credit lines) and trade receivables. The difference between trade payable and trade receivable is called hereafter the *net trade credit position* of a firm. When the trade credit position is positive, the firm is a net borrower regarding its supplier-customer relationships. As the payment term law prevents the payment of invoice beyond 60 days, the question we address is: to what extent the net trade

¹⁰Like 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).

credit position of a firm prior to the lockdown amplified the liquidity stress due to the lockdown?

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 the inability of a customer to pay an invoice, must declare 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. Somehow similar to chapter 11 in the US, a firm that is unable to pay its creditors must self-declare that situation to the commercial court within 45 days. (ii) The banking default could also be used as an information of firm's liquidity stress. The 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 January 1, 2019 to December 31, 2020. Following [Boissay and Gropp \(2013\)](#) and [Barrot \(2016\)](#), we aggregate DS data at monthly frequency and run the following OLS regression:

$$DS_{ft} = \alpha.TC_{y-1} + \gamma.[TC_{y-1} \times post_t] + Controls_{y-1} + firm\ FE + industry \times month\ FE + \epsilon_{f,t} \quad (1)$$

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. 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. A set of lagged firm controls is added X_{y-1} : firm's cash level scaled

by total assets, leverage defined as financial debt over assets, size of the firm (log of total assets). In all specifications, standard errors are clustered at firm level to take into account serial correlation of data (Bertrand et al. (2004)).

For a given firm f with a net trade credit position \widetilde{TC} , trade payables \widetilde{TP} and trade receivables \widetilde{TR} ($\widetilde{TC} = \widetilde{TP} - \widetilde{TR}$), 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 \widetilde{TR} , so the firm *only* has to manage the payment of \widetilde{TC} . But if its customers are unable to pay \widetilde{TR} or pay only a portion of \widetilde{TR} (because it fails short of cash due to the negative activity shock), so the firm face a liquidity stress that is higher than its net trade credit position. Said differently the coefficient α and γ of equation 1 depend on the situation of firms' customers and can be considered as business sector dependent.

4 Results

4.1 The trade credit channel of payment default

Table 2 presents the main results of our analysis on the impact of the crisis on payment default to suppliers and how trade credit amplified it. We focus on what happened during the early stages of the crisis to identify the effect of the sanitary shock on corporate liquidity before public support fully kicks in. Massive liquidity support provided by different public schemes (e.g. state-guaranteed loans or government subsidies through *Fonds de Solidarite*) have indeed rapidly alleviated corporate liquidity stress in most sectors.

We estimate equation 1 from January 2019 to July 2020. Our dependent variable is a monthly firm-level indicator variable set to 1 if the firm misses a payment due to at least one of its supplier in month t (such event includes failure to pay as well as late payment), and 0 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 after the onset of crisis, i.e after February 2020. Our *Post* period thus encompasses 2 months of lockdown, from mid-March to mid-May 11, and roughly 2 months of post-lockdown period. Trade credit position is one fiscal-year lagged trade credit position of the firm. We define it as the difference between payables and receivables, so that firms with positive trade credit positions are net borrowers while those with a negative trade credit position are net lenders. All continuous independent variables have been standardized to facilitate the interpretation of coefficient. All specifications include firm fixed effects and industry-month fixed effects defined at the Nace 2-digit level (88 industry categories). As we are identifying within firm our effects are not coming from the comparison of 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 payment default

We first show that, while trade credit position is not a determinant of payment default in general (col.1 and col.2), the larger the trade credit position prior to the crisis, the higher the probability of default after the onset of the crisis. Indeed in column (2), the coefficient of the interaction between trade credit position and the *Post* dummy is highly significantly positive.

In column (3), we complement our analysis by controlling for other determinants of default. Just like for the trade credit position, all control variables are one-year-lagged. While the size of the firm does not explain the likelihood of payment default before the crisis, larger firms default less during the crisis. While higher leverage significant increases the probability of default in general, its role however has not changed during the crisis. Finally, cash holdings both help to reduce the probability of default in normal times and significantly more so during the crisis. These findings are 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. A one standard deviation increase in trade credit position translated into a 0.001 percentage point increase in the probability of payment default between March and June 2020. Given the average pre-Covid level of default probability, this means an increase by 3% of the probability of defaulting.

4.1.2 The effect is dynamic and materializes over a 2-month window

At first sight, the overall impact of trade credit position on firm's payment default seems moderated over the March-July period, but the situation is strongly heterogeneous within that period. In column (4) we split our post period into 5 months to better understand the dynamic of the effect and how long it lasted. By definition, the effect shall not last more than 2 months, even in absence of policy support, as trade credit positions are capped to 2 months of turnover, since French firms are required by law to pay their suppliers within 60 days since the introduction of the law of Modernization of the Economy in 2008. As reported in column (4), the probability of payment default due to firm trade credit position prior to the crisis is strongly higher in March and April while it becomes non significant in May and June. In April 2020, a one standard deviation increase in trade credit position leads to a 13% higher probability of payment default.

