Bank Quality, Judicial Efficiency and Loan Repayment Delays in Italy

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Abstract

Italian firms delay payment to banks weakened by past loan losses. Exploiting Credit Register data, we fully absorb borrower fundamentals with firm-quarter effects; thus, identification reflects firm choices to delay payment to some banks but not others, depending upon their health. This selective delay occurs more where legal enforcement of collateral recovery is slow. Poor enforcement encourages borrowers not to pay, once the value of their bank relationship comes into doubt. Selective delays occur even by firms able to pay all lenders. Credit losses in Italy have thus been worsened by the combination of weak banks and weak legal enforcement.

JEL Codes: G0, G3, K0, K2

The long and deep recession after the financial and foreign debt crises in Europe has left a legacy of non-performing loans on Italian banks' balance sheets. In December of 2015, bad loans summed to about 200 billion, a large figure that represents approximately 11% of the

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total amount of loans given (18% including other troubled loans not written off). Unlike other recent banking problems, where losses were concentrated in real estate or sovereign debt exposure, close to 80% of these bad debts came from bank lending to non-financial businesses (Bank of Italy, 2016).[1]

In this paper, we show that the combination of weak bank balance sheets and inefficient legal enforcement leads borrowers to delay debt repayment. Borrowers selectively delay payment to banks already weakened by past bad loans while continuing to pay healthier banks. We emphasize that ineffective legal enforcement exacerbates this problem, as the magnitude of our estimates increases in areas of Italy where it takes longer to resolve disputes about the recovery of collateral, while accumulated bad loans do not have a significant effect in areas where legal enforcement is quick and efficient. For example, where legal inefficiency is high (top quartile of its distribution), a one standard deviation increase in a bank's past bad loans raises payment delays by about 50%, relative to the unconditonal mean.[2]

Our data allow us to capture a firm's decision to delay repayments at the level of the bank-borrower. Obviously, there can be multiple causes for a delay in loan repayments, ranging from firm financial distress to strategic considerations about how such behavior may affect their ongoing or future relationship with lenders. With regard to the latter, a firm will be trading off the short-term gain of keeping control of financial resources (i.e., by not paying now), against the potential future loss of impairing their relationship with the current lender(s) or with potential future lender(s). The balance of this trade-off may depend on the financial health of the lender and its internal enforcement capacity, on the ability of the firm to borrow elsewhere, and on the institutional environment that affects the ex post ability to recover collateral or otherwise force repayment through the judicial

[1] The stock of bad loans has fallen to 160 billion in 2017 but remains substantial.

[2] The Wall Street Journal reports that, "The snail's pace of Italy's courts throws sand into the wheels of the economy in myriad ways. Banks struggle to resolve bad loans because bringing deadbeat debtors to court takes by far the longest in Europe." (Zempano, 2014)

process. Everything else equal, a firm ought to be more likely to delay repayment to weaker banks because the expected value of the continuation of the relationship is smaller. Bond and Rai (2009) show formally that concern over the long-run viability of a lender can lead to a 'borrower run' in which repayment incentives for individual borrowers depend on the payments by other borrowers. Since the lender fails given enough defaults, this externality can lead to an equilibrium in which borrowers default because they expect other borrowers to default. The incentive to delay debt payment may also be enhanced if weak banks are less able to enforce contracts.

To test how bank health affects repayment behavior, we exploit a unique data set, the Italian Credit Register, which contains detailed information on all bank loans above 30,000 Euros. The data include information on repayment delays and the degree of impairment of loans, including those that fall short of being formally classified as "bad" by the bank. The solvency of Italian firms and the quality of loans has been strongly affected by the double dip recession following the global financial crisis of 2007 to 2009 and the sovereign debt crisis of 2010 to 2011.[3]

We match these data to bank balance sheets reported to the Bank of Italy, as well as with borrower balance-sheet data collected by the Balance Sheet Register. (These data have been provided by lenders for information-sharing purposes since 1983.) The data can also be matched to measures of local judicial (in)efficiency in recovering collateral, that can be calculated by using information from the Italian Ministry of Justice.[4] While civil law and procedures are formally the same across Italy, the real-world effectiveness of the court system varies widely, depending upon local jurisdictional court proceedings (Carmignani and Giacomelli (2009); Giacomelli and Menon (2013)). We exploit this regional and sub-regional

[3] In seven years, manufacturing firms lost 17% of its productive capacity and net job destruction reached almost one million.

[4] The data are downloadable from the web page of the Italian Ministry of Justice. See https://reportistica.dgstat.giustizia.it/

variation to test how legal enforcement affects repayment behavior as firms will be more willing to delay loan repayment the harder it is for lenders to protect their interests through the courts.

As in other studies, we exploit the fact that many Italian firms borrow from multiple banks. This feature allows us to introduce firm-specific, time-varying effects to absorb fundamentals that may determine firm decisions to delay loan repayment. Our identification thus comes solely from variation in bank characteristics, characteristics of the bank-firm relationship, and, importantly, on the efficiency of the court system. In other words, we test how the *same firm* behaves with respect to *different banks*, depending upon the strength of the bank's balance sheet, the local judicial environment, and the nature of the past bank-firm relationship.

The results suggest that bank balance sheet strength - particularly past bad loans - affects the probability of a delay in loan repayment. In our basic specification, the stock of past bad loans increases the probability of borrower delays. This effect increases as legal efficiency decreases. Thus, on average banks with weaker balance sheets due to past (and non-collectible) bad loans experience more future defaults (in the form of temporary delays in repayment, many of which ultimately become permanently impaired). That is, we observe borrowers withholding payment to weak banks. To allay concern that our results reflect reverse causality (whereby bank balance sheet health is reduced by borrow payment delays) as well as omitted variables, we construct an instrument for bank weakness that depends *only* on each bank's 2007 lending portfolio shares (across different sectors and provinces), combined with losses based on *aggregate* loan outcomes at the sector and province level (excluding, for each firm, loans in the sector-province cell the firm belongs to). These results are qualitatively similar to our baseline models. In addition, we verify that late repayment harms lenders, as their profits decrease with past levels of payment delays.

Are distressed borrowers merely selecting which banks to pay by allocating a fixed but limited cash-flow budget across lenders? Or, are borrowers paying less than they otherwise would because lenders are weak? We find that some of the payment delays motivated by weak enforcement are, in fact, truly strategic in that borrowers pay less than they otherwise would because one or more of their lenders is distressed. We first re-estimate the original model stratified by borrower health, and we show that even the safest firms - those with high credit quality and/or ample cash to pay all of their banks - still choose not to pay some of their banks because of the confluence of their high past losses and weak legal enforcement. We then show that total payment delays aggregated up to the borrower level increase as a firm's lenders collectively face more past losses; as in the borrower-bank regressions, the result is driven by areas with weak legal enforcement.

Our results suggest no significant effect of past bad loans on current payment delays in provinces where legal enforcement in Italy is strongest. Thus, our key result requires two conditions: first, the lender must be weakened by past losses and thereby less able to commit to extending future credit; second, the lender's ability to collect ex post must be weak due to poor legal enforcement. The results suggest that improving banks' ex post ability to enforce contracts (in court) improves borrowers' ex ante incentives to repay. Moreover, the beneficial effect of legal enforcement on borrower incentives is stronger for already-impaired lenders.

Concern over declines in credit quality has prompted attempts in the recent past aimed at streamlining insolvency proceedings and making the process by which lenders can repossess collateral on defaulted loans more effective. According to our paper, legal reforms to improve the efficiency of the courts can potentially be beneficial to Italy's banks by improving borrower repayment incentives.

The structure of the paper is as follows. In Section I we will review briefly the theoretical and empirical literature and discuss our contribution. In Section II we will describe the data we use in our empirical analysis and outline the growing importance for the Italian banking system of delayed loan repayment and bad loans generally. Section III contains a description of our identification strategy, econometric methods and empirical results. Section IV concludes.

I. Literature Review

How does our contribution relate to the previous literature? Using a global games framework, Bond and Rai (2009) prove the existence of multiple equilibria in loan repayment behavior, with one equilibrium characterized by an unraveling of borrowers' incentives to pay.[5] The crucial tradeoff weighs the present benefit of default against the expected loss of future access to credit conditional on default. The expected value of future access to credit depends upon the likelihood that other borrowers will repay their loans, as this affects banks' lending ability. This externality can lead to outcomes in which a borrower defaults because she expects others to do so. Carrasco and Salgado (2014) model a similar outcome in the context of a costly state verification model.[6] Equilibria with partial or complete default emerge in this case as the result of banks' limited resources in auditing borrowers, resulting in a reduction in the incentive for them to repay when defaults are expected to be high across many borrowers. Drozd and Serrano-Padial (2018) allow for banks' enforcement capacity to be endogenously determined in the context of a global games model. Negative enforcement externalities may lead to a clustering of defaults as the incentive to repay weakens when the capacity constraint is binding.

In these theoretical frameworks, bank financial health mitigates the probability of borrower defaults. Conversely, these theories point to an indirect cost of financial distress to banks related to their relative inability to collect on outstanding debt. Existing research has looked for indirect costs of financial distress from incentive problems due to asset substitution and debt overhang (Jensen and Meckling (1976)), as well as from declining sales due to loss of customer goodwill (e.g., Altman (1984), Hortaçsu et al. (2013); for a review, see Altman et al. (2017)). But there is little empirical evidence of this sort of indirect distress costs to banks due to borrower decisions to pay or not pay depending on lender health.

[5] On global games see, for instance, Morris and Shin (2001).

[6] See Gale and Hellwig (1985) and Townsend (1979).

Consistent with models such as Bond and Rai (2009), Breza (2012) finds that repayment rates on micro-finance loans are sensitive to the defaults of peers, using defaults initiated by a local government official as a source of variation unrelated to borrower fundamentals. Our empirical work focuses on indicators of overall bank health, but of course the probability of loan repayment will depend critically on borrower fundamentals. To isolate the effect of bank fundamentals, we study firms that borrow from more than one lender, and we control for firm specific and time varying factors that affect a firm's repayment capacity (either actual or expected).

Beyond bank health, theory emphasizes the importance of the institutional environment in which contracting takes place. In particular, the ability of creditors to recover the money lent will mitigate the incentive to delay repayment. Hence, we study the interaction between efficiency of the local courts and bank health. Since La Porta et al. (1997) and La Porta et al. (1998), financial economists have emphasized the importance of legal contract enforcement in shaping financial relationships. Many of the empirical studies emphasize how measures of enforcement affect ex ante contract terms such as ownership of debt and equity, the use of collateral and covenants in debt contracts, and the availability and price of credit (see Roberts and Sufi (2009) for a survey of the empirical literature). Djankov et al. (2003) show that civil-law countries like Italy tend to have greater legal formalism and experience longer delays in resolving commercial disputes (collecting on bad checks or evicting non-paying tenants) compared to common law countries. Jappelli et al. (2005) study Italy, as we do, and show that credit is more available and, in some specifications, at lower prices in regions with better enforcement in court.

