WORKING paper

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# Information Salience and Credit Supply: Evidence from Payment Defaults on Trade Bills

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## Abstract

This paper provides novel evidence that information salience shapes banks' lending decisions. We use a setting in which information about a borrower's payment default on trade bills is available to all banks, but it appears more prominently to the bank managing the payment transaction (the reporting bank). We show that reporting banks reduce lending to defaulting borrowers more than other lenders. This effect is more pronounced when the default information presents salient attributes unrelated to the borrower's creditworthiness and for the branch of the reporting bank that directly observes the missed payment. Information gaps between the reporting bank and other lenders cannot explain our findings.

Keywords: Bank Lending, Payment Defaults, Salience, Information Sharing Mechanisms.

JEL classification: G21, G32, G40.

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# Non-Technical Summary

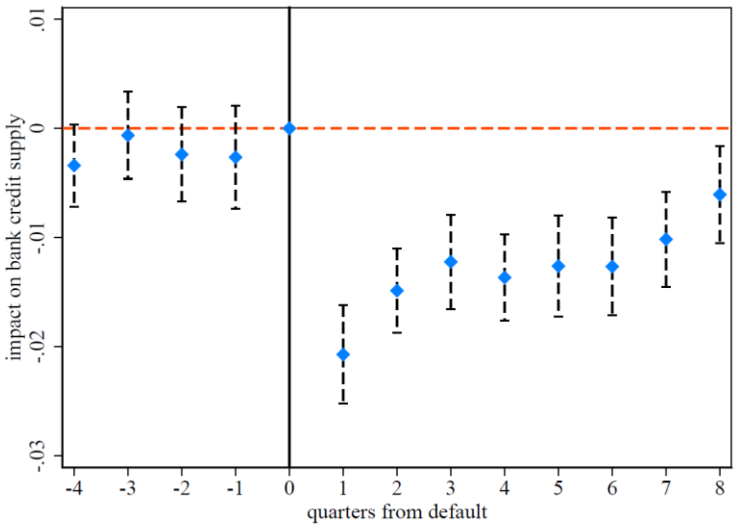
How do financial intermediaries process information and use it in credit decisions? Specifically, are banks, which are sophisticated institutions, impacted by the display of information? In this paper, we provide evidence that they are. We show that the *salience* of information about borrowers affects banks' lending decisions, with salience being defined as the property to attract the decision maker's attention automatically and involuntarily.

Our empirical analysis exploits the specificities of the revelation process of trade bill payment default information in France. This offers an ideal setting to study the role of information salience in banks' lending decisions. The reason is that when a firm fails to pay its supplier on time, the bank operating the payment (henceforth, the reporting bank) observes the default and is obliged, by law, to notify the Banque de France of the default within four working days. The Banque de France then stores this information on its platform, accessible to all lenders. The fact that the information about the default of the borrower is involuntarily received by the reporting bank and the regulatory obligation that requires this bank to notify the default to the central bank increase the prominence—that is, the salience—of the default for the reporting bank. All other lenders, both those with and without a relationship with the defaulting firm, acquire the default information by accessing the Banque de France's platform, a much less salient way to obtain it.

Existing literature emphasizes that salience amplifies the magnitude of decisions and that risk aversion increases when a negative payoff is made more salient. Hence, under the salience hypothesis, we expect that reporting banks would reduce credit supply to defaulting firms more than other lenders. To test this hypothesis, we consider credit registry data from 2012Q1 to 2019Q4, from which we derive the quarterly credit growth at the firm-bank level. Then, we merge these data with firm-quarter information on payment defaults.

In our baseline analysis, we compare the credit flow offered by the reporting bank vis-à-vis that of other lenders. We focus on firms that borrow from multiple banks at the same time. This permits us to compare the reaction of the reporting bank to that of other lenders for the *same* borrower, while absorbing the effect of firm-time-specific shocks. We find that all banks decrease their loan supply to defaulting firms. Yet, most importantly, the reaction of the reporting bank is about six times that of other lenders.

**Figure 1. Reaction of the reporting bank vs. other lenders to the firm payment default**




Note: This figure studies the credit flow of the reporting bank vis-à-vis that of other lenders depending on the distance from time 0, which is the last quarter before the reporting bank reports the company default and is taken as the reference quarter.

Figure 1 visualizes this result by plotting the difference in credit flows between the reporting bank and other lenders around the time the reporting bank reports the payment default. Time 0 denotes the quarter before the default materializes. We see clearly that the reporting bank cuts its lending to the firm relatively more immediately after the default, in line with the salience hypothesis. Importantly, however, reporting and non-reporting banks behave similarly before the firm's default.

We further test the salience hypothesis by investigating whether the effects amplify when the prominence of the default increases. We find evidence of this. In particular, we document that: *i*) banks' reaction is greater when the bank branch lending to the defaulting firm coincides with the bank branch reporting the default; *ii*) the loan supply reduction is larger the fewer are the defaults reported by the bank branch the day the borrower defaults; and *iii*) the reaction to a borrower's default is greater the more time has elapsed since the last payment default reported by the bank branch.

Finally, we consider a battery of tests to dismiss possible alternative hypotheses. First, we provide evidence that our results are not due to firms targeting specific banks at the time of default. Next, we tackle in multiple ways the hypothesis by which information gaps between reporting and non-reporting banks explain our results. In particular, we examine whether differences in the characteristics of the bank-firm relationship and of the lender drive our results by matching bank-firm relationships. Even when we compare reporting banks and other lenders that are similar in terms of length of the relationship with the defaulting firm, market share in the firm's local market, sector specialization, amount of credit granted to the firm, and size, we still find a more pronounced reaction to the payment default of reporting banks, lending further support to the salience hypothesis.

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# Saillance de l'information et offre de crédit : une illustration à partir des incidents de paiement sur effets de commerce


## RÉSUMÉ

Cet article documente le rôle que joue la manière dont les informations sont mises en évidence dans l'offre de crédit bancaire. Dans notre cadre d'analyse, l'information selon laquelle un emprunteur a fait défaut sur le paiement d'un effet de commerce est disponible pour toutes les banques, mais elle est d'autant plus visible pour la banque qui gère l'opération de paiement (la banque déclarante). Nous montrons que les banques déclarantes réduisent les prêts aux emprunteurs défaillants plus que les autres prêteurs. Cet effet est d'autant plus prononcé que l'information sur le défaut a des caractéristiques saillantes sans rapport avec la solvabilité de l'emprunteur et que le crédit vient du guichet de la banque déclarante qui a observé directement le défaut de paiement. Possibles asymétries d'information existantes entre la banque déclarante et les autres prêteurs ne permettent pas d'expliquer ces résultats.



Mots-clés : prêts bancaires, défauts de paiement, saillance, mécanismes de partage d'informations.




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# I Introduction

In today's age of information abundance, understanding how financial intermediaries process information and use it in credit decisions is of paramount importance. A growing body of the behavioral economic literature has found that decision makers are drawn to give disproportionate weight to *salient* information, with salience being defined as the property to attract the decision maker's attention "bottom up," automatically and involuntarily (Bordalo et al., 2022). A key question is, therefore, whether the display of information impacts decision makers in sophisticated institutions like banks. This paper provides evidence that the salience of information about borrowers affects banks' lending decisions.

Investigating the impact of salience on banks' credit decisions presents several challenges. First, to determine whether salience plays a role, we must be in presence of new information available to lenders that is relevant enough to potentially trigger a revaluation of the credit supply. Second, and most importantly, we need that this new information is displayed in different forms among lenders. If these two conditions are met, the empirical test should feature a comparison of the credit supply of the different lenders, all receiving the new information, but each observing it with a different display. In this test, to avoid the possibility that information gaps cause differences in lending behavior, it is important that lenders differ only in the way the new information is presented to them.

The revelation process of trade bill payment default information in France offers an ideal setting to study the role of information salience in banks' lending decisions. Firms' trade relationships are an important source of information for banks (Mian and Smith, 1992; Biais and Gollier, 1997). In particular, payment defaults on suppliers can be useful signals for financial intermediaries since a default may reveal the distress of the customer firm and an incipient propagation of a negative shock through the supply chain (Boissay and Gropp, 2013; Jacobson and von Schedvin, 2015). Payment default events are hence relevant information shocks offered to banks that may trigger a recalibration of the credit supply. In France, trade bill payments are settled by banks in a computerized and centralized way. If a firm fails to pay its supplier on time, the bank operating the payment (henceforth, the reporting bank) is obliged, by law, to notify the Banque de France of the default within four working days. The central bank then records the default in a data set called *Centrale des Incidents de Paiement sur Effets* (CIPE), and makes it accessible to all banks on its platform. The fact that the default information is involuntarily received by the reporting bank and the regulatory obligation that imposes on this bank the notification of the default to the central bank increase the prominence—that is, the salience—of the default for the reporting bank. All other lenders, both those that hold a relationship with the defaulting firm and those that do not, acquire the default information by accessing the CIPE data set through the Banque de France's platform, a much less salient way to obtain it.

In our baseline empirical test, we compare the credit flow offered by the reporting bank vis-à-vis that of other lenders. To the extent that salience amplifies the magnitude of decisions (Dessaint and Matray, 2017; Frydman and Wang, 2020) and risk aversion increases when a negative payoff is made more salient (Bordalo et al., 2012, 2022), under the salience hypothesis, reporting banks should reduce the supply of credit to defaulting firms more than other lenders. We employ credit registry data from 2012Q1 to 2019Q4, and derive quarterly credit growths at the firm-bank level. The richness of the information we have access to on bank-firm relationships and on the type and frequency of payment defaults helps us in disentangling the impact of salience from confounding effects.

Our focus is on firms that borrow from multiple banks at the same time. This allows us to control for time-varying firm-specific demand shocks using firm×time fixed effects, a standard in the empirical corporate finance literature since Khwaja and Mian (2008). Our sample of more than 18 million firm-bank-quarter observations reveals that reporting a default is associated with a significantly lower supply of credit to the defaulting firm. To benchmark the reaction of the reporting bank, we determine how other lenders respond to the default. We consider a less saturated specification, in which we can include a binary variable indicating if the firm defaults. Specifically, we replace the firm×time fixed effects with sector×county×size×time fixed effects to control for loan demand, following the approach developed by Degryse et al. (2019). We find that all banks decrease their loan supply to defaulting firms. Hovewer, we establish that the reaction of the reporting bank is about six times that of other lenders.[1]

[1] In the absence of firm×time fixed effects, distinguishing between loan supply and loan demand effects is harder, and it could be that firms reduce their loan demand in case of default. However, the limit of this interpretation is that it is precisely when a firm defaults on a payment that it has greater demand for liquidity and credit.

