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Activity shocks and corporate liquidity: the role of trade credit

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Abstract

We show both theoretically and empirically how trade credit financing may magnify the impact of activity shocks on corporate liquidity. Using unique daily data on payment defaults on suppliers in France, we quantify the magnitude of the short-term cyclical liquidity stress induced by trade payment obligations, exploiting the Covid-19 crisis as an exogenous shock. A one standard deviation rise in net trade credit position increases firm's default probability by 10% during the lockdown. We find higher impacts for downstream sectors — up to 30% increase in the retail trade – for financially constrained firms, and a contraction in investment.

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

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

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NON-TECHNICAL SUMMARY

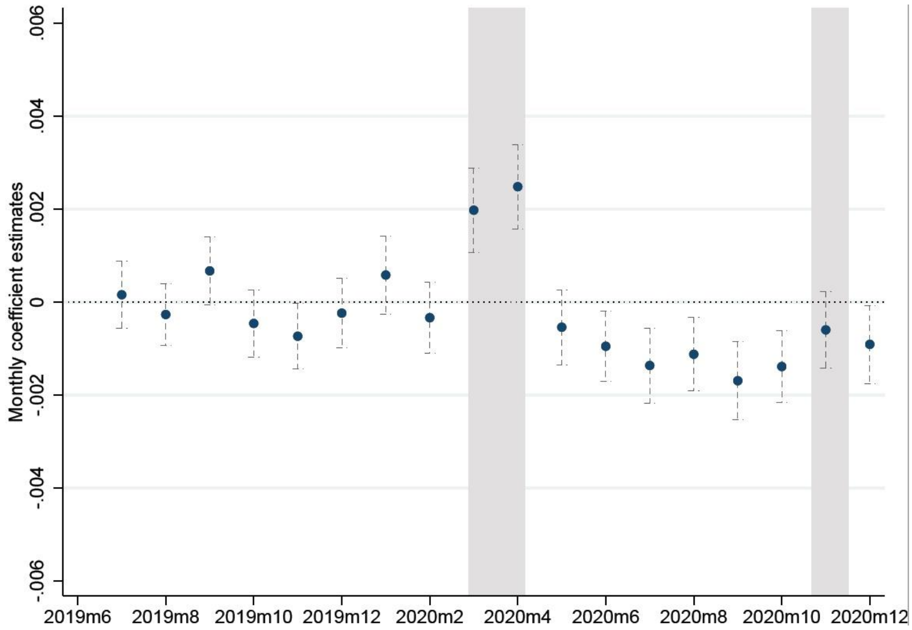
Short-term funding of non-financial firms essentially comes from suppliers. In 2019, trade payables of French firms exceeded EUR 660 billion, more than seven times higher than short-term bank funding. Such numbers highlight how critical the reliance on trade credit is for firms' liquidity in France, as in other countries. That economic importance is reflected in the large number of publications analyzing the role of trade credit in the economy. However, our article aims to improve our understanding of the role of trade credit by pointing out a new feature of trade credit: we show that a firm's net trade credit position strongly influences the impact of a sudden activity shock on firm's liquidity needs.

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.

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 shortterm 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.

Chocs d'activité et liquidité des entreprises : le rôle du crédit inter-entreprises

RÉSUMÉ

Nous montrons théoriquement et empiriquement comment le crédit inter-entreprises peut amplifier l'impact de chocs d'activité sur la liquidité des entreprises. En utilisant des données journalières uniques sur les défauts de paiement aux fournisseurs en France, nous quantifions l'ampleur du stress de liquidité cyclique à court terme induit par les obligations de paiement commercial, en exploitant la crise de la Covid-19 comme choc exogène. Une augmentation d'un écart-type de la position nette de crédit inter-entreprises augmente la probabilité de défaut de l'entreprise de 10 % pendant la période de confinement. Nous constatons des impacts plus importants pour les secteurs en aval - jusqu'à 30 % d'augmentation dans le commerce de détail - pour les entreprises soumises à des contraintes financières, et une contraction de l'investissement.

Mots-clés : Entreprise, Financement d'entreprise, crédit inter-entreprises, liquidité, défaut de paiement, Covid-19, confinement, pandémie

Activity shocks and corporate liquidity: the role of trade credit

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September 13, 2023

Abstract

We show both theoretically and empirically how trade credit financing may magnify the impact of activity shocks on corporate liquidity. Using unique daily data on payment defaults on suppliers in France, we quantify the magnitude of the short-term cyclical liquidity stress induced by trade payment obligations, exploiting the Covid-19 crisis as an exogenous shock. A one standard deviation rise in net trade credit position increases firm's default probability by 10% during the lockdown. We find higher impacts for downstream sectors — up to 30% increase in the retail trade – for financially constrained firms, and a contraction in investment.

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Keywords: Trade credit, liquidity, payment defaults, Covid-19.

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1 Introduction

Short-term funding of non-financial firms comes essentially from suppliers. For example, in 2019, trade payables of French firms exceeded EUR 660 billion, more than seven times greater than their short-term bank funding.[1] That importance has also been observed in other countries, such as the United States, Germany, Italy, or China.[2]

Reflecting its economic significance, a large volume of literature analyzes the role of trade credit in the economy. Trade credit has been characterized as an alternative to bank credit for financially constrained firms (Biais and Gollier, 1997), as an inter-firm liquidity insurance mechanism (Wilner, 2000; Cuñat, 2007), or as a propagation factor of shocks throughout the economy (see, e.g., Kiyotaki and Moore, 1997; Jacobson and von Schedvin, 2015; Costello, 2020). Our paper aims to deepen our understanding of the role of trade credit by highlighting a novel, but economically important characteristic of trade credit: we show that the net trade credit position of a firm greatly influences the impact of a sharp activity shock on the firm's liquidity needs. High trade credit usage exposes firms to greater liquidity shortages at the time of the activity shock as firms find themselves trapped by their trade credit repayment obligations. This leads the most constrained ones to default on paying their suppliers.

We characterize both theoretically and empirically the temporary and cyclical nature of the liquidity stress induced by trade payment obligations, and quantify its economic magnitude. Trade credit arises from suppliers acting as lenders by granting a payment delay to their clients, the latter being trade credit borrowers. As a given firm is generally both a client and a supplier in the supply chain, we focus

[1] Source: French National Institute of Statistics and Economic Studies (INSEE), and Banque de France FIBEN data.

[2] Barrot (2016) points out that in the United States "Accounts payable are three times as large as bank loans [...]." According to the BACH database, accounts payable are equivalent to 50% of bank loans for the average firm in Germany in 2019 (over a 35,500 firms sample), and more than 140% in Italy (468,000 firms). 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 [...]".

on its net trade credit position. This balance reflects payment terms negotiated between a firm, its suppliers and its customers.

When demand brutally falls, sales plummet leading to a sharp reduction in cash flows. However, firms still need to meet the payment obligations contracted before the shock. For net trade credit borrowers, this leads to cash outflows in times of depressed cash flows, potentially leading to liquidity shortage and to payment default. We provide a simple and straightforward analytical framework to capture this pattern.

Guided by this framework, we then empirically assess how corporate liquidity needs of more than 170,000 French firms vary during an activity shock, depending on firms' ex ante reliance on trade credit financing. We measure liquidity stress using granular data on payment defaults on suppliers provided by the Banque de France. Data encompasses missed, partial as well as delayed payments on trade bills for all non-financial businesses in France, at a daily frequency, for 2019 and 2020.

The challenge in empirically identifying the trade credit mechanism is twofold. The first obstacle is to get an activity shock that is exogenous to the firm. To do so, we rely on the first nationwide lockdown in response to the Covid-19 outbreak in France in 2020. While we use the 2020 lockdown for identification reasons, the theoretical mechanism we depict holds for any significant unexpected drop in firms' sales.

The second challenge lies in disentangling the trade credit mechanism from the direct effect of the unexpected economic shock on demand. We address this challenge by estimating the likelihood of payment default for firms that suffer shocks of similar magnitude, but differ in their usage of trade credit. To this end, we break down the analysis by sector and rely on the within time-industry heterogeneity of a firm's trade credit position at the time of the lockdown, along with a particularly rich set of controls. We complement our analysis by focusing solely on the retail sector for which we use the French government decision to shut down some stores. This results in a quasi-homogeneous 100% drop in activity for all non-essential stores that ended up being closed.

The novel aspect of our study lies in its examination of a sharp shock in economic activity and offers new insights into the role of trade credit in mitigating or, on the contrary, amplifying this shock. This contrasts with the existing evidence, which primarily focuses on shocks to financial constraints that affect the availability of supplier's finance.

A first strand of the literature shows that trade credit can be a source of resilience, offering a margin of adjustment when the firm faces unexpected liquidity shocks : cash-rich suppliers help to preserve the liquidity of low-cash clients by extending trade credit. This view emphasizes the financing motive behind the prevalence of trade credit in presence of liquidity shocks caused by credit crunches (Garcia-Appendini and Montoriol-Garriga, 2013; Coricelli and Frigerio, 2019; Costello, 2020) or customers defaults (Boissay and Gropp, 2013; Jacobson and von Schedvin, 2015). Trade credit can then serve as a substitute for bank finance for credit-constrained firms (Biais and Gollier, 1997; Burkart and Ellingsen, 2004) or as a liquidity insurance mechanism between unconstrained suppliers and constrained customers (Cuñat, 2007).

In contrast, we examine another source of liquidity shocks: major and unexpected variations in economic activity and show how the underlying mechanisms are different from the shocks previously considered in the literature. In particular, we highlight the peculiar temporality of the impact of trade credit on liquidity needs, which is mechanically "cyclical" for any given firm when activity drops.

While literature has offered empirical evidence that trade credit can act as a buffer against liquidity shocks (e.g., Garcia-Appendini and Montoriol-Garriga, 2013), we show the other side of the coin: when faced with a sudden drop in sales, financial commitments with respect to suppliers inherited from past activity generate a liquidity squeeze. Indeed, as postponing trade payment is costly (damage to the buyer-seller relationship, deterioration of the company's reputation, potential downgrades by credit rating agencies, etc.), these short-term financial obligations put pressure on firm's immediate liquidity needs at a time of reduced cash flows.

Another strand of literature shows that trade credit chains constitute a channel through which liquidity shocks are propagated in the economy (see, e.g., Kiyotaki and Moore, 1997; Jacobson and von Schedvin, 2015; Costello, 2020). In particular, during financial crises, trade credit is a source of contagion of financial shocks through the production chain, giving rise to a significant amplification mechanism (see, e.g., Raddatz, 2010; Coricelli and Frigerio, 2019). We complement this view showing how trade credit can amplify liquidity shocks *prior to* any contagion along the supply chain.

Finally, we contribute to the literature on the impact of Covid-19 on business distress. To the best of our knowledge, we are the first to highlight that trade credit matters in explaining business dynamics during the Covid-19 crisis. Several papers use firm-level data to estimate cash flows or business failures during the crisis (Díez et al., 2021; Carletti et al., 2020; Schivardi and Romano, 2020; Gourinchas et al., 2022), but they do not model, or discuss, the relationship between the Covid shock, trade credit, and liquidity. Assessing in-time liquidity needs and understanding the forces that are driving them is critical as they may prevent the firm from surviving until the next period. Understanding this dynamics is then crucial for policymakers seeking to enable illiquid but solvent companies to remain afloat until revenues recover.

We derive three main sets of results. First, we show that a high trade credit exposure amplifies the effect of major and unexpected activity shocks on payment default. Using the Covid-19 outbreak in France for identification reasons, we show that a one standard deviation increase in net trade credit position leads to a rise in the probability of default of 10% for the average firm. We show also that this effect is temporary and cyclical: when activity recovers, a high trade credit exposure translates into higher cash inflows.

Second, we show that the amplifier effect of trade credit is heterogeneous among firms. We highlight four key determinants of that heterogeneity: (i) trade credit positions' impact on payment default is stronger in, but not limited to, downstream sectors. For instance, in the retail trade sector, a one standard deviation increase in net trade credit position leads to a rise in the probability of default of up to 30%. The effect is even stronger (close to 40%) on the sub-sample of "non-essential" retail traders that had to close their doors during the lockdown; (ii) the activity shock a company is facing needs to be big enough for the trade credit mechanism to materialize; (iii) financially constrained firms are more impacted; while (iv) firms that manage to hedge liquidity stress via sufficient cash buffers, factoring and/or accounts receivable financing, are less impacted.

Finally, we document in a conditional correlation analysis that firms entering the crisis with high net trade credit position also tend to invest less and see a drop in their total assets in the year following the Covid shock.

The rest of the paper is organized as follows. Section 2 shows how activity shocks impact firms through trade credit, and why the underlying mechanisms are different from the other shocks considered in the literature. Section 3 describes the Spring 2020 lockdown, the fiscal support measures, and the payment term legislation and practice in France. Section 4 describes the data. Section 5 sets out the identification strategy. Section 6 presents our empirical results. Section 7 presents complementary evidence, robustness checks, and caveats. Section 8 discusses the external validity of our results and Section 9 concludes.

2 Conceptual framework

Several papers analyze the interactions between liquidity shocks and trade credit financing. However, this literature deals almost exclusively with liquidity shocks caused by credit crunches (Garcia-Appendini and Montoriol-Garriga, 2013; Coricelli and Frigerio, 2019; Costello, 2020) or customers defaults (Boissay and Gropp, 2013; Jacobson and von Schedvin, 2015).[3] Our paper adds an important dimension by examining another source of liquidity shocks: major and unexpected variations in

[3] Another paper by Amberg et al. (2021) considers a liquidity shock caused by fraud and failure of a cash-in-transit firm.

economic activity, which will directly affect firm cash flow through trade credit as detailed in this section.

A simple model of cash flow is presented in the online Appendix A in order to illustrate the specificity of a liquidity shock due to a drop in activity. That appendix also highlights the cyclical nature of the impact of activity shocks through trade credit. This analytical exercise then serves as a guide for the empirical strategy we implement in Section 5.

The underlying mechanisms at play can be summarized as follows: When demand suddenly falls (e.g., during a lockdown), the firm still needs to meet its payment obligations towards its suppliers contracted before the shock. However, cash flows decrease as demand drops. If the firm is a net trade credit borrower (respectively a net trade credit lender), this leads to cash outflows (respectively inflows) and to liquidity stress (or an increase in liquidity) potentially leading to payment default. In other words, such a "trade credit channel" implies that the existing net credit position of a firm amplifies the liquidity stress caused by an activity shock, prior to any propagation effect through the supply chain.

When activity recovers, [4] it is the other way around. Depressed demand has lowered input needs, thus reducing the level of payables issuance during the lockdown, while the rebound in sales boosts cash and receivables, leading to cash inflows for initially net borrowers (respectively outflows for net lenders).

That dynamic contrasts with a "business as usual" situation. If firm's activity is stable over time, its trade credit position is unchanged (other things being equal), so that there are no liquidity flows induced by the trade credit mechanism described above. This is just as if the debt to suppliers and the credit to customers were continuously rolled over.

[4]The demand shock is not necessarily temporary, but maylast because of new habit formation in consumption patterns. In other words, one cannot discount the possibility that activity does not recover.

3 Background

3.1 The spring 2020 lockdown in France

In response to the outbreak of Covid-19, the French government ordered the first nationwide lockdown on 17 March 2020 in an attempt to curb the spread of the virus. We use this event as our main source of identification. The event was large, sudden, unexpected, and of unknown duration, with a direct effect on business activity. It thus offers a unique opportunity to analyze the impact of a negative activity shock to corporate liquidity, which is totally unrelated to any financial shock.

The event was large: it was a nationwide lockdown, and all businesses deemed as "non-essential" had to close their physical operations.[5]

The event was sudden and unexpected: France was among the first countries across the world to implement a nationwide lockdown. Most European countries actually decided 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 restrictions were announced on 12 March 2020 in France and involved the closure of universities, schools, as well as bans on public gatherings. They were followed by closures of bars, cinemas and restaurants, before a nationwide lockdown was enforced on 17 March.[6]

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

3.2 A negative shock that hit businesses heterogeneously

Covid-19 was an unprecedented shock for business activity, with heterogeneous effects across sectors. During the last week of March, turnover was one third (-35%)

[5] The so-called “essential activities” (*activités essentielles*) are listed in the Decree 2020-293 of 23 March 2020.

[6] Cf. Decree 2020-260 of 16 March 2020.

lower than in normal times, with falls of as much as 52% in manufacturing, 89% in construction and 36% in market services.[7] Table 5 also records very large and fairly heterogeneous drops in sectoral GDP in April and May 2020: for instance, a 59% drop in the accommodation and food sector and a 54% drop in construction, while the shocks are somewhat less pronounced in the real-estate (-3%) or information (-11%) sectors.

3.3 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 economic impact of the health-related measures taken to limit the spread of the Covid-19 pandemic. Table 1 lists the four main measures implemented in France to help firms overcome their liquidity issues. It includes (i) a State credit-guarantee scheme for new corporate loans (EUR 130 billion distributed at the end of 2020 to more than 600,000 firms), (ii) a deferral of tax payment and social security contributions (EUR 20 billion), (iii) a job retention scheme (EUR 26.5 billion), and (iv) specific subsidies for SMEs (the so-called "solidarity fund"). Overall, French companies benefited from a massive injection of cash: some EUR 187.5 billion over the March-December 2020 period, i.e., 7% of France's GDP in 2019. This amount covers both subsidies (20%) and loans (80%).

These measures were implemented very quickly after the beginning of the lockdown. Then, at the end of April 2020 (i.e., around 45 days after the beginning of the first lockdown), French firms had received more than EUR 55 billion in State-guaranteed loans already, EUR 1 billion in public aid via the "solidarity fund" for SMEs, and subsidies to cover the labor costs of more than 8 million workers.[8]

We will focus on the relationship between trade credit and the reliance on the State guarantee scheme in Appendix C.