A number of other studies use changes in bankruptcy laws, mechanisms, or regulations as exogenous shocks to enforcement costs to trace out the effects on credit supply. For example, Scott and Smith (1986) find that increased debtor protection following the 1978 bankruptcy reform in the US, and hence weaker enforcement, was followed by an increase in interest rates on loans to small borrowers. Fedaseyeu (2015) exploits changes in state regulation of debt collectors - an important enforcement mechanism outside bankruptcy - and finds that credit supply to high-risk borrowers increases with less restrictive regulation of the debt collection business. Gropp et al. (1997) show that reductions in enforcement from state-level variation in the amount that individuals can shield in bankruptcy from their creditors via the homestead exemption both constrains credit supply and increases credit demand. Rodano, Serrano-Velarde, and Tarantino (2016) exploit Italian legal reform in 2005 - prior to the beginning of our sample - and find improved credit conditions thereafter. Most recently, Ponticelli and Alencar (2016) find that legal reform to Brazilian courts led to better access to secured credit and higher investment.

A number of recent studies have found that credit supply by distressed banks was constrained in Italy during both the 2007 to 2009 global financial crisis as well as the more recent sovereign debt crisis (e.g., Albertazzi and Marchetti (2010), Bolton et al. (2016), and Bofondi et al. (2017)). In addition, bank distress stemming from exposure to risky sovereign debt reduced credit supply and helped propagate the sovereign debt crisis from distressed to non-distressed countries across the Euro system (e.g., Popov and Van Horen (2014), De Marco (2019)).[7] Our study helps in rationalizing this behavior, as we show that past losses raise the risk of future firms delaying their debt repayment (holding constant borrower fundamentals); hence, it makes sense that distressed banks would raise the price and restrict access to credit when extending new loans.

As far as we know there is no empirical evidence of borrower payment delays motivated by concern about bank loan losses or insolvency. Ivashina and Scharfstein (2010) do provide evidence that US firms drew more on their credit lines with banks that had a relationship with Lehman, but the mechanism they emphasize stems not from borrower unwillingness to re-pay their debt (our mechanism), but instead from borrower concern that liquidity would not be available in the future for the lending bank, leading to increased drawdowns on existing credit

[7]On the real consequences of credit supply shocks in Italy see Cingano et al. (2016) and Balduzzi et al. (2018).

lines. Similarly, Ippolito et al. (2016) show that Italian firms with multiple credit lines drew more from banks that had higher pre-crisis exposure to the interbank market and thereby were more liquidity constrained. Their paper emphasizes the traditional source of bank instability: liquidity risk. Trautmann and Vlahu (2013) provides experimental evidence that solvent borrowers may be more likely to default strategically when their bank's expected strength is low and when their own expected repayment capacity is low. Survey-based evidence of strategic behavior by US households in mortgage markets has been provided in Guiso et al. (2013). They find that the propensity to default by households, even if solvent, is affected by both pecuniary and non-pecuniary factors such as views of fairness and morality. It is also related to the exposure to other people who have strategically defaulted.

We share with Ippolito et al. (2016) the focus on Italian firms and the use of the Italian Credit Register. Our emphasis, however, is on debt repayment and that is motivated by concern about a bank's viability and ability to extend credit itself in the medium term, as opposed to having short term funding issues. Moreover, our contribution provides evidence on the key role of the courts as a determinant of the likelihood of debt repayment.[8]

II. Data Description

To estimate our model we need information about the (ex post) performance of bank loans extended to non-financial corporations, the financial health of their lenders (banks), the efficiency of the judicial system, and characteristics of borrowers as well as the type of

[8]"The complex regulatory system, the relative inefficiency of public procedures and government action, the slowness of the justice system [...] all hinder the reallocation of productive resources to the most efficient firms, which is one of the main mechanisms of productivity growth. [...]The large stock of non-performing loans also reflects the very long and variable duration of insolvency and credit recovery procedures, due in turn to the country's cumbersome civil justice system. These widespread inefficiencies depress potential buyers' valuations of impaired assets and discourage their sale on the market" (Ignazio Visco, Governor's Concluding Remarks, Bank of Italy, 2015a).

lending relationship they have with their banks. Our dataset thus combines four sources of information existing in Italy: (i) the Balance Sheet Register; (ii) the Credit Register; (iii) measures on the functioning of the judicial system estimated from data provided by the Ministry of Justice; and, (iv) the Bank of Italy's Supervisory Reports.

The Balance Sheet Register provides our sample of non-financial firms. It consists of around 32,000 industrial firms, 99% of which are unlisted. The Register accounts for more than 70% of industrial sector value added over the fiscal years 2008 to 2013. The Balance Sheet Register is a proprietary database set up and managed by Cerved SPA, using data deposited by firms at the local Chambers of Commerce, as required by Italian law. Data from the Balance Sheet Register have been used extensively since 1983 by both lenders to assess firm soundness as well as by scholars to investigate various research questions.

The Credit Register, an archive maintained by the Bank of Italy, provides lender-borrower level data on characteristics of loans extended by banks operating in Italy. The data include information on loan type (credit lines, term loans), size, maturity, the pledging of real collateral, personal guarantees, accounts receivable, and ex post performance. Loans are reported when tranches exceed Euro 30,000 by the entire population of credit institutions. Hence we capture all but the very smallest firms borrowing from banks.

We use data from the Ministry of Justice to build a measure of enforcement for creditors based on the length of legal proceedings across Italy. Specifically, we use court-level data on the mean time to resolve matters regarding the execution of property. Following Carmignani and Giacomelli (2009) and Giacomelli and Menon (2013), we apply the formula adopted by the Italian Ministry of Justice and the Italian National Institute of Statistics (Istat) to calculate the court-level indicators on the length of proceedings in 2007. The length of court proceedings is an inverse measure of efficiency (or a measure of inefficiency) and is defined as:

$$D_t = \frac{P_t + P_{t+1}}{E_t + F_t} \tag{1}$$

where D_t is time to resolve matters regarding the execution property in years, P_t are pending cases at the beginning of 2007, F_t are new cases filed during 2007 and E_t are cases ending with a judicial decision or withdrawn by the parties during 2007. We multiply D_t by 365 to obtain the length in days. We are careful to measure judicial efficiency before the onset of the banking losses that began in the wake of the sovereign debt crisis (and before the beginning of our sample in 2008). Measured this way, we avoid reverse causality whereby a high level of distressed loans, by clogging up the courts, leads to an increase in the measure of judicial inefficiency. We focus on the length of proceedings to recover collateral because these most closely relate to the enforcement of debt contracts.[9]

In assigning each loan contract to a judicial jurisdiction, we use the judicial court located where the bank owning the branch has its legal residence. This choice is motivated by the fact that, in loan contracts, banks usually indicate the judicial court where the bank has its legal residence as the one that will be in charge in case of legal disputes with the borrowing firm. Ex post enforcement, however, requires several steps. First, lenders need an injunction from the court typically located in the province of its head office. Having gotten an injunction, to take possession of collateral the lender then must adjudicate before the court in the location of the collateral, which is likely, but not certain, to coincide with the firm's location. The latter, in turn, may or may not coincide with the legal location of the bank. Thus, legal enforcement in two provinces may matter. Since the process always begins in the bank's province, we report most of our models using legal enforcement measured in the province of lender's head office. The time to get an injunction or to recover the collateral

[9]Other measures of court efficiency are in use in the literature, such as case-load per judge and length of bankruptcy proceedings (Rodano et al. (2016), Ponticelli and Alencar (2016)). The measure we use is most pertinent for our setting. In fact, the duration of execution proceedings reflects the time necessary for a bank to recoup the collateral posted by a delinquent borrower, while the amount of cases per judge might be associated with different levels of legal efficiency (for instance, due to heterogeneities on human and organizational resources across the courts). Execution proceedings also cover a broader set of events of delinquency, as they might occur even without bankruptcy.

are highly correlated and conclusions are, therefore, insensitive to this choice.[10] We present results using the latter measure, but we also report a robustness test in which we remove any ambiguity about legal efficiency by including only observations in which the lender and borrower reside in the same province.

Finally, we obtain bank balance sheet data from the Supervisory Reports collected by the Bank of Italy, which is in charge of banking supervision in Italy. We use aggregate data for banks belonging to banking groups or holdings, and individual data for stand-alone banks, as we want to avoid measurement errors in our bank quality indicators due to infra-group reallocations of resources.[11]

A. *Some facts on judicial efficiency, loan quality and bank quality in Italy*

The formal classification of problematic loans adopted by Italian banks is quite detailed and includes four categories: (i) "Past due/overdrawn more than 90 days", (ii) "substandard loans", (iii) "restructured loans" and (iv) "bad loans." "Past due/overdrawn by more than 90 days" are exposures (other than those classified as bad loans, substandard or restructured) whose repayments have been delayed by the borrowers for more than 90 days on a continuous basis. "Substandard loans" are exposures to counterparties which face temporary difficulties expected to be overcome within a reasonable period of time. Specifically, this class includes two subsets of problematic loans: the first one includes loans which are "objectively" substandard, such as loans or credit lines which are past due or overdrawn; the second group includes loans classified by the lender as "substandard" according to a judgmental basis only, meaning without any formal loan repayment delays to the bank in question or overdrawing on existing credit lines. This judgment could also depend upon a delay in payments to *other*

[10] The correlation between the variable on the length of the first part of the judicial process ("Processi di Cognizione Ordinaria") and that for the proceedings of property executions is close to 0.7.

[11] Data on branches of foreign banks operating in Italy have been discarded from the dataset, as aggregate data are not available for holdings which are headquartered outside Italy.

lenders. "Restructured loans" are exposures in which lenders, as a result of the deterioration of the borrower's financial situation, agree to change the original conditions, giving rise to a loss for the creditor. Finally, the "bad loans" category includes exposures to insolvent counterparties (even if not legally ascertained), regardless of any loss estimate made by the bank and irrespective of any possible collateral or guarantee.e[12]

[Table I here]

Table Ia shows the relative importance of these four categories and how they have evolved over time. Loans were broadly performing well before the 2007 to 2009 financial crisis: the share of performing loans exceeds 98% in 2006 to 2008. The quality of lending began to worsen in 2009 (96% performing), and then fell in each year through 2014; that is, after the 2007 to 2009 financial crisis and especially after the sovereign debt crisis, which was accompanied by a worsening of the real performance of the Italian economy.[13]

In Table Ib we report the transition matrix (looking ahead one year) for all the borrowers in Italy based on data on loan quality published by the Bank of Italy.[14] These data indicate

[12]As of September 2014, non-performing exposures are classified according to definitions established by the European Banking Authority. The new definitions, to be used for harmonized supervisory financial reporting across Europe, are basically in line with those that were in force in Italy before the break and that were used by banks to classify the quality of the loans we analyze in this paper.

[13]The large volume of bad loans also reflects constraints, rigidities and incentives that lead Italian banks to keep impaired assets on their books much longer than banks in many other countries. Among others, the unfavorable tax treatment of write offs as well as the length of bankruptcy procedures limit the incentives for banks to sell problematic loans and restrain the development of a large secondary market for these assets. In May 2015, the Italian Government has taken measures to make loan losses immediately tax deductible. With regard to the length of the proceedings, measures undertaken in recent years to address the issue are commented in Giacomelli et al. (2017).