We further test the salience hypothesis by investigating whether the effects amplify when the prominence of the default increases. A priori, the default carries higher prominence when the credit officer works in the same bank branch that observes and reports the default. Hence, if salience plays a role, banks' reaction should be greater when the bank branch lending to the defaulting firm coincides with the bank branch reporting the default. We find evidence of this. Second, we analyze whether reporting branches react differently to a payment default in case they report a larger number of firms defaulting the same day. Since isolated payment defaults are more visible, the salience of a payment default is higher if a bank branch reports a limited number of these events. In line with the salience hypothesis, we find that the fewer are the defaults reported by a bank branch the day the borrower defaults, the larger is the loan supply reduction. Also in line with the salience hypothesis, we find that the reaction to a borrower's default is greater the more time has elapsed since the last payment default reported by the bank branch. All these results hold even after controlling for potential shocks that may hit the bank branch's clientele and correlate with the reported number and frequency of payment defaults.

The above evidence suggests that the salience of information about borrowers matters for banks' lending decisions. Yet, an interpretation hinging on salience requires that all banks share a similar set of information about defaulting borrowers and that there is no special relationship between the reporting bank and the borrower. That is, that there is a level playing field amongst lenders. Otherwise, the different reactions of the reporting bank and other lenders might be partly explained by information gaps between them or the characteristics of the bank-firm relationship.

While the reporting bank is certainly aware of the payment default of its borrower, the other banks may not have accessed such information for different reasons, ranging from negligence to lack of incentives to monitor, and to the need to pay a negligible but still positive cost to access the CIPE data set. Additionally, even when non-reporting banks access information, the frequency of access could be low, thus hindering a timely response. This would lead to lenders other than the reporting bank to react to the payment default less than the reporting bank, even if information salience did not play a role. Even though it is not possible to observe whether all banks access payment default information, we can alleviate this concern building on anecdotal evidence as well as through a battery of tests.

First, we know that the Banque de France's platform is widely accessed by banks. For instance, in 2018 this platform registered 13.3 million of accesses while reporting information on 7.9 million firms.[2] Importantly, the single most accessed piece of firm-level information is a summary containing trade bill payment default information, together with the company credit rating and information about the company managers. The reliance of banks on the information available on the Banque de France's platform is also documented by existing studies for what concerns the information about managers and company ratings (Cahn et al., 2021, forthcoming). Overall, this suggests that it is unlikely that lenders are not informed about firms defaulting on trade bills before granting a loan.

To further understand whether banks actually routinely and timely access the CIPE data set we conduct an empirical test. The test exploits the heterogeneity in the reason behind the payment default. Our sample comprises payment defaults that are due to either liquidity problems of the customer firm or litigation—that is, disagreement—between the customer firm and its supplier. We show that a default due to liquidity problems conveys a more negative signal about the quality of the customer firm—that is, a higher probability of corporate liquidation—than a litigation-related payment incident. This difference provides us with an opportunity to assess whether gaps in the access to default information exist. Since non-reporting banks can differentiate between liquidity- and litigation-related defaults only by accessing the CIPE data set in a timely manner, observing that their reaction to the default varies depending on the reason of default would not be in line with the information gap explanation. We find that non-reporting banks cut lending significantly more after a liquidity-related payment default than after a litigation-related one, thus suggesting that these banks do acquire payment default information.

We also examine whether differences in the characteristics of the bank-firm relationship and of the lender drive our results. It could be, in fact, that the reporting bank is special to the borrower, being, for instance, the main credit provider. To alleviate this concern, we match bank-firm relationships based on the length on the relationship, the bank's market share in the firm's local market, the bank's sector specialization, the amount of credit granted to the borrower before the default, and bank size. Even when

[2]See the Annual Report of the Banque de France, which is available at https://www.banque-france.fr/liste-chronologique/le-rapport-annuel-de-la-banque-de-france.

we compare reporting banks and other lenders that are similar along these dimensions, we still find a more pronounced reaction of reporting banks. This finding lends additional support to the view that our results cannot be explained by information asymmetries among banks.

Finally, we provide tests indicating that our results are not due to firms targeting specific banks at the time of default. We also show that the effects on credit supply are more pronounced precisely for the types of credit that are more easily adjustable by banks—that is, credit lines and short-term credit.

Our paper contributes to several strands of the literature. First, we provide novel evidence that salience impacts banks' lending decisions. Existing literature shows that banks exploit limited attention in dealing with depositors (Stango and Zinman, 2014) and when they design securities for investors (Célérier and Vallée, 2017). Also, Nguyen et al. (2022) document that lenders' attention plays a role in pricing climate risk. To our knowledge, we are the first to show that banks' lending behavior is distorted by the salience of information about borrowers. Exploiting how information on trade bill payment defaults is made available to lenders, we provide evidence that banks exposed to a more salient display of this information reduce credit supply more. Our results thus add to a growing literature showing that salience affects decision-making processes of financial market investors (Barber and Odean, 2007; Cosemans and Frehen, 2021; Frydman and Wang, 2020), homebuyers (Agarwal and Karapetyan, 2022), and corporate managers (Dessaint and Matray, 2017).

Second, we extend the literature on trade credit by documenting a spillover effect from trade payment defaults to bank lending. Prior works have focused on several aspects of trade credit relationships, ranging from interfirm liquidity provision (Biais and Gollier, 1997; Cuñat, 2007; Boissay and Gropp, 2013; Garcia-Appendini and Montoriol-Garriga, 2013, 2020) to corporate defaults propagating through the supply chain (Boissay and Gropp, 2013; Jacobson and von Schedvin, 2015). Adding to the literature that examines how banks exploit information gathered from trade credit relationships (Mian and Smith, 1992; Biais and Gollier, 1997), we show that banks react to this information, but, most importantly, that their reaction depends on the prominence of this information.

Finally, our paper adds to the policy debate on the role and design of information sharing mechanisms. In credit markets, information sharing mechanisms provide many benefits in alleviating information asymmetry problems between borrowers and lenders, like reducing adverse selection (Pagano and Jappelli, 1993), moral hazard (Padilla and Pagano, 2000), and information monopolies (Padilla and Pagano, 1997). In our setting, the firm-specific information on payment defaults that banks acquire through their lending activity must be reported to the central bank, limiting the informational advantage that the reporting bank can extract from this information (Dell'Ariccia and Marquez, 2004; Schenone, 2010; Agarwal and Hauswald, 2010). Yet, we provide evidence not only that the existence of information sharing mechanisms affects firms' access to credit (see, e.g., Jappelli and Pagano, 2002; Djankov et al., 2007; Barth et al., 2009; Doblas-Madrid and Minetti, 2013; Hertzberg et al., 2011; Giannetti et al., 2017), but also that the design of these mechanisms plays a role. Precisely, we shed light on the fact that the way regulators organize the reporting activity of lenders into information sharing arrangements affects the supply of credit. Our results indicate that to improve the effectiveness of information sharing mechanisms their design should account for behavioral biases.

The remainder of the paper is organized as follows. Section II provides the institutional details and describes the data we employ. Section III presents the identification strategy and discusses the results. Section IV provides additional empirical tests. Finally, Section V offers concluding remarks and policy implications.

## II Institutional Details and Data

### *A Payment Defaults on Trade Bills*

The main focus of this paper is on payment defaults on bills of exchange, which are common instruments used to settle business-to-business payments in France. Bills of exchange are written documents through which a supplier of goods or services orders its customer to pay the sum due on an established date. The trade bill is issued by the supplier and must be accepted by the customer.[3] The payment is then executed by the customer's bank in a computerized and centralized way.

Once a firm does not pay in full or in time the trade bill to its supplier, the customer's bank in charge of the payment—that is, the reporting bank—must report the event of default to the Banque de France within four working days. Banks are required by law to

[3]Figure OA1 in the Online Appendix depicts the typical functioning of a bill of exchange. In the paper, the term trade bills and bills of exchange are used in an interchangeable manner.

report the missed payment of their clients when the amount due is above €1,524. However, the central bank encourages banks to notify defaults of any amount, thus including those below this threshold. The amount of the payment default is communicated to the Banque de France together with the date of the event and the identifier of the defaulter. Banks must also specify if the default was triggered by the firm's illiquidity—in case, for example, the amount due was not available on the customer's bank account—or by a disagreement between the firm and its supplier—regarding, for example, the quality of the goods delivered.

The Banque de France centralizes this information in the CIPE data set and makes it available to all lenders in the credit market. Precisely, all banks have access to information on firms' payment defaults on demand and remotely through the Banque de France's platform. This platform gives them access to FIBEN (*FIchier Bancaire des ENtreprises*), a proprietary database of the Banque de France, of which the CIPE data set is part.

FIBEN contains a wide range of firm-level information. It is organized in "modules," each of which contains a different piece of information, including firm balance sheet data, credit exposure, and information on firm managers. Banks can request the access to one or more modules, paying a small fee for each one. The information on payment defaults (date, number and amount of the defaults) is summarized in the module *Panorama de l'entreprise et du dirigeant*, which has a cost of €3.7 per access. This module was the most accessed by banks in 2018, as shown in Figure OA2 in the Online Appendix. In the Online Appendix, we also report an example of an extract of this module that shows how information on payment defaults is displayed for banks (Figure OA3).

### *B Sample Description & Variables*

We make use of two data sets maintained by the Banque de France. The first is the CIPE data set, which collects firms' payment defaults on trade bills on a daily basis. Also employed by Boissay and Gropp (2013) and Barrot (2016), this data set contains the identifier code of the bank that reports the default (CIB code), the identifier of the defaulter (SIREN code), and the amount and reason of default. The second data set we consider is the French credit registry (SCR), which provides monthly information on all credit exposures larger than €25,000 of financial institutions towards non-financial firms. These credit exposure data are also available at the bank branch level.

We consider the period between 2012Q1 and 2019Q4, and aggregate the universe of payment default events at the firm-quarter level. In parallel, we collapse the credit registry data both at firm-bank-quarter-level and firm-bank branch-quarter level. We then merge these two latter samples with the CIPE data by using the firm identifier code. As detailed below, to implement our identification strategy, we only consider firms with multiple banking relationships. We thus consider a total of 1,666,351 payment defaults, of which 757,136 (45%) are for illiquidity and 909,215 (55%) for litigation.

Firms are classified on the basis of their size to three size baskets, that is, micro, small and medium, and large.[4] Firm sector is coded following the *Nomenclature Économique de Synthèse*, while firm location identifies the county (French department) where the firm is headquartered. There are 12 distinct sectors and 96 counties in our sample.