[7] See INSEE, Economic Outlook, March 2020.

[8] The numbers reported in this subsection (including Table 1) come from various publications from the French Ministry for the Economy and Finance, Bpifrance and from the French Ministry of Labor and Employment.

3.4 Payment terms in France: legislation and practice

3.4.1 Legislative framework

Within Europe, companies operate in a fairly similar legislative context regarding payment terms. France is no exception. Payment terms are framed by the European Union legislation, in particular by the Directive 2011/7/EU of the European Parliament (often referred to as the "Late Payment Directive", or "LPD" hereafter). That legislation, in force since 2013, applies to all Member States of the European Union.[9]

The LPD recommends payment terms of up to 60 days for companies and up to 30 days for public authorities. A payment default occurs in the event of a late or missed payment of a supplier's invoice by a client. The law also provides remedies for late payments (i.e., interest rate for late payments and compensation for recovery costs). However, the LPD allows Member States to enact stricter rules than those necessary to comply with the Directive. Most Member States[10] made use of this possibility. In particular, Croatia, France, the Netherlands, and Spain enacted a maximum payment term of 60 days with no possibility for derogation. In Austria, Bulgaria, Denmark, Finland, Germany, and Sweden, the maximum payment term is even shorter and comprises 30 days or less. More stringent payment terms can also apply at the sector level in particular in the food and beverage industry.[11]

3.4.2 The enforcement mechanisms in practice

Restrictions are enforced in France by two mechanisms: (i) external auditors of firms have to notify the Ministry of Economy and Finance in the event of repeated incidents of missed payment deadlines, and (ii) the French administration carries

[9] As an EU member at that time the United Kingdom also implemented the Directive – through the Late Payment of Commercial Debts Regulations 2013 (SI 395/2013).

[10] Austria, Bulgaria, Croatia, Denmark, Finland, France, Germany, Ireland, Lithuania, Poland, Spain, Sweden, the Netherlands and the United Kingdom.

[11] In the food and drink sector, nine Member States (including France and Italy) have adopted legislation setting out maximum payment terms shorter than 60 days.

out audits and imposes sanctions.[12]

In practice however, the legal restrictions on payment terms are far from being fully enforced. Firstly, the extent to which firms use the Late Payment Directive is limited. As stated above, under the LPD, debtors are entitled to interest for late payment and compensation for recovery costs. But, according to a 2021 report by the debt-collection company Intrum,[13] the majority of French firms (58-59%) "never" uses these instruments,[14] while 23-25% use it "sometimes", and only 16-19% "always" use it. Furthermore, a 2022 survey by the French Ministry of Economy[15] concludes that "at many instances" clients just do not pay the penalty fees.

Secondly, the number of audits carried out by the French administration is relatively small (around 2,300 a year on average); so is the number of fines imposed (fewer than 200 fines a year). Thirdly, even if re-negotiating payment terms longer than 60 days is theoretically forbidden, firms that agree to extend the payment period have a rather cheap alternative at hand. As mentioned by Boissay and Gropp (2013), they may reach a new agreement and the supplier may produce a new invoice with a later date of payment (leading to implicit payment terms longer than 60 days).[16]

In the end, France's legislation does not translate into fewer (or more) late payment compared to other European countries, which makes our empirical set up reasonably general. In global terms, as mentioned by Altares, France has "a similar performance in terms of punctual payments to the majority of markets analyzed".[17] For example, the percentage of late payments of more than 30 days is 8.0% in France in 2019, while the European median is 7.1%. Compared to other major economies, France has similar figures to Spain (7.8%) and the United Kingdom (8.1%), and performs

[12] Fines of up to EUR 2,000,000, with the requirement to publicize the penalty in a journal of legal notices or on the firm's website.

[13] Intrum, European Payment Report 2021 – France.

[14] Of which 2-3 percentage points just do not know the Directive.

[15] DGCCRF, *Contrôle des délais de paiement interprofessionnels*, 14 April 2022.

[16] The main French lobby for public works (FNTP) also considers as a common practice the fact that some clients quibble about minor anomalies in the invoice in order to force the supplier to produce a new invoice. Fighting against such practices (the so-called "hidden delays") is considered a priority (see the *Rapport de l'Observatoire des délais de paiement 2021*, June 2022).

[17] Altares Payment Study 2020.

better than Italy (10.5%) and China (26.3%), but worse than Germany (2.1%) and the United-States (6.9%).

4 Data

We merge the FIBEN financial statement database of the Banque de France and the CIPE database on payment defaults. We discard firms belonging to the financial, utility and public sectors. Firms filing for bankruptcy in 2019 are also excluded.

4.1 Firms' balance sheet data

Data on firms' characteristics (i.e., balance sheet, income statement, and credit risk measured by the Banque de France's rating) come from the Banque de France's FIBEN database (*FIchier Bancaire des ENtreprises*). Firms' information compiled from tax returns is collected annually for firms with sales above EUR 0.75 million. We use panel data covering two years: 2018 and 2019.

4.2 Payment defaults on suppliers

Data on firms' payment defaults comes from the CIPE database (*Centrale des Incidents de Paiement sur Effets*) of the Banque de France. Payment defaults on suppliers are collected 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.[18] The data cover information about the due date of the payment, the amount of the default, as well the motive for the default (dispute, liquidity issue or solvency issue). A payment default is defined as a trade bill that is not paid on time and/or in full.

Figure 1 plots the cumulative number of defaults within three consecutive years (2018 to 2020), scaled by the total number of payment default events over the year.

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

It reveals a clear jump in defaults in spring 2020, which illustrates the negative impact of the first lockdown. Figure 2 plots the (unscaled) cumulative number of defaults. It highlights that, after soaring during the first lockdown in 2020, payment defaults increase at a much slower pace than in the previous two years.

Two related effects may explain this post-lockdown declining trend in the number of payment defaults. Firstly, it may just reflect a contraction in trade between firms due to the economic crisis. To capture this effect, the dashed line in Figure 3 displays the evolution of the number of defaults scaled by value added, month by month. The post-lockdown fall is less marked when controlling for business fluctuations. However, the reduced activity in 2020 far from fully explains the drop in payment defaults compared to 2019, which is still very strong.

Secondly, as stated above, there was extensive government support to corporate liquidity at that time. Indeed, despite the sharp drop in sales in 2020 (-7.8% compared to 2019), three out of four companies managed to strengthen their cash balances by year-end 2020 (Bureau and Py, 2021). In the end, around 650,000 payments defaults were recorded in 2020, versus 870,000 on average during the previous two years (2018 and 2019).

4.3 Payment defaults on suppliers as a measure of liquidity stress

We use payment defaults on suppliers as presented above as our main dependent variable of interest to measure the liquidity stress experienced by French firms. We aggregate daily information on defaults at the monthly level.

The advantages of this indicator are manifold. The main one is its timeliness: a bank observing a client's inability to pay an invoice must report that situation to the Banque de France within four days after the event. By comparison, 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 because it is insolvent must file for bankruptcy to the commercial court within 45 days. Moreover, this 45-day constraint was suspended in France from March 2020 to June 2020, and commercial courts closed their doors during the lockdown, which led to much slower digital procedures. In the end, despite the strength of the economic shock, slower procedures combined with extensive government support contributed to a strong decrease in the number of firms filing for bankruptcy in France (see Figure 4).[19]

Compared with bankruptcies, measuring corporate defaults through payment defaults is thus an earlier and much broader measure of default, capturing liquidity issues, which is the purpose of this paper and whose dynamics were not altered during the first months of the Covid crisis. As illustrated on Figure 4, note also that, in normal times, payment defaults and bankruptcy filings exhibit a high correlation in France, the dynamic of the former leading the dynamics of the latter. This correlation is discussed further in Section 6.3.2.

In addition, firms have to report the underlying reasons for default and to differentiate defaults due to liquidity reasons from other types of default (defaults due to solvency issues or defaults related to disputes). We will use this rich source of information in robustness tests of our identified liquidity effect.

4.4 Summary statistics

Our sample contains 175,539 firms. To prevent outliers from affecting the 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.

4.4.1 Payment defaults statistics and firm-level characteristics

We present summary statistics for all relevant variables in Tables 2 to 4. Table 2 presents descriptive statistics on payment defaults in 2019. On average, for a given

[19] Bankruptcy procedures were first halted for administrative reasons. Then government fiscal support provided ample liquidity to firms (see Section 3.3), leading to an unprecedented drop in bankruptcy filings (-39% in 2020 compared to 2019).

month, 3% of firms in our sample exhibit at least one payment default. Taking solely firms that default, the median monthly amount is EUR 1,500 per firm. The average is EUR 12,000.

Table 3 focuses on firm-level balance sheet characteristics. Trade credit positions are very heterogeneous across firms. 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 lenders, while a bit less than half of the firms are net trade credit borrowers.[20]

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%. The average apparent cost of debt, calculated as interest expenses divided by financial debt, is 6% prior to the crisis.

Regarding other operating and financial costs firms have to meet, the average firm has a wages to sales ratio of 30% and a rent to sales ratio of 4%. Only 1% of our firms have non-performing loans (NPL), which explains why the average ratio of NPL to total loans is so low. However conditional on having NPL, the average NPL ratio equals 50 percent. Finally, one firm out of five (22%) in our sample benefited from a State-guaranteed loan in the first half of 2020. These loans are analyzed in Appendix C.

Table 3 also presents summary statistics relating to financing constraints and hedging (that is, issues that will be explored in Sections 6.2.1 and 6.2.2). 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,[21] and 52% of firms did not pay any dividends.

[20]More detailed descriptive statistics on trade credit positions are presented in Section 4.4.2.

[21]We use the internal credit ratings provided by the Banque de France. Risky ratings are defined as ratings below the eligibility threshold of the General Collateral Framework of the Eurosystem and are equivalent to a BBB+.

4.4.2 Trade credit by sector

In Table 4 we zoom in on our source of exposure to the Covid shock: the observed net trade credit position of firms by sector, prior to the crisis. Trade credit positions are highly heterogeneous across sectors. Clustering payment terms by industry captures the respective positions of the firm and its customer in the supply chain (Barrot, 2016). Thus, downstream industries tend to be net debtors as consumers pay cash, while upstream industries tend to be net creditors as they pay their suppliers with a delay. 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 in 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. Given that downstream sectors, such as retail trade and accommodation, were among the hardest hit by the public health measures taken in response to the pandemic, the activity shock was larger in sectors with positive net trade credit exposure. However, this heterogeneity of the shock and of net trade credit positions across sectors is not the source of variation driving our results as our estimations are done within sector, at a very granular (4-digit) level.

As shown in Table 4 significant heterogeneity remains within industries. Section 5 on the empirical strategy will provide further insights showing that that there is wide variation in trade credit across firms within sectors, while Appendix B analyzes the main drivers of the heterogeneity of trade credit positions within industries.

4.4.3 Within-firm variation of the net trade credit over time

We use the balanced panel presented in Appendix B of 145,000 firms over the 2016-2019 period to assess the volatility of individual net trade credit positions over time. The various indicators we look at converge to the conclusion that trade credit positions are fairly stable over time.

As an illustration, in Figure 5 we plot the relation between firms' trade credit position in 2016 and 2017 and, for robustness, between 2016 and 2019. The correlation almost perfectly aligns with the 45-degree line, showing that firm trade credit exposure is very stable over time.

At the individual level, we calculate that 78% of the firms in our sample keep a net trade credit with the same sign (positive or negative) four years in a row. In addition, we consider the yearly distributions of individual net trade credit positions, and look at the proportion of firms that remain in the same quintile of the distribution over time. We find that 42% of firms remain in the same quintile four years in a row. More broadly, 85% remain in the same quintile or move, at most, to the adjacent quintile.

The implications for our empirical strategy is that our exposure to treatment, i.e., to the Covid shock, can be thought of as a structural characteristic of the firm, which is stable over time. The shock will magnify the effect of the net trade credit position and the interaction between both, the shock and firm's net trade credit position, will drive changes in the likelihood of payment default.

5 Empirical strategy

The goal of our analysis is to understand to what extent the trade credit position of a firm can lead the firm to default on suppliers in a period of a major drop in sales. Our variable of interest is the net trade credit position of the firm, defined as the difference between trade payables and trade receivables, scaled by sales. A firm with a positive net trade credit position is thus a net borrower from its clients. Across sectors, the net trade credit of a firm is very dependent on how upstream or downstream this sector is. Roughly 30% of the variance of net trade credit positions between firms is thus explained by the sector (defined at the 4-digit level, see Appendix B for further analysis). Within sectors, there is also substantial variation in net trade credit positions across firms, as we will detail below.

We run our estimations over the January 2019 to June 2020 period. Our analysis of the liquidity shock thus focuses on the early stages of the pandemic, before public support fully kicks in (see Section 3.3 for details about the implementation of liquidity support schemes). We further decompose the period of interest between March-April 2020 (seven weeks of lockdown) and May-June 2020 (when the reopening of the economy and full government support partially cancel out the impact of the shock).

Following Boissay and Gropp (2013) and Barrot (2016), we aggregate default data at monthly frequency and use the specification described below (see equation (1)) to estimate how firms' trade credit exposure affect their liquidity needs and their ability to pay their suppliers in the presence of a cash flow shock due to a drop in activity.

Our empirical specification mimics the conceptual framework derived in Section 2 (see also the online Appendix A for further details). That is, in the presence of an activity shock, a firm f defaults on its supplier at time t, if the induced shock to cash flows ΔCash Flow is too large (e.g., larger than its cash holdings). A part of that induced cash flow comes from the trade credit channel (see the second term of equation (7)), and that part is determined by (i) the degree magnitude of the activity shock, i.e., the drop in sales, and (ii) the net trade credit position of the firm.

$$\begin{aligned} DS_{f,t} = \gamma_1.TC_{f,y-1} + \gamma_2.[TC_{f,y-1} \times \text{Post}_t] + \beta_1.X_{f,y-1} + \beta_2.[X_{f,y-1} \times \text{Post}_t] \\ + \alpha.Z_{f,t-3} + \kappa_f + \theta_{Industry,t} + \epsilon_{f,t} \end{aligned} \tag{1}$$

where DS_{ft} is a dummy set to one if firm f defaults on a supplier in month t. The variable TC_{y-1} is the one fiscal year lagged net trade credit position of a firm at time

t. The trade credit position is defined as the difference between trade payables and trade receivables, scaled by sales. In the robustness part of the paper, we separately analyze the contribution of accounts payable and accounts receivable. The dummy *Post* is set to one from March 2020 and to zero prior to March 2020. *Post* is decomposed further into two dummy variables, the first one being equal to one in March and April 2020 and the second in May and June 2020. The set of lagged firm controls which is added in our baseline specification, X_{y-1}, includes firm size (log of total assets), cash holdings scaled by total assets, leverage defined as financial debt over assets, as well as the firm Altman Z-score. We also add monthly covariates, with a lag of one quarter, Z_{t-3}, such as the ratio of non-performing loans (NPL) to total loans or the share of short-term loans out of total loans. Short-term loans have a maturity of less than one year. The definition of each variable is detailed in Table 15. κ_f is a firm fixed effect and $\theta_{Industry,t}$ are industry-by-time fixed effects, defined at a very granular level (NACE 4-digit). All continuous independent variables are standardized to facilitate the interpretation of coefficients. We cluster standard errors at the firm level, which corresponds to the level of our identifying variation.

Our coefficient of interest is γ_2. That coefficient captures the likelihood of payment default relating to a firm's trade credit position at the time the lockdown occurs. Firms cannot readily adjust their trade credit exposure as these trade credit positions are entirely inherited from their past activity. Consequently, high trade credit debt at the time of the shock is independent from the shock itself and will induce a temporary liquidity squeeze when sales fall (see Section 2).

To properly identify the effect of a firm's trade credit position at the time of the activity shock, we need to control for several effects. First, the firm's trade credit position (without any interaction) makes it possible to control for the out-of-crisis relation between firm's trade credit position and defaulting on a supplier. Second, defaulting on a supplier may be due to firm's financial weakness (see discussion in Appendix B of within-sector determinants of trade credit positions). Firm fixed effects partially address this issue by capturing unobserved time-invariant features of firms, and in particular, potential unobserved time-invariant differences in financial strength that might affect a firm's probability of defaulting. We cannot have firm-by-time fixed effects as it would be perfectly collinear with our effect of interest.

The remaining source of potential endogeneity is that our trade credit variable may be correlated with some unobservable time-varying characteristics related to the firm's financial health or its repayment possibilities. For example, a drop in short-term credit supply could lead the firm to increase its reliance on trade credit, while at the same time undermining its ability to pay its suppliers. We address this issue in the following manner. First, we add time-varying controls that capture financial constraints and credit risk, using size, leverage, cash holdings as well as the Z-score (Altman score)[22] of the firm, all interacted with the post period. The interaction term prevents the estimation from being biased if these other balance-sheet characteristics affect the sensitivity of payment default to the shock. Second, we also control for the monthly liquidity needs of the firm as well as its repayment capability. To this end, we use monthly information available in the French credit register on (i) the share of firm loans with a maturity of less than one year, as a proxy for high or low liquidity needs, and on (ii) loan impairment (using the firm share of non-performing loans out of its total loans).