[14]Table Ib reports a transition matrix, which is based on the data published in the Bank of Italy's Annual report. Data refer to the universe of banks and financial intermediaries operating in Italy and to the population of non-financial companies recorded in the Register (see Bank of Italy (2015b), Table A6.15,

that in the first part of the sampled period around half of loans past due or overdrawn become performing again. However, after the sovereign debt crisis many of them eventually end up in the bad-loan category. For example, as of 2009, 51% of late or overdrawn loans were performing one year later. In contrast, this probability falls to just 27% by the end of 2013. During the latter years, the typical scenario for a loan would be to move first from the late category to the substandard category (probability > 40%) and then to transition from substandard to the bad loans category (probability around 25%). As the transition matrix shows, once a loan goes bad, it stays bad ("bad loans" is effectively an absorbing state).

The focus of this study is a borrower's decision to delay repayment to its bank. In order to measure this outcome, we construct *late payment* as an indicator that equals one if the firm has a loan with a bank classified as 'past due/overdrawn', or 'objective (past due/overdrawn) substandard', and equal to zero if the loan is 'performing'. We consider loans in both of these categories because they are similar in nature: each shares the characteristic of being past due/overdrawn for more than 90 days but not yet restructured or written down. Given the supervisory practices by the Bank of Italy and their uniformity, marking loans as late/past due is not subject to discretion by banks. We focus on the initial phase of the process of the loan quality deterioration because we want to avoid measurement errors when we capture the firm's loan repayment behavior: in particular we want to capture, as much as possible, a firm's *decision* to delay its payments. Therefore, we discard the "judgmental" component of "substandard loans", which are based on the subjective choice of the lender, and "restructured loans", which depend upon a bargaining between the bank and the firm. We also discard in our dependent variable those loans classified as "bad loans", which reflect a bank's final determination that the loan will not be repaid.

page 56, Banche e societa finanziarie: matrici di transizione tra classi di anomalia nel rimborso dei prestiti). Transitions are obtained by comparing the classification of a single borrower, at the beginning and at the end of the observation periods, across the loan quality classes as they are defined in the methodological appendix to the table (see page 197).

Table Ia and Figure 1 show the development of *late payment* - our dependent variable - over time. The share of these loans increases almost monotonically, starting in 2009. A similar development is observed when we exclude credit lines from the ratio and consider the aggregate, which includes term loans only. (See the Appendix A for a description of the variables and their data sources.)

[Figure 1 here]

Table II reports the distribution of the duration of the property execution proceedings, which has a median that exceeds three years in 2007. Significant disparities are observable across Italy, however, with the duration ranging from under one year for the Court of Crema to close seven years for that of Cosenza. Figure 2 shows a marked contrast between the areas of the northern and the southern parts of Italy, with the latter characterized by a significant higher length of the judicial proceedings. That said, heterogeneity exists across court jurisdictions operating within these two broad areas. For example, the estimated length of the proceedings in the Judicial Courts of Ragusa and Brindisi - both localized in the South - are equal to 3,336 and 1,137 days, respectively.

[Table II & Figure 2 here]

Table III reports basic summary statistics on the characteristics of banks during our sample (2008 to 2013), as well as means split based on the level of legal efficiency. Our key measure of bank health - bad loans / total assets - varies substantially, reflecting both changes across time (as in Figure 1), as well as substantial variation in the cross section. We also capture liquidity-risk exposure of banks in two ways, one from each side of the balance sheet. Italian lenders rely strongly on stable sources of funding; that is deposits from residents and bank bonds held by households, which account for around 60% of their balance sheets. Stable funding also varies dramatically across the sample, with some banks having around 90% stable funds and others relying mainly on other sources of funds, such as, inter alia, short-term wholesale funds. For asset liquidity, we again observe substantial variation, with the share of assets in bonds and cash varying from 5% to almost half of the balance sheet. We also control for lender size. As in most countries, most of the 695 banks employed in this study are small, with a median asset size of 430 million Euro, but the largest banks have over 200 billion Euro in total assets.

[Table III here]

Columns 4 and 5 of Table III show that only two characteristics differ substantially between areas with above v. below average legal efficiency: loan losses and asset liquidity are both higher in the areas with relatively inefficient law. Capital and exposure to losses on sovereign bonds (*govbshock*) also differ statistically, but the economic magnitudes of these differences are small. The higher level of loan losses reflects the greater difficulty to banks of recovering loans that have gone into default.

Table IV contains statistics on the borrowers based on firm-year level data for the years 2008 to 2013, and includes both firms that do and not selectively pay late and that borrow from multiple banks as well as from one bank. This sample contains about 30,000 firms per year.

[Table IV here]

The median firm has about 50 employees and 15 million Euros in assets. Leverage varies substantially, with a standard deviation of 19% around a mean of about 30%. Firm age averages about 25 years. Overall, our sample is dominated by privately held, small and medium-sized firms. That said, our main results discussed below absorb with a quarter-firm dummy the direct effects of constant and time-varying firm characteristics to focus on bank effects on repayment behavior. Comparing across areas by legal efficiency, we see that firms are slightly younger and riskier in areas with weak law, but these differences are small (despite statistical significance).

The regression sample (see, for instance, Table V) is based on data at the firm-bank-quarter level and thus has about 2.6 million observations for the period 2008Q4 to 2013Q4. We include all firms except those with just one bank relationship. There are around 500,000 quarterly observations on distinct firms. The average number of banks per firm is about 5, resulting in 2.6 million loan level observations.[15] The sample breaks down as follows: about 0.2% paid late on all of their bank loans; 92.8% were paying all of their banks on time; and about 7% were late on some loans but not others.

III. Econometric Methods and Results

We estimate a linear probability model that links borrower payment delays to a set of bank effects, firm-time effects and measures of bank characteristics, as follows:

$$y_{i,b,t} = \sum_{k=1}^{K} \alpha_k x_{k,b,t-1} + \theta_{i,t} + \delta_b + \varepsilon_{i,b,t} \tag{2}$$

where i denotes firm, b denotes bank and t denotes time (based on quarterly frequency). The outcome $y_{i,b,t}$ (*late payment*) equals an indicator variable set to 1 if the firm has a loan repayment delay or overdrawn with the bank in the quarter and 0 if loans granted by the bank to the firm are performing in the quarter. Explanatory variables ($x_{b,t-1}$) are time-varying bank characteristics from the end of the previous period. We include the log of bank assets to capture bank size (*lntot*) and consider capitalization (*cap*), the amount of stable sources of funding (*stable funding*), and liquid assets (*liquidity*) as bank-level covariates, all scaled by assets. Our definition of *stable funding* includes both deposits and bonds held by retail customers; this definition follows the one used by the Bank of Italy because banks view bonds placed with households as close substitutes for retail time deposits. To capture the strength of the (lending) relationship between the bank and the firm, we use the share of loans from bank b to firm i (*bkshare*). We also include a measure of losses on sovereign bonds (*govbshock).*

Our main variable of interest is the ratio of past bad loans to total assets (*badloans*), a measure of bank health that captures the extent to which a bank has already experienced

[15] More precisely, the total number of observations reported in Table V, 2,656,565, equals 511,672 x 5.27 - 39,946, where 39,946 is the number of observations on loans to firms with only one lender.

high levels of borrower default. We will allow the effects of bad loans to vary according to the judicial efficiency of the local courts (measured by the log of the average length of property execution proceedings (*inefflaw*)). That is, we interact bad loans (as well as other bank co-variates) with this variable. In addition, we report interactive models based on firm credit quality.

To absorb unobserved heterogeneity at the bank level, we control for bank fixed effects (δ_b). These effects capture time invariant components of managerial quality, the quality of governance, lending practices, market structure, and so on.[16] Since our main variable of interest varies at the bank level over time, we cluster standard errors at the bank level. The firm-time effects ($\theta_{i,t}$) control non-parametrically for all characteristics of borrowers that might lead to late payments across all lenders, such as lack of investment opportunities or business fundamentals related to risk, poor cash flow or low profit realizations, as well as other hard-to-measure time-varying attributes.[17] By absorbing these effects, we focus on a firm's decision as to which of its banks to pay and which not to pay. Identification of our main coefficients is driven by firms paying some of their banks but not others (in a given quarter). Any borrower paying all of its banks on time or failing to pay all of its banks (about 93% of the sample) will be absorbed by the firm-time effect. Thus, we can interpret the α_k coefficients as measures of 'selective' repayment delay - the extent to which a firm chooses not to pay, in the sense of not repaying the loan plus interest when it is due, with respect to one bank vs. another. We include the 93% of non-selective delay observations in the regressions because they help pin down the bank-specific fixed effect (some banks have higher or lower overall levels of late payments than others).

One concern with our identification strategy may be reverse causality, or that banks with

[16] Appendix B, Table BI reports our core models without bank fixed effects.

[17] See Khwaja and Mian (2008) and many others. The routine we use to run the high-dimensional fixed effect models is based on Correia S., (2016), "A Feasible Estimator for Linear Models with Multi-Way Fixed Effects," http://scorreia.com/research/hdfe.pdf.

payment delays may be less willing to write down loans than healthier banks (to conceal their problems). Another concern is that heterogeneity in unobserved loan terms (e.g., covenants) might lead to more payment delays. Time-varying differences in bank lending practices that affect both past *badloans* and delayed payments could confound the interpretation of our results. To address this issue, we build a Bartik-style instrument for *badloans* using the variation over time of overall loan-loss rates that are sector and province specific, with bank-specific weights from each loan category as a fraction of total loans, measured prior to the beginning of the sample (Fall 2007).[18] To ensure that the instrument does not pick up a spurious relationship between payment delays and *badloans*, in the construction of the instrument we leave out loans to firms in the same province and sector as the firm in question (see, for example, Granja et al. (2017)). In other terms, we give a weight of zero to the loss rate in the sector-province cell a firm belongs to in calculating the instrument for *badloans*, making it time and bank-firm specific.[19] We multiply this proxy by each bank's loans-to-assets ratio from the preceding quarter so that it has units comparable to

[18]Lending sectors are divided into the following non-overlapping categories: consumers; family business (split by agriculture and fishing, construction, industry and services); large non-financial corporations (nfc) (agriculture and fishing, construction, industry and services); small nfc (agriculture and fishing, construction, industry and services); government; and, other financial institutions (banks excluded).