The positive coefficients in March and April, when activity collapses, and the negative coefficient in July, when activity bounces back, are consistent with the role of the trade credit. Accounts payable have to be paid within 60 days. So accounts payable registered in February had to be paid by the end of April. At that time firms forced to shutdown had no or few sales, so no or few cash inflows. This explains liquidity stress in March and April coming from trade credit position. As the lockdown ended on May 11, 2020, the situation becomes different for two reasons: (i) the activity increases progressively, so cash inflows increase, (ii) there are no or few accounts payable from the past 60 days (in particular for firms forced to shutdown during the lockdown). This explains why the coefficient of July is significantly negative.

Last, we take a closer look at the dynamic of the effect over time. Figure 3 shows the estimation results of a dynamic version of equation (1), where we interact the Trade Credit position with dummies for each month instead of a unique ex-post period. Probability of defaults starts to increase around lockdown. The effect fades away after the economy reopens in May, and even reverse over the summer. Interestingly as we extended our estimation period in this set up we can compare the effects of the first and second lockdown: in November as entire sectors are forced to shutdown 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.

All those results might vary depending on firm's business sectors. This is the focus of the next section.

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

In columns (1) to (12) of table 3, our baseline results are broken down by industry. Our variable of interest is an indicator variable set to one for the March-May 2020 period.

As reported in columns (1) to (12) of table 3, all business sectors did not suffer from a liquidity stress due to their trade credit position contracted prior to the lockdown. Firm's trade credit position explains firm's payment default only in manufacturing, construction, retail and wholesale trade, accommodation and food services. The effect is not significant for the other sectors. The higher liquidity stress coming from payment deadline of accounts payables in some business sectors reflects their degree of "downstreamness" position in the supply chain.

The retail trade sector has been particularly impacted by the liquidity stress from trade credit positions, the coefficient (0.010) reported in column (3) is significantly higher than any other coefficients. To investigate this effect deeper, we estimate our

baseline regression with all observations and interact the main variable of interest with a dummy set to one for firms in the retail trade sector and zero otherwise. As reported in column (4), in March-May 2020, the liquidity stress coming from trade credit position contracted prior to the lockdown was significantly higher in the trade sector compared to any other sectors.

4.3 A focus on the trade sector

We have shown that the trade sector suffered from a much more acute liquidity stress in March-May 2020 due to its trade credit position contracted prior to the lockdown. In this section we are interested in the potential heterogeneity that may have prevailed within the retail sector, in particular between retail traders that had to close their doors compared to those that could carry their activity on during the lockdown because their activity was considered *essentielle* by the French government.

In table 4 we carry out the main regression and focus the analysis on the retail traders that had to close their door during the lockdown. As reported in column (1) of table 4 for retail traders forced to close their doors, there is a statistical significant relationship between firm's trade credit position prior to the lockdown and the probability of payment default: a one standard deviation increase in trade credit position leads to a 1.9 p.p. higher probability of payment default. That coefficient is around five times higher than the ones reported for the whole economy (see column (4) of table 2), and around two times higher than the ones reported for all retail traders (see column (3) of table 3).

In 2019, the average rate of payment default in the retail trade sector was 4.2%. So the economic impact of the lockdown on those firms forced to close their doors was very important.

4.4 Heterogeneity of the effect : how the trade credit channel has amplified financial vulnerabilities

Next we investigate the role of liquidity constraints on the probability of payment default. We first want to verify that our trade credit effect is not capturing other firm characteristics linked with financial vulnerabilities and more particularly liquidity constraints. In table 5 we first show that the trade credit channel does survive anytime we add additional controls capturing firm liquidity risk, and that the trade credit channel actually amplifies the effect of each of these liquidity vulnerabilities. We first use the size of the *parent* company of the firm as a proxy for being liquidity constrained or not. As we already control for the size of the firm itself (size of the legal unit), the size of the group the firm belongs to is 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 show that belonging to a parent firm which is an SME or being a standalone firm indeed increases the probability of payment default, an effect, which is distinct from the trade credit channel (col. 1). In col. 2 when we interact this feature with the trade credit position of the firm we show how trade credit amplifies the liquidity stress. Firms that do not benefit from intra group liquidity and were facing high trade credit position (net debtor) when the crisis hit, have a significantly higher probability of default.

Next, we use the internal rating of the firm granted by the Banque de France (BdF) at the end of 2019, as a proxy for being liquidity constrained. BdF assigns credit ratings to all French non-financial companies with turnover above 750,000 euros. This rating is an assessment of firms' ability to meet their financial commitments over a three-year horizon. We define a dummy which 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 3, we show that low rated firms have a higher probability to default on payment after the start of the Covid crisis. Note that this effect is orthogonal to the trade credit channel itself, which persists and whose magnitude stays unaffected. Next, we interact the low rating dummy with the trade credit position the firm had prior to the crisis. The effect is 50% higher than the baseline effect, showing how the trade credit channel amplifies financial vulnerabilities by weakening the liquidity position of firms that were already fragile but would have defaulted in the absence of crisis. Such firms will need a liquidity bridge to overcome this stress period.