Finally, as (i) the firm's trade position is strongly linked to the industry the firm belongs to (see Section 4.4.2) and (ii) the scope of our analysis is at firm-month level, we add industry-by-time fixed effects (industry is defined at the 4-digit level). These fixed effects absorb the between-industry relation between trade credit and defaulting on a supplier, at the time of the shock and, more generally, absorb industry-

[22]For manufacturing firms, the Altman Z-score is computed as:

$$Z - score = 1.2 \times A + 1.4 \times B + 3.3 \times C + 0.6 \times D + 1 \times E \tag{2}$$

where A stands for working capital over total assets, B for retained earnings over total assets, C for earnings before interest and tax over total assets, D for equity value over total liabilities, and E for sales over total assets. For non-manufacturing firms, the Altman Z-score is computed as:

$$Z - score = 6.56 \times A + 3.26 \times B + 6.72 \times C + 1.05 \times D \tag{3}$$

See Altman et al. (2014).

specific shocks that could directly drive defaults. In a robustness check, we show that our estimates hold up with even finer sets of fixed effects to ensure that this is not the difference in the shock intensity, within industry across size or across location, which is driving our results.

Our identification thus relies on the within time-industry heterogeneity of a firm's trade credit position at the time of the lockdown shock. Figure 6 provides visual evidence for this source of variation and shows that there are wide variations in trade credit across firms within sector at a given point in time, which explains why we can control for time-varying unobserved differences across sectors.

All in all, the coefficient γ_2 captures the within-industry impact of the interaction between firms' trade credit position and the Covid shock on default on suppliers, filtered from the effects of (i) the out-of-crisis relation between firms' trade credit position and defaults on suppliers, (ii) time-invariant firm's features, and (iii) several time-variant firm characteristics.

Finally, to provide an estimate of coefficient γ_2 on firms that suffer a similar magnitude of shock, we break down the analysis by sector (see Section 6.1.3). We also use the government decision to shut down some retail stores during the lockdown as an additional experiment to demonstrate the robustness of our results while almost perfectly controlling for the size of the shock. Indeed all the stores that ended up being closed experienced a quasi-homogeneous 100% drop in activity.

6 Results

6.1 The amplifier effect of trade credit

6.1.1 High trade credit exposure amplifies the effect of the activity shock on payment default

We now move on to a presentation of our baseline estimation results. Table 6 shows how reliance 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 start by checking that the trade credit position of a firm is not a determinant of payment default in general. As shown in column (1) of Table 6, trade credit does not affect the likelihood of payment default prior to the initiation of the lockdown. This validates our identification strategy as it shows that high trade credit firms are not more likely to default than low trade credit firms in normal times.

During the crisis period on the other hand, the larger the initial trade credit position of the firm, the higher the probability of default. As reported in column (2), the coefficient of the interaction between the trade credit position (TC) and the *Post* dummy is very significantly positive. In column (3) we divide our post-Covid period into two sub-periods of two months, which corresponds to (i) the lockdown period, in March and April 2020, and (ii) the reopening of the economy in May and June 2020 (the lockdown ended on 11 May). We show that the probability of default increases significantly during the lockdown period for high trade credit firms, while it decreases once the economy reopens, albeit to a lesser extent. The magnitude of the drop in the likelihood of default is four times lower than that of the increase in default likelihood. Our estimate in column (3) implies that a one standard deviation increase in the net trade credit position increases the monthly probability of payment default by 0.24 percentage point in March and April 2020. 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 and the theoretical analysis developed in Section 2. As French firms are 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 progressively increases so that cash comes in, and (ii) there are no or few payables inherited from the past weeks as sales were depressed during lockdown. So, in a context of low accounts payable, cash inflows significantly and rapidly improve firm's liquidity position. This explains why the coefficient of May-June is significantly negative.

In column (4), we supplement our analysis by controlling for other determinants of payment default: namely firm's cash holdings, leverage and size. Our results emphasize that cash holdings are a critical margin of adjustment to handle liquidity needs: high-cash firms have a significantly lower probability of defaulting on their payment to suppliers. Adding these firm-level controls does not impact our coefficient of interest which remains highly statistically significant. In column (5) we interact these additional control variables with our *Post* variable. While cash holdings significantly help reduce default probability in normal times, they reduce it to an even greater extent during the crisis. We also observe that larger firms and lower leverage firms have a lower probability of default during the crisis. Importantly, the coefficient of the interaction term $TC \times March - April$ remains unaffected. We can thus rule out the possibility that systematic differences in crisis trends in firms' cash holdings, leverage or across firms of different size drive our results.

Finally, in columns 6 to 9, we address the concern that trade credit-dependent firms within an industry might be financially weaker, so that their likelihood of default may be more sensitive to the activity shock. Not properly controlling for some correlation between financial weakness and our trade credit variable may indeed be a threat to our identification. To control for financial strength characteristics that might drive payment default outcomes, we augment our baseline panel regressions with three additional variables, as well as with their interaction with the *Post* period. The first one controls for the share of non-performing loans out of firms' total loans, but only applies to 1% of our firms. The second one is the share of loans with a maturity of less than one year out of firms' total loans, as a proxy for the size of its liquidity needs. The third is the Z-score of the firm as a proxy for its overall credit risk. If the effects that we are picking up reflect contemporaneous negative shocks in the firm's financial health, the interaction of these variables with the *Post* period should subsume the main variable of interest. Instead, in all cases, our coefficient of interest on *Trade Credit* × *March-April* remains stable and significantly negative. As reported in column (9), a one standard deviation rise in the net trade credit position increases the monthly probability of payment default by 0.31 percentage point in March and April 2020. This amounts for the average firm to a significant 10% (=0.31%/3%) increase with respect to the pre-Covid period level. Hence, firms' net trade credit position has a direct effect on their probability of payment default faced with an activity shock, ahead of their credit risk and intensity of short-term liquidity needs.

6.1.2 The effect is short-term and materialises straightaway

Next, we estimate a dynamic version of equation (1) to better understand the dynamic of the effect and how long it lasts. We increase our sample period towards the end of 2020 and split it into monthly time dummies. We interact the trade credit position with these time dummies from July 2019. Figure 7 shows the estimation results and illustrates the cyclical dynamics of trade credit.

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 estimates. The probability of default starts to increase right at 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 defaults. At that time firms 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.

6.1.3 Controlling for the size of the shock: A preliminary industry-level approach

In order to fully disentangle the trade credit mechanism from the direct effect of the unexpected economic shock on demand, we now estimate the likelihood of payment default for firms that suffer shocks of similar magnitude, but differ in their usage of trade credit. To this end, we first break down the analysis by sector and rely on the within time-industry heterogeneity of a firm's trade credit position at the time of the lockdown, along with a particularly rich set of controls.

By estimating our regressions within sectors, assuming activity shocks are homogeneous, we condition our results on the size of the shock. We carry out a difference-in-differences analysis by keeping the trade credit ratio constant, using the pre-crisis level of net trade credit of the firm and we compare high and low users of trade credit. High reliance on trade credit is characterized by having a net trade credit ratio in the above-median part of the sectoral trade credit distribution. This treatment is absorbed by our firm fixed effect and our variable of interest is the interaction between the lockdown time period, in March-April 2020, and the high reliance on trade credit. We use the same set of control variables as for the most demanding baseline specification, including Z-score, non-performing loans and short-term liquidity needs, in addition to other firm characteristics, all interacted with the crisis period. Table 7 shows the results and Table A5 in the appendix provide the same results with time-varying trade credit exposure as in our baseline set-up.

The trade credit effect on liquidity stress is not uniform and varies a lot across sectors. We also observe that trade credit positions' impact on payment default is stronger in, but not limited to, downstream sectors like retail trade, and accommodation and food, that is, sectors with structurally positive net trade credit positions. In the retail trade sector, our estimates imply that firms with high reliance on trade credit have a 23% (=0.93%/4%)[23] higher probability of defaulting on their suppliers

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

than firms with low reliance on trade credit during the lockdown. High use of trade credit also significantly increases the probability of payment defaults in wholesale trade, construction or manufacturing.

Finally, the amplifier effect does *not* materialize in sectors which experienced the lowest activity shocks (i.e., Real-estate, Agriculture, and Information). That is consistent with the aforementioned result that the trade credit position is not a determinant of payment default in normal times. All in all, it suggests that the activity shock needs to be big enough for the trade credit amplifier mechanism to materialize in a significant way.

6.1.4 Controlling (perfectly) for the size of the shock: A focus on the effect of mandatory business closures in the retail trade sector

As a final experiment to demonstrate the robustness of our results when almost perfectly controlling for the size of the shock, we focus on the retail trade sector and use the French government decision to shut down some stores (designated as "non essential") but not others (designated as "essential") during the lockdown. All the stores that were mandated to close experienced a quasi-homogeneous 100% drop in sales (the only exception being those that were already selling on-line and might have managed to maintain a click-and-collect activity). On the other hand, for stores that were allowed to carry on their business, the absence of a drop in sales does not allow us to uncover a trade credit amplifier effect.

In Table 8, we carry out our estimations separately on the sub-sample of "non-essential" retail traders that had to close their doors during the lockdown and on the sub-sample of "essential" retail traders that were allowed to carry on their activity during the lockdown. Note that we cannot compare the two sub-samples to interpret our results as the causal effect of government-mandated closures on payment default, as businesses that were allowed to stay open also experienced changes in sales growth at the exact same time, but positive ones, driven by substitution effects. In columns (1) and (2), we use our baseline specification (i.e., column (9) of Table 6). In columns

(3) and (4), we use a difference-in-differences specification, similar to the one used in the previous section, in which "High trade credit users" are the firms with a net trade credit ratio lying above the median of the sample distribution in the year preceding the Covid crisis. As shown in Table 8, only retail traders that were forced to shut down during the lockdown suffer a significant liquidity stress, which led to a strong increase in payment defaults.

To provide an idea of the economic significance of our estimated effects, we can relate it to the pre-treatment period probability of default of around 3.0% a month. On average, a one standard deviation increase in net trade credit position increases the monthly probability of payment default by roughly 0.3 percentage point (p.p.) in March and April 2020. This amounts to a significant 10% (=0.3/3.0) increase with respect to the pre-Covid period level for the average firm.

As the average firm in our economy is a net trade credit lender, with a negative trade credit to sales ratio of -0.04 (see Table 3), this average effect masks a lot of heterogeneity. The magnitude of the effect is indeed two to three times larger in sectors in which firms are structurally net trade credit borrowers such as retail trade. In the retail trade sector, the coefficient estimate of 0.0125 (see Table A5) translates in a surge in the default probability of more than 30% for a one standard deviation increase in net trade position. The effect is even stronger (close to 40%) – with our cleanest set-up – on the sub-sample of "non-essential" retail traders that had to close their doors during the lockdown.

To gauge the relative importance of trade credit margins, we can compare the size of the impact of net trade credit positions on payment default with the size of the impact of cash holdings. The estimated cumulative effect tied to net trade credit from March to June ranges for the average firm from around $+0.002$ to $+0.003$, while the counterbalancing benefits of holding cash lies around -0.002 (see Table 6). Both effects are thus roughly symmetric, indicating that the average effect of trade credit is similar in magnitude to the average effect of cash holdings. We thus view our trade credit results as economically significant.

Note also that those estimations hold prior to any contagion along the supply chain. The main implication for our estimations is that they may be seen as a lower bound, given only the most direct costs are measured.

6.2 Inter-firm heterogeneity

The average impacts estimated so far hide heterogeneity among firms. What are the determinants of that heterogeneity? We have seen above that *(i)* trade credit positions' impact on payment default is stronger in downstream sectors, and that *(ii)* the activity shock a company is facing needs to be big enough for the trade credit amplifier mechanism to materialize. In this section we consider two additional and closely related sources of heterogeneity: financial weakness and hedging strategies.

6.2.1 Financially constrained firms are more impacted

We first investigate the role of financial constraints on the probability of payment default. If trade credit position put firm's 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.

In Table 9, we run similar regressions to the main regression (column (9) of Table 6) except that we add a dummy D tagging financially constrained firms and interact that dummy D with firms' 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: 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. We already control for the size of the firm itself (total assets of the firm) and interpret this variable as a proxy for the existence of internal capital markets. The idea is that subsidiaries of large entities can benefit from transfers of liquidity from the group. In column (2) the dummy D is equal to one when the 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.[24] In column (3) the dummy D is equal to one when a firm has an industry marginal revenue product of capital (MRPK) above the industry median in the pre-Covid period.[25] 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.

Table 9 presents the triple difference estimates of the effect of the amplifier effect of trade credit on payment defaults conditional on our five proxies for financial constraints. Financially weaker firms experience a 0.0013 to 0.0019 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.

6.2.2 Hedging liquidity stress

We now study whether firms can offset the amplifier effect of trade credit by hedging the associated liquidity risk. In Table 10, we run similar regressions to the main regression (column (9) of Table 6) except that we add a dummy D tagging firms that have access to ways of managing liquidity risk during the Covid-19 crisis.

Firms have several ways of managing liquidity risk. First, they can retain cash holdings. In column (1), the dummy D is then set to one for cash-rich firms defined as firms with above-median level of cash prior to the Covid-19 crisis. Our triple interaction estimate ($HighCash \times TC \times Post$) shows that high-cash firms have a significantly lower probability of defaulting on their suppliers relative to low-cash firms in the crisis period. In addition, the magnitude of the coefficient is twice as

[24] This is approximately equivalent to having a long-term rating lower than BBB-/Baa3 from S&P/Moody's, just below the investment grade threshold.

[25] Following Bau and Matray (2023), we compute the pre-Covid period within-industry MRPK as the sales to capital ratio or the value added 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 average measure is above the industry median.

large as that 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.

Second, firms can rely on accounts receivable financing (ARF). 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. Receivable financing can take various forms and we consider both accounts receivable loans and factoring in our set-up.[26]

In columns (2) to (4) of Table 10, the dummy D is set to one for firms that strongly relied on factoring or account receivable financing prior to the Covid-19 crisis.[27] These regressions are carried out on firms having positive account receivable prior to the crisis. The effect is not significant for the average firm (column (2)), nor within the sample of small firms (column (3)). However, within the sample of large firms (column (4)), which also use ARF the most, high users with positive net trade credit exposure default less than low or non-users.

We also investigate heterogeneity regarding the availability of undrawn lines of credit but did not find any significant effect on that side. The absence of effect may stem 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). Thus firms that most needed to may not have actually been able to use them. The absence of effect may also come from the concentration, prior to the shock, of undrawn credit lines among the largest firms. So small firms did not have the opportunity to draw on such credit facilities (see Vinas, 2020), even though they were more impacted by the shock.

[26]Accounts receivable loans implies that firms got a loan by pledging their receivables. In the case of factoring the borrower sells its receivables to a factoring institution and transfers the risk of non-payment to the factor. We pool the two instruments as their use is rare.

[27]We calculate the firm yearly average amount of receivables financing from the Credit register data, and report it to the face value of receivables. A firm is a high user of ARF if its ratio lies above the median for firms using receivables financing (i.e., around 25%). However, while more than 10% of large firms use receivable financing, this is only the case for 5% of smaller firms.

6.3 Real effects

6.3.1 Payment defaults and investment dynamics

The trade-credit related change in liquidity needs we have identified so far is reflected in firms defaulting on paying their suppliers. These defaults suggest an imperfect ability to substitute trade credit financing with other sources of funding such as short-term credit. As such, payment defaults should have real effects. In the absence of any other margins of adjustment, firms can save on cash by reducing planned investments or by liquidating assets. To ascertain such effects, we estimate the conditional correlation between firm assets and investment expenditures, and payment defaults using yearly balance sheet data over the 2018-2021 period. We estimate the following specification:

$$\begin{gathered} I_{f,t} = \beta_1.Default_{f,t-1} + \beta_2.Default_{f,t-1} \times Covidperiod + \\ \delta.X_{f,t-1} + \kappa_f + \theta_{Industry,t} + \epsilon_{f,t} \end{gathered} \tag{4}$$

where $I_{f,t}$ is a variable measuring firm investments or firm change in total assets in year t, *Default* is a dummy which takes the value 1 if the firms has experienced at least one payment default during year t, and κ_f and $\theta_{Industry,t}$ denote firm and industry-year fixed effects respectively. Standard errors are clustered at the firm level.

In Table A6, we find that firms defaulting on paying their suppliers tend also to invest less and see a drop in their total assets. This effect is stronger in 2021 but not in 2020. We need to be cautious, though, in interpreting these results. In particular, firms that carry on defaulting on payment in 2020, in a period of extensive government support, are also likely to be firms with the worst financial health, with no financial leeway to invest.

The absence of additional effects in 2020 may be due to extensive liquidity support. One could also hypothesize that payment default may have been a way for the firm to protect investment and existing assets.

6.3.2 Payment defaults as predictors of bankruptcies

The relation between payment default and bankruptcy is virtually impossible to assess during the Covid-19 period as bankruptcy procedures in France were halted for administrative reasons, and because government fiscal support provided ample liquidity to firms, leading to an unprecedented drop in bankruptcy filings (cf. Section 4.2), which has prevailed until the end of 2021.[28]

However, in order to confirm the economic importance of our results, it remains very necessary to assess the link between payment defaults and bankruptcies. The pre-Covid period offers a much cleaner set-up to do so. In Table 11, we then test if, before the Covid period, both liquidity and dispute defaults are significant predictors of bankruptcy filings.

We run a linear probability model linking the monthly probability of filing for bankruptcy with payment default events from January 2017 to December 2019 using firm fixed effects as well industry-by-month fixed effects at the 4-digit level, thus absorbing the impact of sectoral shocks. We use a dummy set to one when the firm has defaulted at least once on one of its due bills over the previous three months and separately consider defaults due to liquidity issues, from defaults due to disputes between the supplier and her client. We discard defaults that are registered after the firm has already filed for bankruptcy ("solvency defaults"). We control for our baseline firm-level time-varying characteristics, as well as for the credit quality of the firm by introducing a dummy variable set to one for firms with below investment grade credit rating in the rating scale of Banque de France.

