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 non-reporting 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 reporting and non-reporting banks cannot explain our findings.

Keywords: Bank Lending; Payment Defaults; Salience; Information-Sharing Mechanisms.
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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., 2021). A key question is, therefore, whether the display of information impacts the decision-making process of 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. As suggested by Mian and Smith (1992) and Biais and Gollier (1997), firms' trade relationships are an important source of information for banks. Specifically, the information about firms defaulting on a payment can be a useful signal for financial intermediaries since a default may reveal firm distress and an incipient propagation of a negative shock through the supply chain (Boissay and Gropp, 2013; Jacobson and von Schedvin, 2015). For these reasons, payment default information is a relevant information shock 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 make the prominence—that is, the salience—of the default for the reporting bank high. 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 increases risk aversion (Bordalo et al., 2012, 2021), under the salience hypothesis, reporting banks should reduce the supply of credit to defaulted firms more than other lenders. We employ credit registry data from 2012Q1 to 2019Q4, which detail quarterly loan 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, so that 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 establish that following the default reporting banks reduce credit supply five times more than other lenders.[1]

We further test the salience hypothesis by investigating whether the effects amplify when the default is made more prominent for the bank. A priori, the default carries higher prominence when the credit officer works in the same branch that observes and reports the default. Hence, if salience plays a role, banks' reaction should peak when the bank branch lending to the defaulted firm coincide 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 the same day a larger number of firms defaulting. 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 stronger is the loan supply reduction. Also in line with the salience hypothesis, we find that the reaction to a borrower's default is stronger 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 matters. Yet, an interpretation hinging on salience requires that all banks share a similar set of information about the defaulted borrowers. 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 informational gaps between them. Indeed, 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 the lack of incentives to monitor, and to the need to pay a negligible but still positive cost to access the CIPE data set. 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

[1] In the absence of firm$\times$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 when it defaults on a payment that a firm has greater demand for liquidity and credit.

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, 2022). 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 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 borrower—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, 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. 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, and bank size. Even when we compare reporting

[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`.

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 driven by bank-specific credit demand. Also, we show that the effects on credit supply are more pronounced precisely for the types of credit that are easily adjustable by the banks and for the non-collateralized portion of outstanding credit (i.e., 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), when they design securities for investors (Célérier and Vallée, 2017) and price climate risk (Nguyen et al., 2022). To our knowledge, we are the first to show that the salience of information about borrowers impacts bank credit supply. 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 the 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). However, the literature is mostly silent on whether and how banks exploit information gathered from trade credit relationships. We show that banks react to this information, but, most importantly, that banks' reaction depends on the prominance of this information.

Another strand of the literature documents the importance of the proprietary firm-specific information that banks acquire through their lending activity, which can be a source of informational advantage (Dell'Ariccia and Marquez, 2004; Schenone, 2010; Agarwal and Hauswald, 2010). While the information on payment defaults is firm-specific, it is not proprietary. In fact, it is readily available to all banks. Yet, our paper shows that lenders that are required to process and report this information to the public authority react differently to it. In doing that, we provide evidence that not only the existence of information sharing mechanisms affect 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 that the design of these mechanisms also plays a role. Precisely, we shed light on the fact that the way regulators design the reporting activity of lenders into information-sharing arrangements affects the supply of credit.

The remainder of the paper is organized as follows. Section II provides the institutional details and introduces the data. Section III presents the empirical 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 payments between a customer and a supplier in France. Bills of exchange are written documents through which the supplier of goods or services orders its customer to pay the sum due on a fixed day. 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 to the supplier'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 bank in charge of the payment—that is, the reporting bank—must report the event of default to the Banque de France within four days of the due date of payment. Banks are required by law to report the missed payment of their clients when the amount due is above €1,524. Yet, the central

[3]Figure A1 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.

bank encourages 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. Also, banks must specify if the default was triggered by the firm's illiquidity (e.g., when the amount due was not available on the customer's bank account) or by a disagreement between the firm and its supplier (e.g., disputes about goods or payments).

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.

Together with the list of firms' payment defaults, FIBEN contains a wide range of firm-level information. This database is organized in "modules", each of which contains a different piece of information, including firms' balance sheet data, credit exposure, and information on the firms' managers. Banks can request the access to one or more modules, paying a small fee for each one. For example, the information on payment defaults (number of defaults, date and amounts) are summarized in the module *Panorama de l'entreprise et du dirigeant*, which has a cost of €3.7 per access. This module is the most accessed by banks in 2018 as shown in Figure A2 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 lenders (Figure A3).