[19]Obviously we rescale the other weights so that they sum to one. Goldsmith-Pinkham et al. (2018) point out that the Bartik instrument is equivalent to using a weighted-average of a large set of instruments based on cross-sectional shares, with weights based on time-varying aggregate shocks. In our setting, the instruments represent each bank's exposure to various sector-provinces, and the weights depend on the aggregate loss rates in those cells. The usual identification assumption holds, which is that the instrument - a weighted sum of the portfolio shares - needs to be uncorrelated with the error term. To alleviate concern about this (fundamentally untestable) assumption, we leave out part of the instrument based on exposures in the sector-province for the firm in question. It seems reasonable to assume that this component of the instrument is the one most likely to be correlated with the error. In other words, the instrument is based portfolio shares in all sector-provinces except the one that pertains to this firm.

badloans. This instrument gets all of the cross-sectional variation in loss rates from pre-crisis lending shares, and all of its time-series variation from overall loan losses across all banks. The instrument brings additional information even with the inclusion of a bank fixed effect, because it has both cross-bank and over-time variation. While the weights could reflect unobserved differences across banks, this heterogeity does not vary with time and is controlled for by the bank fixed effect. To summarize, the instrument captures only variation in *badloans* due to a bank's ex ante exposures to different loan segments (except the one a firm belongs to), but no variation from the evolution of each bank's lending practices over time.

Our study rests on the assumption that borrowers pay attention to the quality of their banks' balance sheets, as it might influence lenders' ability to extend credit in the future and be a proxy for banks' internal enforcement capacity. This is a very plausible assumption because bank balance sheet information is easily available and widely disseminated. The problem of bad loans has been particularly well publicized, as the national and international press have been focusing on credit quality as the main factor determining bank fragility in Italy.

In addition, Italian banks can observe firm loan repayment behavior through access to the Credit Register. Hence, a firm engaged in selective delay likely expects other banks to understand and observe this behavior. Our model thus requires that firms have a greater incentive to delay repayment to weaker banks relative to stronger ones, either because they expect less future credit from the weaker ones or because weaker banks are less able to enforce existing loan contracts, even when all banks have access to the same information.

A. *Baseline result: Accumulated bad loans encourage firms to delay repayment*

Table V reports our baseline specification (with no interactive effects). Our sample covers the period 2008Q4 to 2013Q4. These regressions focus strictly on the total effect of bank variables on a firm's choice to delay loan repayment. We report OLS models with firm-time and bank fixed effects in column (1), and the first-stage and second-stage IV models in columns (2) and (3). We also report the same set of models including only term loans, which helps ensure that our results reflect borrower payment delays.[20] Some early payment delays may be missed in the credit line data because delayed re-payments will not be captured until the borrower exceeds the credit limit (as long as the drawn balance remains below the limit, we have no way to determine what motivates the borrower). A second problem with credit lines is that the bank's choice to cut credit limits could make repayment delays more likely. No such problems exist with respect to term loans, since the balance of the loan is fixed throughout the life of the loan.

[Table V here]

We find strong evidence that bank weakness leads firms to delay loan repayment. Firms with more than one bank selectively delay against the weaker one(s). Specifically, delay is more likely at banks with high levels of past bad loans. These effects are large, both statistically and economically. For example, a one standard deviation increase in bad loans (a change of about 0.027) is associated with an increase in delay of about 0.3 percentage points ($= 0.027 \times 0.114$; see Table V, column 1), which is large relative to the average probability of about 3% (recall Table Ia). The IV results are substantially stronger than OLS, with a coefficient on *badloans* more than twice as large. The instrument is relevant, as it is well correlated with actual *badloans*, easily passing standard tests for weak instruments. (The Kleibergen-Paap F-statistic equals 22.3, with a p-value less than 1%.) As we have emphasized, the instrument uses only variation in loan losses due to bank ex ante exposure to aggregate losses. Since the instrument does not use variation in banks' actual losses, the IV eliminates the possibility of bias from different write down practices. For example, if weak banks - banks experiencing a high level of delays - are less willing or slower to write off loans,

[20]In an earlier draft we also report models with bank profits as an additional regressor. These results are similar to those reported here. We leave this variable out because it is reported bi-annually, rather than quarterly.

this could bias the OLS coefficient down relative to the IV. The IV estimator purges this source of bias because it does not use variation in this bank's write down behavior (only the average across all banks). The increase in repayment delays to a bank with a large stock of past bad loans is consistent with a decrease of the future value of the relationship with such bank, because the bank is less likely to be a source of future funding. It is also consistent with a lower probability of the firm being actually punished if the bank's enforcement capacity is limited and becomes stretched as a result of bad loans accumulation.

The results are similar comparing the full sample with the sample using only term loans, although magnitudes are a bit smaller using just term loans. In the OLS model, for example, we see a somewhat smaller coefficient for the sample with only term loans (0.066 vs. 0.114); both have similar statistical significance. The lower absolute magnitude reflects the fact that the the average level of late payments is lower for term loans (recall Table I). Given that almost 40% of the loans in Italy are credit lines (as of December, 2014), we focus on the full-sample results in subsequent tables.[21]

We also find some evidence in the full sample that banks with greater losses from sovereign exposure face higher levels of firms' delay.[22] However, the coefficient is significant only at the 10% level, so this evidence is less statistically robust. Therefore, there is no strong evidence that the repayment delays are the consequence of banks' balance sheet fragility due to the amount of Italian government bonds held in banks' portfolio. In addition, firms are more likely to delay as their share of borrowing from a bank increases; this effect may be rationalized by interpreting *delay* as a form of flexibility called for by distressed borrowers to "relationship" lenders, or it might simply reflect the idea that firms facing financial constraints

[21] We lose observations in models that exclude credit lines because firms which have only a credit line from a given bank in a given quarter must be dropped from this sub-sample.

[22] Banks were holding large quantities of Italian government bonds in the years we consider. See, among others, Gennaioli, Martin, and Rossi (2018), Battistini, Pagano, and Simonelli (2014), and Bottero, Lenzu, and Mezzanotti (2015).

have more to gain (at least in the short term) by withholding payments to banks to whom they owe more.

We find no evidence that bank size or other characteristics affect repayment behavior. We also find no evidence that bank liquidity stress - either from a low share of assets in liquid investments or heavy reliance on wholesale funds (low stable funds) - affects repayment. This last non-result contrasts sharply with that of Ippolito et al. (2016), who show that firm drawdowns on credit lines increase at banks facing funding pressures around the Lehman bankruptcy. The difference in results is likely to reflect the different periods investigated by the two papers. Specifically, we do not focus on the immediate aftermath of the Lehman bankruptcy, but consider a longer period which is characterized by massive injection of liquidity by the European Central Bank that strongly alleviated liquidity shortages and funding problems of European banks.

B. Judicial efficiency

Table VI reports the model augmented with interactions of the bank characteristics with our measure of enforcement - the natural log of the average durations for property execution proceedings (*inefflaw*) - which varies widely across judicial courts (recall Figure 2).[23] In the IV version of this model, we report two first-stages - one for the direct effect of *badloans* and the other for its interaction with *inefflaw* (since both are treated as endogenous variables). Here and in subsequent tables, we include but do not report the other bank characteristics, along with their interactions with *inefflaw*.

[Table VI here]

These results show that bank weakness affects firm-level repayment choices most in areas with weak enforcement. Like the non-interactive models, both the OLS and IV coefficients on *badloans* and its interaction with *inefflaw* are jointly statistically significant at the 1%

[23]The main effect of *inefflaw* is absorbed by the bank fixed effect since *inefflaw* is time-invariant and the jurisdiction is assigned on the basis of the legal residence of the bank.

level (F-test = 24.35 in OLS and 16.64 in IV); the economic magnitude of in *badloans* at the mean is larger in the IV model (as it was in the non-interactive model), with a somewhat flatter profile as one move from the most to the least efficient regions based on *inefflaw*.[24]

[Figure 3 here]

To understand magnitudes, Figure 3 plots the marginal effect of *badloans* on payment delays as a function of the level of judicial inefficiency, from the 5th to the 95th percentile of its distribution. We report the marginal effect of bad loans from both the OLS and IV approaches, with 95% confidence bands around the IV estimate. The effect of *badloans* increases in the length of time for property execution in court. At the mean, the marginal effect of bad loans is significant and similar to what we find in the non-interactive regressions of Table V. The effect implies that a one standard deviation increase in bad loans would increase delays by about 0.35 percentage points from the OLS model (and more than double from the IV, as in the simpler model). In contrast, where enforcement is poor - one standard deviation lower than average (e.g. Cosenza) - the effect increases substantially. In courts with good enforcement (e.g. Crema), the effect of past bad loans on delays is small and not statistically significant. This variation emphasizes the importance of legal enforcement, as we see evidence of firms selectively withholding payment against weak banks where their ex post ability to enforce is weak, while the effect is not significant for locations where the courts are efficient. Thus, where enforcement is weak borrowers pay mainly to preserve access to future credit, much as the incentive of sovereign governments to repay debt resides primarily in their concern about borrowing in future years (Shleifer, 2003). As illustrated in the figure, the difference between the OLS and IV estimates is within sampling error (i.e., both plot within the 95% confidence interval of the IV estimator) for areas with above-average legal inefficiency; for areas with below-average legal inefficiency, the marginal effect from OLS is smaller but only slightly outside the confidence interval for the IV estimate. Since the OLS

[24]The instruments are relevant, with a Kleibergen-Paap F-statistic of 19.43 (p-value $< 1\%$).

estimate for the marginal effect of *badloans* 'lives' within (or very near) the 95% confidence interval across most of the distribution, we focus on the OLS approach in subsequent tables.

Do late payments harm lenders? As we have suggested, some late payments may reflect flexibility or implicit liquidity supplied by a firm's relationship lender, as we find late payments increase with a bank's relative lending share. But overall, lagged payment delays are associated with lower bank profits. Table VII reports bank-year level panel regressions of profit (return on equity) against lagged bank characteristics (along with bank and time effects). Even in models that control for past bad loans, payment delays remain negative and statistically significantly related to profits. The coefficient suggests that a one standard deviation increase in late payments decreases profit by about 6% of its unconditional mean.

[Table VII here]

C. *Loan Repayment: Strategic or Just Selective?*

Our identification exploits only variation from firms who select to delay payment to one (or more) lender(s) while continuing to pay others. Are these delays truly strategic, in that some borrowers pay less than they otherwise would because one or more of their lenders is distressed? Or, are they just selective, in that borrowers, when sufficiently cash constrained, actively choose to withhold payment from their weaker banks? Such selective behavior, while interesting, would imply that the overall amount of debt repayment is not affected by bank weakness, although the distribution of delays across lenders is affected.

Quantifying the amount of truly strategic behavior is difficult, but one approach we can offer is to estimate our model separately by borrower credit worthiness. Truly strategic payment delays - delays from firms that could pay all of their banks - involves an incremental cost to a firm's reputation in credit markets because payment delays are observable to all lenders (via the Credit Register). Cash-constrained firms, in contrast, face no cost from selective delay because the reputational hit is unavoidable: the firm simply lacks the resources to pay all its banks. Since strategic delay involves trading off the short-term benefit of maintaining control over current cash against the long-run cost of reduced access to credit, we would expect a smaller impact of bank health (*badloans*) on delay for higher-quality firms.