As expected, firms with low cash holdings and low-rated firms have a higher probability of going bankrupt. Neither the net trade credit position of the firm nor its leverage is associated with any significant effect on bankruptcy. Finally, the probability of bankruptcy is positively and significantly correlated with both dispute and liquidity defaults, the magnitude of the effect being ten times larger for the latter.

[28]See Banque de France website for detailed statistics.

These simple regressions suggest two things. First, payment defaults are significant predictors of bankruptcies, which strengthens the economic significance of the results highlighted in this paper. Second, the results confirm our intuition that dispute defaults are not all technical defaults and that some may hide financial vulnerabilities. This does not necessarily imply misreporting or strategic behavior, as logistical difficulties may worsen the situation of an already vulnerable company.

However, because we cannot disentangle the true nature of default events, we deem it preferable to consider all defaults, irrespective of the underlying reason reported by the bank.

7 Complementary evidence, robustness checks, and caveats

7.1 Complementary evidence

The online Appendix provides three sets of additional evidence about the amplifier effect of trade credit. First, Appendix C documents, in a conditional correlation analysis, that firms entering the crisis with high net trade credit position have benefited more from State-guaranteed loans than firms with low trade credit position. This piece of evidence, though illustrative, is consistent with the fact that they were in greater need of government liquidity support. Second, Appendix D shows that, during the Covid episode the trade credit amplifier effect was unique and that other operational or financial expenses such as wages, interest payments or rents did not generate a similar liquidity squeeze. We interpret our findings as the combined result of limited flexibility in debt payables management (renegotiating costs) 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 through short-time work schemes in France. Finally, in Appendix E we differentiate payment defaults based on the reasons for the default. We show clear evidence that "liquidity defaults" drive the overall effect, even though defaults due to litigations ("dispute defaults") also see a significant rise.

7.2 Robustness to other measures of the trade credit channel: Receivables and payables

In this paper, the firm's exposure to the trade credit channel is measured through the net trade credit position, computed as the difference between the 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 12, we then 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.[29] We expect a negative coefficient as accounts receivable 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 column (2), we consider accounts payable as the variable of interest. As expected, the coefficient is not significant prior to the crisis, but is positive and significant in the lockdown period.

Lastly, in column (3), we carry out the main regression with both payables and receivables as the main variables of interest. Prior to the crisis, the coefficients remain not significantly different from zero. But they become significant and with the expected signs (i.e., positive for payables, and negative for receivables) when they are interacted with the *Post* dummy.

[29] Just like in the main regression that information is one-year-lagged.

7.3 Robustness to the intensity of payment defaults

In Table 13, 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 13, whatever the dependent variable describing a firm's payment default, the main result remains: 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 of the default (columns (3) and (4)).

7.4 Robustness to empirical specification and sample definition

In Table 14, 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 acccordingly 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 exact same time for all firms. The main result remains. 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 columns 5 to 7 of Table 14: the results are unchanged and even stronger in these tests.

7.5 Strategic defaults

A caveat in our analysis is related to strategic defaults. The first kind of strategic default is the mischaracterization by the firm of the nature of default, so as to avoid being downgraded. More precisely the buyer may contest the quality of the good (dispute default) instead of recognizing her inability to pay because of liquidity issues (liquidity default). We show empirical evidence in Appendix E and Section 6.3.2 that is consistent with such behavior. That is why we do not use the information on the reasons underlying the default in our baseline scenario.

However, another kind of strategic behavior – that we do not model – may exist: one cannot fully discount the hypothesis that, during a period of major turbulence, some liquid firms defaulted strategically in order to keep their cash.[30] This is important for our analysis as: (i) net trade credit debtors have more incentives to default strategically, and (ii) we are not able to identify strategic defaults.[31] However, we believe that the likelihood of strategic defaults should not be overestimated because of the high associated costs (damage to the buyer-seller relationship, deterioration of the company's reputation, political pressure, potential downgrades by credit agencies, etc.). Most importantly, it does not call into question the interest of our results,

[30] For instance, one of the France's largest retailers, Le Printemps group, announced that on 20 March 2020 it was suspending payment of all outstanding supplier invoices. However, a few hours later, the Minister for the Economy and Finance used the "name and shame" mode via Twitter to criticize the group, and asserted that Le Printemps had just made a commitment to respect legal payment terms.

[31] Indeed dispute defaults by liquid firms during the first lockdown may well be strategic but it is also somehow "normal" that such disagreements on the delivery of goods increase during the lockdown because of disruptions to supply chains.

but rather supports our point that the trade credit is a channel of liquidy stress in period of activity shock.

8 External validity

8.1 Specificities of the French case

To what extent can our results be generalized to other contexts? As detailed above (see section 3.4), French legislation on payment terms is derived from the European Union legislative framework. Thus, at least within Europe, companies operate in a fairly similar legislative context.

However, one may argue that France differs from other major economies (e.g., the United States) as it defines maximum payment terms that, in principle, cannot be derogated by the parties involved. However, we have shown that in practice: (i) the enforcement mechanism in place is weak, and (ii) France ends up with a similar performance in terms of punctual payments to many other economies worldwide.

Are the costs of default different in France? As mentioned previously, the Banque de France can downgrade firms after a payment default. *Ceteris paribus*, it increases the cost of default compared to countries without such a mechanism. On the other hand, Plantin et al. (2013) argue that French bankruptcy law is unique in terms of international comparison as procedures in France offer a relatively lower level of protection of the interests of creditors relative to those of shareholders. This suggests that, from the firm point of view, bankruptcy costs may be relatively lower in France;[32] and so are default costs, *ceteris paribus*, if one sees a default as a first step toward bankruptcy. Overall, considering those two opposite effects, we cannot conclude that the costs of default are significantly different in France compared to other countries. More broadly, one may argue that most of these costs are fairly similar across most economies: damage to the buyer-seller relationship, deterioration

[32] As far as one considers the traditional shareholder-value framework where management should aim at maximizing shareholder wealth.

of the company's reputation, etc.

8.2 Beyond Covid-19

The Covid-19 outbreak provides a textbook case of a massive and exogenous activity shock. However, our results are not specific to the Covid crisis. Sharp activity shocks, i.e., massive and largely unanticipated activity shocks, are not unique to the Covid pandemic and likely to materialize again in the future in different instances. Sources of major activity shocks include geopolitical tensions (embargos, tariff wars, military war, etc.), or new pandemics. The Intergovernmental Panel on Climate Change (IPCC, 2022) indicates that environmental damages may foster pandemics, which may in turn prompt governments to apply individual movement restrictions and/or gathering bans (in the absence of vaccines and antiviral medication) – leading to major activity shocks. On the geopolitical side, no more than two years after the start of the Covid-19 outbreak, the Russian invasion of Ukraine on 24 February 2022 induced a sudden and major activity shock for exporting firms as Ukrainian imports fell by more than 70% within a month.[33]

9 Conclusion

In this paper we show that a firm's trade credit position greatly influences the impact of an activity shock on the firm's liquidity needs, prior to any propagation effect along the supply chain. We characterize both theoretically and empirically the temporary and cyclical nature of the liquidity stress induced by trade payment obligations.

Using the exogenous and unexpected Covid-19 shock in France in 2020, we estimate that, on average, a one standard deviation increase in the net trade credit position of a firm increases its monthly probability of payment default by 10% during the lockdown compared to the pre-Covid period level. This "amplifier" effect of trade

[33]Source: https://tradingeconomics.com/ukraine/imports.

credit depends on both the intensity of the shock and the extent to which firms rely on trade credit financing. As such, it is highly heterogeneous across and within sectors. It was much more pronounced in sectors that experienced the sharpest activity shocks, such as the retail trade sector for instance, with large variations within the sector and high trade credit users being the most exposed. In addition, at the firm level, financial constraints exacerbated the liquidity stress induced by trade credit, while, conversely, high cash buffers enabled firms to counterbalance it. While we put the spotlight on the role of firms' trade credit using the Covid-19 outbreak for identification reasons, the theoretical mechanism we depict holds for any significant unexpected drop in firms' sales.

Understanding better how firms working capital financing shape the transmission of shocks to their liquidity needs constitutes a fruitful avenue for future research and is central for policymakers seeking to enable illiquid but solvent companies to remain afloat until revenues recover.

References

Altman, E. I., M. Iwanicz-Drozdowska, E. K. Laitinen, and A. Suvas (2014). Distressed Firm and Bankruptcy Prediction in an International Context: A Review and Empirical Analysis of Altman's Z-Score Model. Working paper, NYU.

Amberg, N., T. Jacobson, E. von Schedvin, and R. Townsend (2021). Curbing shocks to corporate liquidity: The role of trade credit. *Journal of Political Economy 129*(1), 182–242.

Barrot, J.-N. (2016). Trade Credit and Industry Dynamics: Evidence from Trucking Firms. *Journal of Finance 71*(5), 1975–2016.

Bau, N. and A. Matray (2023). Misallocation and Capital Market Integration: Evidence From India. *Econometrica 91*(1), 67–106.

Berger, A. and G. Udell (1998). The economics of small business finance: The roles of private equity and debt markets in the financial growth cycle. *Journal of Banking and Finance 22*(6-8), 613–673.

Biais, B. and C. Gollier (1997). Trade Credit and Credit Rationing. *Review of Financial Studies 10*(4), 903–937.

Blanchard, O., T. Philippon, and J. Pisani-Ferry (2020). A new policy toolkit is needed as countries exit COVID-19 lockdowns. Policy Briefs 20-8, Peterson Institute for International Economics.

Boissay, F. and R. Gropp (2013). Payment Defaults and Interfirm Liquidity Provision. *Review of Finance 17*(6), 1853–1894.

Bureau, B. and L. Py (2021). Health crisis: French companies maintained their repayment capacity in 2020. *Banque de France Bulletin 238*(6), 1–16.

Burkart, M. and T. Ellingsen (2004). In-Kind Finance: A Theory of Trade Credit. *American Economic Review 94*(3), 569–590.

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.

Coricelli, F. and M. Frigerio (2019). Interenterprise Credit and Adjustment during Financial Crises: The Role of Firm Size. *Journal of Money, Credit and Banking 51*(6), 1547–1580.

Costello, A. M. (2020). Credit market disruptions and liquidity spillover effects in the supply chain. *Journal of Political Economy 128*(9), 3434–3468.

Cuñat, V. (2007). Trade Credit: Suppliers as Debt Collectors and Insurance Providers. *Review of Financial Studies 20*(2), 491–527.

Dass, N., J. R. Kale, and V. Nanda (2015). Trade Credit, Relationship-specific Investment, and Product Market Power. *Review of Finance 19*(5), 1867–1923.

Demmou, L., G. Franco, S. Calligaris, and D. Dlugosch (2021). Liquidity shortfalls during the COVID-19 outbreak: Assessment and policy responses. OECD Economics Department Working Papers 1647, OECD Publishing.

Díez, F. J., R. Duval, J. Fan, J. Garrido, S. Kalemli-Özcan, C. Maggi, S. Martinez-Peria, and N. Pierri (2021). Insolvency prospects among small and medium enterprises in advanced economies: Assessment and policy options. Technical report, IMF Staff Discussion Note 2021-002.

Fabbri, D. and L. F. Klapper (2016). Bargaining power and trade credit. *Journal of Corporate Finance 41*, 66–80.

Fabbri, D. and A. M. C. Menichini (2010, June). Trade credit, collateral liquidation, and borrowing constraints. *Journal of Financial Economics 96*(3), 413–432.

Fisman, R. and I. Love (2003, February). Trade Credit, Financial Intermediary Development, and Industry Growth. *Journal of Finance 58*(1), 353–374.

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.

Giannetti, M., M. Burkart, and T. Ellingsen (2011). What You Sell Is What You Lend? Explaining Trade Credit Contracts. *Review of Financial Studies 24*(4), 1261–1298.

Giannetti, M., N. Serrano-Velarde, and E. Tarantino (2021). Cheap Trade Credit and Competition in Downstream Markets. *Journal of Political Economy 129*(6), 1744–1796.

Gourinchas, P.-O., S. Kalemli-Ozcana, V. Penciakova, and N. Sander (2022). Estimating SME Failures in Real Time: An Application to the COVID-19 Crisis. Working Paper 27877, National Bureau of Economic Research.

IPCC (2022). Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Technical report, Cambridge University Press.

Jacobson, T. and E. von Schedvin (2015). Trade credit and the propagation of corporate failure: An empirical analysis. *Econometrica 83*(4), 1315–1371.

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

Klapper, L., L. Laeven, and R. Rajan (2012). Trade credit contracts. *Review of Financial Studies 25*(3), 838–867.

Lin, T.-T. and J.-H. Chou (2015). Trade Credit and Bank loan: Evidence from Chinese Firms. *International Review of Economics and Finance 36*, 17–29.

McGuinness, G., T. Hogan, and R. Powell (2018). European trade credit use and SME survival. *Journal of Corporate Finance 49*, 81–103.

Ng, C. K., J. K. Smith, and R. L. Smith (1999). Evidence on the Determinants of Credit Terms Used in Interfirm Trade. *Journal of Finance 54*(3), 1109–1129.

Petersen, M. A. and R. G. Rajan (1997). Trade credit: Theories and evidence. *Review of Financial Studies 10*(3), 661–691.

Plantin, G., D. Thesmar, and J. Tirole (2013). Reforming French Bankruptcy Law. Technical report, French Council of Economic Analysis – Notes 7.

Raddatz, C. (2010). Credit Chains and Sectoral Comovement: Does the Use of Trade Credit Amplify Sectoral Shocks? *Review of Economics and Statistics 92*(4), 985–1003.

Schivardi, F. and G. Romano (2020). A Simple Method to Estimate Firms Liquidity Needs during the COVID-19 Crisis with an Application to Italy. *Covid Economics 35*, 51–69.

Sufi, A. (2009). Bank lines of credit in corporate finance: An empirical analysis. *Review of Financial Studies 22*(3), 1057–1088.

Vinas, F. (2020). Outstanding loans to enterprises increased sharply in France in the first half of 2020. *Banque de France Bulletin 232/7*, 1–7.

Wilner, B. S. (2000). The Exploitation of Relationships in Financial Distress: The Case of Trade Credit. *Journal of Finance 55*(1), 153–178.

10 Figures

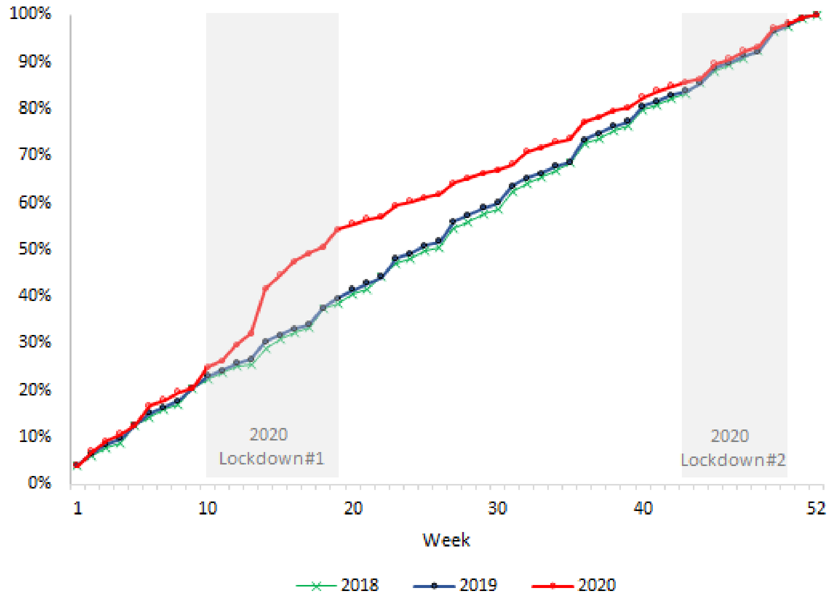


Figure 1: Cumulated number of payment defaults on trade bills, scaled by the total number of payment default events over the year

Notes: 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 total number of payment default events over the year. The shaded areas represent lockdown periods in 2020.

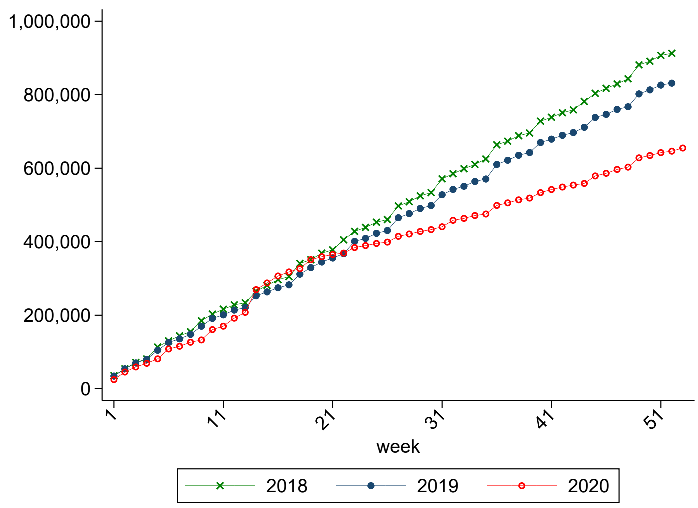


Figure 2: Cumulated number of payment defaults on trade bills

Notes: 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.