Finally, we test whether the strength of banking relationships could have helped relationship borrowers to overcome the crisis by providing continuation lending, in the spirit [Bolton et al. \(2016\)](#), or equivalently if firms engaged in transaction lending were worse off. Our first proxy for transaction lending is the number of banks the firm had a relationship with during the past two years. We define a "transaction borrower" as a firm having more than 3 banks over that period (col. 6 and 7). Finally, as some firms have several banks but still concentrate most of their borrowing with a main lender, we next use the HHI of a firm borrowing among its banks to define transaction borrowers as firms whose borrowings are really spread across banks. We define transaction borrowers as firms whose HHI of credit borrowing is in the first quartile of the distribution. Once again the interaction between the trade credit channel with such characteristics magnifies the probability of default. This result is consistent with transaction borrowers not benefiting from easier access to liquidity from their bank in times of temporary liquidity shock.

In table 6, we carry out several robustness tests. In column (1), the analysis is focused on independent firms, in column (2) we rely on a finer set of industry fixed effects (4-digit level) and in columns (3) to (5) further controls are added. In column (3), we take an alternative definition of firm size based on their administrative definition (SMEs, intermediate-sized firms, large firms) and interacted it with time. In column (4), we take into account the geographical situation of firms by adding

a county×size fixed effect. And in column (5) we set all together size×month and county×month fixed effects. The main results are robust to those tests.

In the next section we discuss the policy implications of our findings.

5 Discussion on liquidity needs and fiscal measures

Understanding the trade credit dynamics is central for public policies (i) seeking to enable illiquid but solvent companies to remain afloat until revenues recover and/or (ii) seeking to provide firms sufficient liquidity to absorb temporary cash flow deficits and to avoid propagating liquidity shocks along the supply chain.

5.1 Trade credit, distribution of liquidity needs and fiscal measures

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 very generously allocated with limited eligibility criteria e.g. irrespective of a firm business sector, size or cash holding level ¹¹. However some of these features have shaped firm’s liquidity needs during the lockdown and should be taken into consideration carefully as we enter a period of withdrawal or targeted renewal of some of the emergency support that has been provided.

For instance, as shown in this paper, retail traders are particularly impacted when a demand shock hits, as depressed sales comes in hand with payment obligations to suppliers inherited from the previous period, which creates 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) but always get paid cash by customers.

¹¹See e.g. <https://www.bruegel.org/publications/datasets/covid-national-dataset/> for a synthesis of the national measures applied worldwide.

This makes those firms particularly exposed to a cash shortfall in case of any unexpected negative demand, even if they are solvent. That fragility is summarized in firms' trade credit positions. However, as stated above, retail traders may theoretically benefit (*ceteris paribus*) from their trade credit position after the lockdown is removed. Our empirical estimates suggest that the post-lockdown benefits are smaller though 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. But in any case for the firm to seize those benefits, it requires it to survive to the lockdown. Therefore, providing liquidity bridges, of amount tailored over 2-month of turnover, in downstream sectors and for firms with high level of trade credit positions (net debtors) is absolutely essential to prevent bankruptcy of illiquid but solvent firms over the short-run.

Providing a socially optimal allocation rule of fiscal measures is out of the scope of this paper. In particular, we do not address the rising question of the creation of zombie firms that may have been induced by large-scale government interventions in 2020.

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 ask. In France, State-guaranteed loans are limited to 25% of the sales reported in the year prior to the crisis. As stated above, firm's accounts payable can reach 60 days 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 to face a two-month lockdown despite the use of a State-guaranteed loan.

6 Conclusion

In this paper, we have shed light on the time-varying effects of trade credit adjustments on corporate liquidity during the early stages of the COVID-19 shock. The unique feature of our set up 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 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 to survive until the next period. Understanding the cyclical trade credit dynamics is thus central for policy makers seeking to enable illiquid but solvent companies to remain afloat until revenues recover.