To test these ideas, we augment our core model with interaction terms based on borrower quality. In the first two columns, we separate firms into three bins using the z-score, which summarizes credit quality.[25] Firms with z-scores less than or equal to three are defined as 'safe', those with scores between four and six as 'vulnerable', and those with scores equal to and above seven as 'risky'. In the last two columns, we instead separate firms into three bins based on the interest coverage ratio (EBITDA / Interest Expenses); firms with interest coverage below one are the most constrained; firms with coverage between one and two are intermediate; and firms with coverage above two are not cash constrained, as they have more than enough cash to pay all of their lenders.

The results (Table VIII) suggest, first, that the effect of bank distress on delay is robust across all three firm types; in each case we see that the bad loans ratio affects loan repayment delays most in areas with weak legal enforcement. Second, magnitudes increase across the three bins. This ranking makes sense because the reputational costs of delay increase as firm credit quality improves. High-quality firms discount the reputational costs of delay on future credit access the least, while low-quality firms discount this cost the most. In each bin, the marginal effect of bad loans on delay is close to zero in areas with high levels of judicial efficiency and then increases, becoming positive and significant, as judicial efficiency worsens. Figure 4 illustrates these patterns, plotting the marginal effect of bad loans on delay by firm type across the distribution of judicial efficiency (*inefflaw*), using the z-score as the classification criterion. Even for the safest category of firms, we find evidence that repayment delays increase with bank distress in areas of poor legal enforcement: as shown,

[25] The *score* variable measures the probability of a firm defaulting on the basis of an adaptation to Italy of Altman (1968)'s approach, developed by Cerved SPA and regularly used by Italian banks to assess a firm's riskiness. The Score index ranges from one for firms least likely to default to nine for firms most likely to default.

in Figure 5, the marginal effect of bad loans on delay becomes positive and statistically significant for most of the distribution of legal inefficiency above its average. Results are very similar when we use the interest coverage ratio to classify firms.

[Table VIII and Figures 4 & 5 here]

This suggests that truly strategic behavior sometimes occurs. Payment delays are higher when lenders are weak (due to high bad loans) and legal enforcement is poor, even for the lowest risk borrowers. Low risk borrowers have the capacity to pay but sometimes choose not to pay, indicating the presence of strategic behavior that goes beyond the selection of which lender to pay, and indicating the possibility of less overall debt repayment due to bank weakness and poor enforcement. These results also help rule out the idea that the effects we observe reflect differences in bank enforcement practices, as the safe borrowers have sufficient cash flow to continue paying their loans regardless of bank enforcement.

Another way to asses the importance of strategic behavior is to ask: are payment delays higher at firms whose lender(s) are collectively weak? To answer, we aggregate up the earlier regressions to the firm-year level (from the firm-bank-quarter level) by constructing the average payment delays and the average bank losses, weighted by the size of the exposure to each bank. Thus we can not absorb firm fundamentals with firm-time fixed effects. So, we control for firm fixed effects and industry-time effects and include time-varying fundamentals such as firms' initial leverage, cash flow, sales growth, interest coverage ratio, z-score, size and age (only available yearly). We do this for firms with both multiple and single banking relationships (the latter ones were effectively taken out by the firm-time fixed effects in the previous analysis). In one specification we also add as a separate regressor the firm-time effects estimated from the model of repayment delays at the firm-bank-time level. The latter can help in capturing other unobserved time and firm specific determinants of repayment delays. In this case we, obviously, limit ourselves only to firms with multiple banking relationships.

As shown in Table IX and in Figure 6 (based on the results of column 3), overall payment delays are higher at firms whose average bank has experienced higher losses, and this effect is greater in areas with weak legal enforcement. Accounting for both the direct and interactive terms, an increase in past losses in areas between the first quartile and the median level of legal inefficiency is not statistically different from zero. In contrast, were legal inefficiency is closer or above its median value (which is smaller than the mean: 1,331 versus 1,511), the estimated marginal effect of bank losses becomes statistically different from zero. At the mean value of enforcement, a one standard deviation increase in bad loans leads to an increase in the share of late payments of approximately 0.37 percentage points ($= [-1.229 + 0.187 \times ln(1,511)] \times 0.027$), using the results in column (3). The effect increases by about 50% when enforcement is one standard deviation poorer. This marginal effect is very similar in magnitude to what we estimate in our more disaggregated models. Our results help explain why credit supply has been shown to respond so strongly to the strength of legal enforcement (Jappelli et al. (2005)).

[Table IX and Figure 6 here]

D. Robustness Tests

To rule out possible alternative interpretations of our results, Table X reports six tests of our main model with legal efficiency interactions (i.e., the models of Table VI). First, we report the model after discarding all data beyond the first quarter in which a loan becomes late (or overdrawn). Second, we control for four dimensions of loan terms. Third, we reduce our sample and include only observations in which the bank and the borrower reside in the same court jurisdiction. Fourth, we replace bank fixed effects with bank-firm effects. Fifth, we test whether our results are subsumed by three measures of culture. And sixth, we test whether the results differ between mutual banks and private banks.

D.1. First Delay

The regression of column (1) reports the main result with just the first instance in which a loan becomes late on a payment (or overdrawn). This test alleviates the concern that persistence in the error term leads to a bias in estimating the effects of past bad loans on delayed repayment. The problem is twofold. First, once borrowers become late on a loan, that lateness becomes persistent; late borrowers tend to stay late for many consecutive quarters. Second, loans that are late (or overdrawn) often transition to the bad-loan account. This pattern is evident in the transition matrix described earlier (recall Table Ib). Persistence in the error term after loans become late would therefore induce a contemporaneous correlation between the error and the level of bad loans for observations after the first instance of delay. To remove this source of bias, we simply drop all observations after a loan first enters the state of late payment. The basic pattern of the regression results remains similar, with even stronger statistical significance. The magnitudes fall, but this is as expected because by dropping all instances of late payments after the first one, we reduce the mean level of the dependent variable by more than 50%.

D.2. Control for Loan Terms

Our model makes no assumption regarding loan terms. That said, if loan terms vary systematically with bank health, the main specification could be misleading. For example, suppose weak banks make loans with higher rates of interest; if so, a firm may be more likely to delay payment to save cash. As we have emphasized, our model fully absorbs all firm-level fundamentals by capturing firm-quarter fixed effects. However, loan terms - interest rates, collateral, and maturity - are not captured this way, since these may vary across a firm's banking relationships. We therefore control for the loan interest rate, the share of loans with maturity less than one year, the average ratio of collateral in accounts receivable to loan size, and the average ratio of real-estate collateral to loan size. Each of these variables reflects variation at the firm-lender-quarter level, so coefficients remain identified even with the firm-quarter fixed effects. In some cases loan terms are not available, so the sample falls in these models.[26]

We find in column (2) that higher interest rates are associated with more payment delays, which seems sensible given that the firm can save more cash resources by delaying payment on more expensive loans. We find that shorter maturity loans are more likely to delay. And we find some evidence that collateral mitigates late repayments (at least for accounts receivable; real estate collateral does not enter the model robustly). But what is most salient for us: adding these variables does little to our results of interest. In fact, we find somewhat stronger results, although this in part may reflect differences in the sample.

D.3. Borrower and Lender in Same Court Jurisdiction

Next, we include only instances in which lender and borrower are located in the same court jurisdiction. This alternative sample, which is much smaller than our main sample, accounts for possible measurement error in mapping legal enforcement into the data. As noted above, ex post enforcement requires lenders first to receive an injunction from the court jurisdiction of its head office and, to reposess collateral (or other borrower's assets), they also need to adjudicate in the court located near the collateral. Thus, legal enforcement in both court jurisdictionss may matter. By focusing on cases in which the two overlap, we can test whether potential mis-classification could generate (or bias) our findings.[27]

These results (column (3)) again support the idea that lender weakness (bad loans)

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[26]Specifically, data on interest rates on loans are available from the Bank of Italy's Loan Interest Rate Survey, which collects data from around 200 banks accounting for over 90% of total outstanding loans.

[27]The large drop in the sample occurs because the majority of loans are extended by the largest banks with branches located across the whole of Italy. So, even though borrowers are usually located near a branch of their lender, they often are not located near the lender's head office. Thus, this sample filters out most loans extended by the largest banks and suggests robustness with respect to lender size as well as legal efficiency measures.

raises delay in areas with weak enforcement. If anything, these results are stronger than those reported in our main model, meaning that the effect of bad loans on delay exhibits greater sensitivity to legal efficiency in this smaller sample.

D.4. Controlling for Possible Endogeneity of Borrower-Lender Matching

With the results of column (4), we rule out the possibility that endogenous matching between firms and banks could explain our results. For example, one concern might be that firms sometimes choose a lender located in an area with poor legal enforcement with the intention of withholding payment. We do this by simply incorporating a unique fixed effect for each bank-firm pair. These effects will 'control' non-parametrically for all aspects driving the firm's choice of its lender. The result has a somewhat flatter interaction with legal efficiency, but with similar effects in terms of sign and statistical significance. At the mean level of legal enforcement, the effect of a one standard deviation increase in bad loans on repayment delays equals 0.2 percentage points ($=0.027(-1.078 + 0.163 \times ln\,(1511))$).

D.5. Law v. Culture

One may wonder whether the differences in the importance of bank health across court jurisdictions proxy for more complex and subtle differences in culture across Italy. For example, cultural differences in trust and respect for others outside the family (social capital for short) may affect firm's willingness to engage in selective payment delays. If legal efficiency is correlated with local variation in culture, our emphasis on legal ex post contract enforcement could be misplaced.[28] One simple measure of cultural differences across Italy is mere geography, with the North having more social capital and better formal institutions in general than the South. As we have seen, we have meaningful variation within both macro

[28] Guiso et al. (2004) report significant correlations of various provincial measures of both social capital and financial development with legal inefficiency. See also, Putnam et al. (1994) Guiso et al. (2013) and Guiso et al. (2016).

regions, but judicial efficiency is generally higher (*inefflaw* is lower) in the North. However, the inclusion of a North-South dummy is a coarse way to control for differences in social norms. Therefore, we also consider two direct measures that plausibly relate to the local level of social capital: the amount of blood donations by province (*blood*) and the frequency of fake checks by province (*fake*).[29] These measure of socal capital are also correlated with legal inefficiency, as one would expect, but again less than perfectly (see Appendix B, Table BII).

To test whether these alternative sources of variation affect our results, we incorporate additional regressors interacting the bank characteristics with each measure of social capital into our core model (i.e., the one with interactions with judicial efficiency). Our focus is on the interaction between *badloans* with these measures. The model with the North-South dummy appears in column (5), while those for the finer measures of social capital appear in columns (6) and (7). As before, the direct effects of these additional variables gets aborbed by the fixed effects. What matters for us is that none of these additional terms is significant, nor does their inclusion affect the economic magnitude or significance of the coefficent of the interaction between *badloans* and *inefflaw*. So, we conclude that judicial inefficiency is the key factor determining the marginal effect of accumulated bad loans on the decision to delay payments.