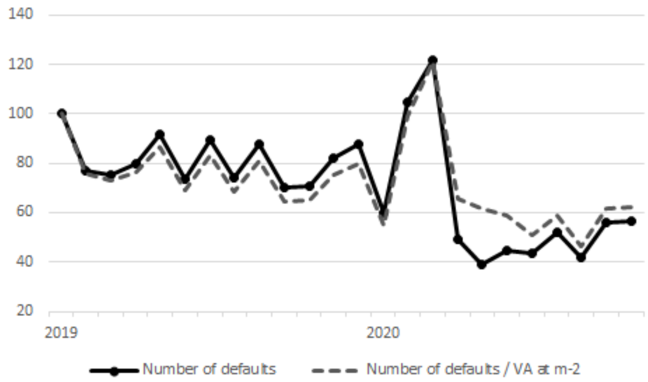


Figure 3: Monthly number of payment defaults on trade bills (Jan. 2019 = 100)

Notes: This Figure plots the monthly number of payment defaults on trade bills (solid line) and the monthly number of defaults on trade bills scaled by the monthly value added of firms (dashed line), in 2019 and 2020. We consider value added at month *m-2* in order to reflect the maximum payment terms of 60 days in France. Both series are set to 100 in January 2019.

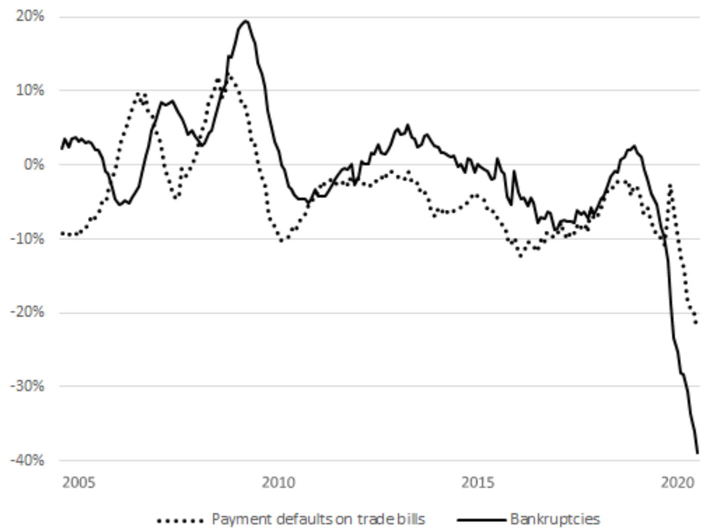
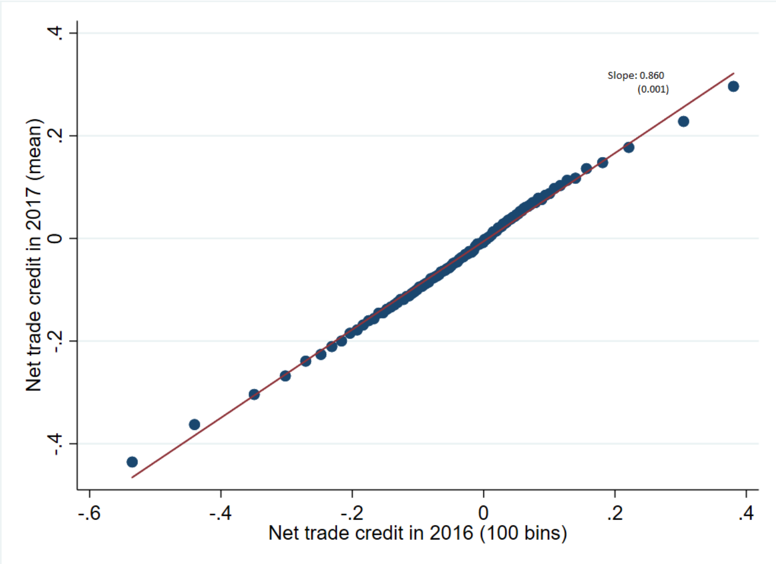


Figure 4: Payment defaults on trade bills vs. Bankruptcies (year-on-year growth rates of the cumulated number of defaults – resp. bankruptcies – over 12 months)

Notes: This Figure depicts the evolution of the number of payment defaults on trade bills (dashed line), and of the number of firms that file for bankruptcy (solid line). Series are built following a two stage process: (i) for each month of the January 2015 to December 2020 period, we compute the cumulated number of defaults (resp. the cumulated number of firms that file for bankruptcies) over the last 12 months; then (ii) we calculate year-on-year growth rates.
Lecture: In November 2006, the cumulated number of payment defaults over the Dec. 2005-Nov. 2006 period is 9% higher than the cumulated number of payment defaults over the Dec. 2004-Nov. 2005 period.

(a) 2016 vs. 2017



(b) 2016 vs. 2019

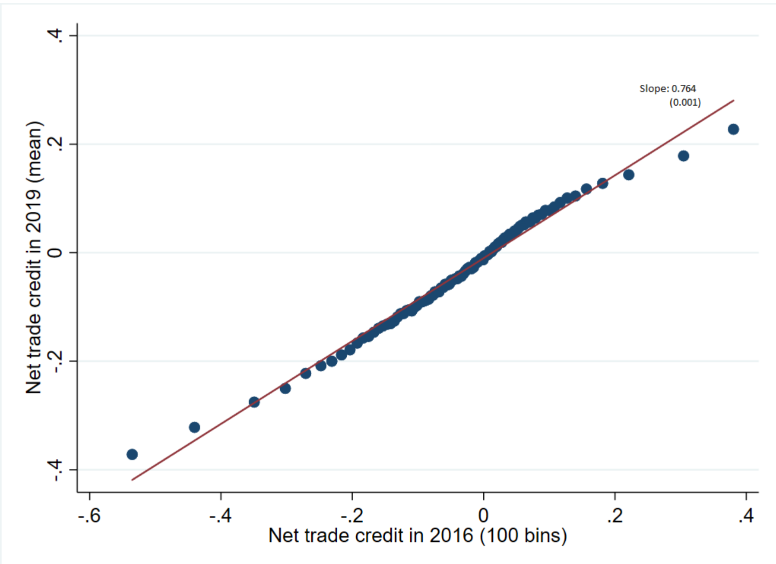


Figure 5: Binscatter plots of firm's net trade credit positions in two different years

Notes: The two panels are binned scatter plots of the net trade credit position (scaled by sales) for a firm i in 2016 vs. its net trade credit position in 2017 and 2019. The graphs are made based on the 145,000 companies present in the balanced sample using 100 quantile bins. The line is the result of an OLS linear regression (with the standard deviation in brackets).

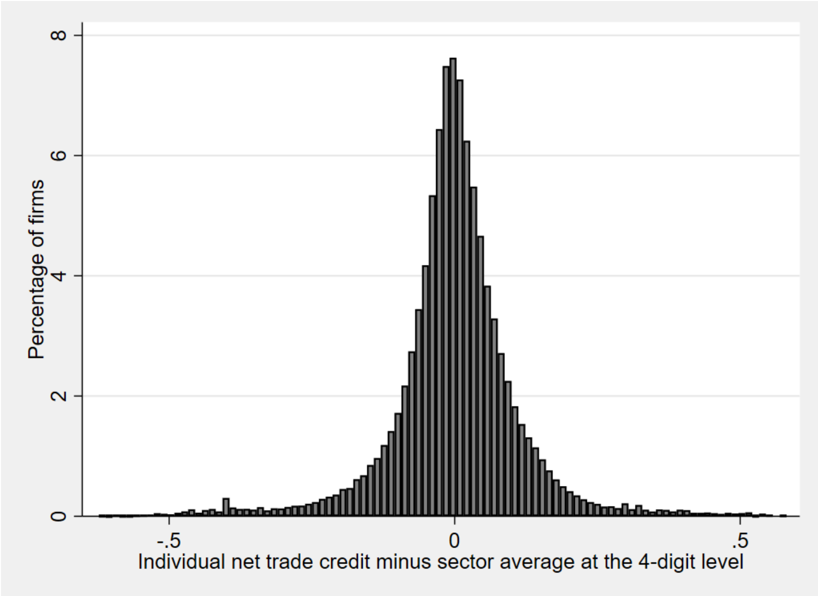


Figure 6: Within-industry heterogeneity of individual net trade credit positions

Notes: This Figure plots the histogram of the within-industry trade credit position in year 2019, that is, the difference between the ratio of net trade credit to sales for a firm i in industry j, and the average ratio of net trade credit to sales for all firms in industry j.

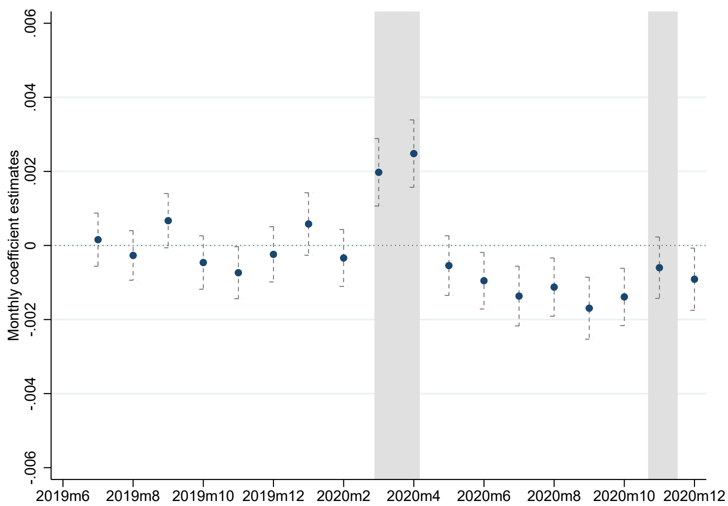


Figure 7: Monthly coefficient estimates of the effect of trade credit position on the probability of firm payment default

Notes: The observations are at firm $\times$ month level. 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)). The sample period of estimation is 2019m1 to 2020m12. Coefficients for each month, starting in 2019m7 are plotted, along with 95% confidence intervals.

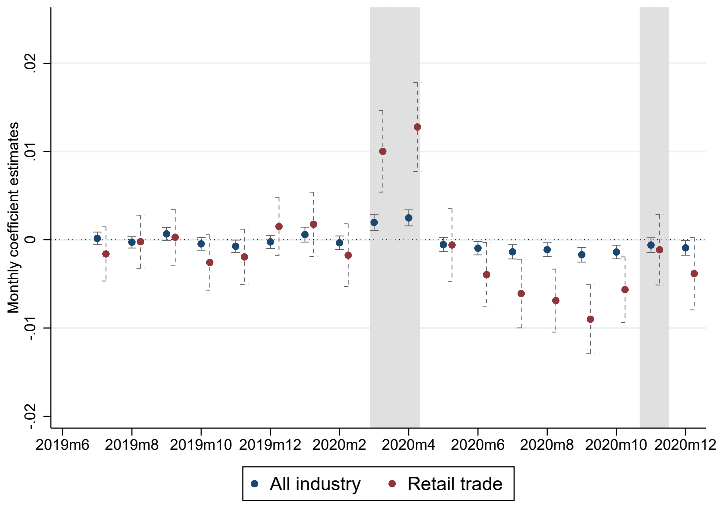


Figure 8: Monthly coefficient estimates of the effect of trade credit position on the probability of firm payment default : retail trade industry vs. all industries

Notes: The observations are at firm × month level. 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 7 as well as the results of the same estimation from the retail trade sector only. The sample period of estimation is 2019m1 to 2020m12. Coefficients for each month, starting in 2019m7 are plotted, along with 95% confidence intervals.

11 Tables

Table 1: The main measures implemented in France to help firms overcome their liquidity issues in 2020

	EUR billion	% of 2019 GDP
Subsidies		
Job retention scheme	26.5	1.1%
"Solidarity fund"	11	0.5%
Loans		
State-guaranted loans	130	5.4%
Deferrals of social security contributions	20	0.8%

Notes: Amounts at the end of 2020. Data from the French Ministry for the Economy and Finance, and from the French Ministry of Labor and Employment.

Table 2: 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 3: Firm-level characteristics (2018-2019)

Main balance-sheet characteristics	Mean	p5	p25	Median	p75	p95	Std.Dev.	N firms
Net trade credit to sales	-0.04	-0.26	-0.10	-0.02	0.04	0.15	0.14	172,198
Receivables to sales	0.14	0.00	0.03	0.12	0.20	0.39	0.14	172,198
Payables to purchases	0.17	0.04	0.09	0.13	0.20	0.43	0.14	172,198
Total assets	24.65	0.32	0.76	1.55	4.20	32.21	822.74	172,198
Sales in million euros	17.63	0.87	1.38	2.49	6.14	40.01	308.89	172,198
N of employees	56	1	6	12	30	150	853	172,198
Cash holdings to assets	0.19	0.00	0.04	0.13	0.29	0.60	0.19	172,198
Debt in million euros	9.61	0.00	0.07	0.25	0.89	9.02	401.70	172,198
Leverage (Debt to assets)	0.24	0.00	0.05	0.16	0.34	0.76	0.25	172,198
Apparent cost of debt	0.06	0.00	0.01	0.02	0.04	0.24	0.18	172,198
Non-performing loans to total loans	0.01	0.00	0.00	0.00	0.00	0.00	0.10	172198
Altman score	1.58	-2.27	0.62	1.79	2.89	4.79	2.25	172,198
Wages and benefits to sales	0.30	0.03	0.14	0.26	0.41	0.72	0.21	172,198
Rents to sales	0.04	0.00	0.01	0.03	0.06	0.14	0.05	172,198
State-guaranteed loan dummy	0.22	0.00	0.00	0.00	0.00	1.00	0.41	172,198
Financing constraints	Mean	p5	p25	Median	p75	p95	Std.Dev.	N firms
Return on assets	0.08	-0.09	0.02	0.06	0.13	0.31	0.13	172,198
Risky credit rating dummy	0.69	0.00	0.00	1.00	1.00	1.00	0.46	172,198
Non dividend payer dummy	0.50	0.00	0.00	1.00	1.00	1.00	0.50	172,198
Small firm dummy	0.79	0.00	1.00	1.00	1.00	1.00	0.41	172,198
Value added to capital (MRPK)	1.56	0.00	0.32	0.69	1.45	6.03	2.97	172,198

Table 4: Firm-level statistics by sector (1/2)

	Mean	p5	p25	Median	p75	p95	Std. dev.	No.firms
Accommodation and Food								
Net trade credit to sales	0.06	-0.02	0.03	0.05	0.09	0.20	0.08	10,149
Payables to purchases	0.15	0.04	0.08	0.12	0.18	0.37	0.13	10,149
Receivables to sales	0.02	-0.02	0.00	0.01	0.02	0.11	0.06	10,149
Agriculture								
Net trade credit to sales	-0.02	-0.33	-0.11	-0.02	0.06	0.31	0.18	2,074
Payables to purchases	0.22	0.04	0.10	0.16	0.27	0.57	0.17	2,074
Receivables to sales	0.16	-0.02	0.06	0.13	0.22	0.49	0.16	2,074
Construction								
Net trade credit to sales	-0.08	-0.27	-0.14	-0.08	-0.02	0.09	0.12	21,680
Payables to purchases	0.17	0.06	0.11	0.15	0.20	0.34	0.10	21,680
Receivables to sales	0.20	0.02	0.12	0.19	0.26	0.41	0.13	21,680
Corporate services								
Net trade credit to sales	-0.13	-0.44	-0.21	-0.13	-0.04	0.11	0.17	24,845
Payables to purchases	0.23	0.03	0.10	0.17	0.29	0.67	0.20	24,843
Receivables to sales	0.23	0.01	0.13	0.20	0.30	0.58	0.17	24,845
Health								
Net trade credit to sales	-0.04	-0.27	-0.09	-0.02	0.03	0.12	0.13	5,731
Payables to purchases	0.17	0.03	0.08	0.13	0.21	0.42	0.15	5,731
Receivables to sales	0.11	0.00	0.02	0.07	0.14	0.39	0.14	5,731
Information								
Net trade credit to sales	-0.11	-0.42	-0.20	-0.11	-0.02	0.15	0.17	5,534
Payables to purchases	0.25	0.05	0.12	0.19	0.29	0.70	0.20	5,534
Receivables to sales	0.24	0.02	0.13	0.21	0.31	0.61	0.17	5,534
Manufacturing								
Net trade credit to sales	-0.05	-0.22	-0.11	-0.05	0.01	0.12	0.11	28,679
Payables to purchases	0.18	0.06	0.11	0.15	0.21	0.40	0.12	28,679
Receivables to sales	0.17	0.02	0.10	0.16	0.21	0.36	0.11	28,679
Real-estate								
Net trade credit to sales	-0.05	-0.36	-0.11	-0.02	0.03	0.20	0.17	4,532
Payables to purchases	0.24	0.02	0.09	0.16	0.29	0.82	0.23	4,532
Receivables to sales	0.14	0.00	0.02	0.09	0.18	0.49	0.17	4,532
Recreation and other services								
Net trade credit to sales	-0.02	-0.23	-0.08	0.00	0.05	0.18	0.14	2,389
Payables to purchases	0.18	0.03	0.09	0.14	0.23	0.48	0.16	2,388
Receivables to sales	0.11	-0.00	0.01	0.08	0.17	0.36	0.14	2,389
Retail trade								
Net trade credit to sales	0.05	-0.06	0.02	0.05	0.08	0.18	0.08	36,206
Payables to purchases	0.12	0.03	0.06	0.10	0.14	0.27	0.09	36,206
Receivables to sales	0.04	0.00	0.00	0.02	0.05	0.16	0.07	36,206

Table 4: Continued (2/2)

Transportation								
Net trade credit to sales	-0.07	-0.22	-0.11	-0.07	-0.02	0.07	0.11	8,701
Payables to purchases	0.16	0.04	0.08	0.13	0.18	0.38	0.14	8,701
Receivables to sales	0.17	0.04	0.11	0.14	0.19	0.37	0.11	8,701
Wholesale trade								
Net trade credit to sales	-0.03	-0.19	-0.08	-0.02	0.02	0.13	0.11	21,678
Payables to purchases	0.15	0.03	0.09	0.13	0.18	0.35	0.12	21,678
Receivables to sales	0.15	0.02	0.09	0.13	0.19	0.33	0.11	21,678

Table 5: Activity shock in April and May 2020 – Percentage drop in sectoral GDP, with respect to 2019

	Sectoral GDP drop in%
Accommodation and food	-59%
Agriculture	-5%
Construction	-54%
Corporate services	-26%
Health	-20%
Information	-11%
Manufacturing	-26%
Real-estate	-3%
Recreation and other services	-45%
Trade	-31%
Transportation, storage	-35%

Source: Banque de France.