References

- Bank of England (2020, May). Technical annex: The cash-flow deficit of uk companies in a covid-19 scenario. Technical report.
- Baqae, D. and E. Farhi (2020, May). Nonlinear production networks with an application to the covid-19 crisis. Working Paper 27281, National Bureau of Economic Research.
- Barrot, J.-N. (2016). Trade credit and industry dynamics: Evidence from trucking firms. *The Journal of Finance* 71(5), 1975–2016.
- Barrot, J.-N., B. Grassi, and J. Sauvagnat (2020, July). Sectoral Effects of Social Distancing. Working Papers hal-02896730, HAL.
- Bertrand, M., E. Dufo, and S. Mullainathan (2004, 02). How Much Should We Trust Differences-In-Differences Estimates?*. *The Quarterly Journal of Economics* 119(1), 249–275.
- Boissay, F. and R. Gropp (2013, 01). Payment Defaults and Interfirm Liquidity Provision*. *Review of Finance* 17(6), 1853–1894.
- Bolton, P., X. Freixas, L. Gambacorta, and P. E. Mistrulli (2016, 06). Relationship and Transaction Lending in a Crisis. *The Review of Financial Studies* 29(10), 2643–2676.
- Carbo-Valverde, S., R.-F. Francisco, and G. F. Udell (2016). Trade credit, the financial crisis, and sme access to finance. *Journal of Money, Credit and Banking* 48(1), 113–143.
- Cardoso-Lecourtois, M. (2004, August). Chain Reactions, Trade Credit and the Business Cycle. Econometric Society 2004 North American Summer Meetings 331, Econometric Society.
- Carletti, E., T. Oliviero, M. Pagano, L. Pelizzon, and M. G. Subrahmanyam (2020). The COVID-19 Shock and Equity Shortfall: Firm-Level Evidence from Italy. *Review of Corporate Finance Studies* 9(3), 534–568.
- Cunat, V. (2006, 07). Trade credit: Suppliers as debt collectors and insurance providers. *The Review of Financial Studies* 20(2), 491–527.
- Demmou, L., F. Guido, S. Calligaris, and D. Dlugosch (2020). Corporate sector vulnerabilities during the covid-19 outbreak: assessment and policy responses. Technical report.
- Garcia-Appendini, E. and J. Montoriol-Garriga (2013). Firms as liquidity providers: Evidence from the 2007–2008 financial crisis. *Journal of Financial Economics* 109(1), 272 – 291.
- Gonzalez, O. (2020). Les structures de production et les rapports de force figent la situation en matière de délais et de retards de paiement. *Bulletin de la Banque de France* (227).

Kiyotaki, N. and J. Moore (1997, January). Credit Chains. Edinburgh School of Economics Discussion Paper Series 118, Edinburgh School of Economics, University of Edinburgh.

Schivardi, F. and G. Romano (2020). A simple method to estimate firms liquidity needs during the covid-19 crisis with an application to Italy. *CEPR Covid economics: Vetted and Real-Time Papers*.

7 Figures

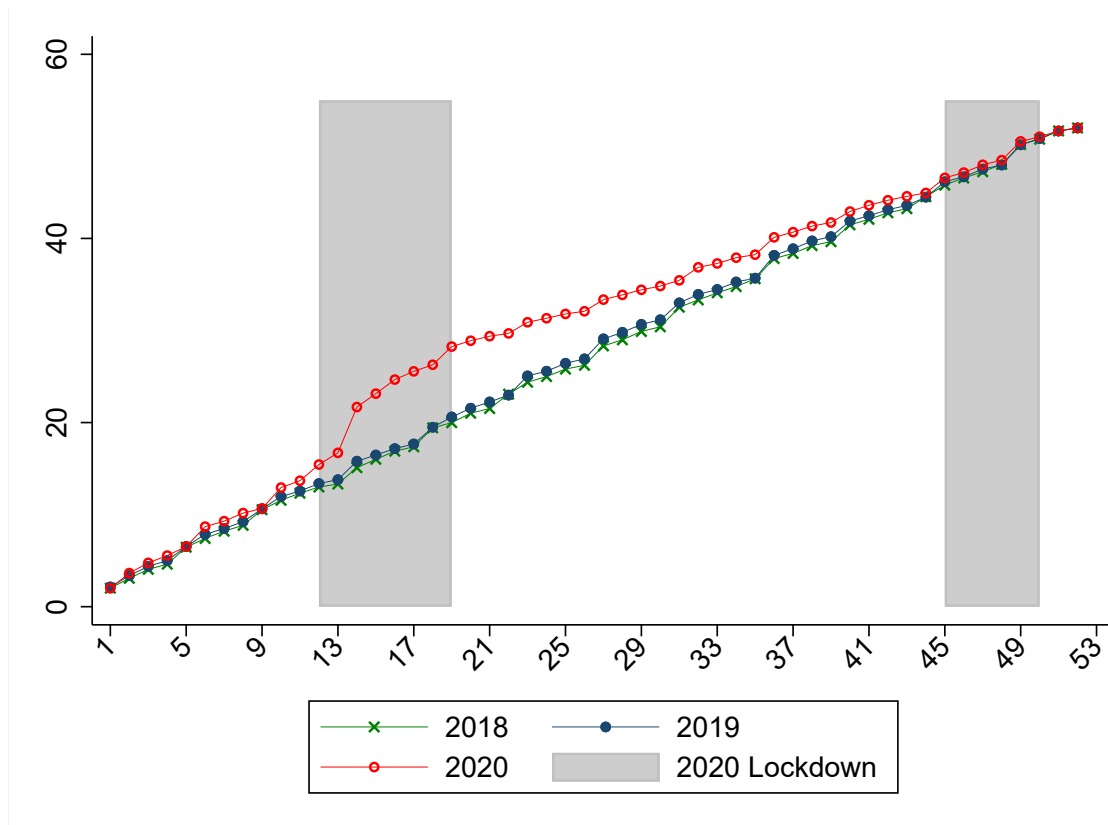


Figure 1 – Cumulated number of payment defaults on trade bills, scaled by the average weekly number of payment default events over the year

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.