Panel A of Table I presents the summary statistics for the sample at the firm-bank-quarter level. The description of the variables is provided in Table A1 of the Appendix. For each bank-firm relationship, we observe the outstanding volume of bank credit (variable *log credit*). We compute the change in the logarithm of the outstanding volume between quarters (variable $\Delta$ *log credit*) to capture the flow of credit that each bank grants to the firm. We compute similar variables for the variation in the credit line available to the borrower (variable $\Delta$ *log credit line*) and for the flow of short-term and long-term credit (variables $\Delta$ *log ST credit* and $\Delta$ *log LT credit*, respectively). The variables $\Delta$ *log credit* and $\Delta$ *log LT credit* have negative mean and median, consistent with borrowers repaying their total bank debt, and in particular the one long-term. Conversely, we observe a positive average flow for both credit lines and short-term bank credit.

The next set of variables relates to payment defaults. We build an indicator defining whether the firm defaults on at least one payment in the quarter (variable *default*) and another indicator defining whether the bank is the reporting bank (variable *reporting bank*). We see that 9.6% of the observed bank-firm observations relate to a borrower that misses at least one payment to one of its suppliers.[5] 2.7% of the observed bank-

[4]Micro-firms include firms with less than 10 employees, and which have total sales up to €2 million or total assets up to €2 million. Small- and medium-sized firms include firms that are larger than micro-firms. They have up to 250 employees, and their total sales are up to €50 million or their total assets are up to €43 million. Large firms include the rest of the firms.

[5]The payment default statistics and the number of observations in our sample cannot be compared to those in Boissay and Gropp (2013), who find that about one-fifth of the firms either default or face default at least once per quarter. The reason is that the unit of analysis is different: bank-firm-quarter in our sample, firm-quarter in Boissay and Gropp (2013).

firm relationships are with a bank that reports a missed payment. We split the defaults according to their reason in liquidity- and litigation-related defaults (variable *liquidity default* and variable *litigation default*, respectively). Observations with litigation-related defaults are about twice more prevalent than those with liquidity-related defaults. Consequently, banks report more litigation-related payments defaults (variable *reporting bank (litigation default)*) than ones due to liquidity reasons (variable *reporting bank (liquidity default)*).

Our data include the firm credit ratings that are produced by the Banque de France. In the period we consider, the credit rating scale has 12 levels: it goes from the level "3++" that is assigned to firms with the highest credit quality to the level "9", which is assigned to those with the lowest credit quality. The rating "P" is assigned to firms in distress. We classify speculative-grade firms as those with a credit rating equal to "5+" or below. We choose that level as a threshold because below it lenders cannot pledge their loans as collateral in their refinancing operations with the central bank (Mésonnier et al., 2022). As not all borrowers in the credit registry are rated, we build an indicator variable (*unrated*) defining whether the firm's credit rating is not attributed.[6] Unrated firms represent about 43.9% of the observations in our sample, while borrowers rated at the speculative-grade level account for 26.7% of the sample.

We derive a set of characteristics that relate to the bank-firm relationship. The binary variable *young* identifies bank-firm relationships in which the bank has been exposed to the borrower for less than three years. This variable aims to capture relationships in which banks are relatively poorly informed about the borrower's credit quality (see, e.g., Ioannidou and Ongena, 2010; López-Espinosa et al., 2017). 36.1% of the bank-firm pairs in our sample are classified as young relationships. The variable *bank exposure* is the amount of credit granted to the borrower over the total credit extended by the bank. This variable captures the risk for the bank of being held up by the borrower (see, e.g., Davydenko and Strebulaev, 2007; Li et al., 2019). The average (median) exposure of a bank to a borrower is 0.019% (0.004%). The local market power of the bank is captured by the variable *market share*, which is the credit granted by the bank to borrowers headquartered in the firm's county divided by the total loans outstanding in that county.[7]

[6]Firms are unrated if the yearly total sales are below €750,000 and the outstanding amount of bank loans is below €380,000.

[7]De Jonghe et al. (2019) and Giannetti and Saidi (2019) also employ a similar definition to compute the market share of a bank, although at the sector level rather than the county level.

In line with De Jonghe et al. (2019), we compute the variable *sector specialization*, which is a measure of the bank's specialization in the sector. It represents the credit granted by the bank to borrowers operating in the firm's sector divided by the total credit extended by the bank. Finally, we measure bank size by the logarithm of the total outstanding volume lent by the bank (variable *bank size*).

Panel B of Table I summarizes the variables we use in the analyses at the firm-bank branch-quarter level. Similarly to what we do at firm-bank-quarter level, we build an indicator defining whether the bank branch is the reporting bank (variable *reporting bank branch*). 2.1% of the observed bank branch-firm relationships are with a branch that reports a missed payment. For the cases in which the bank branch reports a default, we report two additional variables. *same-day reported defaults* shows the number of firms whose default is reported by the branch the day the company defaults. We find that, on average, bank branches report the default of 4.49 firms per day, but the variation is significant, with the variable ranging from 1 (5th percentile) to 20 (95th percentile). The variable *days from last default reported by branch* is the distance in days from the last default reported by the branch (regardless of the defaulting companies involved). We find an average of 10.29 days between reported defaults. The distance at the 95th percentile is of 34 days, which suggests that the reporting of a payment default for a bank branch is not a rare event.

[Please insert Table I about here]

## III Identification Strategy and Results

### *A Identification Strategy*

As discussed in Section II, banks receive information about a trade bill payment default of a customer in different ways. All lenders except the reporting bank receive such information through the Banque de France's platform. Conversely, the reporting bank obtains it involuntarily and has to report the default to the central bank. These two elements make the salience of the default higher for the reporting bank than for other lenders. Following Dessaint and Matray (2017) and Frydman and Wang (2020), under the hypothesis that salience plays a role, we should thus observe a difference in behavior between the reporting bank and other lenders, and the reporting bank should be more aggressive in its decision making.

In particular, since lending is a risky activity for banks, our setting can be seen as a choice under risk. As explained by Bordalo et al. (2012), if salience plays a role, the decision maker may give disproportionate weight to a negative payoff made more salient and be more risk-averse. In our case, this implies that following the reporting of a payment default—that is, a negative salient signal—the bank may give relatively more weight to the event of bankruptcy of the defaulting borrower. This may then lead the reporting bank to behave in a more risk-averse manner. So, while we expect that all banks cut lending after the realization of a payment default, under the salience hypothesis the reporting bank should do that significantly more.

To understand whether this is the case, we consider firms maintaining at least two banking relationships at the same time. We then compare the lending supply of the banks that manage the payment transaction and report the default to the central bank with those of other banks that lend simultaneously to the same firm. The regression equation is the following:

$$\Delta\, log\, credit_{jbt} = \beta\, reporting\, bank_{jbt} + \eta_{jb} + \eta_{bt} + \eta_{jt} + \varepsilon_{jbt}, \tag{1}$$

where the outcome variable $\Delta\, log\, credit_{jbt}$ is the flow of bank credit from bank $b$ to firm $j$ between time $t-1$ and time $t$. $reporting\, bank_{jbt}$ indicates if the bank is the reporting bank for the default of firm $j$ happened at time $t$. $\eta_{jb}$ denotes the firm×bank fixed effects, $\eta_{bt}$ refers to the bank×time fixed effects whereas $\eta_{jt}$ is the firm×time fixed effects. $\varepsilon_{jbt}$ is the idiosyncratic error term.

The coefficient of interest in Equation 1 is $\beta$. It captures the difference between the bank credit flow granted by the reporting bank to a defaulter and that of other lenders. If salience plays a role in banks' decision making, we expect $\beta < 0$. Indeed, $\beta < 0$ would suggest that the reporting bank offers less credit to defaulting borrowers than other lenders. The firm×bank fixed effects control for time-invariant characteristics related to the firm-bank pairing. The bank×time fixed effects control for every shock impacting the bank at time $t$, for example, shocks to the bank's funding conditions. The inclusion of the firm×time fixed effects allows us to identify the parameter $\beta$ solely by comparing the credit flow supplied to the same defaulter by different lenders (reporting bank and other lenders).

The identification of the salience effect through the parameter $\beta$ requires two assumptions. First, reporting banks should not possess superior information about the dynamics of the defaulting borrowers. Second, the demand of credit of a firm should be symmetric across lenders, which is the standard assumption in the Khwaja and Mian (2008) setting. This implies that firms do not switch their demand towards specific banks at the time they default on a trade bill. We extensively investigate these identifying assumptions with a set of dedicated analyses in Section IV.

### *B Results*

#### *B.1 Baseline Firm-Level Effects*

We examine whether salience shapes banks' lending decisions using our baseline model (Equation 1). Estimation results appear in column (5) of Table II. The table also presents in columns (1) to (4) other less-saturated specifications. Standard errors are two-way clustered at the firm and bank level. Our focus is on the coefficient on *reporting bank*, as this variable identifies whether the bank is the reporting bank of the observed trade payment incident at time $t$.

[Please insert Table II about here]

Columns (1) to (4) do not include firm×time fixed effects. This allows us to add the binary variable *default*, which identifies if firm $j$ defaults on at least one trade credit supplier at time $t$. The coefficient on *default* provides an estimate of the reaction of a non-reporting bank to the payment default of its borrower. In columns (2) to (4), we control for firm demand using sector×county×size×time fixed effects following Degryse et al. (2019). Depending on the column, we also include rating×time fixed effects and bank×time fixed effects that control for the time-varying effect of firm credit quality and bank-time-specific shocks, respectively.

The coefficient on *default* is always negative and statistically significant at the 1% level. This suggests that all banks react to trade payment defaults by reducing the credit flow extended to the borrower by about 0.21-0.32 pp. The coefficient on the variable of interest *reporting bank*, which depicts an incremental—that is, extra—effect to that of *default*, is also negative and statistically significant at the 1% level in all specifications. This indicates that banks that directly observe and report the default decrease their lending to defaulting firms more than other lenders.

Examining the coefficient estimates of *reporting bank* and *default*, we can observe that the reduction in credit supply due to the payment default is *significantly* larger in case the bank is reporting the default. The incremental reduction in credit supply associated with reporting the default varies from 1.06 to 1.15 pp, depending on the specification. Yet, the overall reduction in credit supply by the reporting bank corresponds to the sum of the coefficients on *reporting bank* and *default*, and ranges beween 1.27 and 1.47 pp. Hence, according to column (4)—our preferred specification amongst columns (1)-(4)—following a default, the reporting bank reduces its credit supply 6 times more than other lenders. This finding is in line with the salience hypothesis, which posits an amplification of the decision maker's reaction.