D.6. Does Governance Explain Payment Delays? Mutual v. Private Banks

Past bad loans may reflect a bank's poor ability to enforce repayment having nothing to do with borrower incentives to delay payment. Our empirical model rules out any explanation, such as poor governance, related to time-invariant bank characteristics by including bank fixed effects. But if the quality of governance affects the way time-varying bank characteristics affect repayment delays, the fixed effect will not be sufficient. In our last test, we

[29]See the Appendix A for precise definitions. We would like to thank Luigi Guiso for providing us with the social capital data.

therefore estimate our model after allowing the effect of bad loans (and other bank balance sheet variables) to depend upon an observable (and plausible) measure of bank governance based on its ownership structure. Anecdotal evidence suggests that mutual (cooperative) banks in Italy are less contestable (because the number of votes does not correspond to the number of shares held) and may be more subject to local political pressure, both of which may inhibit their ability or incentive to enforce contracts. We therefore estimate our model after allowing all of the slope coefficients to vary between private and mutual banks (last column of Table X).[30] This analysis provides no evidence of differential effects, thereby suggesting that poor governance can not explain why bank distress generates repayment delays.

[Table X here]

IV. Conclusions

This paper is the first to provide evidence that weak balance sheets combined with inefficient legal enforcement together erode borrower repayment incentives. As we show, borrowers choose to delay payment in response to their bank's past accumulation of bad loans. These results are strong, both statistically and economically, at those Italian banks operating in areas with weak legal enforcement. Most of the finance and economics literature, as well as the policy and regulatory apparatus, have viewed the roots of bank vulnerability as stemming from exposure to liquidity risk. Although exposure to credit risk is a well-known source of bank losses, we find a *new channel* through which credit risk might impair bank stability: delay in payments motivated by bank weakness. We even demonstrate that

[30]On the general issue of the importance of bank ownership structure and political connections in Italy, see Sapienza (2004) and Faccio (2006).In order to strengthen the governance of mutual banks and improve their ability to collect capital on the market, a reorganization of the Italian mutual banks sector took place in 2019. Two holdings gathered the large part of mutual banks, which entered into the direct supervision from the SSM. The remaining mutual banks are left under direct supervision of the national authority.

where enforcement is weak, the safest borrowers delay loan repayment to the less-healthy banks and that exposure to weaker banks increases total repayment delays aggregated up at the firm level. Our results help explain why the law and finance literature has found weak enforcement of creditor rights to be so detrimental to well functioning debt markets (La Porta et al., 1998).

Our results point to a new source of indirect financial distress cost, as weak banks are less able to engage in one of their core functions, the collection of debts. It seems likely that better legal enforcement, such as improving the speed and certainty with which creditors can take possession of borrower's collateral, can alleviate this cost, as we find no effect on loan repayment delays and, hence, on lender health where legal enforcement is good. Our paper also contributes to the debate on the role of information and market discipline on bank stability: while access to timely and reliable information enables investors to assess risks inherent to financial assets and to allocate capital efficiently, full transparency might sometimes have detrimental effects if it leads to overreaction by market participants. In bad times, dissemination of information on lender fragility can erode borrower payment incentives, making weak banks even weaker.

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Appendix A: Variable Definition and Sources

Loan quality and lending relationship - Source: Credit Register, Bank of Italy

late payment (0,1): bank, firm, quarter-level, =1 if the firm has a past due/overdrawn with the bank in the quarter; = 0 if loans granted by the bank to the firm are performing in the quarter;

bkshare: bank, firm, quarter-level, firm's share of borrowing from the bank in the quarter;

past due/overdrawn: exposures (other than those classified as bad loans, substandard or restructured) whose repayments have been delayed by the borrowers for more than 90 days on a continuous basis;

*substandard: e*xposures to counterparties which face temporary difficulties expected to be overcome within a reasonable period of time;

objective substandard: past due/overdrawn classified as "substandard";

restructured: exposures in which lenders, as a result of the deterioration of the borrower's financial situation, agree to change the original conditions, giving rise to a loss for the creditor;

*bad loans: e*xposures to insolvent counterparties (even if not legally ascertained), regardless of any loss estimate made by the bank and irrespective of any possible collateral or guarantee;

Bank characteristics - Source: Supervisory Reports, Bank of Italy

total assets: bank, quarter-level; eur millions;

lntot: bank, quarter-level; total assets, eur millions (log of);

badloans: bank,quarter-level, bad loans/total assets, ratio;

profits: bank-level, by-annual, return on equity, ratio;

liquidity: bank, quarter-level, (cash and gov. bonds) /total assets, ratio;

capital: bank, quarter-level equity/total assets, ratio;

stable funding: bank, quarter-level, deposits from residents and bank bonds with households/total assets, ratio;

govbshock: bank, quarter-level, losses from sovereign bonds holdings; source: Author's estimates based on data from Supervisory Reports, Bank of Italy. See the upcoming description for details;

We follow De Marco (2015) to compute the change in the value sovereign holdings (*govbshock*) using the change in the yield ($\triangle yield$) for each type of bond (based on maturity and country), multiplied by the product of the bond's duration times its share of the bank's total assets (*govbondshare*). We limit ourselves to bonds issued by the Italian government because they represent the vast majority of holdings of sovereign bonds. *Govbshock* is defines as

$$govbshock_{b,t} = \sum_m duration_{m,t} \times \Delta yield_{m,t} \times govbondshare_{m,t-1}, \tag{A1}$$

where m denotes the original bond maturity. For a zero coupon bond the formula can be written as:

$$duration_{m,t} = \frac{2m}{1 + yield_{m,t}}. \tag{A2}$$

For a par bond, the formula simplifies to

$$duration_{m,t} = \frac{1}{yield_{m,t}} \left[1 - \frac{1}{(1 + yield_{m,t})^{2m}} \right]. \tag{A3}$$

We apply the first formula when we know that the sovereign bonds are discount bonds and an average of the two formulae when we have no such information.

Efficiency of justice - Source: Authors' estimates from data disseminated by the Italian Ministry of Justice

inefflaw: court jurisdiction-level, Length of Property executon proceedings in days (log of);

Firm characteristics - Source: Balance sheet register

employees: firm, year-level;

firm assets: firm, year-level;

debt/assets: firm, year-level;

age: firm, year-level;

z-score: firm, year-level (9 risk classes).

Social capital

blood: number of blood pouches donated per million of inhabitants in each province in 1995 (source AVIS (Associazione Italiana Volontari Sangue));

fake: number of fake checks issued in each province in 1996 divided by the number of inhabitants. Data bank constructed by L. Guiso).

Appendix B

Table BI: Comparing Results With and Without Bank Fixed Effects

The table presents regressions of *late payment* as a function of a set of bank characteristics. The model allows the effect of bank variables to vary with (the natural log of) duration for property execution proceedings in 2007 (*inefflaw*). In the IV models, the instrument for badloans is based on the weighted average system-wide loss rates, where the weights reflect each bank's loan portfolio in 2007. Late payment (0,1) is equal to 1 if the firm has a loan repayment delay with the bank in the quarter; 0 if loans granted by the bank to the firm are performing in the quarter. The sample covers the period 2008Q4 to 2013Q4. While not reported, bank controls (*lntot*, *stable*, *liquidity*, *cap*, *govbshock*) and firm controls (*bkshare*), as well as their interactions with *inefflaw* are included. The description of variables and their sources are given in the Data Appendix. Standard errors (in parentheses) are clustered at the bank-level. Asterisks denote significance at the 1%(***), 5%(**), 10%(*) level, respectively.

	OLS		2nd-Stage IV	
	(1)	(2)	(3)	(4)
badloans	-1.303**	-0.354	-0.637	-0.963**
	(0.245)	(0.376)	(0.423)	(0.414)
*badloans*inefflaw*	0.197***	0.062	0.124**	0.144**
	(0.035)	(0.054)	(0.054)	(0.056)
*firm*time fixed effect*	yes	yes	yes	yes
bank fixed effect	yes	no	yes	no
N	2,656,565	2,656,571	2,618,038	2,618,042

Table BII: Correlation Matrix Variables Representing Social Capital

This table reports the correlation between pronvince-level characteristics. *South* is an indicator equal to one for provinces in the southern half of Italy. *Legal inefficiency* is the duration of property execution proceedings in 2007. *Bounced checks* is the number of checks returned, per capita. And, *Blood* is the number of units of blood donated per capita.

	South	Judicial Inefficiency	Bounced Checks
	(1)	(2)	(3)
South			
Judicial Inefficiency	0.71		
Bounced Checks	0.53	0.47	
Blood	-0.56	-0.38	-0.35

Table I: Summary Statistics

The table shows statistics on loan quality for a sample of around 32,000 industrial firms based in Italy. The description of variables and their data sources are given in Appendix A.

(a) Loan Quality in Italy (Sampled Firms)

	2006	2007	2008	2009	2010	2011	2012	2013	2014
Performing	0.986	0.987	0.982	0.956	0.936	0.922	0.909	0.880	0.853
Bad Loans	0.000	0.000	0.002	0.008	0.017	0.025	0.035	0.052	0.071
Restructured	0.002	0.002	0.002	0.007	0.014	0.017	0.018	0.016	0.019
Past Due/Overdrawn	0.009	0.008	0.010	0.013	0.012	0.015	0.011	0.011	0.008
Substandard	0.003	0.002	0.005	0.016	0.021	0.021	0.027	0.040	0.049
o.w.:objective substd.	*0.001*	*0.001*	*0.001*	*0.008*	*0.011*	*0.012*	*0.016*	*0.024*	*0.029*
Late Payments	0.010	0.009	0.011	0.021	0.023	0.028	0.028	0.038	0.041
Late payments, excl. Credit Lines	0.008	0.007	0.010	0.018	0.018	0.019	0.023	0.031	0.034

(b) Transition Matrix for the Universe of All Borrowers

		Performing	Past Due/Overdrawn	Substandard/Restructured	Bad Loans
		Loan State at 12/2010			
Loan State at 12/2009	Performing	94.62%	1.11%	3.04%	1.22%
	Past Due/Overdrawn	50.74%	10.45%	27.56%	11.25%
	Substandard/Restructured	10.84%	0.63%	66.15%	22.38%
	Bad Loans	0.23%	0.02%	0.66%	99.09%
		Loan State at 12/2011			
Loan State at 12/2010	Performing	94.85%	0.97%	3.15%	1.02%
	Past Due/Overdrawn	52.52%	13.12%	25.35%	9.01%
	Substandard/Restructured	8.55%	0.40%	68.68%	22.37%
	Bad Loans	0.29%	0.02%	0.34%	99.35%
		Loan State at 12/2012			
Loan State at 12/2011	Performing	92.71%	1.54%	4.34%	1.41%
	Past Due/Overdrawn	35.28%	12.08%	39.64%	13.00%
	Substandard/Restructured	6.17%	0.44%	70.30%	23.09%
	Bad Loans	0.11%	0.01%	0.38%	99.50%
		Loan State at 12/2013			
Loan State at 12/2012	Performing	91.77%	1.20%	5.60%	1.42%
	Past Due/Overdrawn	33.53%	13.01%	42.19%	11.27%
	Substandard/Restructured	4.17%	0.34%	64.69%	30.80%
	Bad Loans	0.10%	0.01%	0.29%	99.60%
		Loan State at time 12/2014			
Loan State at 12/2013	Performing	92.39%	1.04%	5.67%	0.90%
	Past Due/Overdrawn	27.49%	13.70%	46.91%	11.90%
	Substandard/Restructured	3.97%	0.22%	71.86%	23.94%
	Bad Loans	0.10%	0.01%	0.27%	99.62%

Table II: Judicial Efficiency in Italy: Length of Property Execution Proceedings

The table presents descriptive statistics on duration of property execution proceedings in 2007 (days, court-level data).

	mean	sd	p5	p25	p50	p75	p95
# of days	1,511	887	526	795	1,331	2,012	3,336

Table III: Bank Characteristics

The table shows statistics on bank characteristics used in our analysis for the full sample and for the subsample of banks located in areas with judicial inefficiency below or above the mean (equal to a duration of collateral recovery of 1331 days). The main sample covers the period 2008Q4 to 2013Q4. The description of variables and their sources are given in Appendix A. Asterisks denote significance in the difference in means, at the 1%(***), 5%(**), 10%(*) level, respectively.