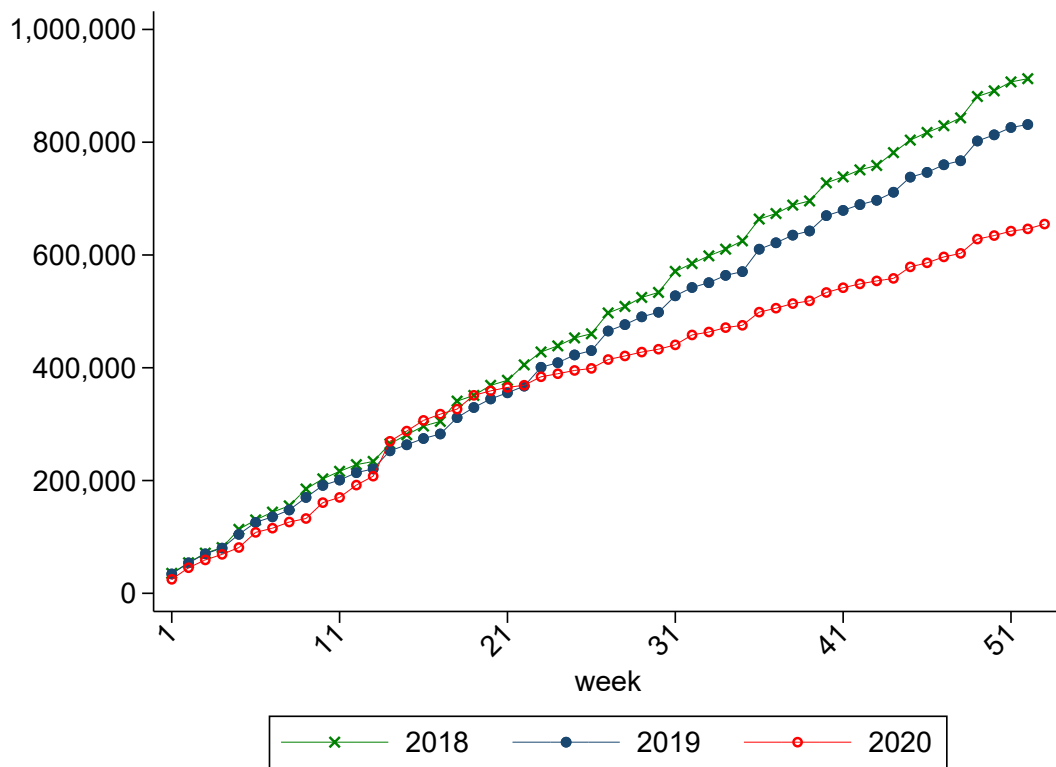


Figure 2 – Cumulated number of payment defaults on trade bills

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 scaled by the number of payment default events in the first week of the year.