B Sample Description & Variables

We make use of two data sets maintained by the Banque de France. The first is the CIPE, which collects firm's payment defaults on trade bills on a daily basis as detailed in the previous section. 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 type of default. The second data set we consider is the French credit registry, which provides monthly information on all credit exposures larger than

€25,000 of financial institutions towards non-financial firms. The credit exposure data are also available at the bank branch level.

We aggregate payment default information from the CIPE data set at the firm-quarter level. We consider all payment defaults between 2012Q1 and 2019Q4. We aggregate the credit registry data both at firm-bank-quarter-level and firm-bank branch-quarter level. We then merge these two samples with the CIPE data by using the firm identifier code. As detailed below, to implement our identification strategy, we focus on a sample of firms with multiple banking relationships. Our sample thus includes 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.[4] Firm sector is coded following the Nomenclature Economique 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 of the main variables at the firm-bank-quarter level. The description of the variables is provided in Table A1 of the Online Appendix. For each bank-firm relationship, we observe the outstanding volume of bank credit (variable *log bank credit*). We compute the change in the logarithm of the outstanding volume between quarters (variable Δ *log bank credit*) to capture the flow of credit that each bank grants to the firm. In our sample, the average and median flows of credit are negative, implying reduction of the outstanding credit towards the borrower. This negative sign is explained by the scheduled debt payments made by the borrowers. We compute similar variables for the variation in the credit line available to the borrower (variable Δ *log credit line*); and for the flow of short-term and long-term credit (variables Δ *log short-term bank credit* and Δ *log long-term bank credit*, respectively). As expected, Δ *log long-term bank credit* has a negative mean and median, consistent with borrowers making scheduled payments. We observe an increase in the average of both credit lines and short-term debt.

[4] Size categories are micro, small and medium, and large. 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.

The next set of variables relates to payment defaults. We build an indicator defining whether the firm defaulted on at least one payment in the quarter (variable *company defaults*) and another indicator defining whether the bank is the reporting bank (variable *bank reports company default*). 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-firm relationships are with a bank that is in charge of reporting a missed payment. We split the defaults according to their reasons in liquidity- and litigation-related defaults. Payment defaults for litigation reasons (variable *company defaults for litigation reasons*) are about 2.5 times more common than liquidity-related ones (variable *company defaults for litigation reasons*). Consequently, banks report more litigation related payments defaults (variable *bank reports company default for litigation reasons*) than ones due to liquidity reasons (variable *bank reports company default for liquidity reasons*).

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 firms as rated at the speculative grade level when their credit rating is below the level "4". Indeed, when the rating of a borrower is below such level, their lenders are not allowed to 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 the indicator variable (*unrated company*) defining whether the firm's credit rating is not available.[6] Unrated firms represent about 43.1% 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 lending relationship* identifies bank-firm relationships in which the bank has been

[5] The payment defaults 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. In fact, the unit of analysis is different: bank-firm-quarter in our sample, firm-quarter in (Boissay and Gropp, 2013).

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

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 to the company* 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 hold up by the borrower (e.g., Davydenko and Strebulaev, 2007; Li et al., 2019). The average (median) exposure of a bank to a borrower is 0.01% (0.05%). The local market power of the bank is captured by the variable *bank local 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. Indeed, a large share of the local market may facilitate the collection of information about local borrowers (Hauswald and Marquez, 2003; Agarwal and Hauswald, 2010).[7] Following De Jonghe et al. (2019), we compute the variable *share of bank portfolio in the sector*, 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 (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 *bank branch reports company default*). On average, a bank branch reports 2.1 defaults per quarter (median 0). The variable *N defaults reported the same day* shows the number of defaults that are reported per day by the branch. These statistics are reported on the sample of firm-branch-quarter observations for which the branch reports to the central bank at least one payment default for the firm. On average, bank branches report 4.49 defaults per day but this variable varies from 1 (the 5th percentile) to 20 (95th percentile). We calculate the distance in days between each reported default by a branch and the previous one (variable *N days from last default reported by branch*). 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.