Column (5) effectively corresponds to Equation 1. The inclusion of firm×time fixed effects allows us to identify more cleanly the difference in the loan flow offered by the different banks to the same defaulter. The result confirms that reporting banks reduce the credit flow more than non-reporting ones by 0.91 pp. Therefore, while all banks have access to the same information, the way this information is offered to them shapes their lending decisions. An interpretation of these baseline results is that the salience of the negative-payoff outcome makes reporting banks become more risk-averse, as predicted by Bordalo et al. (2012).[8]

### *B.2 Graphical Analysis*

To further strengthen the results of Section III.*B.1*, we plot the difference in firm-bank credit flow around the firm's trade bill default depending on whether the lender is the reporting bank. To do that, we estimate a modified version of Equation 1:

$$\Delta\, log\, credit_{jbt} = \sum_t \beta_t \mathbb{1}_{jbt}^{reporting\, bank} + \eta_{jb} + \eta_{bt} + \eta_{jt} + \varepsilon_{jbt}, \tag{2}$$

where $\sum_t \mathbb{1}_{jbt}^{reporting\, bank}$ denotes a set of binary variables capturing the time between quarter $t$ and the quarter before bank $b$ reports firm $j$'s default. Hence, $\mathbb{1}_{jbt}^{reporting\, bank}$ is equal

[8]For robustness, Table OA1 in the Online Appendix replicates this baseline analysis by adding monobank firms to the sample. The estimated effects are remarkably similar to those in Table II.

to one $t$ quarters after (or before if $t$ is negative) borrower $j$ defaults on a trade bill and bank $b$ is the reporting bank. The coefficient $\beta_t$ on $\mathbb{1}_{jbt}^{reporting\,bank}$ captures the difference in credit flows between the reporting and non-reporting banks at time $t$ relative to $t = 0$, that is, the quarter before the default materializes.

The coefficients are plotted in Figure 1. We see clearly that the reporting bank cuts relatively more its lending to the firm immediately after the default, which supports the findings in Table II. Importantly, before the firm's default, reporting and non-reporting banks behave similarly: the trends of the credit flow are not statistically different. This is in line with the idea that reporting banks deviate from other lenders precisely at the time of default. That is, the relative change in their behavior does not predate that event.

[Please insert Figure 1 about here]

### *B.3 Shifting the Prominence of Information*

If the documented difference in the reactions of reporting banks and other lenders is driven precisely by information salience, it should vary with the degree of prominence of the received information.

Thanks to the granularity of our data, we can compare the lending decisions of branches of reporting banks that report themselves the default versus those of non-reporting branches of reporting banks. As the information is more prominent for the analysts that work at the branch that reports the default to the central bank, if salience plays a role we should observe that the drop in lending is more pronounced when lending branch and reporting branch coincide. We run our baseline model on a sample that is now at the firm-bank branch-quarter level, and in which we add the variable *reporting bank branch.* This dummy identifies if the branch reports the company's payment default.

Results are reported in columns (1) to (3) of Table III. We include the same set of fixed effects used in the baseline analysis except that we replace firm×bank with firm×bank branch fixed effects. In column (3), we also augment the model with bank branch×time fixed effects. These fixed effects account for different dynamics of the loan portfolios across branches and control for every shock experienced by the clientele of a particular branch in a given quarter. For instance, these fixed effects control for the fact that a period of industry downturn may increase the number of defaulting borrowers for branches specialized in that industry and that, consequently, those branches might suddenly adjust the liquidity provided to all their clients. *reporting bank branch* enters negatively and statistically significant in all models while the variable *reporting bank* remains negative and statistically significant. These results indicate that the cut in lending is especially evident for the reporting branches of the reporting banks, which is consistent with our conjecture.

[Please insert Table III about here]

Next, we exploit our payment default data to identify the degree of prominence of each payment default. We consider two dimensions: the number of defaults reported by a branch and a branch's past experience. In theory, the salience of a default information should be higher the lower is the number of defaults reported by a branch's analysts on a specific day. For instance, when a branch must deal with the reporting of only one default in a day, this event appears more prominently to the analysts. Additionally, the past experience of a branch may affect the salience of an event and thus interfere with the bank's lending decision. Precisely, the more time has elapsed from the last default reported by a branch, the more salient the event is.

We interact the variable *same-day reported defaults*, which captures the number of firms whose default is reported by the branch the day the company defaults, with the variable *reporting bank branch*. The idea is to assess whether the reporting branch adjusts its lending to the defaulting firm more strongly when a lower number of defaults is reported the same day. The negative coefficient on the interaction term that appears in columns (4)-(6) of Table III is in line with this prediction. Interestingly, this finding relates to the literature on consumer behaviour, precisely to works that document that the number of available products to consumers affects their attention (Chandon et al., 2009; Castro et al., 2013).

Following the same reasoning, we investigate the effect of the time elapsed from the last default reported by the branch. We interact the variable *days from last default reported by branch* with the variable *reporting bank branch*. Results are in columns (7)-(9) of Table III. Parameter estimates tell us that reporting branches cut lending more to defaulting borrowers especially when the last default they reported happened in the less recent past, thus suggesting that the salience of the event affects banks' credit supply. This finding is also in line with the large literature that documents that past experience of individuals affect their subsequent decisions (see, e.g., Greenwood and Nagel, 2009, Malmendier and Nagel, 2016 and Dittmar and Duchin, 2016).

### *B.4 Increase in Risk Aversion*

Our baseline results suggest that banks become more risk-averse when the payment default appears to them in a more prominent way. Examining how the effect changes with the firm risk can also help to further confirm this explanation. If reporting a payment default exacerbates the bank's risk aversion, the cut in credit flow that follows the default should magnify precisely when the firm risk is a priori higher. That is, the effect should be more pronounced when the non repayment of the borrowed funds is more likely or the associated losses are larger.

We measure the probability of non repayment by the credit rating of the firm, and in particular by the variables *speculative grade* and *unrated*.[9] We interact *speculative grade* and *unrated* with variables that identify the reporting bank and the defaulting firm. Results are reported in Table IV, columns (1) and (2). We still find a negative and significant coefficient on *reporting bank*. Importantly, however, the coefficients of the interactions provide strong evidence that the difference in the banks' reaction is more pronounced when the borrower is unrated or speculative-grade. This test also offers another important insight. It could be argued that "surprise"—another attribute related to salience (Bordalo et al., 2022)— could affect the banks' response to the default payment. However, the fact that the difference in banks' reaction is more pronounced for speculative grade firms also suggests that it is precisely the prominence of the default information rather than its surprise that drives our results. Indeed, if the salience effect had been related to the surprise component, it should have magnified in case of default of investment grade firms.

[Please insert Table IV about here]

As a measure of the associated losses for a bank we consider the bank's exposure towards the defaulting borrower. The idea is that the higher the exposure of the bank, the higher is the probability of the bank to incur in large losses in case of borrower's bankruptcy. We interact the variable *bank exposure* (in log) with both *reporting bank* and *default*. Based on our prediction, *bank exposure* should amplify the reaction of the reporting bank. This is what we find. Columns (3) and (4) of Table IV show that

[9] Indeed, the opaqueness and the small size of unrated firms lead them to have, on average, higher probability of bankruptcy with respect to non-speculative firms.

the coefficient on the interaction term is stable and statistically significant at the 1% across both specifications. Overall, these findings are in line with the hypothesis that information salience alters banks' risk aversion, and hence their lending decisions.

## IV Additional Analyses

### *A Information Gaps Among Banks*

We investigate the identifying assumptions behind Equation 1. The first assumption is that there is a level playing field amongst lenders, that is, reporting banks do not possess superior information about the dynamics of the defaulting borrowers. The questions are therefore whether all banks know about the payment default of a given borrower and whether banks' relationships with the borrowers play a role.

#### *A.1 Do Non-reporting Banks Know About the Payment Default?*

The payment default can generate an information gap between banks because non-reporting banks may not acquire such information from FIBEN. Indeed, while it is indisputable that the reporting bank knows about the payment default of its own borrower, other lenders may not have collected such information on the platform for different reasons, ranging from negligence to the lack of incentives to monitor, and to the need to pay the negligible but still positive cost of accessing the information. Even when accessing the information, the acquisition could take place infrequently, potentially leading to a delayed response by non-reporting banks. Thus, this information gap—and not information salience—could at least partly explain the different adjustments made by the two groups of banks. Even though it is not possible to observe whether non-reporting banks access payment default information, we can alleviate this concern building on both anecdotal and empirical evidence.

**Anecdotal Evidence** Data on the accesses by banks to the Banque de France's platform suggest that banks widely access the platform. For instance, the 2018 Annual Report of the Banque de France reports that its platform registered 13.3 million of accesses, while reporting information on 7.9 million firms.[10] Importantly, the single most accessed piece

[10] These statistics are available at `https://www.banque-france.fr/liste-chronologique/le-rapport-annuel-de-la-banque-de-france`.

of information is the summary containing the company credit rating, information on the company managers as well as the presence and number of trade bill payment defaults (Figure OA2 in the Online Appendix). The reliance of banks on the information available on the Banque de France's platform is also documented by existing studies for what concerns the information on managers and that on company ratings (Cahn et al., 2021, forthcoming). Overall, this suggests that it is unlikely that non-reporting banks are not informed about firms defaulting on trade bills. However, this anecdotal evidence cannot say much about the frequency of the access to the payment default information.

**Information Content of the Reasons Behind Payment Defaults** Non-reporting banks should have incentive to acquire borrowers' information on payment default on trade bills if such information contains valuable information about the borrower's credit quality. The literature provides plenty of evidence that these defaults have an information content (see, e.g., Cuñat, 2007; Boissay and Gropp, 2013; Jacobson and von Schedvin, 2015). We take a closer look at whether the payment default helps predicting firms' failure.

We regress a binary variable that identifies whether a firm fails over the subsequent year on *default*, which captures if a firm defaults on a trade bill. Failure is defined as the firm's liquidation, that is, the occurrence of *liquidation judiciaire*. We control for sector, county, size, rating and time fixed effects. We employ both a probit model and a linear probability model.

Results for the probit model are reported in column (1) of Table V. The estimates suggest that a payment default to a supplier is positively associated with a higher probability of failure over the following year. We obtain a similar finding when using a linear probability model, whose estimation results are reported in columns (2) to (5), each column employing a different degree of saturation.

[Please insert Table V about here]

Differently from Boissay and Gropp (2013), our sample of payment defaults includes missed payments caused by either illiquidity or litigation. We examine whether the reason of default affects the ability of predicting firm failure. In column (6) of Table V, we interact the variable *default* with an indicator variable for payment defaults due to illiquidity. Although defaults due to litigation have some ability in predicting firm bankruptcy—as captured by the positive and statistically significant coefficient of *default*— such ability is smaller with respect to the default payments due to illiquidity.