	Full sample			Duration <1331	Duration >1331	
Bank variable	Mean	S.dev	Median	Mean	Mean	Mean difference t-stats
assets (millions of Euros)	36,902	126,677	430	36,639	37,562	0.406
bad loans	0.033	0.027	0.027	0.029	0.043	28.812***
profits	0.021	0.023	0.021	0.021	0.022	0.510
liquidity	0.157	0.143	0.121	0.138	0.208	24.830***
govbshock	-0.056	0.272	0.001	-0.052	-0.068	2.980***
cap	0.119	0.026	0.123	0.119	0.120	3.075***
stable funding	0.594	0.305	0.667	0.570	0.664	0.167

Table IV: Firm Characteristics

The table shows statistics on firm characteristics employed in our analysis for the full sample and for the subsample of banks located in areas with judicial inefficiency below or above the mean (equal to a duration of collateral recovery of 1331 days). The sample covers the period 2008 to 2013. The description of variables and their sources are given in Appendix A. *Z-SCORE*: 1 low risk; 9 high risk. Asterisks denote significance in the differnce in means, at the 1%(***), 5%(**), 10%(*) level, respectively.

	All sample			Duration <1331	Duration >1331	
Firm-level variables	Mean	S.dev	Median	Mean	Mean	Mean difference t-stats
employees	154	1,195	49	149	201	1.88*
assets (millions of Euros)	62	842	15	61	75	1.52
debt/assets	0.30	0.19	0.30	0.29	0.30	1.05
age	25	16	23	26	24	10.56***
riskyness (*Z-SCORE*)	4.7	1.9	5.0	4.6	4.7	7.80***

Table V: Late Payments and Bank Bad Loans

The table presents regressions of *late payment* as a function of a set of bank characteristics. In the IV models, the instrument for badloans is based on the weighted (by sector and province) average system-wide loss rates, where the weights reflect each bank's loan portfolio in 2007. *Late payment* (0,1) is equal to 1 if the firm has a loan repayment delay with the bank in the quarter; 0 if loans granted by the bank to the firm are performing in the quarter. The sample covers the period 2008Q4 to 2013Q4. The description of variables and their sources are given in Appendix A. Standard errors (in parentheses) are clustered at the bank-level. Asterisks denote significance at the 1%(***), 5%(**), 10%(*) level, respectively.

	All loans			Term loans only		
	OLS	IV		OLS	IV	
		1st-Stage	2nd-Stage		1st-Stage	2nd-Stage
	(1)	(2)	(3)	(4)	(5)	(6)
Bartik instrument		0.589***			0.594***	
for bad loans		(0.125)			(0.127)	
badloans	0.114**		0.273***	0.066***		0.195**
	(0.045)		(0.066)	(0.026)		(0.067)
bkshare	0.012***	-0.00001	0.012***	0.011***	0.0001	0.011***
	(0.002)	(0.0001)	(0.002)	(0.001)	(0.0002)	(0.001)
lntot	-0.001	-0.0017	0.000	0.000	0.0017	0.000
	(0.001)	(0.0012)	(0.001)	(0.000)	(0.0012)	(0.001)
stable	0.002	-0.0041	0.001	0.001	-0.00401	0.001
	(0.005)	(0.0133)	(0.005)	(0.0027)	(0.013)	(0.003)
liquidity	-0.006	0.017	-0.011	0.009	0.017	0.006
	(0.009)	(0.018)	(0.008)	(0.008)	(0.018)	(0.008)
cap	0.021	0.004	0.018	-0.0227	0.003	-0.025
	(0.028)	(0.0316)	(0.027)	(0.17)	(0.032)	(0.018)
govbshock	0.002*	0.0027	0.002*	0.001	0.0028	0.001
	(0.001)	(0.0025)	(0.001)	(0.001)	(0.0026)	(0.001)
*firm*time fixed effect*	yes	yes	yes	yes	yes	yes
bank fixed effect	yes	yes	yes	yes	yes	yes
N	2,656,565	2,618,038	2,618,038	2,404,773	2,369,501	2,369,501

Table VI: Late Payments and Judicial Efficiency

The table presents regressions of *late payment* as a function of a set of bank characteristics. The model allows the effect of bank variables to vary with (the natural log of) duration for property execution proceedings in 2007 (*inefflaw*). In the IV models, the instrument for *badloans* is based on the weighted (by sector and province) average system-wide loss rates, where the weights reflect each bank's loan portfolio in 2007. *Late payment* (0,1) is equal to 1 if the firm has a loan repayment delay with the bank in the quarter; 0 if loans granted by the bank to the firm are performing in the quarter. The sample covers the period 2008Q4 to 2013Q4. While not reported, bank controls (*lntot*, *stable*, *liquidity*, *cap*, *govbshock*) and firm controls (*bkshare*), as well as their interactions with *inefflaw* are included. The description of variables and their sources are given in Appendix A. Standard errors (in parentheses) are clustered at the bank-level. Asterisks denote significance at the 1%(***), 5%(**), 10%(*) level, respectively.

	OLS	IV		
		1st-Stage for *badloans*	1st-Stage for *badloans***inefflaw*	2nd-Stage
	(1)	(2)	(3)	(4)
Bartik instrument		-1.563**	-16.171***	
for bad loans		(0.687)	(5.291)	
*instrument***inefflaw*		0.303***	2.879***	
		(0.101)	(0.784)	
badloans	-1.303***			-0.637
	(0.245)			(0.423)
*badloans***inefflaw*	0.197***			0.124**
	(0.035)			(0.054)
*firm*time fixed effect*	yes	yes	yes	yes
bank fixed effect	yes	yes	yes	yes
bank controls with full set of interactions	yes	yes	yes	yes
N	2,656,565	2,618,038	2,618,038	2,618,038

Table VII: Bank Profits and Late Payments

The table presents bank-time regressions of profits (return on equity) on lagged bank characteristics. The sample covers semi-annual data between 2008 and 2013. The description of variables and their sources are given in Appendix A. Standard errors (in parentheses) are clustered at the bank-level. Asterisks denote significance at the 1%(***), 5%(**), 10%(*) level, respectively.

	(1)	(2)	(3)
late payments	-0.017**	-0.023**	-0.020*
	(0.006)	(0.011)	(0.011)
lntot		0.003**	0.003**
		(0.001)	(0.001)
cap		0.02	0.027*
		(0.038)	(0.037)
govbshock		-0.011***	-0.011***
		(0.002)	(0.002)
liquidity		0.026***	0.029***
		(0.008)	(0.008)
stable		-0.001	-0.001
		(0.005)	(0.005)
badloans			-0.089**
			(0.043)
bank fixed effect	yes	yes	yes
time fixed effect	yes	yes	yes
N	5,307	3,364	3,364

Table VIII: Late Payments, Bank Quality and Judicial Efficiency, by Firm Riskiness

he table presents regressions of *late payment* as a function of a set of bank characteristics. The model allows the effect of bank variables to vary with (the natural log of) duration for property execution proceedings (*inefflaw*) and by borrower riskiness. Borrowers are sorted in risk bins (safe, vulnerable, risky) based on their z-score or their interest coverage ratio. The *Late payment (0,1)* is equal to 1 if the firm has a loan repayment delay with the bank in the quarter; 0 if loans granted by the bank to the firm are performing in the quarter. The sample covers the period 2008Q4 to 2013Q4. The description of variables and their sources are given in Appendix A. Standard errors are clustered at the bank-level. Asterisks denote significance at the 1%(***), 5%(**), 10%(*) level, respectively.

	By z-score	By coverage ratio
	(1)	(2)
*badloans*safe*	-0.978***	-1.158***
	(0.271)	(0.230)
*badloans*vulnerable*	-1.210***	-1.339***
	(0.241)	(0.408)
*badloans*risky*	-1.818***	-1.683***
	(0.553)	(0.662)
*inefflaw*badloans*safe*	0.145***	0.169***
	(0.038)	(0.033)
*inefflaw*badloans*vulnerable*	0.181***	0.208***
	(0.034)	(0.059)
*inefflaw*badloans*risky*	0.284***	0.268***
	(0.076)	(0.085)
*firm*time fixed effect*	yes	yes
*bank*risk class fixed effect*	yes	yes
bank controls with full set of interactions	yes	yes
N	2,656,566	2,656,566

Table IX: Share of Late Payments at the Firm Level

The table presents regressions of *late payment* as a function of a set of bank characteristics. The variable *late payment* is equal to the amount of late payments as a share of total loans, computed as averages of quarterly data and excluding bad loans. The variables *expbad* and *explegal* correspond to the firm's exposure to bank bad loans and to bank legal inefficiency, respectively; exposure is calculated as the weighted average across banks associated with each firm, where the weights are the share of loans from each bank. Firm controls (log of total assets, sales growth, cashflow, z-score, debt-to-assets ratio, coverage, age), available at an yearly frequency, are included in the regressions. The firm*time effects from loan-level regressions are obtained from Column (1) of Table VI. All covariates, except for age and the firm-year effects from the loan-level regressions, are lagged one period.The sample covers the period 2008 to 2013. The description of variables and their sources are given in Appendix A. Standard errors are clustered at the firm level. Asterisks denote significance at the 1%(***), 5%(**), 10%(*) level, respectively.