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

[Please insert Table I about here]

III Empirical Strategy and Results

A Identification Strategy

As discussed in Section II, banks receive information about the payment defaults of their customers on trade bills in different ways. Since lending is a risky activity for the bank, our setting can be seen as a choice under risk (Bordalo et al., 2012). The default on a trade bill is a priori unrelated to a default in the repayment of the bank loan outstanding. Yet, it makes the possible default in credit (i.e., the negative payoff from the point of view of the lender) more visible. While this is the case for all lenders, it is more accentuated for the reporting banks, increasing their risk-aversion. Thus, if the prominence of the information matters, then we should observe a different behavior of reporting and non-reporting banks, with reporting banks being more aggressive in their decision making. To understand whether this is the case, we consider firms maintaining at least two banking relationships. We then compare the lending decisions 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:

$$\Delta\, log\, bank\, credit_{jbt} = \beta\, bank\, reports\, company\, default_{jbt} + \eta_{jb} + \eta_{bt} + \eta_{jt} + \varepsilon_{jbt} \tag{1}$$

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

The coefficient of interest in Equation 1 is β, which captures the change in bank credit flow to a defaulter granted by the reporting bank relative to other lenders. $\beta < 0$ would suggest that the reporting bank decreases lending to defaulting borrowers more 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 β solely by comparing the credit flow supplied to the same defaulter by different lenders (reporting and non-reporting banks).

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

B Results

B.1 Baseline Firm-Level Effects

We examine whether salience shapes banks' lending decisions using the model presented in Section *A*. In Table II, we estimate the baseline model of Equation 1 as well as several less-saturated specifications. Standard errors are two-way clustered at the firm and bank level. Our focus is on the coefficient of *bank reports company default*, 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]

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

The coefficient estimate of the variable of interest *bank reports company default* is negative and statistically significant at the 1% level with all specifications. This indicates that banks that directly observe and report the default decrease their lending to defaulting firms more than non-reporting banks. The coefficients of *company defaults* are negative and statistically significant at the 1% level. This suggests that all banks react to trade payment defaults, reducing the credit extended to the borrower. Comparing the coefficient estimates of *bank reports company default* to the ones of *company defaults*, we can observe that the magnitude of the decrease in credit supply due to the payment default is significantly smaller than the magnitude of the decrease in case the bank is reporting the default. This finding is in line with the salience hypothesis.

Column (5) corresponds to Equation 1. The inclusion of firm×time fixed effect 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. Therefore, while all banks have access to the same information, the way this information is presented to them shapes their lending decisions. Overall, an interpretation of the baseline results is thus that salience of the negative-payoff outcome makes reporting banks become more risk-averse, as predicted by Bordalo et al. (2012).

B.2 Graphical Analysis

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

$$Y_{jbt} = \sum_{t} \beta_t \mathbb{1}_{st}^{bankreportsdefault} + \eta_{jb} + \eta_{bt} + \eta_{jt} + \varepsilon_{jbt} \tag{2}$$

where $\sum_t \mathbb{1}_{st}^{bankreportsdefault}$ are a series of binary variables that indicate the time between the quarter and the quarter of the firm's default. Precisely, $\mathbb{1}_{st}^{bankreportsdefault}$ is equal to one t quarters after (or before if t is negative) the borrower j defaulted on a trade bill and the bank

b is the reporting bank. The coefficient β_t on $\mathbb{1}_{st}^{bankreportsdefault}$ captures the difference in the credit supply between the reporting and non-reporting banks at time t relative to the reference level, i.e. the quarter in which the default happens ($t = 0$).

The coefficients are plotted in Figure 1. Three results emerge from this graphical analysis. First, before the firm's default on the supplier, reporting and non-reporting banks behave similarly: they grant non-statistically different flows of credit to the firm. Second, the reporting bank cuts relative more its lending to the firm immediately after the default, which supports the findings in Table II. Third, following the drop in lending in the quarter after the default, the reporting bank keeps lending less to the firm but the effect attenuates over time.

[Please insert Figure 1 about here]

Overall, we find that reporting banks adjust their lending decisions to defaulted firms more decisively than non-reporting ones exactly at the time the event occurs, which is consistent with the salience hypothesis.