In light of this result, we check whether the response of reporting and non-reporting banks varies depending on the type of payment default. This is of particular interest because non-reporting banks can only distinguish between liquidity- and litigation-related defaults if they acquire the information by accessing the CIPE data set. Moreover, this access has to be made with a frequency that allows the non-reporting bank to react without delay to the payment default. Thus, a difference in response for non-reporting banks in case of liquidity-related defaults would also lend support to the view that banks frequently and systematically access the Banque de France's platform.

In Table VI, we consider our baseline model and interact both *reporting bank* and *default* with a binary variable that identifies defaults for liquidity reasons. If non-reporting banks do not access the information, the coefficient on the interaction with *default* should not be statistically different from zero. We find that the coefficients on *default* $\times$ *liquidity default* is negative and statistically significant, suggesting that the effect on bank lending for non-reporting banks is stronger when the default is due to the firm's illiquidity. This result supports the view that non-reporting banks do acquire payment default information in a timely manner. We still find that banks that report the default have a stronger response than non-reporting ones, confirming previous results.

[Please insert Table VI about here]

Collectively, both the anecdotal evidence and the results in Table VI provide indications that non-reporting banks acquire the information on trade defaults.

### *A.2 Bank-Borrower Relationship*

Although both reporting and non-reporting banks possess information about payment defaults, they may have different levels of knowledge of the borrowers. This could be due, for example, to differences in the type of relationship they have with the borrowing firm, which may, in turn, drive the different banks' reaction to the payment default.

To rule out this concern, we consider a propensity score matching approach. The idea is to compare only lenders that are equally knowledgeable about the defaulting firm. We thus match the relationship the borrower has with the reporting bank with similar relationships the same borrower has with other lenders.

Following prior works, the matching is based on a set of characteristics that proxy for the amount of private information the lenders hold on the borrower. First, the length of the bank-firm relationship (Petersen and Rajan, 1994; Ongena and Smith, 2001; Ioannidou and Ongena, 2010; López-Espinosa et al., 2017). Second, the market share of the bank in the borrower's county. Indeed, holding a large share of the local market may facilitate the collection of information about local borrowers (Hauswald and Marquez, 2003; Agarwal and Hauswald, 2010). Third, the bank's specialization in the sector of the borrower. This may favour the collection of information on borrowers operating in that sector (see, e.g., De Jonghe et al., 2019; Paravisini et al., forthcoming). Lastly, the bank credit granted to the firm by the bank, which captures the exposure of the bank towards the borrower, and the total credit extended by the bank, which is a measure of the size of the bank. The size of the bank can indeed influence its lending technology (Stein, 2002; Berger et al., 2017).

To implement our propensity score matching approach, we consider only firms at the time they default on a trade bill. We focus on borrowers that while holding more than one lending relationship have only one bank reporting the default in the quarter. Using a probit specification, we estimate for each bank-firm relationship the probability for the lender of being a reporting bank—that is, the matching score—based on the characteristics described above. We report the results of this model in column (1) of Table VII. We find that banks that have a young relationship with the defaulting borrower, that are specialized in its sector, and are large in size are less likely to be the reporting bank. On the other hand, we find that banks with a dominant position in the borrower's local market and that are more exposed towards the borrower are more likely to be the reporting bank.

[Please insert Table VII about here]

We match the lending relationship of a defaulting borrower with its reporting bank with the lending relationships that the same borrower has with non-reporting banks, based on the probability for the lender of being the reporting bank. Precisely, we retain those lending relationships with non-reporting banks that are associated with a propensity score that is at most 0.1 distant from the score of the lending relationship with the actual reporting bank.[11] We implement our baseline analysis on the matched sample.

[11] Table OA2 in the Online Appendix reports the covariate balance for matched bank-firm relationships. It shows that the comparability of lending relationships significantly increases after matching.

The results are shown in columns (2) and (3) of Table VII. The coefficient on *reporting bank* is negative and significant in both specifications considered, thus suggesting that the reporting bank reacts more than equally-informed non-reporting banks. This result provides further confirmation to the information salience hypothesis.

### *B Bank-Specific Credit Demand*

Our second identifying assumption is that firm-level credit demand is symmetric across lenders (Khwaja and Mian, 2008). As noted by Altavilla et al. (2021), credit demand can vary, not just at the firm level, but also at the bank-firm level. It is therefore possible that, after the payment default, borrowers ask more credit to lenders that have characteristics that are not associated with being the reporting bank. As a consequence, one concern could be that our findings are driven by a relatively lower demand of credit to reporting banks. While we have already shown in Section IV.*A.2* that our main results hold when we compare reporting and non-reporting banks that have similar characteristics, we provide additional tests on the bank-specific credit demand issue in this section.

We control for the potential heterogeneity of firms' credit demand across banks by considering three different sets of fixed effects. First, on top of firm×bank and firm×time fixed effects, we include bank×sector×county×size×time fixed effects. The idea behind these fixed effects derives from the methodology proposed by Degryse et al. (2019), which controls for firm demand by using sector×county×size×time fixed effects. By adding these fixed effects, we control for the fact that borrowers that share size, sector and location may have a specific demand of credit towards specific banks at a given time $t$. Altavilla et al. (2022) employ a similar approach, but without accounting for the size of the borrower. Second, we consider bank×default×time fixed effects to control for bank-specific demand by defaulting firms. Finally, we employ bank×sector×county×size×default×time fixed effects. These fixed effects allow us to control for bank-specific demand of defaulting borrowers which share size, sector and location.

[Please insert Table VIII about here]

The results are reported in Table VIII. The coefficient on *reporting bank* is still negative and significant across all specifications considered. Importantly, its magnitude is similar to the one in Column (5) of Table II. Overall, these results are reassuring in that our findings are not driven by bank-specific demand of defaulting borrowers.

### *C Type of Bank Credit*

In the analyses discussed in the previous sections, we have treated bank credit as an homogeneous aggregate. However, bank credit varies in terms of type of contract and maturity. In this section, we replicate our baseline analysis to investigate the impact of the salience of information on credit lines, short-term bank credit and long-term bank credit, separately. The analysis on credit lines and short-term bank credit is particularly helpful to mitigate the concern that our results can be affected by scheduled repayments, which impacts more severely long-term bank credit.[12]

Our prediction is that the extra reduction in loan supply of reporting versus non-reporting banks should be more pronounced for credit lines and short-term loans for at least two reasons. First, banks can adjust more easily credit lines than term loans. Second, credit lines and short-term bank credit are usually less likely to be collateralized than long-term bank credit (Benmelech et al., 2020). Hence, if reporting banks' risk aversion increases following the borrower's payment default, their differential reaction should be stronger in the case of credit lines and short-term bank credit.

[Please insert Table IX about here]

Table IX reports estimation results. The coefficients on *reporting bank* confirm our expectation that there is a stronger reaction of reporting banks in case of credit lines and short-term bank credit. The fact that salience of information about borrowers has a significant impact on the supply of credit lines is of particular importance given the large use of this type of credit for corporations (see, e.g, Sufi, 2007 and Campello et al., 2012). The coefficient is still significant in the case of long-term bank credit, but implies a smaller effect.

## V Conclusions

This paper shows that the salience of information affects banks' lending decisions. We use a setting in which information about borrowers' payment default on trade bills

[12]Unfortunately, credit registry data do not allow us to remove scheduled repayments from the flow of credit to the borrower.

is available to all banks but it appears more prominently to the bank that manages the payment transaction (the reporting bank).

Using a within-firm estimator to control for firm demand (Khwaja and Mian, 2008), we find that reporting banks cut the supply of credit to defaulting borrowers more than non-reporting banks. Consistently with the hypothesis that this reaction hinges on information salience, we show that the effect varies depending on the prominence of the event that is observed by the reporting bank. We show that the branches of reporting banks that directly process the payment defaults react more strongly than non-reporting branches of reporting banks. Additionally, the reporting branches react more especially when the number of events they process in a day is lower and when the time elapsed since the last event they observed becomes larger.

We implement a battery of tests to document that information gaps between the reporting banks and other lenders cannot explain our results. Additionally, we show that increases in the demand of credit by defaulting borrowers towards non-reporting banks are unlikely to be the drivers of our results.

Overall, we shed light on the importance of the salience of borrowers' information in the credit market. Our results may have important policy implications in terms of the design of information sharing systems. In fact, if banks respond to the salience of the information they receive, policy makers should not only pay attention to the optimal amount of information that should be shared amongst lenders, but also to the way this information is reported and displayed.

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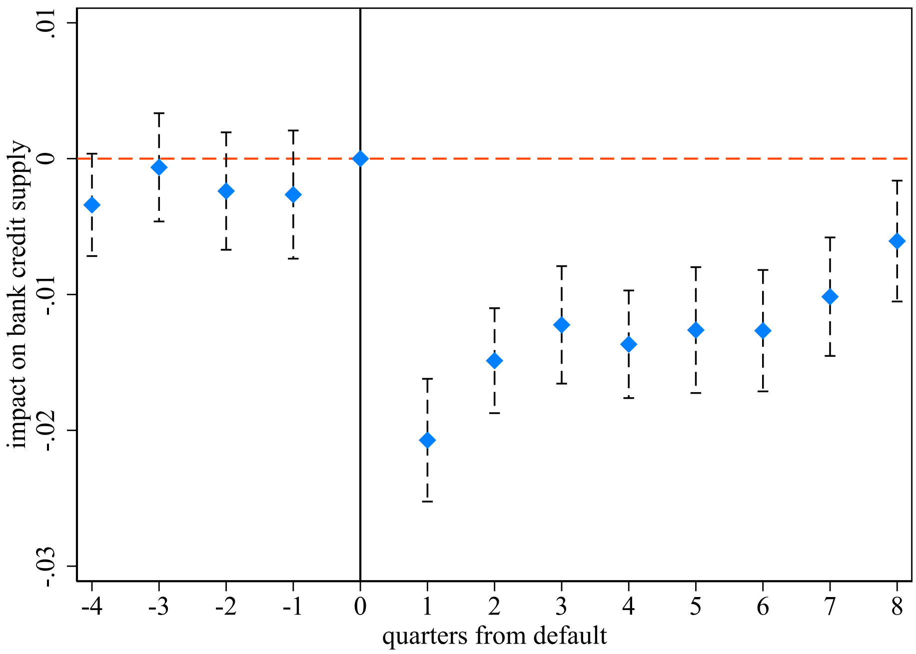
# VI Figures

**Figure 1**

**Salience of payment defaults**

This figure studies the difference between the credit flow of the reporting bank and that of other lenders around the time the reporting bank reports the firm's payment default. We run the specification of Equation (2), which includes a set of dummies 0/1 identifying the distance with respect to the quarter before the bank reports the defaults. We plot the coefficients on these dummies for $t$ between -4 and +8. Time 0 is the last quarter before the default and is taken as the reference quarter. The regression is estimated on a sample composed of bank-firm relationships for which the bank reports at most one default in the sample period. Confidence intervals are obtained by two-way clustering standard errors at the bank and firm level.