Table 6: Does trade credit position explain firms' payment default during the Covid-19 crisis?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
TC × Post		0.0009***							
		(0.0003)							
TC × March-April			0.0024***	0.0024***	0.0024***	0.0025***	0.0024***	0.0031***	0.0031***
			(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
TC × May-June			-0.0006**	-0.0006**	-0.0005*	-0.0005*	-0.0006*	0.0001	0.0001
			(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Trade credit (TC)	0.0002	-0.0001	-0.0001	0.0001	0.0002	0.0002	0.0002	-0.0003	-0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Cash holdings				-0.0010***	-0.0010***	-0.0010***	-0.0010***	-0.0011***	-0.0011***
				(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Leverage				0.0006**	0.0003	0.0003	0.0003	0.0004	0.0004
				(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Size				0.0001	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
				(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Non performing loans (NPL)						0.0130**			0.0124**
						(0.0051)			(0.0051)
Liquidity needs							0.0023***		0.0020**
							(0.0008)		(0.0008)
Z-score								-0.0007***	-0.0007***
								(0.0002)	(0.0002)
Cash × Post					-0.0010***	-0.0011***	-0.0009***	-0.0011***	-0.0010***
					(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Leverage × Post					0.0004*	0.0004*	0.0004*	0.0006***	0.0006***
					(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Size × Post					-0.0047***	-0.0047***	-0.0047***	-0.0048***	-0.0048***
					(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
NPL × Post						-0.0119***			-0.0101**
						(0.0045)			(0.0046)
Liquidity needs × Post							0.0008		0.0015
							(0.0011)		(0.0011)
Z-score × Post								0.0007***	0.0006***
								(0.0001)	(0.0001)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N firm clusters	172,198	172,198	172,198	172,198	172,198	172,198	172,198	172,198	172,198
N	3,099,564	3,099,564	3,099,564	3,099,564	3,099,564	3,099,564	3,099,564	3,058,782	3,058,782
Adj-R^2	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.26

Notes: The regressions examine to what extent the firm's trade credit position prior to the Covid-19 crisis explains its probability of payment default to suppliers during the Covid-19 crisis. 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. TC is the firm's net trade credit position prior to the crisis, computed as the difference between accounts payable and accounts receivable scaled by firm's sales. $March - April$ and $May - June$ are indicator variables set to one respectively in March and April 2020, and May and June 2020. *Post* is an indicator variable set to one from March 2020 on, and to zero before. Control variables include one-year lagged cash holdings, leverage, size, and Altman Z-score, as well as a three-month lagged ratio of non-performing loans over total loans (NPL) and the share of short-term loans out of total loans (Liquidity needs), and those same variables interacted with the dummy *Post*. All continuous independent variables have been standardised to facilitate the interpretation of coefficients. The definitions of these variables are 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 7: Sectoral analysis: does trade credit position explain firms' payment default during the Covid-19 crisis?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
High TC × March-April	0.0063**	0.0065**	0.0093***	0.0096***	0.0041***	0.0063	0.0026	0.0002	0.0016	0.0006	0.0012	-0.0023
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)
High TC × May-June	-0.0048***	0.0034	-0.0025	0.0009	-0.0010	0.0107**	0.0079*	-0.0004	0.0041*	0.0008	0.0009	0.0011
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.005)	(0.005)	(0.001)	(0.002)	(0.002)	(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	10,149	21,680	36,206	21,678	28,679	2,389	2,074	24,845	5,731	5,534	4,532	8,701
N	180,228	385,086	641,334	385,134	511,272	42,288	36,606	441,090	101,928	98,100	80,604	155,112
Adj-R^2	0.14	0.21	0.23	0.25	0.17	0.17	0.15	0.17	0.18	0.15	0.17	0.17
Industry	Accomodation, food	Construction	Retail trade	Wholesale trade	Manufacturing	Recreation	Agriculture	Corporate Services	Health	Information	Real estate	Transport, storage

Notes: This Table presents sector-level difference-in-differences regressions examining the effect of trade credit position on the probability of payment default to suppliers during the Covid crisis, by comparing firms with high and low reliance on trade credit prior to the crisis. 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. TC is the firm's net trade credit position prior to the crisis, computed as the difference between accounts payable and accounts receivable scaled by the firm's sales. $HighTC$ is an indicator variable which takes the value one when the firm net TC ratio lies in the above-median part of the sectoral trade credit distribution. $March-April$ and $May-June$ are indicator variables set to one respectively in March and April 2020, and May and June 2020. $Post$ is an indicator variable set to one from March 2020 on, and to zero before. Control variables include one-year lagged cash holdings, leverage, size, and Altman Z-score, as well as a three-month lagged ratio of non-performing loans over total loans (NPL) and the share of short-term loans out of total loans (Liquidity needs), and those same variables interacted with the dummy $Post$. All continuous independent variables have been standardised to facilitate the interpretation of coefficients. The 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 8: Focus on the retail trade sector: how does trade credit position explain firms' payment default during the lockdown?

	(1) Shutdown	(2) Open	(3) Shutdown	(4) Open
TC × March-April	0.0151***	0.0034		
	(0.002)	(0.004)		
TC × May-June	-0.0004	-0.0039		
	(0.002)	(0.003)		
High TC × March-April			0.0196***	0.0002
			(0.003)	(0.002)
High TC × May-June			-0.0025	-0.0019
			(0.003)	(0.002)
Trade credit (TC)	0.0009	0.0082**		
	(0.002)	(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
N firm clusters	18,480	17,726	18,480	17,726
N	327,222	314,112	327,222	314,112
Adj-R^2	0.25	0.30	0.25	0.30

Notes: This Table focuses on the subsample of firms operating in the retail trade industry and breaks down the analysis between firms that were forced to shutdown during the lockdown (columns (1) and (3)) and firms that keep operating as they were deemed "essential" by the French government (columns (2) and (4)). Regressions whose results are reported in columns (1) and (2) follow our baseline specification – see column (9) of Table 6. The regressions whose results are reported in columns (3) and (4) follow the specification presented in Table 7. All continuous independent variables have been standardised to facilitate the interpretation of coefficients. The 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 9: Effect of firms' trade credit position on their payment default conditional on financing constraints

	Size	Credit risk	Capital constraints	Profitability	Dividend payout
	(1)	(2)	(3)	(4)	(5)
	D=1 if SME	D=1 if High	D=1 if High	D=1 if None	D=1 if High
D × TC × Post	0.0014***	0.0019***	0.0018***	0.0017***	0.0013***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
TC × Post	0.0006	0.0006	0.0009***	0.0005	0.0008**
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
D × Post	0.0068***	0.0040***	0.0009*	0.0017***	0.0013**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
TC × D	0.0005	0.0004	0.0001	0.0009	-0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Trade credit (TC)	-0.0006	-0.0009	-0.0003	-0.0009	-0.0002
	(0.001)	(0.001)	(0.000)	(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
N firm clusters	172,198	122,617	172,198	172,198	172,198
N	3,058,782	2,181,180	3,058,782	3,058,782	3,058,782
Adj-R^2	0.22	0.22	0.22	0.22	0.22

Notes: In this Table, we analyse how the effects of the trade credit channel varies with the intensity of financing constraints. We follow our baseline specification – see column (9) of Table 6 – and augment it with a triple interaction term, by including a dummy D identifying the presence of financing constraint. We interact this dummy D with firm's trade credit position and the *Post* dummy identifying the onset of the Covid-19 crisis. We consider five dimensions for financing constraints: size (column (1)), credit risk (column (2)), capital constraints (column (3)), profitability (column (4)) and dividend payout (column (5)). In column (1), D is set to one if a firm is a standalone firm or if it belongs to a SME-sized group in 2019, and to 0 otherwise. In column (2), D is equal to one when a firm's rating prior to the Covid-19 crisis is below the minimum credit rating required for a loan to be eligible as collateral under the General Collateral Framework of the ECB. In column (3), 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, 2023). In column (4), D is equal to one when a firm has a return on assets below the 2018-2019 industry median. In column (5), D is equal to one when a firm did not pay any dividends in 2018 and 2019. All continuous independent variables have been standardised to facilitate the interpretation of coefficients. Standard errors, reported in parentheses, are clustered at firm level. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

Table 10: Effect of firms' trade credit position on their payment default conditional on hedging liquidity risk

	Liquidity	Risk management of receivables		
	(1) D=1 if High cash	(2) D=1 if Accounts receivable financing	(3) Small firms	(4) Large firms
D × TC × Post	-0.0029***	-0.0181	-0.0156	-0.0791**
	(0.001)	(0.014)	(0.015)	(0.038)
TC × Post	0.0021***	0.0014***	0.0015***	-0.0004
	(0.000)	(0.000)	(0.000)	(0.001)
D × Post	-0.0022**	0.0033*	0.0030	0.0012
	(0.001)	(0.002)	(0.002)	(0.007)
TC × D	0.0002	0.0347**	0.0342**	0.0552*
	(0.000)	(0.014)	(0.015)	(0.032)
Trade credit (TC)	-0.0003	-0.0003	-0.0002	-0.0004
	(0.000)	(0.000)	(0.000)	(0.001)
D	0.0004	-0.0016	-0.0020	0.0088
	(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
N firm clusters	172,198	162,946	153,002	9,859
N	3,058,782	2,845,086	2,670,516	173,058
Adj-R^2	0.22	0.22	0.21	0.35

Notes: 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 ways of managing liquidity risk. They can rely on precautionary 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 our baseline specification (see column (9) of Table 6) and augment it with a triple interaction term with an indicator variable D, which captures management of liquidity risk prior to the Covid-19 crisis. In column (1), the dummy D is set to one for firms with an above-median ratio of cash to assets. In columns (2) to (4), the dummy D is set to one for firms with a ratio of accounts receivable financing to receivables lying above the median for firms using receivables financing. Regressions in columns (2) to (4) are carried out on firms having positive account receivable prior to the crisis. In column (2), the analysis is run on all those firms, in columns (3) and (4), the analysis is broken down between small firms (column(3)) and large firms (column (4)). All continuous independent variables have been standardised to facilitate the interpretation of coefficients. Standard errors, reported in parentheses, are clustered at firm level. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

Table 11: Impact of firms' payment default due to illiquidity and disputes on the likelihood of bankruptcy, before the Covid-19 period

	(1)	(2)	(3)	(4)	(5)
At least one dispute default 3m	0.00007***		0.00007***	0.00007***	0.00007***
	(0.0000)		(0.0000)	(0.0000)	(0.0000)
At least one liquidity default 3m		0.00088***	0.00088***	0.00088***	0.00088***
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
Trade Credit				0.00002	0.00002
				(0.0000)	(0.0000)
Cash holdings				-0.00001*	-0.00001***
				(0.0000)	(0.0000)
Leverage				0.00000	-0.00001
				(0.0000)	(0.0000)
Size				0.00010	0.00012*
				(0.0001)	(0.0001)
Risky rating					0.00019***
					(0.0000)
Firm FE	Y	Y	Y	Y	Y
Industry-month FE	Y	Y	Y	Y	Y
N firm clusters	154,513	154,513	154,513	154,513	154,513
N	4,979,081	4,979,081	4,979,081	4,979,081	4,979,081
Adj-R^2	0.04	0.04	0.04	0.04	0.04

Notes: The regressions examine the determinants of the likelihood of bankruptcy prior to the Covid-19 crisis, among which payment defaults to suppliers. Defaults due to solvency reasons are discarded from the analysis as such events occur after the firm has filed for bankruptcy. The dependent variable is a dummy equal to 1 if the firm filed for bankruptcy in month t, and 0 if not. TC is the firm's net trade credit position prior to the crisis, computed as the difference between accounts payable and accounts receivable scaled by firm's sales. *At least one dispute default 3m* takes the value 1 during the 3 month-period over which a firm defaults on paying its suppliers due to litigation reasons, and 0 otherwise. *At least one liquidity default 3m* takes the value 1 during the 3 month-period over which a firm defaults on paying its suppliers due to liquidity motives, and 0 otherwise. Other control variables include one-year lagged cash holdings, leverage, size, as well a dummy set to one when the firm has a high-yield credit rating in the Banque de France rating scale (non eligible to General Collateral Framework of the ECB). All continuous independent variables have been standardised to facilitate the interpretation of coefficients. The definition of these variables are 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 12: Robustness: Does firms' gross accounts receivable and/or payable explain firms' payment default during the Covid-19 crisis?

	(1)	(2)	(3)
Receivables × Post	-0.0010***		-0.0014***
	(0.000)		(0.000)
Payables × Post		0.0004*	0.0009***
		(0.000)	(0.000)
Receivables	0.0005		0.0005
	(0.000)		(0.000)
Payables		0.0001	-0.0001
		(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
N firm clusters	172,198	172,198	172,198
N	3,058,782	3,058,782	3,058,782
Adj-R^2	0.26	0.26	0.26

Notes: In this Table, we use gross exposures – firm's accounts receivable and payable – instead of the net trade credit position of a firm. In column (1), we run our baseline specification (see column (9) of Table 6) except we substitute the net trade credit position with the one-year lagged level of firm's accounts receivable scaled by sales. In column (2), we substitute the net trade credit position with the one-year lagged level of firm's accounts payable scaled by sales. In column (3), we include both accounts receivable and accounts payable, as well as their interaction with the dummy *Post*, which is set to one over the period March to June 2020, and to zero before. All continuous independent variables have been standardised to facilitate the interpretation of coefficients. 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 dependent variable: Does firms' trade credit position explain the intensity of firms' payment default during the Covid-19 crisis?

	(1) Number of defaults	(2) Probability of multiple defaults	(3) AuD/Sales	(4) Amount under default
TC × Post	0.00242***	0.00109***	0.00001***	0.01523***
	(0.000)	(0.000)	(0.000)	(0.002)
Trade credit (TC)	-0.00016	-0.00003	0.00000	-0.00077
	(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
N firm clusters	172,198	172,198	172,198	172,198
N	3,058,782	3,058,782	3,058,782	3,058,782
Adj-R^2	0.28	0.21	0.18	0.23

Notes: In this Table, we carry out a set of robustness tests of our baseline specification (see column (9) of Table 6) by substituting the main dependent variable with variables describing the intensity of payment defaults. In column (1), the dependent variable 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 amount of default 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 amount of default of a given firm in a given month plus one euro. All continuous independent variables have been standardised to facilitate the interpretation of coefficients. 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 sample composition and to the specification: does trade credit position explain firms' payment default during the Covid-19 crisis?

	Independent firms	Fiscal year end December	Unbalanced panel	Industry-level clusters	Finer set of fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TC × Post	0.0024***	0.0011***	0.0011***	0.0016***	0.0015***	0.0019***	0.0019***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trade credit (TC)	-0.0000	0.0001	0.0003	-0.0003	-0.0003	-0.0005	-0.0005
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Covariates	Y	Y	Y	Y	Y	Y	Y
Covariates x Post	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y
Industry-month FE	Y	Y	Y	Y	Y	Y	Y
Size category-month FE					Y		Y
County-month FE						Y	Y
N firm clusters	54,382	122,033	249,921		172,198	133,041	133,041
N industry clusters				554			
N	948,258	2,284,128	3,855,000	3,058,782	3,058,782	2,247,666	2,247,666
Adj-R^2	0.26	0.27	0.28	0.26	0.26	0.27	0.27

Notes: In this Table, we challenge our results by running our baseline regression (see column (9) of Table 6) 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 fiscal year-end in December. In column (3), the regression is carried out using an unbalanced panel where we do not require firms to be present in both the pre-Covid and the Covid period (identified by *Post*). In columns 4 to 7, we challenge our baseline specification by changing the clustering level (column (4)), and by adding finer sets of fixed effects: size-month fixed effects (column (5)), county-month fixed effect (column (6)), both (column (7)). All continuous independent variables have been standardised to facilitate the interpretation of coefficients. 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)
Non performing loans	Ratio of non-performing loans (NPL) in month m over total loans in month m
Liquidity needs	Share of short-term loans in month m out of total loans in month m
Z-score	Altman Z-score in year t
High TC	Firms with a net trade credit ratio above the median of the sample distribution in the year preceding the Covid crisis
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

Online appendix

Activity shocks and corporate liquidity: the role of trade credit

Benjamin Bureau, Anne Duquerroy, Frédéric Vinas

A Conceptual framework: activity shocks, liquidity and trade credit

Several papers analyze the interactions between liquidity shocks and trade credit financing. However, this literature deals almost exclusively with liquidity shocks caused by credit crunches (Garcia-Appendini and Montoriol-Garriga, 2013; Coricelli and Frigerio, 2019; Costello, 2020) or customers defaults (Boissay and Gropp, 2013; Jacobson and von Schedvin, 2015).[34] Our paper adds an important dimension by examining another source of liquidity shocks: major and unexpected variations in economic activity, which will directly affect firm cash flow through the trade credit channel as detailed in this section.