B.3 Shifting the Prominence of Information

If the documented difference in the reaction of reporting and non-reporting banks 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 the same financial institution. 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 for them. We run our baseline model on a sample that is now at the firm-bank branch-quarter level, and we add the variable *bank branch reports company default*. 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 but we replace firm×bank with firm×bank branch fixed effects. In Column (3), we augment the model with bank branch×time fixed effects, which account for different dynamics of loan portfolios across branches and control for any shock experienced by a branch in a quarter. In fact, a period of industry downturn may increase the number of defaulting borrowers for branches specialized in that industry and, consequently, those branches might suddenly reduce liquidity to all firms. *bank branch reports company default* enters negatively and statistically significant in all models while the variable *bank reports company default* remains negative and statistically significant. These results indicate us 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]

We also exploit our data to identify different degrees of prominence of payment defaults depending on the number and the frequency of reported defaults by the branch. In theory, the salience of the default information should be higher the lower it is the number of defaults reported by the branch's analysts on a specific day. For example, when the branch must deal with the reporting of only one default in a day, this event appears more prominently to the analysts, potentially leading to a more pronounced reaction. Additionally, the past experience of the 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 the branch, the more salient the event may appear.

We interact the variable *log N defaults reported the same day*, which captures the number of defaults the branch reports the day the company defaults, with the variable *bank branch reports company default*. 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 in 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 *log N days from last default reported by branch* with the variable *bank branch reports company default*. Results are in columns (7)-

(9) of Table III. The coefficients 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

While our baseline analysis is already a choice under risk setting, we examine in this section the effect of an increase in bank's risk aversion. Banks should be more risk-averse when risk is higher. As a consequence, if salience pays a role, the effect we find in the baseline analysis should be more pronounced when extreme events (i.e, events that may generate large losses for the bank) are more likely to happen after the payment default. In fact, when decision makers are influenced by cognitive biases, extreme events may receive disproportionate weight in investment decisions (Bordalo et al., 2012, 2013).

The probability of such events increases with the probability of bankruptcy of the borrower, and thus in case of riskier borrowers. We focus on speculative-grade firms (i.e,. variable *speculative grade company*) and unrated firms (i.e., variable *unrated company*). 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. We interact *speculative grade company* and *unrated company* with variables that identify the reporting bank and the defaulting firm. Results are reported in Table IV, Columns (1) and (2). We find a negative and significant coefficient on *bank reports company defaults*. Importantly, the coefficients of the interactions provide strong evidence that the difference in the banks' reaction is more pronounced when the borrower is unrated or riskier.

[Please insert Table IV about here]

We also investigate how our baseline results vary with the exposure of the bank toward the defaulting borrower. We interact the variable *bank exposure to the company* with both *bank reports company defaults* and *company defaults*. The higher the exposure of the bank, the higher should be the probability of the bank to incur in large losses in case of borrower's bankruptcy.

Based on our prediction, this should amplify the reaction of the reporting bank. This is what we find. Columns (3) and (4) of Table IV show that the coefficient of the interaction term is stable and statistically significant at the 1% across both model specifications. Overall, all our findings are in line with our explanation based on saliency of the revealed information about payment default.

IV Additional Analyses

A Informational Gaps Among Banks

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

To be sure that the explanation of our findings hinges precisely on salience, we need to be certain that non-reporting and reporting banks operate under the same information set.

The payment default can generate an information gap between banks because non-reporting banks may not acquire such information from FIBEN. In fact, while it is indisputable that the reporting bank knows about the payment default of its own borrower, non-reporting banks 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. 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 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.[8] Importantly, the single most accessed piece 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 A2). The reliance of banks on the information available

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

on the Banque de France platform is also documented by existing studies for what concerns the information on managers and that on company ratings (Cahn et al., 2021, 2022). Overall, this suggests that it is unlikely that non-reporting banks are not informed about firms defaulting on trade bills.

Informational Content of the Reasons Behind Payment Defaults Non-reporting banks should have the 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 informational 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 firm's probability of failure.

[Please insert Table V about here]

We regress a binary variable that identifies whether a firm fails over the subsequent year on *company defaults*, which captures if a firm defaults on a trade bill. Failure is defined as the firm's liquidation, i.e. 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 liquidation over the following four quarters. We obtain a similar result when using the linear probability model. These results are reported in Columns (2) to (5), with each column employing a different degree of saturation of the model.

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

In light of this result, we check wether the response of reporting and non-reporting banks varies depending on the type of payment default. This is of particular importance because non-reporting banks can only distinguish between liquidity- and litigation-related defaults if they acquire the information by accessing the CIPE data set.