# VII Tables

**Table I**

## Summary statistics

This table presents the summary statistics of the samples considered in the analysis. Variable definitions are in Table A1 in the Appendix.

*Firm-bank sample* (unit of obs: firm-bank-quarter)

| | N | Mean | Median | St. dev. | 5th pctile | 95th pctile |
|---|---|---|---|---|---|---|
| Δ log credit (t-1;t) | 18,092,193 | -0.028 | -0.039 | 0.211 | -0.300 | 0.368 |
| Δ log credit line (t-1;t) | 970,455 | 0.013 | 0.000 | 0.731 | -1.211 | 1.253 |
| Δ log ST credit (t-1;t) | 3,364,128 | 0.007 | 0.000 | 0.651 | -1.053 | 1.086 |
| Δ log LT credit (t-1;t) | 8,875,800 | -0.036 | -0.046 | 0.184 | -0.250 | 0.233 |
| log credit (t-1) | 18,092,193 | 5.067 | 4.828 | 1.300 | 3.434 | 7.701 |
| reporting bank (t) | 18,092,193 | 0.027 | 0.000 | 0.162 | 0.000 | 0.000 |
| reporting bank (liquidity default) (t) | 18,092,193 | 0.009 | 0.000 | 0.094 | 0.000 | 0.000 |
| reporting bank (litigation default) (t) | 18,092,193 | 0.019 | 0.000 | 0.138 | 0.000 | 0.000 |
| default (t) | 18,092,193 | 0.096 | 0.000 | 0.295 | 0.000 | 1.000 |
| liquidity default (t) | 18,092,193 | 0.028 | 0.000 | 0.165 | 0.000 | 0.000 |
| litigation default (t) | 18,092,193 | 0.074 | 0.000 | 0.262 | 0.000 | 1.000 |
| speculative grade (t-1) | 18,092,193 | 0.267 | 0.000 | 0.443 | 0.000 | 1.000 |
| unrated (t-1) | 18,092,193 | 0.439 | 0.000 | 0.496 | 0.000 | 1.000 |
| bank exposure (t-1, in %) | 18,092,193 | 0.019 | 0.004 | 0.051 | 0.000 | 0.095 |
| young (t-1) | 18,092,193 | 0.361 | 0.000 | 0.480 | 0.000 | 1.000 |
| market share (t-1, in %) | 18,092,193 | 6.266 | 2.962 | 8.996 | 0.038 | 28.102 |
| sector specialization (t-1, in %) | 18,092,193 | 18.208 | 13.215 | 18.165 | 1.418 | 55.847 |
| bank size (t-1) | 18,092,193 | 15.289 | 15.160 | 1.598 | 12.761 | 18.541 |

*Firm-bank branch sample* (unit of obs: firm-bank branch-quarter)

| | N | Mean | Median | St. dev. | 5th pctile | 95th pctile |
|---|---|---|---|---|---|---|
| Δ log credit (branch-level) (t-1;t) | 17,892,412 | -0.028 | -0.039 | 0.211 | -0.298 | 0.367 |
| reporting bank (t) | 17,892,412 | 0.027 | 0.000 | 0.161 | 0.000 | 0.000 |
| reporting bank branch (t) | 17,892,412 | 0.021 | 0.000 | 0.144 | 0.000 | 0.000 |
| same-day reported defaults (t) | 377,731 | 4.486 | 1.000 | 10.481 | 1.000 | 20.000 |
| days from last default reported by branch (t) | 377,731 | 10.289 | 5.000 | 16.882 | 1.000 | 34.000 |
| default (t) | 17,892,412 | 0.096 | 0.000 | 0.294 | 0.000 | 1.000 |

**Table II**

## Salience of trade bill payment defaults and bank credit supply

In this table, we study the effects of the salience of trade bill payment defaults on bank credit supply. The dependent variable is the change between quarter *t-1* and quarter *t* in the log of outstanding bank credit at the firm-bank-level. *reporting bank* is a dummy 0/1 capturing if the bank reports to the central bank at least one trade bill payment default for the company during quarter *t*. *default* is a dummy 0/1 capturing if the company defaults on at least one trade supplier during quarter *t*. The sample includes firms that have at least two lending relationships in the same quarter. Each column represents a different degree of saturation of the specification. Standard errors are two-way clustered at the firm and bank level. *t*-statistics are in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

| | $\Delta$ log credit (t-1;t) | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| reporting bank (t) | -0.0115*** | -0.0115*** | -0.0110*** | -0.0106*** | -0.0091*** |
| | (-11.82) | (-11.89) | (-11.74) | (-11.29) | (-12.23) |
| default (t) | -0.0032*** | -0.0032*** | -0.0021*** | -0.0021*** | |
| | (-8.03) | (-7.99) | (-5.12) | (-5.23) | |
| Firm × bank FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Sector × time FE | ✓ | | | | |
| County × time FE | ✓ | | | | |
| Size × time FE | ✓ | | | | |
| Sector × county × size × time FE | | ✓ | ✓ | ✓ | |
| Rating × time FE | | | ✓ | ✓ | |
| Firm × time FE | | | | | ✓ |
| Bank × time FE | | | | ✓ | ✓ |
| Observations | 18,092,193 | 18,092,193 | 18,092,193 | 18,092,193 | 18,092,193 |
| $R^2$ | 0.09 | 0.10 | 0.10 | 0.11 | 0.42 |

**Table III**

## Shifting the prominence of trade bill payment defaults

In this table, we study the effects of the salience of trade bill payment defaults on bank credit supply by shifting the prominence of the defaults. The dependent variable is the change between quarter *t-1* and quarter *t* in the log of outstanding bank credit at the firm-bank branch-level. In Columns (1)-(3), we investigate whether a reporting branch of a reporting bank reacts differently from a non-reporting branch of a reporting bank (*reporting bank branch*). In Columns (4)-(6), we analyze whether the reaction of a reporting branch changes depending on the number of firms whose default is reported by the branch the day the company defaults (*same-day reported defaults*). In Columns (7)-(9), we analyze whether the reaction of a reporting branch changes depending on the time distance from the last default that the branch reported, independently on the companies involved (*days from last default reported by branch*). As in Table II, *reporting bank* is a dummy 0/1 capturing if the bank reports to the central bank at least one trade bill payment default for the company during quarter *t*. *default* is a dummy 0/1 capturing if the company defaults on at least one trade supplier during quarter *t*. The sample includes firms that have at least two lending relationships in the same quarter. Each column represents a different degree of saturation of the specification. Standard errors are two-way clustered at the firm and bank level. *t*-statistics are in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

| | Δ log credit (branch-level) (t-1;t) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| reporting bank (t) | -0.0077*** | -0.0057*** | -0.0055*** | -0.0077*** | -0.0057*** | -0.0055*** | -0.0077*** | -0.0057*** | -0.0055*** |
| | (-5.09) | (-4.01) | (-3.74) | (-5.09) | (-4.03) | (-3.76) | (-5.08) | (-4.01) | (-3.75) |
| reporting bank branch (t) | -0.0033* | -0.0043*** | -0.0042** | -0.0057*** | -0.0065*** | -0.0065*** | 0.0001 | -0.0012 | -0.0007 |
| | (-1.85) | (-2.64) | (-2.48) | (-2.99) | (-3.77) | (-3.63) | (0.03) | (-0.65) | (-0.38) |
| — × log same-day reported defaults (t) | | | | 0.0034*** | 0.0031*** | 0.0031*** | | | |
| | | | | (5.72) | (5.34) | (5.17) | | | |
| — × log days from last default reported by branch (t) | | | | | | | -0.0022*** | -0.0020*** | -0.0023*** |
| | | | | | | | (-4.08) | (-4.13) | (-4.61) |
| default (t) | -0.0020*** | | | -0.0021*** | | | -0.0020*** | | |
| | (-5.14) | | | (-5.15) | | | (-5.13) | | |
| Firm × bank branch FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Sector × county × size × time FE | ✓ | | | ✓ | | | ✓ | | |
| Rating × time FE | ✓ | | | ✓ | | | ✓ | | |
| Firm × time FE | | ✓ | ✓ | | ✓ | ✓ | | ✓ | ✓ |
| Bank × time FE | ✓ | ✓ | | ✓ | ✓ | | ✓ | ✓ | |
| Bank branch × time FE | | | ✓ | | | ✓ | | | ✓ |
| Observations | 17,892,412 | 17,892,412 | 17,892,412 | 17,892,412 | 17,892,412 | 17,892,412 | 17,892,412 | 17,892,412 | 17,892,412 |
| $R^2$ | 0.11 | 0.43 | 0.45 | 0.11 | 0.43 | 0.45 | 0.11 | 0.43 | 0.45 |