To facilitate the understanding of the economic mechanism at play, we first derive simple analytical expressions of what forces drive cash flow shocks in the case of an activity shock, underlining the specific role of the trade credit channel. We then highlight the cyclical nature of the impact of activity shocks through trade credit. This analytical exercise then serves as a guide for the empirical strategy we implement in Section 5.

[34] Another paper by Amberg et al. (2021) considers a liquidity shock caused by fraud and failure of a cash-in-transit firm.

A.1 Activity shocks and trade credit

A.1.1 A simple model of cash flow

In order to illustrate the specificity of a liquidity shock due to a drop in activity, we consider the usual cash flow statement:

$$\Delta Cash_t = OperatingCF_t + InvestmentCF_t + FinancingCF_t \tag{5}$$

Equation (5) states that a firm's cash flow in period t ($\Delta Cash_t$) is equal to the sum of operating cash flows, investment cash flows and financing cash flows. We only consider operating and financing cash flows, and we assume that bank credit is the sole source of financing cash flows, hereafter noted NBC_t for net bank credit in period t. Operating cash flows can be rewritten as:

$$\begin{aligned} OperatingCF_t = (1-\delta_t^R).Sales_t - (1-\gamma_t^P).Costs_t \\ + \delta_{t-1}^R.Sales_{t-1} - \gamma_{t-1}^P.Costs_{t-1} \end{aligned} \tag{6}$$

Equation (6) states that a firm, with a given sales level in month t, noted $Sales_t$, is only partially paid in t. Indeed δ_t^R share of sales are paid with a delay (for example one period), that is, $\delta_t^R.Sales_t$ receivables are issued at time t. In the same way, γ_t^P is the share of costs in month t that are paid with a delay, and $\gamma_t^P.Costs_t$ is the level of payables issued at time t. The third term is the cash inflow related to receivables of the previous period and the fourth is the cash outflow related to payables.

For simplicity, assume that (i) the costs at time t are proportional to sales (no fixed costs), and that (ii) the relative issuance of receivables and payables is stable over time. The operating cash flow becomes (with $\delta^R = \gamma^P.c$):

$$OperatingCF_t = (1-c).Sales_t + (\delta^P - \delta^R).Sales_t - (\delta^P - \delta^R).Sales_{t-1} \tag{7}$$

The second and third terms of equation (7) are the change in firm's trade credit, with $(\delta^P - \delta^R).Sales_t$ the trade credit position at time t and $(\delta^P - \delta^R).Sales_{t-1}$ the trade credit position at time $t-1$. So equation (5) can be rewritten as:

$$\Delta Cash_t = (1-c).Sales_t + \Delta TC_t + NBC_t \tag{8}$$

with ΔTC_t the change in the firm's trade credit, $\Delta TC_t = (\delta^P - \delta^R).\Delta Sales_t$, and $\Delta Sales_t = Sales_t - Sales_{t-1}$.

A.1.2 Different cases of liquidity shocks

The business-as-usual case. In a business-as-usual situation, assuming activity is unchanged ($\Delta Sales_t = 0$), there is no cash flow related to trade credit: $\Delta TC_t = 0$. This is just as if the debt to suppliers and the credit to customers were continuously rolled over: on the receivables side, at time t, the firm issues $\delta^R.Sales_t$ and is paid $\delta^R.Sales_{t-1}$. The same applies on the payables side.

The case of a credit crunch. Relying on the simple accounting framework depicted through equation (8) it is clear that a credit crunch does not affect cash flows through the net trade credit position[35], but through the financing cash flow, NBC_t.

The case of a customer default. Let us now consider the event of a customer default at time t, that is, the firm does not get paid at time t for all its receivables issued at time $t-1$. Only a share of those receivables are paid, noted μ $(0 < \mu < 1)$. All other things being equal, in particular the firm's activity being unchanged ($Sales_{t-1} = Sales_t = Sales$), equation (8) becomes:

$$\Delta Cash_t = (1-c).Sales + \Delta TC_t + NBC_t \tag{9}$$

with $\Delta TC_t = -(1-\mu).\delta^R.Sales < 0$. This leads to a cash outflow through the trade credit channel.

The case of an activity shock. How does a negative activity shock affect the firm's

[35] Though it may have an *indirect* impact on other firms if it propagates along the supply chain, see, e.g., Costello (2020).

cash flow? In the most extreme case, assuming activity becomes null, and in the absence of customers' default, equation (8) becomes:

$$\Delta Cash_t = \Delta TC_t + NBC_t \tag{10}$$

with $\Delta TC_t = -(\delta^P - \delta^R).Sales_{t-1}$. So, if activity drops to zero, the firm's cash flow through the trade credit channel at time t is predetermined by (i) its trade credit position $(\delta^P - \delta^R)$, and (ii) its activity level at time $t-1$, $Sales_{t-1}$.

In more general cases, when activity has decreased but is still positive at time t, equation (8) becomes:

$$\Delta Cash_t = (1-c).Sales_t + (\delta^P - \delta^R).\Delta Sales_t + NBC_t \tag{11}$$

So a firm's cash flow through the trade credit channel at time t is determined by (i) the firm's net trade credit position $(\delta^P - \delta^R)$, and (ii) the activity shock $\Delta Sales_t$. A firm's trade credit position is the sign and magnitude of the term $(\delta^P - \delta^R)$. If the firm is a net trade credit provider ($(\delta^P - \delta^R)<0$), meaning that it has more trade receivables than trade payables, then the firm gets a positive cash flow at time t through its trade credit channel. On the other hand, if the firm is a net trade credit borrower ($(\delta^P - \delta^R)>0$), then the firm gets a negative cash flow through its trade credit channel as it has fewer trade receivables than trade payables. As detailed in Section 4.4.2, the trade credit position is partly linked to a firm's business sector. For example, as retail trade activities are usually paid in cash, with no delay, firms in that sector issue few trade receivables ($\delta^R = 0$). So, in the case of a negative activity shock, such firms get cash outflows structurally through their trade credit channel.

A.1.3 What differentiates liquidity shocks induced by activity shocks?

The underlying mechanisms are very different in the credit crunch and activity shock cases. In the credit crunch case, financing cash flows are stressed (NBC_t) and reliance on trade credit can mitigate that financing shock (Garcia-Appendini and Montoriol-Garriga, 2013; McGuinness et al., 2018). On the other hand, in the activity shock case, it is the other way around: the stress occurs directly through the net trade credit channel, depending on the degree of reliance on net trade credit debt. In this case, financing cash flows (NBC_t) can mitigate the shock.

The customer default and activity shock cases also differ. In the customer default case, the liquidity shock applies on the trade bill of a given customer and depends on receivables. In an activity shock, the liquidity shock is proportional to (i) the firm's net trade credit position and (ii) the activity shock. In the case of an activity shock, the firm has few options to preserve its cash flow. In particular, it is difficult to adjust its trade credit position by decreasing the level of receivables issued at time t or by negotiating a higher level of payables at time t, because sales are much lower and paying late is not costless. The firm can absorb the liquidity shock (i) by using its available cash holdings, (ii) by obtaining short-term financing from its bank, either by drawing on existing credit lines or by applying for a new loan ($NBC > 0$), or (iii) by defaulting on a supplier.

A.2 Liquidity shocks through the trade credit channel are cyclical

We have just seen that trade credit influences the magnitude of the liquidity shock induced by a drop in activity. We now highlight the cyclical nature of this effect.

When demand suddenly falls (e.g., during a lockdown), the firm still needs to meet its payment obligations towards its suppliers contracted before the shock. However, cash flows decrease as demand drops. If the firm is a net trade credit borrower (respectively a net trade credit lender), this leads to cash outflows (respectively inflows) and to liquidity stress (or an increase in liquidity) potentially leading to payment default.

When activity recovers,[36] it is the other way around. Depressed demand has lowered input needs, thus reducing the level of payables issuance during the lockdown, while the rebound in sales boosts cash and receivables, leading to cash inflows for initially net borrowers (respectively outflows for net lenders). These two phases contrast with the "business-as-usual" case (see Section A.1), where there are no liquidity flows induced by the trade credit channel ($\Delta TC_t = 0$).

Figure A1 describes these three situations. It shows the cash flow dynamics due to the trade credit channel over the 2019m1-2020m12 period for two representative firms belonging to two different sectors. More precisely, the Figure shows the evolution of the second term of the equation (11), i.e., the change in firm's net trade credit defined as: $\Delta TC_t = (\delta^P - \delta^R).\Delta Sales_t$. The firm's trade credit position, computed at the 1-digit sector level in 2018, is assumed to be constant over the period, and activity, $\Delta Sales_t$, is proxied by monthly changes in value added at the same sector level. Panel A of Figure A1 focuses on the accommodation and food sector, in which firms typically have more debt payables than account receivables (cf. Section 4.4.2) so that they are net trade credit borrower. Conversely, Panel B focuses on the corporate services sector, in which firms typically have more receivables than payables (cf. Section 4.4.2), so that they are net trade credit lenders.

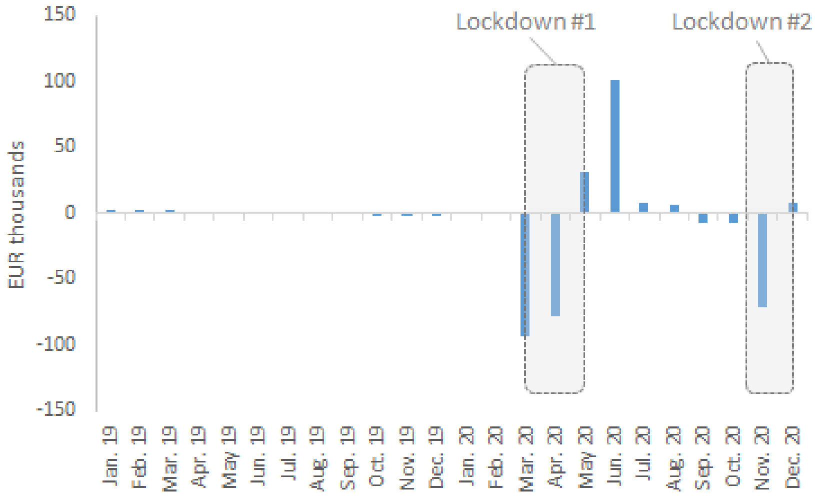
Whatever the sector, the bar charts show that throughout 2019, i.e., during the business-as-usual period, trade credit hardly affects cash flows. In other words, a firm's trade credit position is mainly rolled over. Things are very different in 2020: the average firm in the accommodation and food sector faces sharply negative cash flows due to its trade credit position in March and April, because of the first lockdown (17 March to 11 May 2020). As expected, the end of the lockdown induces positive cash flows in May and June. Another major decline in cash flows occurs in

[36] The demand shock is not necessarily temporary, but may last because of new habit formation in consumption patterns. In other words, one cannot discount the possibility that activity does not recover.

November because of the second lockdown (30 October to 15 December 2020).

On the contrary, in the corporate services sector, the net trade credit position of the average firm attenuates the negative impact of the drop in activity during the first lockdown. Conversely, negative cash flows arise after the lockdown. The impact of the second lockdown is hardly visible, because of a much smaller drop in activity.

(a) Accommodation and food



(b) Corporate services

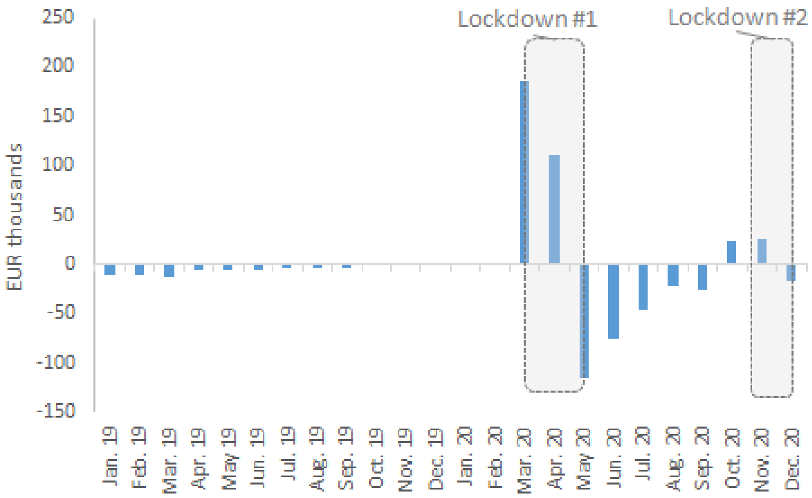


Figure A1: Monthly cash flows due to the trade credit channel

Notes: This figure presents the monthly cash flows due to trade credit (i.e., the second term on the right hand side of equation (11)) for the average firm in the accommodation and food sector (panel A), and for the average firm in the corporate services sector (panel B). Calculations rely on the following *ad hoc* hypothesis: within each sector, the ratio of trade credit over value added is supposed to be constant over time; so that the dynamics of trade credit follows the one of value added. We use the average amount of trade credit within each sector at the end of 2018 (EUR -207,000 in the accommodation and food sector, and EUR +846,000 in the corporate services, respectively) and the growth rate of value added to calculate trade credit in January 2019. Then we calculate monthly variations of trade credit based on the monthly growth rate of value added.

B What drives the within-sector heterogeneity of individual trade credit positions?

The goal of this appendix is to give insights on how and why trade credit varies within industries. We list some of the most prominent determinants of trade credit discussed in the literature, and present correlations calculated using our sample of French firms.[37]

These correlations are presented in Table A1. It relies on a balanced sample of around 145,000 firms present in the FIBEN database over the 2016-2019 period. Correlations are estimated successively for the payables over purchases ratio, the receivables over sales ratio, and the net trade credit ratio, defined as the difference between payables and receivables, scaled by sales. We include industry-by-year fixed effects to focus on within-sector variations, and firm fixed effects to control for the unobserved characteristics of the firm that do not vary over time.

Before proceeding, note that the sole sector (defined at the 4-digit level) explains 14% of the variance of individual payables ratios in our 2016-2019 sample, 34% of the variance of individual receivables ratios between firms, and 29% of the variance between the individual net trade credit positions.[38] So while industry is a key determinant of trade credit, much within-industry heterogeneity remains.

What drives this heterogeneity? According to the existing literature, some of the most prominent determinants of trade credit are firm size, age and financial constraints. The effect of each one of these variables are however theoretically ambiguous. They are also non-independent one from another, younger firms being typically smaller and more constrained.

[37]A fully detailed analysis of the determinants of trade credit is out of the scope our paper. The complexity of the mechanisms at work would require a much longer analysis to properly handle the facts that: (i) the identification of the impacts on the net trade credit ratio is not straightforward but depends on (potentially) different but (mechanically) related impacts on buyers and sellers, (ii) rigorous estimations would require dealing with various endogeneity issues, (iii) the theoretical literature does not always offer clear-cut predictions but, on the contrary, often suggests competing explanations.

[38]If we define the sector at the 1-digit level (like in Table 4), the figures are 6%, 21% and 19%, respectively.

The importance of firm size has been largely emphasized in the analyses of trade credit. On the one hand, as firm size reflects bargaining power (Giannetti et al., 2011, 2021; Dass et al., 2015; Fabbri and Klapper, 2016; Coricelli and Frigerio, 2019), larger firms can extract trade credit from smaller ones. The ratio of payables to sales should thus increase with size, ceteris paribus. Within smaller firms, even within the same sector, the supply of trade credit may thus vary depending on whether firms act as suppliers of inputs for larger firms or not. On the other hand, large firms are also in a better position to offer trade credit, as size reflects scale economies in extending trade credit[39], as well as better endowment with liquid assets and easier access to external finance. Then receivables over sales should increase with size, ceteris paribus. Table A1 shows that net trade credit (payables less receivables over sales) actually increases with size (cf. column (3)) so that empirically the bargaining power effect dominates in our sample over the 2016-2019 period. Note that to the extent that size also captures some form of constraints, this first result suggests that the least constrained firms tend to use trade credit the most in our sample.

Trade credit has also been explicitly related to financial constraints and in particular firm access to short-term liquidity. A large set of papers have looked into the financing role of trade credit and its higher use by financially constrained firms (e.g., Biais and Gollier, 1997; Burkart and Ellingsen, 2004; Fabbri and Menichini, 2010; McGuinness et al., 2018). Financially sound firms with access to outside finance or large cash holdings thus provide liquidity insurance to their constrained suppliers through trade credit provision (Boissay and Gropp, 2013; Garcia-Appendini and Montoriol-Garriga, 2013).

In addition, Klapper et al. (2012) show that only the most creditworthy buyers receive contract with longer maturities. In Table A1, we use the Altman score of the firm as a synthetic measure of its overall credit quality. We show that payables

[39] As Ng et al. (1999) point out: "Fixed costs associated with investigating credit quality, along with fixed costs of managing outstanding credit, are spread over more customers as the firm's customer base expands. Furthermore, the larger the seller's customer base, the greater the likelihood that experience with some customers will yield information on the default risk of others."

are significantly lower for high score firms (column (1)), which is in line with the widespread idea that trade credit is most common among firms that face borrowing constraints, because they are less creditworthy.

Turning to the sellers' side, column (2) of Table A1 shows that receivables and the Altman score are positively correlated. This result is in line with the literature that suggests that financially stronger firms offer more trade credit (Petersen and Rajan, 1997; Ng et al., 1999; Barrot, 2016). Overall, in our sample, net trade credit is significantly higher for low credit score firms (column (3)).

Now looking at cash holdings, the correlation between cash holdings and trade credit borrowings is not clear-cut. Indeed, accounts receivable, accounts payable and cash are mechanically linked: cash-rich firms may be more inclined to extend trade credit (Garcia-Appendini and Montoriol-Garriga, 2013) but constrained firms may preserve their cash holdings by increasing their use of trade credit. Overall, Table A1 shows that cash is positively correlated with debt payables (column (1)) and net debt (column (3)).