In Table VI, we consider our baseline model and interact *company defaults* with a binary variable that identifies defaults for liquidity reasons. If non-reporting banks do not access the information, the coefficient should be not significantly different from zero. However, the coefficients on *company defaults* × *default for liquidity reasons* 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 difference supports the view that non-reporting banks acquire payment default information. We still find that banks that report the defaults 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 Knowledge of Borrowers

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' reactions at the payment default. To rule out this concern, we implement a propensity score matching approach. The idea is to compare lenders that are likely to be equally knowledgeable about the defaulting firm.

We match the relationship the borrower has with the reporting bank with similar relationships the same borrower has with non-reporting banks. Following prior works, the matching is based on a set of characteristics that are a proxy for the amount of private information the lenders hold on the borrower. First, the length of a firm-bank 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, 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, which may favour the collection of information on borrowers operating in that sector (e.g., De Jonghe et al. (2019); Paravisini et al. (Forthcoming)). Lastly, we include 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 as measure of the size of the bank. The size of the bank can indeed influence its lending technology (Stein, 2002; Berger et al., 2017).

We consider firms at the time they default on a trade bill. We focus on borrowers that have more than one lending relationship but have only one bank reporting a 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 (i.e., 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 which 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 positions in the borrower's local market and that are more exposed towards the borrower are more likely to report its default.

[Please insert Table VII about here]

We match the defaulting borrower-reporting bank lending relationship with defaulting borrower-non-reporting bank lending relationships, 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.[9] We implement our baseline analysis on the matched sample. The results are shown in Columns (2) and (3) of Table VII. The coefficient on *bank reports company default* is negative and significant in both specifications, which suggests that the reporting bank reacts more than equally-informed non-reporting banks. This result provides further confirmation to the information salience effect.

[9] Appendix A3 reports the covariate balance for matched bank-firm relationships.

B Bank-Specific Credit Demand

Our 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 may ask more credit to lenders that have characteristics that may correspond to those of non-reporting banks. 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 *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 the 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. Altavilla et al. (2022) employ a similar approach, but without accounting for the size of the borrower. Second, we consider bank×company defaults×time fixed effects to control for bank-specific demand by defaulting firms. Finally, we employ bank×sector×county×size×company defaults×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 of *bank reports company default* 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 subsection, we replicate our main analysis to examine the impact of the salience of information separately on credit lines, short-term bank credit and long-term bank credit.

Our prediction is that the decrease in lending of reporting versus non-reporting banks should be more pronounced for credit lines and short-term loans for at least two reasons. First, Acharya and Steffen (2020) document that crises trigger a "dash for cash," with distressed firms drawing down their credit lines, which exposes banks to increasing liquidity risks. Following this evidence, if the salience of payment default triggers a cut in the credit supply precisely because it worsens banks' perceived credit quality of the borrowers, the drop in lending should be especially pronounced on credit lines. Second, credit lines and short-term loans are usually less likely to be collateralized than long-term loans (Benmelech et al., 2020). We expect banks to react to a salient negative signal on the borrowers by reducing, in particular, the issuance of non-collateralized forms of credit.

[Please insert Table IX about here]

Table IX reports estimation results. The coefficients on *bank reports company default* confirm our expectation that there is a stronger impact when the credit is extended to the borrower in the form of a credit line or when it has a short maturity. The fact that salience of information about borrowers has a strong impact on the supply of credit lines is of particular importance given the large use of this type of credit by corporations (see, e.g, Sufi (2007) and Campello et al. (2012)). The coefficient is still significant in the long-term bank credit regressions, but with a smaller magnitude.

V Conclusions

This paper shows that salience of information affects banks' lending decisions. We use a setting in which information about borrowers' payment default on trade bills is available to all banks but it appears more prominently to the bank that manages the payment transaction (that is, 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 bank branches react more especially when the number of events they process in a day are smaller 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 reporting and non-reporting banks 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 implications at policy level 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 on the optimal amount of information that should be shared among lenders, but also to the way information is reported and displayed.