**Table IV**

## Choice under risk

In this table, we study whether the impact of the salience of trade bill payment defaults on bank credit supply changes when the risk associated with the borrower is higher. The dependent variable is the change between quarter *t-1* and quarter *t* in the log of outstanding bank credit at the firm-bank-level. In Columns (1) and (2), risk is measured by two dummies, *speculative grade* and *unrated*: the former captures if the company was rated "5+" or below as of quarter *t-1*, while the latter captures whether the company was not rated (because too small) as of quarter *t-1*. In Columns (3) and (4), risk is measured by the log of the bank's exposure to the company, which is computed as the percentage of the bank's total credit volume lent to the company. As in Table II, *reporting bank* is a dummy 0/1 capturing if the bank reports to the central bank at least one trade bill payment default for the company during quarter *t*. *default* is a dummy 0/1 capturing if the company defaults on at least one trade supplier during quarter *t*. The sample includes firms that have at least two lending relationships in the same quarter. Each column represents a different degree of saturation of the specification. Standard errors are two-way clustered at the firm and bank level. *t*-statistics are in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

| | $\Delta$ log credit (t-1;t) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| reporting bank (t) | -0.0030*** | -0.0019** | -0.0268*** | -0.0269*** |
| | (-3.69) | (-2.22) | (-4.76) | (-6.26) |
| — × speculative grade (t-1) | -0.0136*** | -0.0131*** | | |
| | (-9.08) | (-9.18) | | |
| — × unrated (t-1) | -0.0077*** | -0.0083*** | | |
| | (-7.06) | (-6.76) | | |
| — × log bank exposure (t-1) | | | -0.0036*** | -0.0039*** |
| | | | (-3.88) | (-5.51) |
| default (t) | -0.0001 | | -0.0041* | |
| | (-0.20) | | (-1.82) | |
| — × speculative grade (t-1) | -0.0043*** | | | |
| | (-5.57) | | | |
| — × unrated (t-1) | -0.0019*** | | | |
| | (-2.62) | | | |
| — × log bank exposure (t-1) | | | -0.0004 | -0.0007* |
| | | | (-1.02) | (-1.93) |
| log bank exposure (t-1) | | | -0.1250*** | -0.1443*** |
| | | | (-18.14) | (-23.03) |
| Firm × bank FE | ✓ | ✓ | ✓ | ✓ |
| Sector × county × size × time FE | ✓ | | ✓ | |
| Rating × time FE | ✓ | | ✓ | |
| Firm × time FE | | ✓ | | ✓ |
| Bank × time FE | ✓ | ✓ | ✓ | ✓ |
| Observations | 18,092,193 | 18,092,193 | 18,092,193 | 18,092,193 |
| $R^2$ | 0.11 | 0.42 | 0.16 | 0.47 |

**Table V**

## Payment defaults and probability of failure

In this table, we study the relationship between payment defaults and probability of failure. The dependent variable is a dummy 0/1 identifying whether a firm gets liquidated (i.e., incurs in the event of *liquidation judiciaire*) over the following year. *default* is a dummy 0/1 capturing whether the company defaults on at least one trade supplier during quarter *t*. In column (6), we study whether the effect is different depending on whether the default is due to liquidity reasons. The parameters are estimated using a Probit model or a linear probability model (LPM). In the case of the probit specification, parameter estimates refer to marginal effects when setting *default* to zero. The sample includes firms that have at least two lending relationships in the same quarter. Each column represents a different degree of saturation of the specification. Standard errors are clustered at the firm level. *t*-statistics are in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

| | company is liquidated (t+1;t+4) | | | | | |
|---|---|---|---|---|---|---|
| | Probit | LPM | LPM | LPM | LPM | LPM |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| default (t) | 0.0154*** | 0.0346*** | 0.0345*** | 0.0347*** | 0.0233*** | 0.0030*** |
| | (116.01) | (79.49) | (79.31) | (79.40) | (63.74) | (11.59) |
| — × liquidity default (t) | | | | | | 0.0680*** |
| | | | | | | (67.63) |
| Conditional probability | 0.0101 | | | | | |
| Time FE | ✓ | ✓ | | | | |
| Sector FE | ✓ | ✓ | | | | |
| County FE | ✓ | ✓ | | | | |
| Size FE | ✓ | ✓ | | | | |
| Sector × time FE | | | ✓ | | | |
| County × time FE | | | ✓ | | | |
| Size × time FE | | | ✓ | | | |
| Sector × county × size × time FE | | | | ✓ | ✓ | ✓ |
| Rating × time FE | | | | | ✓ | ✓ |
| Observations | 6,382,944 | 6,382,944 | 6,382,944 | 6,382,944 | 6,382,944 | 6,382,944 |
| Pseudo-$R^2$ / $R^2$ | 0.10 | 0.02 | 0.02 | 0.03 | 0.09 | 0.10 |

**Table VI**

## Alternative explanation

In this table, we study whether the effects we find in Table II can be explained by an information asymmetry between reporting and non-reporting banks. We do this by investigating whether or not non-reporting banks make a distinction between reasons of default and react differently to them. The dependent variable is the change between quarter *t-1* and quarter *t* in the log of outstanding bank credit at the firm-bank-level. As in Table II, *reporting bank* is a dummy 0/1 capturing if the bank reports to the central bank at least one trade bill payment default for the company during quarter *t*. *default* is a dummy 0/1 capturing if the company defaults on at least one trade supplier during quarter *t*. The main parameter of interest is that on the interaction between *default* and *liquidity default*, which identifies whether non-reporting banks react differently in case the default is for liquidity reasons. The sample includes firms that have at least two lending relationships in the same quarter. Each column represents a different degree of saturation of the specification. Standard errors are two-way clustered at the firm and bank level. *t*-statistics are in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

| | Δ log credit (t-1;t) | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| reporting bank (t) | -0.0026*** | -0.0027*** | -0.0026*** | -0.0019*** | -0.0014** |
| | (-4.00) | (-4.03) | (-3.91) | (-2.97) | (-2.11) |
| — × liquidity default (t) | -0.0251*** | -0.0251*** | -0.0244*** | -0.0252*** | -0.0259*** |
| | (-12.09) | (-12.14) | (-12.05) | (-12.78) | (-15.95) |
| default (t) | -0.0002 | -0.0002 | 0.0001 | 0.0000 | |
| | (-0.54) | (-0.47) | (0.34) | (0.01) | |
| — × liquidity default (t) | -0.0109*** | -0.0108*** | -0.0083*** | -0.0080*** | |
| | (-8.55) | (-8.45) | (-6.51) | (-6.39) | |
| Firm × bank FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Sector × time FE | ✓ | | | | |
| County × time FE | ✓ | | | | |
| Size × time FE | ✓ | | | | |
| Sector × county × size × time FE | | ✓ | ✓ | ✓ | |
| Rating × time FE | | | ✓ | ✓ | |
| Firm × time FE | | | | | ✓ |
| Bank × time FE | | | | ✓ | ✓ |
| Observations | 18,092,193 | 18,092,193 | 18,092,193 | 18,092,193 | 18,092,193 |
| $R^2$ | 0.09 | 0.10 | 0.10 | 0.11 | 0.42 |

**Table VII**

## Propensity score matching approach

In this table, we study the impact of the salience of trade bill payment defaults on bank credit supply employing a propensity score matching approach. Column (1) investigates the characteristics of the lending relationships with reporting banks. We consider firms at the time they default on at least one trade supplier, and focus on those that have more than one lending relationship but have only one bank reporting the default. The dependent variable is a dummy 0/1 capturing if the bank is that reporting bank. The effects are estimated using a probit specification, and parameter estimates refer to marginal effects while setting dummy variables to zero and continuous variables to the sample median. Building on the estimation in column (1), columns (2) and (3) employ a propensity score approach to the analysis of the salience of trade bill payment defaults on bank credit supply. The dependent variable is the change between quarter *t-1* and quarter *t* in the log of outstanding bank credit at the firm-bank-level. The sample includes firms that have at least two lending relationships in the same quarter: sampled firms either never default or, when they default, have only one bank reporting the default. Importantly, in case of companies defaulting, we retain those lending relationships with non-reporting banks that are associated with a propensity score that is at most .1 distant from the propensity score of the lending relationship with the actual reporting bank. The two columns represent different degree of saturation of the specification. In column (1), standard errors are clustered at the firm level, while in Columns (2) and (3), they are two-way clustered at the firm and bank level. *t*-statistics are in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

| | reporting bank (t) | Δ log credit (t-1;t) | |
|---|---|---|---|
| | (1) | (2) | (3) |
| reporting bank (t) | | -0.0043*** | -0.0035*** |
| | | (-3.13) | (-3.04) |
| default (t) | | -0.0036*** | |
| | | (-4.27) | |
| young (t-1) | -0.1496*** | | |
| | (-83.49) | | |
| market share (t-1) | 0.1311*** | | |
| | (146.83) | | |
| sector specialization (t-1) | -0.0488*** | | |
| | (-32.43) | | |
| log credit (t-1) | 0.0235*** | | |
| | (25.63) | | |
| bank size (t-1) | -0.0215*** | | |
| | (-26.54) | | |
| Firm × bank FE | | ✓ | ✓ |
| Sector × county × size × time FE | | ✓ | |
| Rating × time FE | | ✓ | |
| Firm × time FE | | | ✓ |
| Bank × time FE | | ✓ | ✓ |
| Conditional probability | 0.3730 | | |
| Time FE | ✓ | | |
| Sector FE | ✓ | | |
| County FE | ✓ | | |
| Size FE | ✓ | | |
| Observations | 1,309,846 | 16,638,902 | 16,638,902 |
| Pseudo-$R^2$ / $R^2$ | 0.21 | 0.11 | 0.44 |

**Table VIII**

## Firms' credit demand across banks

In this table, we study the effects of the salience of trade bill payment defaults on bank credit supply controlling for potential heterogeneity in firms' credit demand across banks. The dependent variable is the change between quarter *t-1* and quarter *t* in the log of outstanding bank credit at the firm-bank-level. *reporting bank* is a dummy 0/1 capturing if the bank reports to the central bank at least one trade bill payment default for the company during quarter *t*. The sample includes firms that have at least two lending relationships in the same quarter. Each column represents a different degree of saturation of the specification. Standard errors are two-way clustered at the firm and bank level. *t*-statistics are in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

| | $\Delta$ log credit (t-1;t) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| reporting bank (t) | -0.0089*** | -0.0096*** | -0.0095*** |
| | (-10.97) | (-11.41) | (-9.53) |
| Firm × bank FE | ✓ | ✓ | ✓ |
| Firm × time FE | ✓ | ✓ | ✓ |
| Bank × sector × county × size × time FE | ✓ | | |
| Bank × default × time FE | | ✓ | |
| Bank × sector × county × size × default × time FE | | | ✓ |
| Observations | 16,203,264 | 18,090,986 | 15,598,470 |
| $R^2$ | 0.52 | 0.42 | 0.55 |

**Table IX**

## Type of bank credit

In this table, we study the impact of the salience of trade bill payment defaults on different types of bank credit. The dependent variable in Column (1) and (2) is the change between quarter *t-1* and quarter *t* in the log of used credit lines at the firm-bank-level, in Columns (3) and (4) it is the change in the log of outstanding short-term bank-credit at the firm-bank-level, whereas in Columns (5) and (6) it is the change in the log of outstanding long-term bank credit at the firm-bank-level. *reporting bank* is a dummy 0/1 capturing if the bank reports to the central bank at least one trade bill payment default for the company during quarter *t*. *default* is a dummy 0/1 capturing if the company defaults on at least one trade supplier during quarter *t*. The sample includes firms that have at least two lending relationships in the same quarter. Standard errors are two-way clustered at the firm and bank level. *t*-statistics are in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

| | Δ log credit line (t-1;t) | | Δ log ST credit (t-1;t) | | Δ log LT credit (t-1;t) | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| reporting bank (t) | -0.0313*** | -0.0272*** | -0.0284*** | -0.0248*** | -0.0047*** | -0.0036*** |
| | (-6.86) | (-5.62) | (-8.19) | (-7.48) | (-8.16) | (-5.88) |
| default (t) | -0.0068** | | -0.0046* | | -0.0003 | |
| | (-2.35) | | (-1.70) | | (-0.69) | |
| Firm × bank FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Sector × county × size × time FE | ✓ | | ✓ | | ✓ | |
| Rating × time FE | ✓ | | ✓ | | ✓ | |
| Firm × time FE | | ✓ | | ✓ | | ✓ |
| Bank × time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 970,455 | 970,455 | 3,364,128 | 3,364,128 | 8,875,800 | 8,875,800 |
| $R^2$ | 0.16 | 0.53 | 0.11 | 0.48 | 0.18 | 0.55 |