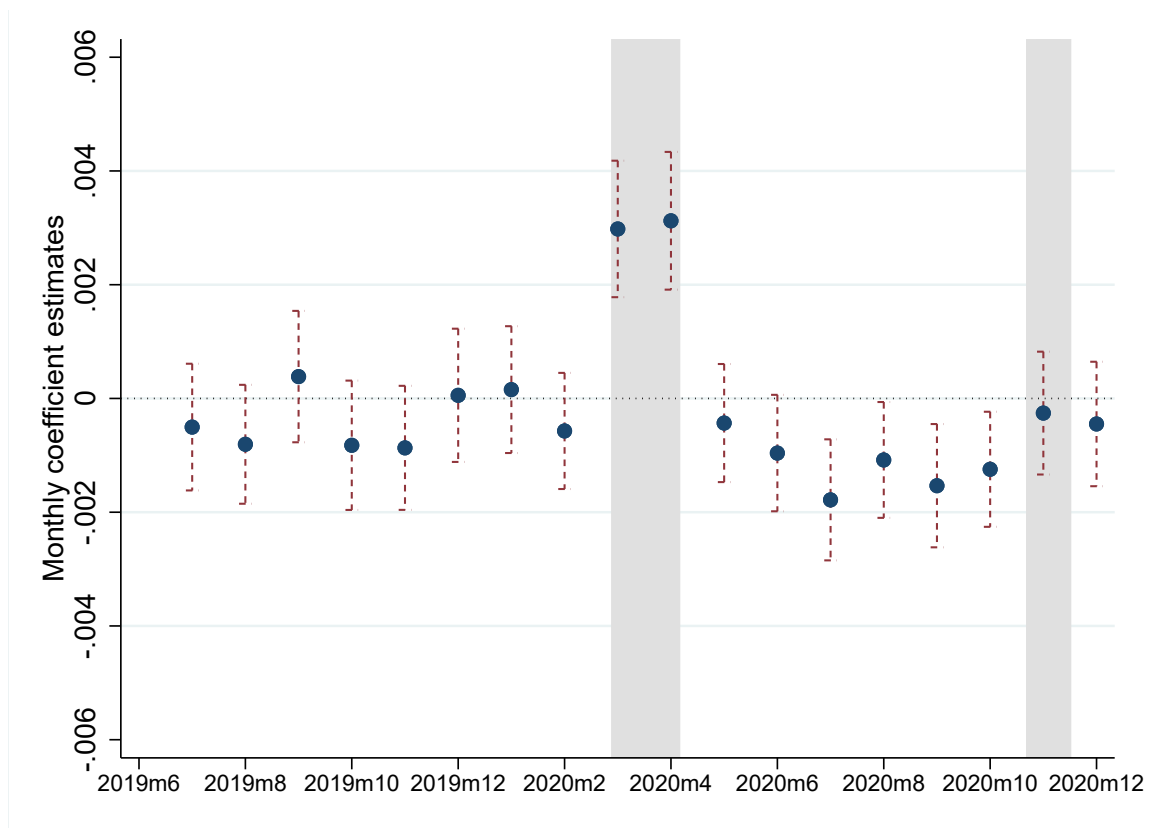


Figure 3 – Monthly coefficient estimates of the effect of trade credit position on the probability of firm payment default

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.

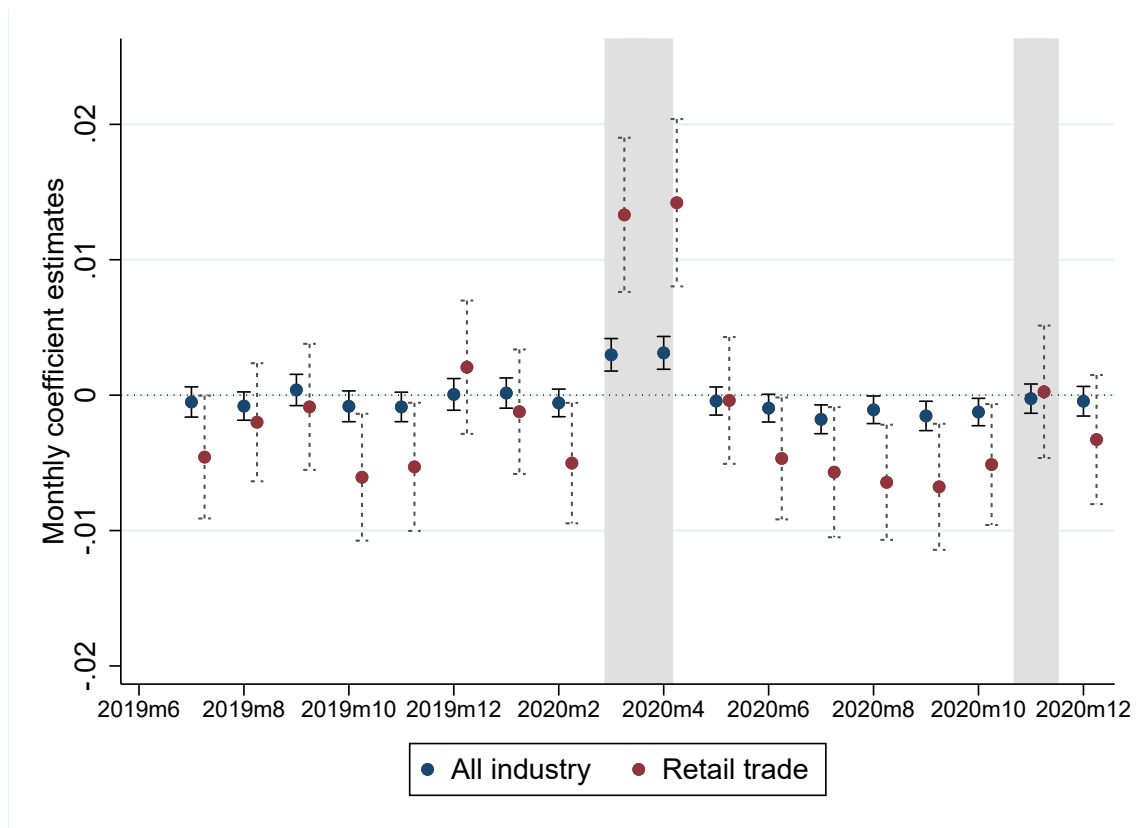


Figure 4 – Monthly coefficient estimates of the effect of trade credit position on the probability of firm payment default : retail trade industry vs. all industry

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 graph3 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.