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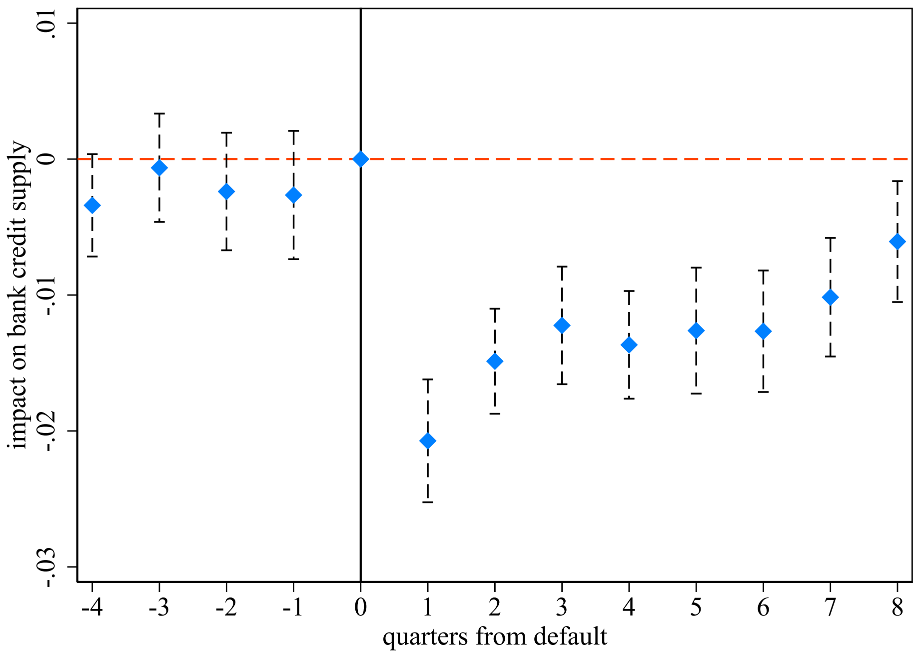
VI Figures

Figure 1
Salience of payment defaults

This figure studies the timing of the change in credit supply from reporting banks relative to the change in credit supply from non-reporting banks. We run the specification of Equation (2), which includes a set of dummies 0/1 identifying the distance with respect to the quarter at which 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 Appendix A1.