# Appendix

**Table A1**

**Variable definitions**

This table provides descriptions and sources of the main variables used in the analyses

| Variable | Definition | Source |
|---|---|---|
| Δ log credit (t-1;t) | quarterly change (between quarter *t-1* and quarter *t*) in the log of outstanding bank credit (drawn and undrawn) at the firm-bank level | SCR |
| Δ log credit line (t-1;t) | quarterly change in the log of used credit lines at the firm-bank level | SCR |
| Δ log ST credit (t-1;t) | quarterly change in drawn bank credit with maturity shorter than one year at the firm-bank level | SCR |
| Δ log LT credit (t-1;t) | quarterly change in drawn bank credit with maturity longer than one year at the firm-bank level | SCR |
| log credit (t-1) | log of total bank credit that the firm obtains from the lender | SCR |
| reporting bank (t) | dummy 0/1 identifying the reporting bank | CIPE |
| reporting bank (liquidity default) (t) | dummy 0/1 identifying the bank that reports a default for illiquidity | CIPE |
| reporting bank (litigation default) (t) | dummy 0/1 identifying the bank that reports a default for disagreement between the firm and the supplier | CIPE |
| default (t) | dummy 0/1 identifying defaulting firm in quarter *t* | CIPE |
| liquidity default (t) | dummy 0/1 identifying defaulting firms for illiquidity in quarter *t* | CIPE |
| litigation default (t) | dummy 0/1 identifying defaulting firms for disagreement in quarter *t* | CIPE |
| speculative grade (t-1) | dummy 0/1 identifying firms rated "5+" or below in the Banque de France (BdF) rating scale | BdF's credit rating data |
| unrated (t-1) | dummy 0/1 identifying firms that are not rated by the BdF | BdF's credit rating data |
| bank exposure (t-1) | credit extended by the bank to the firm divided by the total credit extended by the bank (in %) | SCR |
| young (t-1) | dummy 0/1 identifying the bank-firm relationship that started less than three year before quarter *t-1* | SCR |
| market share (t-1) | total credit extended by the bank to borrowers located in the firm's county divided by the aggregated volume of loans outstanding in that county (in %) | SCR |
| sector specialization (t-1) | total credit extended by the bank to borrowers in the firm's sector divided by the total credit extended by the bank (in %) | SCR |
| bank size (t-1) | log of credit (drawn and undrawn) extended by the bank | SCR |
| Δ log credit (branch-level) (t-1;t) | quarterly change in the log of outstanding bank credit (drawn and undrawn) at the firm-bank branch level | SCR |
| reporting bank branch (t) | dummy 0/1 identifying the reporting branch | CIPE |
| same-day reported defaults (t) | number of firms whose payment default is reported by the branch the same day | CIPE |
| days from last default reported by branch (t) | number of days from the last default reported by the branch (regardless of the defaulting companies involved) | CIPE |

# Online Appendix

**Figure OA1**
**Bill of exchange**
This figure depicts the functioning and parties involved in the issuance and payment of a bill of exchange.

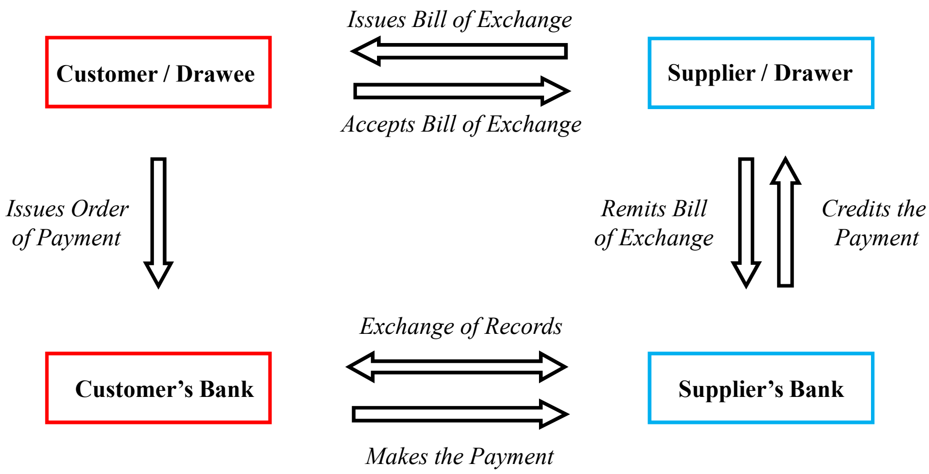


**Figure OA2**

**Top most accessed modules in FIBEN by banks**

This figure reports the list of top 5 most accessed modules by banks in FIBEN. The module *Panorama de l'entreprise et du dirigeant* allows banks to have access to the main characteristics of the borrower and includes the list of its payment defaults on trade bills. The module *Sources de Financement* is the French credit registry. The modules *Fonctions de directions* and *Dirigeants de l'entreprise* contain information on firms' managers. The module *Cotation et son explication* allows banks to collect details on the credit rating of the borrower produced by the central bank.

| Top 5 | TOP 5 de la profession bancaire |
|---|---|
| 1 | Panorama de l'entreprise et du dirigeant (27) |
| 2 | Sources de financement (28) |
| 3 | Fonctions de direction (56) |
| 4 | Dirigeants de l'entreprise (51) |
| 5 | Cotation et son explication (37) |

**Figure OA3**

**Extract of the module *Panorama de l'entreprise et du dirigeant***

This figure reports an extract of an example of the module *Panorama de l'entreprise et du dirigeant*. The figure shows how information on the identifiers, address, credit rating and payment defaults of the borrower is displayed. The lower part of the figure shows that the module clearly reports the date, the number and the amount of borrower's missed payments to suppliers by quarter.

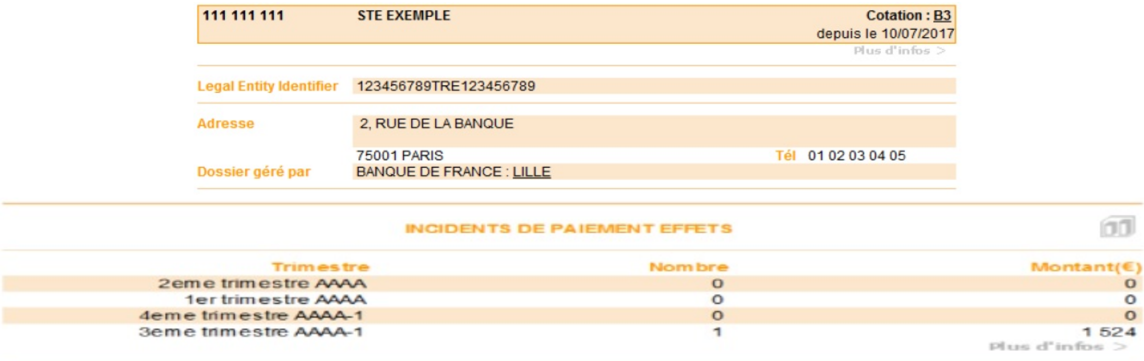


**Table OA1**

**Salience of payment defaults: all firms in the credit registry**

In this table, we study the implications of the salience of trade bill payment defaults on bank credit supply considering all firms in the credit registry and not just those that have at least two lending relationships in the same quarter as in Table II. In case a firm has just one lending relationship, it may not be that lending bank is the one reporting the default when the company defaults on a trade bill: another bank may administer its payments and thus report the default. The dependent variable is the change between quarter *t-1* and quarter *t* in the log of outstanding loans at the firm-bank-level. *reporting bank* is a dummy 0/1 capturing if the bank reports to the central bank at least one trade bill payment default for the company during quarter *t*. *default* is a dummy 0/1 capturing if the company defaults on at least one trade supplier during quarter *t*. Each column represents a different degree of saturation of the specification. Standard errors are two-way clustered at the firm and bank level. *t*-statistics are in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

| | $\Delta$ log credit (t-1;t) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| reporting bank (t) | -0.0098*** | -0.0098*** | -0.0088*** | -0.0086*** |
| | (-13.84) | (-13.87) | (-13.33) | (-12.91) |
| default (t) | -0.0032*** | -0.0031*** | -0.0018*** | -0.0019*** |
| | (-8.18) | (-8.18) | (-4.42) | (-4.65) |
| Firm × bank FE | ✓ | ✓ | ✓ | ✓ |
| Sector × time FE | ✓ | | | |
| County × time FE | ✓ | | | |
| Size × time FE | ✓ | | | |
| Sector × county × size × time FE | | ✓ | ✓ | ✓ |
| Rating × time FE | | | ✓ | ✓ |
| Bank × time FE | | | | ✓ |
| Observations | 44,455,244 | 44,455,244 | 44,455,244 | 44,455,244 |
| $R^2$ | 0.09 | 0.09 | 0.09 | 0.10 |

**Table OA2**

## Covariate balance for matched bank-firm relationships

This table show covariate balance tests for the propensity score matching estimation in Table VII. It reports the difference in means and variance ratio in the characteristics of the bank-firm relationship, bank market power and bank size between reporting and non-reporting banks. The difference in means is measured by the standardized percentage bias, which is the percent difference in means divided by the sample standard deviation of the variable. The differences are reported for the raw (unmatched) samples and for the matched samples.

| | Standardized % bias | | Variance ratio | |
|---|---|---|---|---|
| | Raw | Matched | Raw | Matched |
| young (t-1) | -40.45 | -11.44 | 0.70 | 0.89 |
| market share (t-1) | 89.58 | 15.04 | 0.45 | 0.83 |
| sector specialization (t-1) | -23.11 | -5.21 | 0.83 | 0.92 |
| log credit (t-1) | 4.09 | -4.12 | 0.79 | 0.85 |
| bank size (t-1) | 29.40 | -0.22 | 0.76 | 1.02 |