8 Tables

Table 1 – Firm-level summary statistics

Business sector	statistics	sales (M euros)	total asset (M euros)	net trade credit / sales	cash holdings/total assets	leverage	size
Accommodation, food services	mean	4.1	4.8	6%	20%	47%	7.2
	sd	27.9	84.1	8%	23%	59%	1.0
	N	8 405	8 405	8 405	7 347	7 171	7 347
Agriculture	mean	4.7	12.2	-2%	14%	43%	8.0
	sd	27.2	226.0	19%	17%	32%	1.1
	N	2 069	2 069	2 069	1 868	1 806	1 868
Construction	mean	7.9	8.2	-8%	24%	20%	7.3
	sd	40.0	91.4	13%	22%	24%	1.2
	N	20 239	20 239	20 239	18 531	18 085	18 531
Corporate Services	mean	10.8	62.6	-13%	21%	29%	7.9
	sd	88.1	1 503.9	17%	26%	93%	1.5
	N	17 939	17 939	17 939	16 142	15 683	16 142
Health	mean	9.6	13.5	-4%	22%	30%	7.8
	sd	37.4	116.3	12%	25%	32%	1.5
	N	4 246	4 246	4 246	3 888	3 696	3 888
Information	mean	36.1	76.7	-11%	23%	24%	8.3
	sd	462.0	1 851.6	18%	29%	30%	1.6
	N	3 258	3 258	3 258	2 960	2 906	2 960
Manufacturing	mean	40.3	53.0	-5%	17%	28%	8.2
	sd	788.3	1 639.0	12%	18%	33%	1.5
	N	23 954	23 954	23 954	22 585	22 218	22 585
Real estate	mean	13.5	138.1	-4%	25%	64%	9.3
	sd	49.8	923.8	18%	33%	134%	2.0
	N	3 367	3 367	3 367	2 980	2 898	2 980
Recreation	mean	18.2	11.5	-2%	20%	34%	7.6
	sd	413.6	103.9	13%	21%	42%	1.3
	N	1 772	1 772	1 772	1 599	1 563	1 599
Trade	mean	19.6	9.3	3%	16%	27%	7.6
	sd	238.7	89.0	10%	18%	40%	1.3
	N	43 566	43 566	43 566	40 391	39 532	40 391
Transport, storage	mean	24.3	48.4	-7%	20%	44%	7.7
	sd	379.4	1 176.6	10%	19%	46%	1.4
	N	7 206	7 206	7 206	6 784	6 709	6 784
Total	mean	19.3	30.7	-4%	19%	30%	7.8
	sd	379.7	976.9	14%	21%	53%	1.4
	N	136 021	136 021	136 021	125 075	122 267	125 075

Table 2 – Does trade credit position explain firms' payment default ?

	(1)	(2)	(3)	(4)
TC × Post		0.001*** (0.000)	0.001*** (0.000)	
Trade credit × March				0.003*** (0.001)
Trade credit × April				0.004*** (0.001)
Trade credit × May				-0.000 (0.000)
Trade credit × June				-0.001 (0.000)
Trade credit × July				-0.001*** (0.000)
Trade credit (TC)	-0.000 (0.000)	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)
Cash holdings			-0.001* (0.000)	-0.001* (0.000)
Leverage			0.002** (0.001)	0.002** (0.001)
Size			0.001 (0.002)	0.001 (0.002)
Cash × Post			-0.003** (0.001)	-0.003** (0.001)
Leverage × Post			0.000 (0.000)	0.000 (0.000)
Size × Post			-0.004*** (0.000)	-0.004*** (0.000)
Firm FE	Y	Y	Y	Y
Industry-month FE	Y	Y	Y	Y
N firm clusters	156355	156355	156355	156355
N	2,687,487	2,687,487	2,687,487	2,687,487
Adj-R ²	0.20	0.20	0.20	0.20

The level of observation is firm-month. The dependent variable is a dummy equals to 1 if the firm defaults on at least one trade bill payment to its suppliers in month t , and 0 if not. All continuous independent variables have been standardized to facilitate the interpretation of coefficient. We run a linear probability model over the period 2019-2020m7, with all our explanatory variables being one fiscal year lagged.

Table 3 – Sectoral analysis - Does trade credit position explain firms' payment default ?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TC × March-May	0.004** (0.002)	0.003* (0.001)	0.010*** (0.002)	0.001*** (0.000)	0.002** (0.001)	0.002** (0.001)	0.000 (0.000)	-0.000 (0.002)	0.001 (0.001)	-0.000 (0.001)	0.003 (0.003)	0.000 (0.002)
TC × March-May × Retail				0.009*** (0.002)								
TC × June-July	-0.002 (0.002)	-0.000 (0.001)	-0.004** (0.002)	-0.001* (0.000)	-0.002 (0.001)	-0.003*** (0.001)	-0.000 (0.000)	0.002 (0.002)	-0.000 (0.001)	0.000 (0.001)	0.003 (0.003)	-0.001 (0.002)
TC × June-July × Retail				-0.003 (0.002)								
Trade credit (TC)	-0.001 (0.003)	0.000 (0.002)	0.002 (0.002)	-0.001 (0.000)	-0.000 (0.002)	-0.002 (0.001)	-0.000 (0.001)	-0.001 (0.002)	0.001 (0.001)	-0.000 (0.001)	-0.003 (0.004)	-0.002 (0.002)
TC × Retail				0.001 (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
N firm clusters	8448	18839	35549	156355	23593	27685	18469	4271	3442	3248	1936	2598
N	142,229	331,355	589,303	2,687,487	409,135	489,043	316,662	73,972	58,734	55,851	32,684	42,702
Adj-R ²	0.12	0.24	0.21	0.20	0.20	0.16	0.17	0.19	0.17	0.12	0.13	0.13
Industry	Accomodation, food	Wholesale trade	Retail trade	All industry	Construction	Manufacturing	Corporate Services	Health	Information	Real estate	Recreation	Agriculture

The level of observation is firm-month. The dependent variable is a dummy equals to 1 if the firm defaults on at least one trade bill payment to its suppliers in month t , and 0 if not. We run a linear probability model over the period 2019-2010m7, with all our explanatory variables being one fiscal year lagged, for each one of the industry specified in the last row of the table. In column (4) we define an indicator variable $\hat{\text{Retail}}$ set to 1 when the firm operates in the retail trade sector and to 0 otherwise. We interact it with our explanatory variables to disentangle the additional effect of the trade credit channel in the retail trade sector.