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

	N	Mean	Median	St. dev.	5th pctile	95th pctile
Δ log bank 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 short-term bank credit (t-1;t)	3,364,128	0.007	0.000	0.651	-1.053	1.086
Δ log long-term bank credit (t-1;t)	8,875,800	-0.036	-0.046	0.184	-0.250	0.233
log bank credit to the firm (t-1)	18,092,193	5.067	4.828	1.300	3.434	7.701
bank reports company default (t)	18,092,193	0.027	0.000	0.162	0.000	0.000
bank reports company default for liquidity reasons (t)	18,092,193	0.009	0.000	0.094	0.000	0.000
bank reports company default for litigation reasons (t)	18,092,193	0.019	0.000	0.138	0.000	0.000
company defaults (t)	18,092,193	0.096	0.000	0.295	0.000	1.000
company defaults for liquidity reasons (t)	18,092,193	0.028	0.000	0.165	0.000	0.000
company defaults for litigation reasons (t)	18,092,193	0.074	0.000	0.262	0.000	1.000
speculative grade company (t-1)	18,092,193	0.267	0.000	0.443	0.000	1.000
unrated company (t-1)	18,092,193	0.439	0.000	0.496	0.000	1.000
bank exposure to the company (t-1)	18,092,193	0.019	0.004	0.051	0.000	0.095
young lending relationship (t-1)	18,092,193	0.361	0.000	0.480	0.000	1.000
bank local market share (t-1)	18,092,193	6.266	2.962	8.996	0.038	28.102
share of bank portfolio in the sector (t-1)	18,092,193	18.208	13.215	18.165	1.418	55.847
bank size (log total credit extended) (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 bank credit (branch-level) (t-1;t)	17,892,412	-0.028	-0.039	0.211	-0.298	0.367
bank reports company default (t)	17,892,412	0.027	0.000	0.161	0.000	0.000
bank branch reports company default (t)	17,892,412	0.021	0.000	0.144	0.000	0.000
N defaults reported the same day (t)	377,731	4.486	1.000	10.481	1.000	20.000
N days from last default reported by branch (t)	377,731	10.289	5.000	16.882	1.000	34.000
company defaults (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. *bank reports company default* 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*. *company defaults* 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 bank credit (t-1;t)				
	(1)	(2)	(3)	(4)	(5)
bank reports company default (t)	-0.0115***	-0.0115***	-0.0110***	-0.0106***	-0.0091***
	(-11.82)	(-11.89)	(-11.74)	(-11.29)	(-12.23)
company defaults (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 (*bank branch reports company default*). In Columns (4)-(6), we analyze whether the reaction of the reporting branch changes depending on how many defaults the branch reports the same day the company defaults (*log N defaults reported the same day*). In Columns (7)-(9), we analyze whether the reaction of the reporting branch changes depending on the time distance from the last default that the branch reported, independently on the companies involved (*log N days from last default reported by branch*). As in Table II, *bank reports company default* 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*. *company defaults* 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 bank credit (branch-level) (t-1;t)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
bank reports company default (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)
bank branch reports company default (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 N defaults reported the same day (t)				0.0034***	0.0031***	0.0031***			
				(5.72)	(5.34)	(5.17)			
— × log N days from last default reported by branch (t)							-0.0022***	-0.0020***	-0.0023***
							(-4.08)	(-4.13)	(-4.61)
company defaults (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 company* and *unrated company*: 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, *bank reports company default* 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*. *company defaults* 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 bank credit (t-1;t)			
	(1)	(2)	(3)	(4)
bank reports company default (t)	-0.0030***	-0.0019**	-0.0268***	-0.0269***
	(-3.69)	(-2.22)	(-4.76)	(-6.26)
— × speculative grade company (t-1)	-0.0136***	-0.0131***		
	(-9.08)	(-9.18)		
— × unrated company (t-1)	-0.0077***	-0.0083***		
	(-7.06)	(-6.76)		
— × log bank exposure to the company (t-1)			-0.0036***	-0.0039***
			(-3.88)	(-5.51)
company defaults (t)	-0.0001		-0.0041*	
	(-0.20)		(-1.82)	
— × speculative grade company (t-1)	-0.0043***			
	(-5.57)			
— × unrated company (t-1)	-0.0019***			
	(-2.62)			
— × log bank exposure to the company (t-1)			-0.0004	-0.0007*
			(-1.02)	(-1.93)
log bank exposure to the company (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. *company defaults* 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 *company defaults* 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)
company defaults (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)
— × default for liquidity reasons (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, *bank reports company default* 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. *company defaults* 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 *company defaults* and *default for liquidity reasons*, 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 bank credit (t-1;t)				
	(1)	(2)	(3)	(4)	(5)
bank reports company default (t)	-0.0026***	-0.0027***	-0.0026***	-0.0019***	-0.0014**
	(-4.00)	(-4.03)	(-3.91)	(-2.97)	(-2.11)
— × default for liquidity reasons (t)	-0.0251***	-0.0251***	-0.0244***	-0.0252***	-0.0259***
	(-12.09)	(-12.14)	(-12.05)	(-12.78)	(-15.95)
company defaults (t)	-0.0002	-0.0002	0.0001	0.0000	
	(-0.54)	(-0.47)	(0.34)	(0.01)	
— × default for liquidity reasons (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.

	(1) bank reports company default (t)	(2) Δ log bank credit (t-1;t)	(3)
bank reports company default (t)		-0.0043*** (-3.13)	-0.0035*** (-3.04)
company defaults (t)		-0.0036*** (-4.27)	
young lending relationship (t-1)	-0.1496*** (-83.49)		
log bank local market share (t-1)	0.1311*** (146.83)		
log share of bank portfolio in the sector (t-1)	-0.0488*** (-32.43)		
log bank credit to the firm (t-1)	0.0235*** (25.63)		
bank size (log total credit extended) (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. *bank reports company default* 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.

	Δ log bank credit (t-1;t)		
	(1)	(2)	(3)
bank reports company default (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 × company defaults × time FE		✓	
Bank × sector × county × size × company defaults × 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. *bank reports company default* 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*. *company defaults* 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 short-term bank credit (t-1;t)		Δ log long-term bank credit (t-1;t)	
	(1)	(2)	(3)	(4)	(5)	(6)
bank reports company default (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)
company defaults (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

A Online Appendix

Figure A1
Bill of exchange
This figure depicts the functioning and parties involved in the issuance and payment of a bill of exchange.