Ng et al. (1999) argue that, from a seller's perspective, dealing with an international customer intensifies information problems concerning credit quality and therefore increases the likelihood of demanding cash payment. In line with this reasoning, we find that the correlation between receivables and an export dummy (equals to one if the firm has positive export sales) is significant and negative (column (2))[40]. The impact of exports on payables is also negative and, in the end, the impact of export sales on net debt is not significant.

The age of the firm may also impact its use of trade credit along dimensions than are often linked with its size and liquidity constraints. Berger and Udell (1998), for example, show that trade credit is an essential source of financing for firms at an early stage of development, as access to external finance is more difficult. However,

[40]Note that Ng et al. (1999) also suggest that international customers are more likely to experience delivery delays, and be unfamiliar with the supplier. These factors increase the probability of buyers demanding trade credit, which in turn may increase account receivables of exporters. This effect does not dominate in our estimates.

as trade credit requires trust and reputation, on the buyer side, younger firms may also have more difficulty in benefiting from trade credit financing (Fisman and Love, 2003). On the seller side, alternatively, younger firms lacking tracked records may be compelled to offer longer payment delay thus providing more trade credit, to provide time for customers to verify the quality of the products (Petersen and Rajan, 1997; Ng et al., 1999). Heterogeneity along this dimension is difficult to test in our sample as age is absorbed by our firm fixed effect and as our firms are pretty mature firms (the average firm is more than 20 years old) making it difficult to infer anything about young firms.

In the end, both literature findings and our in-sample empirical tests show that there is no clear-cut evidence or theory unambiguously linking net trade credit to firm characteristics, ahead of the position of the firm in the supply chain. Both financially stronger and weaker firms have incentives to use trade credit. In our empirical strategy, we will control for observable characteristics of the firm as well as for firm fixed effects to capture each one of the above mentioned characteristics (i.e., size, credit quality, and liquidity constraints – but not explicitly for age or for the export dummy variable which are absorbed by our firm fixed effect).

Table A1: The determinants of trade credit

	(1) Payables	(2) Receivables	(3) Net Trade credit
Size	-0.016***	-0.021***	0.008***
	(0.001)	(0.001)	(0.001)
Altman score	-0.017***	0.007***	-0.021***
	(0.000)	(0.000)	(0.000)
Export	-0.002***	-0.002***	0.001
	(0.001)	(0.000)	(0.000)
Cash holdings	0.006***	-0.078***	0.074***
	(0.002)	(0.001)	(0.001)
Adjusted R^2	0.78	0.86	0.84
Firm FE	Y	Y	Y
Industry-year FE	Y	Y	Y
No. firm clusters	136023	136024	136024
No. observations	514739	514713	514713

Notes: This table reports the correlation between firm's payables (column(1)), receivables (column(2)) and firm's net trade credit (column(3)) with several firm's features: firm's size, Altman score, export and cash holdings. *Size* is defined as the log of total assets. *Export* is a dummy equal to one if the firm has positive export sales. Correlation estimations rely on a balanced sample of around 145,000 firms present in the FIBEN database over the 2016-2019 period. Correlations are estimated successively for the payables over purchases ratio, the receivables over sales ratio, and the net trade credit ratio, defined as the difference between payables and receivables, scaled by sales. We include industry-by-year fixed effects at the 4-digit level to focus on within-sector variations, and firm fixed effects to control for the unobserved characteristics of the firm that do not vary over time. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

C Reliance on State-guaranteed loans

As shown in the paper, meeting payment obligations to suppliers contracted through the use of trade credit, put corporate liquidity under stress during the lockdown. As a result, we should expect firms entering the crisis with high net trade credit exposures to be in greater need of government support, ceteris paribus. To check whether this is the case, we test whether a firm's trade credit position is indeed conditionally correlated with State-guaranteed loan demand.[41]

This scheme was tailored as a public guarantee on new loans granted by financial institutions to non-financial firms. The guarantee covered 90% of the loan amounts for SMEs and 70%-80% for larger firms. The interest rate on those loans at cost price was 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 could borrow was capped at three months of its 2019 sales.

In Table A2, we carry out a cross-sectional analysis in which we regress the probability of getting a State-guaranteed loan between March and June 2020 on firm one-year lagged observable characteristics. This evidence is arguably only suggestive as we cannot have firm fixed effects in such a set-up and unobservables may drive the results. To limit such effects, we redefine our industry fixed effect at the finest grain possible (5-digit). Standard errors are clustered at the industry level.

As reported in column (1), the higher the trade credit position of a firm prior to the crisis, the higher the probability of applying and getting a State-guaranteed loan. Adding additional firm-level controls modifies the coefficient estimate slightly, but it remains strongly significantly positive. Looking at other determinants including firm characteristics (column (2)), as expected, we find that cash-rich, low-leverage and larger firms have a lower probability of asking for a State-guaranteed loan. When

[41] We only observe accepted demand. However, final rejection rates were very low. As of 24 July 2020, the rejection rate was 2.7% according to the Ministry of Economy and Finance. In addition, after a rejection, firms were able to apply to the French mediation program in order to have their case settled. The mediator reports that "solutions" were found for around half of cases (cf. 26 January 2021 press release).

we add additional controls for operational expenses (column (3)) as well as for firms' credit risk (column (4)), our main result remains unchanged, meaning that firms' trade credit position prior to the crisis was strongly correlated with State-guaranteed loan demand during the crisis. The effect is even more pronounced in sectors with high exposure to the trade credit channel, as shown by the twice as large magnitude of our last estimate for the retail trade sector in column (5).

Table A2: Determinants of the subscription to State-guaranteed loan

	(1)	(2)	(3)	(4)	(5) Retail Trade
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***	-0.036***	-0.047***
		(0.003)	(0.003)	(0.003)	(0.004)
Leverage		0.013***	0.012***	-0.000	-0.003
		(0.002)	(0.002)	(0.002)	(0.003)
Size		-0.033***	-0.032***	-0.025***	-0.028***
		(0.003)	(0.003)	(0.003)	(0.007)
Wages & benefits/Sales			0.003	0.000	0.004
			(0.003)	(0.002)	(0.006)
Cost of debt			-0.001	-0.002**	-0.005***
			(0.001)	(0.001)	(0.002)
Rents/Sales			0.005**	0.004	0.010
			(0.003)	(0.002)	(0.007)
Risky rating				0.133***	0.126***
				(0.006)	(0.012)
Industry FE	Y	Y	Y	Y	Y
N industry clusters	667	667	667	667	116
N	172,197	172,197	172,197	172,197	57,884
Adj-R^2	0.065	0.088	0.089	0.109	0.128
Industry	All	All	All	All	Retail trade

Notes: In this Table, the dependent variable is an indicator variable which takes the value one if a firm benefits from a State-guaranteed loan over the period March-June 2020, and zero otherwise. In column (1), we investigate the correlation between subscription to a State-guaranteed loan and trade credit position prior to the crisis. In column (2) we add the firm's characteristics (cash holdings, leverage and size). In column (3), we add the firm's expenses (wage bill, interest expenses, rents), and, in column (4), we control for the firm's credit risk. All these variables are calculated prior to the Covid crisis. In column (5), we zoom in on the retail trade sector. All continuous independent variables have been standardised to facilitate the interpretation of coefficients. Standard errors, reported in parentheses, are clustered at firm level. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

D Comparison with operational and financial expenses

In this Appendix, 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.

However, some expenses proved easier to curb than others during the Covid crisis, because of differential policy support treatment. For example, in Europe, one of the main measures 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.[42] 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.[43]

On the other hand, accounts payable are costly to manage. As detailed in Section 3.4.2, the cost of delayed payments is not so much a direct financial cost tied to the strict enforcement of the European Late Payment Directive. But it first materializes through the alteration of 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: negotiation with their suppliers and asking banks for additional debt; the outcome of both solutions is quite uncertain.[44]

However, as stated above, and to the best of our knowledge, papers addressing the impact of the Covid-19 lockdown on firms' liquidity have not considered the

[42] See, e.g., Bruegel's review of the fiscal response to the economic fallout from the coronavirus.

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

[44] For instance, in France, State-guaranteed loans were not supposed to be used to roll over debt.

trade credit channel (see, e.g., Carletti et al., 2020; Schivardi and Romano, 2020; Demmou et al., 2021). They exclusively focus on the role of labor costs, property rental costs and debt interest as sources of liquidity stress. In Table A3, we estimate the impact of those three sources of liquidity stress on default on 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 and *Post*. Not only is our estimate of the trade credit channel 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 firms' liquidity under stress. But the findings suggest that (i) either government support enabled firms to offset those effects (particularly in the case of labor costs), (ii) or that firms may have managed to defer or renegotiate payment (on corporate debt or rents) when needed, so that such expenses did not weigh sufficiently on firm liquidity to materialize in payment default on suppliers. In other words, unlike 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.

Table A3: To what extent do labor, interest or rent expenses explain payment default during the Covid-19 crisis?

	(1)	(2)	(3)
TC × Post	0.0017***	0.0016***	0.0016***
	(0.000)	(0.000)	(0.000)
Wages/Sales × Post	0.0005*		
	(0.000)		
Interest expenses/Debt × Post		-0.0001	
		(0.000)	
Rents/Sales × Post			-0.0002
			(0.000)
Wages & benefits/Sales	0.0003		
	(0.000)		
Interest expenses/Debt		0.0000	
		(0.000)	
Rents/Sales			0.0001
			(0.000)
Trade credit (TC)	-0.0003	-0.0003	-0.0003
	(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
N firm clusters	172,198	172,198	172,198
N	3,058,782	3,058,782	3,058,782
Adj-R^2	0.26	0.26	0.26

Notes: In this Table, we run our baseline regression (see column (9) of Table 6) and control for additional sources of fixed and variable expenses. We add the firm's payroll in column (1), measured as the one-year lagged ratio of wage bill to sales. In column (2), we add the firm's one year-lagged ratio of interest expenses to total debt. We add the one-year lagged ratio of rents to sales in column (3). We interact each of these control variables with the dummy *Post*, which is set to one over the period March to June 2020, and to zero before. Other covariates are defined as in the baseline regression (see Table 6). All continuous independent variables have been standardised to facilitate the interpretation of coefficients. Standard errors, reported in parentheses, are clustered at firm level. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

E Trade credit exposure led to a substantial increase in defaults for liquidity reasons

In this Appendix, we explore the differentiated impact of trade credit exposure on payment defaults based on the nature of the default. Payment defaults encompass a variety of events, the nature of which is available in our data, as banks have to report the reason for any missed payment. There are three broad categories of reasons underlying a default event: some disagreement on the delivery of the goods ("dispute defaults"), the inability of the firm to meet its payment obligations on time because of insufficient funds in its bank account ("liquidity defaults"), and the insolvency of the firm when the firm has already filed for bankruptcy or commenced a liquidation process ("solvency defaults").

Table A4 provides separate results for each one of these subcategories of defaults, showing clear evidence that liquidity defaults are driving the overall effect during the lockdown, even though there is also a significant jump in dispute defaults at that time. After the economy reopens in May and June 2020, the propensity for liquidity defaults decreases significantly.

One critical difference between liquidity and dispute defaults is that liquidity defaults can trigger a downgrade of the Banque de France's rating of the defaulting firm, while dispute defaults do not.[45] While this rating is not public, banks have the information and may use it in their loan granting decisions. Significant liquidity default events can thus endanger the future ability of firms to borrow, or their cost of borrowing, through this rating channel. As such, it is more costly for a firm not to be able to pay its bill on time. Firms thus have incentives to misreport the true nature of the reason for default. Boissay and Gropp (2013) show that

[45] In addition to internal credit ratings by banks, and external ratings by private agencies, various national central banks produce their own corporate credit ratings (including France, Germany, Italy, Portugal and Spain). Their main use is to determine the eligibility of bank loans as collateral for Eurosystem funding. The Banque de France thus assigns credit ratings to all French non-financial companies with a turnover greater than EUR 750,000. The rating is an assessment of firms' ability to meet their financial commitments over a three-year horizon. Firms do not request or have to pay for those external ratings.

firms that default for liquidity reasons are more financially vulnerable than firms that default for disagreement reasons, meaning that reporting is somewhat truthful. However, this does not preclude that some firms mis-characterize the nature of a default for strategic motives. While we expect an increase in dispute events at the onset of the Covid-2019 crisis, as the lockdown created operational constraints which hampered deliveries, incentives not to report the true nature of defaults are also likely to be higher. Indeed avoiding downgrades is especially critical at a time of elevated uncertainty about future ability to access bank finance. For these reasons we consider all payment defaults in our analysis.

Table A4: Impact of trade credit position on changes in firms' payment default by nature of default, during the Covid-19 crisis

	(1) Solvency defaults	(2) Disagreement defaults	(3) Liquidity defaults
TC × March-April	0.0001*	0.0009***	0.0021***
	(0.000)	(0.000)	(0.000)
TC × May-June	0.0000	0.0001	-0.0001
	(0.000)	(0.000)	(0.000)
Trade credit (TC)	-0.0001	0.0001	-0.0002
	(0.000)	(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
N firm clusters	172,198	172,198	172,198
N	3,058,782	3,058,782	3,058,782
Adj-R^2	0.25	0.25	0.24

Notes: The regressions examine to what extent the firms' trade credit position prior to the Covid-19 crisis explains its probability of payment default on suppliers during the Covid-19 crisis. We differentiate default events depending on the underlying reason for default, which is reported by the bank: 1) *solvency*: the firm has already filed for bankruptcy or is engaged in a liquidation process, 2) *liquidity*: the firm cannot meet its payment obligations in full or on time because of insufficient funds in its bank account, 3)*disagreement*: the supplier and the client disagree on the delivery or the quality of the goods. 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. TC is the firm's net trade credit position prior to the crisis, computed as the difference between accounts payable and accounts receivable scaled by the firm's sales. $March - April$ and $May - June$ are indicator variables set to one respectively in March and April 2020, and May and June 2020. *Post* is an indicator variable set to one from March 2020 on, and to zero before. Control variables include one-year lagged cash holdings, leverage, size, and Altman Z-score, as well as a three-month lagged ratio of non-performing loans over total loans (NPL) and the share of short-term loans out of total loans (Liquidity needs), and those same variables interacted with the dummy *Post*. All continuous independent variables have been standardised to facilitate the interpretation of coefficients. The definitions of these variables are detailed in Table 15. Standard errors, reported in parentheses, are clustered at firm level. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

F Additional tables

Table A5: Sectoral analysis: does trade credit position explain firms' payment default during the Covid-19 crisis?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TC × March-April	0.0039***	0.0125***	0.0048***	0.0028***	0.0049*	0.0025	0.0025	0.0006	-0.0009	-0.0004	-0.0001	0.0004
	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
TC × May-June	-0.0012	-0.0009	-0.0007	-0.0002	0.0053**	-0.0037**	0.0005	0.0004	0.0009	0.0003	-0.0007*	0.0023**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Trade credit (TC)	-0.0028*	0.0028	-0.0002	-0.0004	-0.0028	0.0005	-0.0025	-0.0001	-0.0014	-0.0003	0.0006	0.0017
	(0.001)	(0.002)	(0.001)	(0.001)	(0.004)	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)	(0.000)	(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	21,680	36,206	21,678	28,679	2,389	10,149	2,074	24,845	5,731	5,534	4,532	8,701
N	385,086	641,334	385,134	511,272	42,288	180,228	36,606	441,090	101,928	98,100	80,604	155,112
Adj-R^2	0.21	0.23	0.25	0.17	0.17	0.14	0.15	0.17	0.18	0.15	0.17	0.17
Industry	Construction	Retail trade	Wholesale trade	Manufacturing	Recreation	Accomodation, food	Agriculture	Corporate Services	Health	Information	Real estate	Transport, storage

Notes: The regressions reported here are similar to the one reported in column (8)[46] of Table 6, except that the analysis is now broken down by business sector. Standard errors, reported in parentheses, are clustered at firm level. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

Table A6: Payment defaults, investment and assets liquidation

	Investment			Δ Asset	
	(1)	(2)	(3)	(4)	(5)
Payment default t-1		-0.008***	-0.006***	0.000	0.002
		(0.001)	(0.001)	(0.001)	(0.001)
Payment default t-1 × 2020			-0.002		-0.001
			(0.003)		(0.001)
Payment default t-1 × 2021			-0.009***		-0.004**
			(0.003)		(0.002)
Sales growth	0.017***	0.017***	0.017***	0.193***	0.193***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Cash holdings t-1	0.034***	0.034***	0.034***	0.117***	0.117***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Leverage t-1	-0.049***	-0.049***	-0.049***	0.108***	0.108***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Size t-1	-0.031***	-0.031***	-0.031***	0.616***	0.616***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
Z score t-1	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm FE	Y	Y	Y	Y	Y
Industry-year FE	Y	Y	Y	Y	Y
N firm clusters	152,301	152,301	152,301	152,301	152,301
N	578,486	578,486	578,486	578,486	578,486
Adj-R^2	0.38	0.38	0.38	0.66	0.66

Notes: This table reports the analysis of the relation between firm's default in year $t-1$ and respectively firm's investment in year t (column (1), see the equation 4), or the change in firm's total assets in year t (column (2)). The regressions are carried out over the 2018-2021 period. We define investment as the growth rate of the firms' capital stock measured as the difference across periods divided by the average. Change in assets is defined as the difference in the log of total assets. Standard errors, reported in parentheses, are clustered at firm level. *Payment default*$_{t-1}$ is an dummy variable set to one if the firm defaulted on trade bill to suppliers over year t-1. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.