Table 4 – Focus on the retail trade sector - Does trade credit position explain firms' payment default ?

	(Shutdown)
Trade credit \times March	0.019*** (0.003)
Trade credit \times April	0.019*** (0.004)
Trade credit \times May	0.003 (0.003)
Trade credit \times June	-0.003 (0.002)
Trade credit \times July	-0.003 (0.002)
Trade credit (TC)	-0.001 (0.002)
Controls	Y
Controls \times post	Y
Firm FE	Y
Industry-month FE	Y
N firm clusters	17099
N	286,706
Adj-R ²	0.19

The level of observation is firm-month. The dependent variable is a dummy equals to 1 if the firm defaults on at least one trade bill payment to its suppliers in month t , and 0 if not. We run a linear probability model over the period 2019-2010m7, with all our explanatory variables being one fiscal year lagged, on the subsample of firms operating in the retail trade industry that were shutdown by law during the first lockdown in France.

Table 5 – Liquidity constraints, trade credit position and payment default

	Small and Medium-size firms		Non Investment Grade Rating		Transaction Lending			
	(1) D=1 if SME	(2)	(3) D=1 if nonIG	(4)	(5) D=1 if multibank	(6)	(7) D=1 if transactionL	(8)
D × TC × Post		0.002** (0.001)		0.001** (0.001)		0.001* (0.001)		0.002* (0.001)
TC × Post	0.001*** (0.000)	-0.000 (0.001)	0.001*** (0.000)	-0.000 (0.000)	0.001*** (0.000)	0.001 (0.000)	0.001*** (0.000)	0.001** (0.000)
D × Post	0.007*** (0.001)	0.008*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.001 (0.001)	0.001* (0.001)	0.002* (0.001)	0.002** (0.001)
TC × D		0.001 (0.001)		-0.000 (0.001)		-0.000 (0.001)		-0.000 (0.001)
Trade credit (TC)	-0.001 (0.000)	-0.002* (0.001)	-0.000 (0.000)	-0.000 (0.001)	-0.001 (0.000)	-0.000 (0.001)	-0.001 (0.000)	-0.001 (0.000)
Covariates	Y	Y	Y	Y	Y	Y	Y	Y
Covariates x Post	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry-month FE	Y	Y	Y	Y	Y	Y	Y	Y
N firm clusters	156355	156355	156355	156355	156355	156355	152571	152571
N	2,687,487	2,687,487	2,687,487	2,687,487	2,687,487	2,687,487	2,603,518	2,603,518
Adj-R ²	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20

The level of observation is firm-month. The dependent variable is a dummy equals to 1 if the firm defaults on at least one trade bill payment to its suppliers in month t , and 0 if not. We run a linear probability model over the period 2019-2010m7, with all our explanatory variables being one fiscal year lagged, for each one of the industry specified in the last row of the table. In each specification we look at the effect of a given proxy for liquidity constraints. We control for its on the probability of payment default during the sanitary crisis in uneven columns, and we interact it with the trade credit position of the firm in even columns. In col. 1 and 2 D is a dummy equal to 1 if the size of the parent firm is small or medium. In col. 3 and 4 D is a dummy equal to 1 if the firm has an internal credit rating set by the Banque de France at the end of fiscal year 2019 below investment grade. In col. 5 and 6 D is set to 1 if the firm is a transaction borrower, defined as having more than 3 banks. In col. 7 and 8 D is set to 1 if the HHI of firm borrowings among its lenders is in the first quartile of the distribution.

Table 6 – Trade credit position and payment default : robustness checks

	Independent firms	Industry Clusters	Finer set of Fixed Effects		
	(1)	(2)	(3)	(4)	(5)
TC × Post	0.001** (0.001)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Trade credit (TC)	-0.000 (0.001)	-0.001 (0.000)	-0.001 (0.000)	-0.000 (0.000)	-0.001 (0.000)
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
Size category-month FE			Y		Y
County-month FE				Y	Y
N firm clusters	70350		156355	156296	156296
N industry clusters		552			
N	1,118,875	2,687,487	2,687,487	2,609,271	2,609,271
R ²	0.23	0.25	0.25	0.25	0.25

The regressions of this table are similar to the one carried out in column (2) of table 2. In the present table several robustness tests are carried out. In column (1), the analysis is focused on independent firms, in column (2) we rely on a finer set of industry fixed effects (4-digit level) and in columns (3) to (5) further controls are added. In column (3), we take an alternative definition of firm size based on their administrative definition (SMEs, intermediate-sized firms, large firms) and interacted it with time. In column (4), we take into account the geographical situation of firms by adding a county×size fixed effect. And in column (5) we set all together size×month and county×month fixed effects.