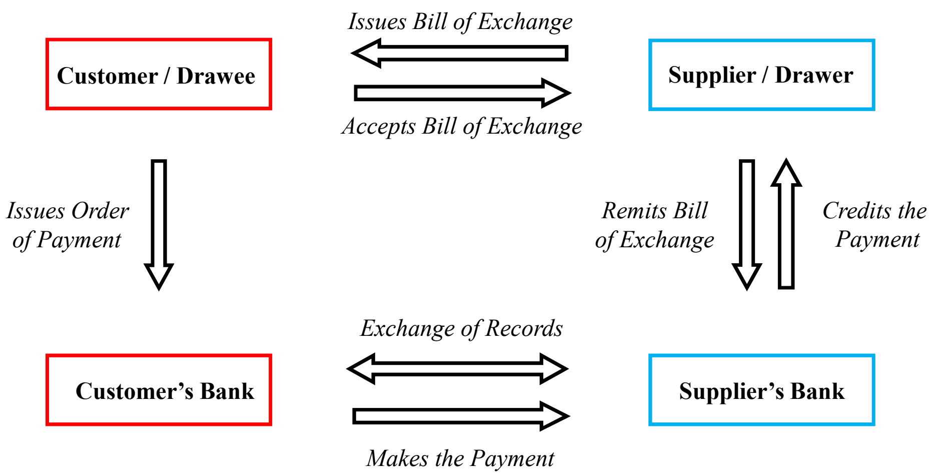


Figure A2

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 A3

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.

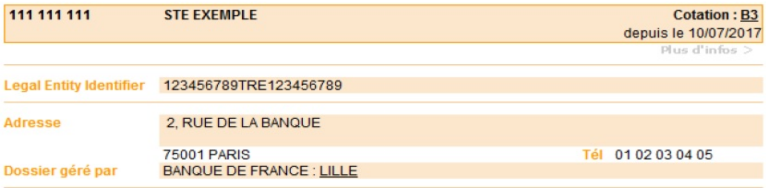


Table A1
Variable definitions

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

Variable	**Definition**	**Source**
Δ log bank 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 short-term bank credit (t-1;t)	quarterly change in drawn bank credit with maturity shorter than one year at the firm-bank level	SCR
Δ log long-term bank credit (t-1;t)	quarterly change in drawn bank credit with maturity longer than one year at the firm-bank level	SCR
log bank credit to the firm (t-1)	log of total bank credit that the firm obtains from the lender	SCR
bank reports company default (t)	dummy 0/1 identifying the reporting bank	CIPE
bank reports company default for liquidity reasons (t)	dummy 0/1 identifying the bank that reports a default for illiquidity	CIPE
bank reports company default for litigation reasons (t)	dummy 0/1 identifying the bank that reports a default for disagreement between the firm and the supplier	CIPE
company default (t)	dummy 0/1 identifying defaultings firm in quarter *t*	CIPE
company default for liquidity reasons (t)	dummy 0/1 identifying defaulting firms for illiquidity in quarter *t*	CIPE
company default for litigation reasons (t)	dummy 0/1 identifying defaulting firms for disagreement in quarter *t*	CIPE
speculative grade company (t-1)	dummy 0/1 identifying firms rated below the level 4 of the Banque de France (BdF) rating scale *t*	BdF's credit rating data
unrated company (t-1)	dummy 0/1 identifying firms that are not rated by the Banque de France (BdF) in quarter *t*	BdF's credit rating data
bank exposure to the company (t-1)	credit extended by the bank to the firm divided by the total credit extended by the bank (in %)	SCR
young lending relationship (t-1)	dummy 0/1 identifying the bank-firm relationahip that started less than three year before quarter *t-1*	SCR
bank local 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
share of bank portfolio in the sector	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 (log total credit extended)	log of credit (drawn and undrawn) extended by the bank	SCR
Δ log bank 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
bank branch reports company default (t)	dummy 0/1 identifying the reporting branch	CIPE
N defaults reported the same day (t)	number of payment defaults reported in the day	CIPE
N 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

Table A2

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 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. *bank reports company default* 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*. *company defaults* 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.

	Δ log bank credit (t-1;t)			
	(1)	(2)	(3)	(4)
bank reports company default (t)	-0.0098***	-0.0098***	-0.0088***	-0.0086***
	(-13.84)	(-13.87)	(-13.33)	(-12.91)
company defaults (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 A3

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 lending relationship (t-1)	-40.45	-11.44	0.70	0.89
log bank local market share (t-1)	89.58	15.04	0.45	0.83
log share of bank portfolio in the sector (t-1)	-23.11	-5.21	0.83	0.92
log bank credit to the firm (t-1)	4.09	-4.12	0.79	0.85
bank size (log total credit extended) (t-1)	29.40	-0.22	0.76	1.02