	(1)	(2)	(3)
expbad	-1.347*	-1.39**	-1.229***
	(0.708)	(0.644)	(0.419)
explegal	-0.007**	-0.008**	-0.006***
	(0.003)	(0.003)	(0.002)
*expbad*explegal*	0.207**	0.212**	0.187***
	(0.104)	(0.094)	(0.061)
*firm*time effect from*			0.720***
loan-level regressions			(0.012)
firm controls	no	yes	yes
firm fixed effects	yes	yes	yes
*year*industry fixed effects*	yes	yes	yes
N	112,506	96,346	91,905

Table X: Robustness Tests

The table presents regressions of *late payment* as a function of a set of bank characteristics. The model allows the effect of bank variables to vary with (the natural log of) duration for property execution proceedings in 2007 (*inefflaw*). *Late payment* (0,1) is equal to 1 if the firm has a loan repayment delay with the bank in the quarter; 0 if loans granted by the bank to the firm are performing in the quarter. The sample covers the period 2008Q4 to 2013Q4. While not reported, bank controls (*lntot*, *stable*, *liquidity*, *cap*, *gov shock*) and firm controls (*bkshare*), as well as their interactions with *inefflaw* are included. The description of variables and their sources are given in Appendix A. Standard errors (in parentheses) are clustered at the bank level. Asterisks denote significance at the 1%(***), 5%(**), 10%(*) level, respectively. We do four robustness tests reported in Columns (1)-(8). Column (1): include only the first quarter in which a loan becomes late (or overdrawn); column (2): control for four dimensions of loan terms (loan interest rate, share of loans with maturity less than one year, average ratio of collateral in accounts receivable to loan size, and average ratio of real-estate collateral to loan size); column (3): include only observations in which the bank and the lender are located in the same court jurisdiction; column (4): include firm-time and bank-firm fixed effects; column (5) allows the effects of *badloans* to vary by region (*south*); column (6) allows the effects of *badloans* to vary by blood donation (*blood*); column (7) allows the effects of *badloans* to vary by fake checks (*fake*) and column (8) allows the effects of *badloans* to vary by mutual/non-mutual (*mutual*).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
badloans	-0.670***	-1.669***	-3.789**	-1.078***	-1.324***	-1.299***	-1.387***	-1.296***
	(0.100)	(0.258)	(1.889)	(0.253)	(0.253)	(0.251)	(0.244)	(0.273)
*badloans*inefflaw*	0.102***	0.253***	0.585**	0.163***	0.199***	0.204***	0.202***	0.196***
	(0.014)	(0.037)	(0.281)	(0.036)	(0.036)	(0.036)	(0.036)	(0.038)
Average interest rate		0.001***						
		(0)						
Share of short-term loans		0.003*						
		(0.001)						
Share of loans backed by real collateral		0.003						
		(0.002)						
Share of loans backed bt acc. reciev.		-0.018***						
		(0.001)						
*badloans*south*					0.013			
					(0.052)			
*badloans*blood*						-0.018		
						(0.016)		
*badloans*fake*							-0.030	
							(0.023)	
*badloans*mutual*								0.013
								(0.056)
*firm*time fixed effect*	yes	yes	yes	yes	yes	yes	yes	yes
bank fixed effect	yes	yes	yes	no	yes	yes	yes	yes
*bank*firm fixed effect*	no	no	no	yes	no	no	no	no
other bank controls with interactions	yes	yes	yes	yes	yes	yes	yes	yes
N	2,622,440	1,861,912	275,639	2,644,991	2,595,609	2,518,001	2,576,418	2,567,789

Figure 1: Late payments and other problematic loans in Italy

The figure presents statistics on problematic loans for a sample of around 32,000 industrial firms based in Italy. The description of variables and their data sources are given in the Data Appendix.

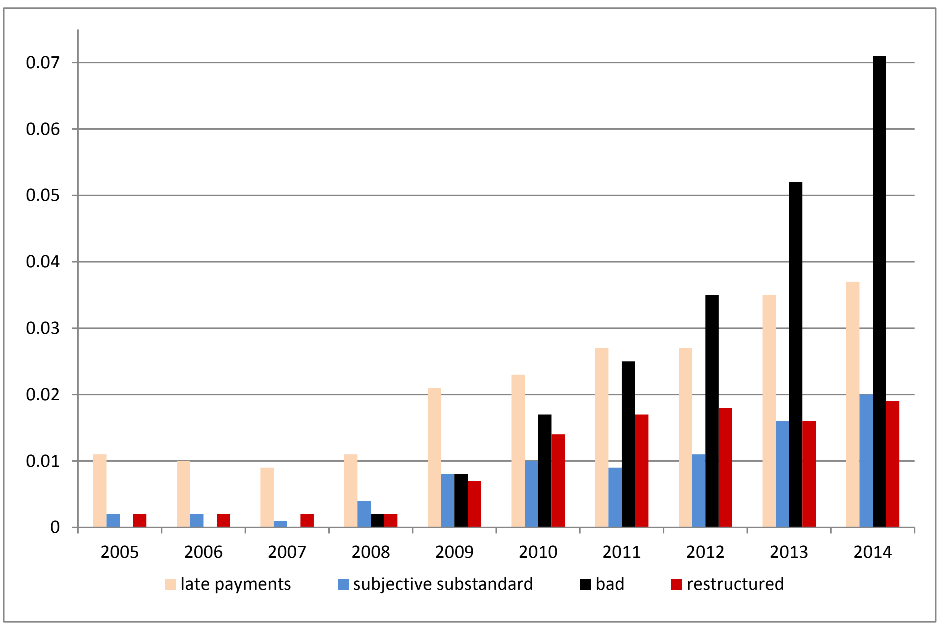

Figure 2: Judicial Efficiency in Italy: Length of Property Prosecution Proceedings across Italian Courts (2007, # of days)

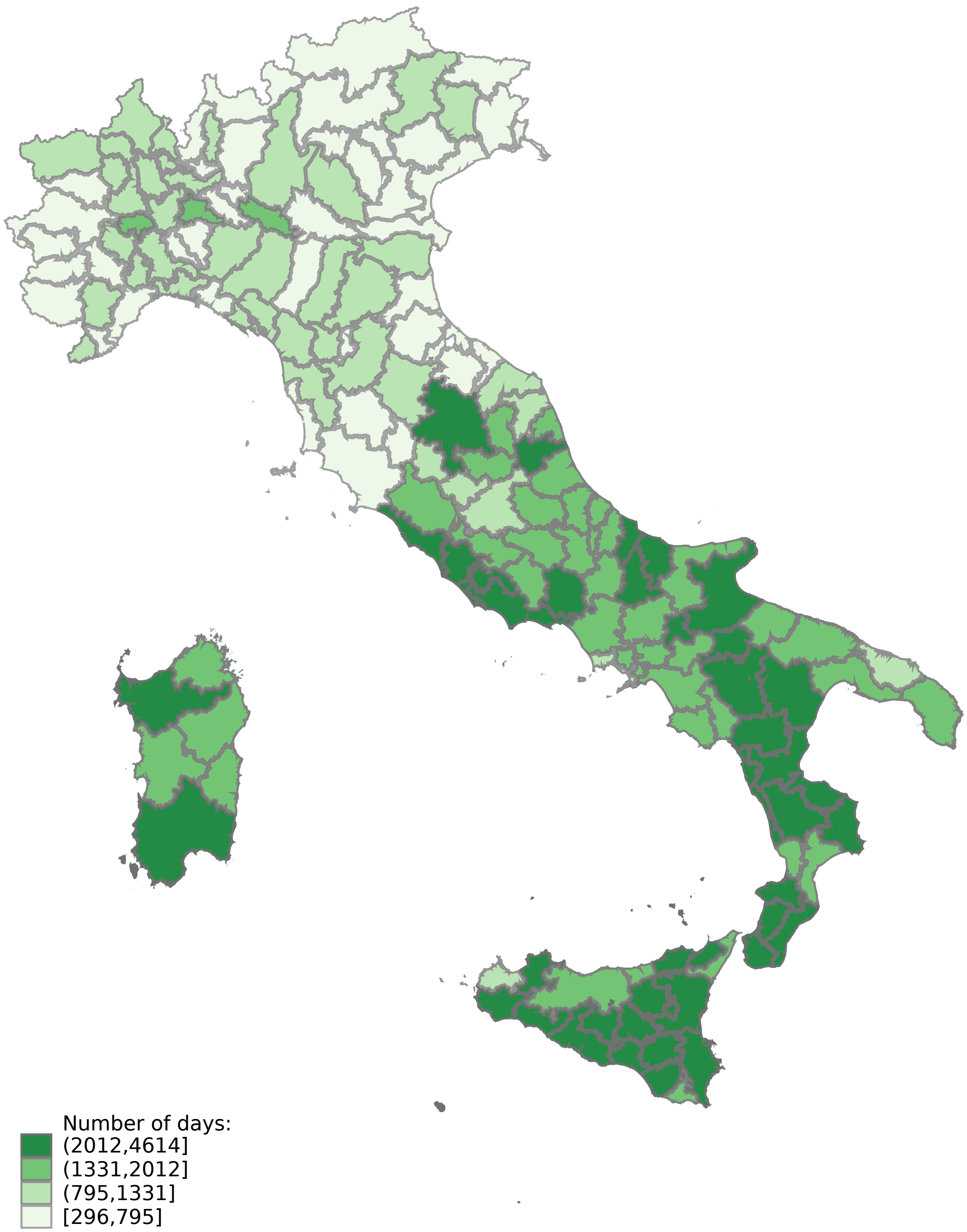

Figure 3: Marginal impacts of banks' bad loans on the likelihood of late payment

The figure plots the marginal effect of banks' bad loans on the likelihood of late payment (vertical axis), as a function of the duration for the property execution proceedings (horizontal axis, number of days) estimated by the IV (red line) and the OLS (black line) models as well as the 95% confidence intervals around the IV estimates.

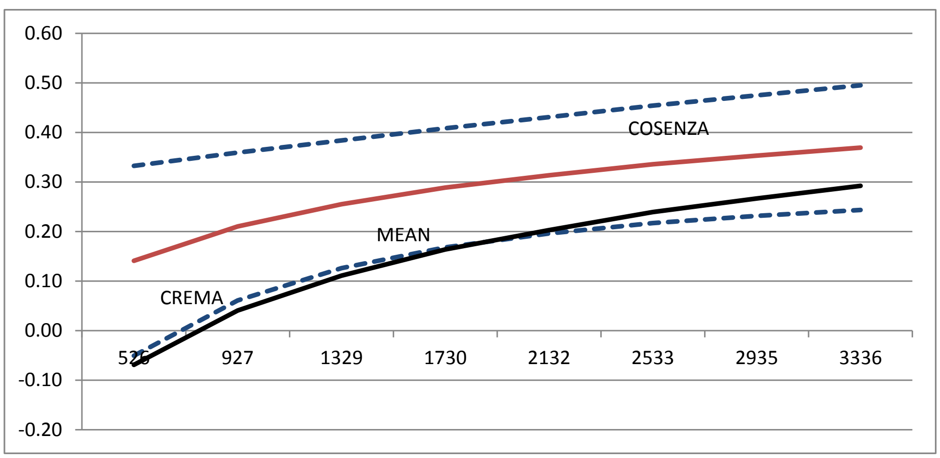

Figure 4: Marginal impacts of banks' bad loans on the likelihood of late payment, by borrower risk type

The figure plots the marginal effect of banks' bad loans on the likelihood of late payment (vertical axis), as a function of the duration for the property execution proceedings (horizontal axis, number of days), for different types of borrowers (safe, vulnerable, risky), based on estimates in column (1) of Table 8.

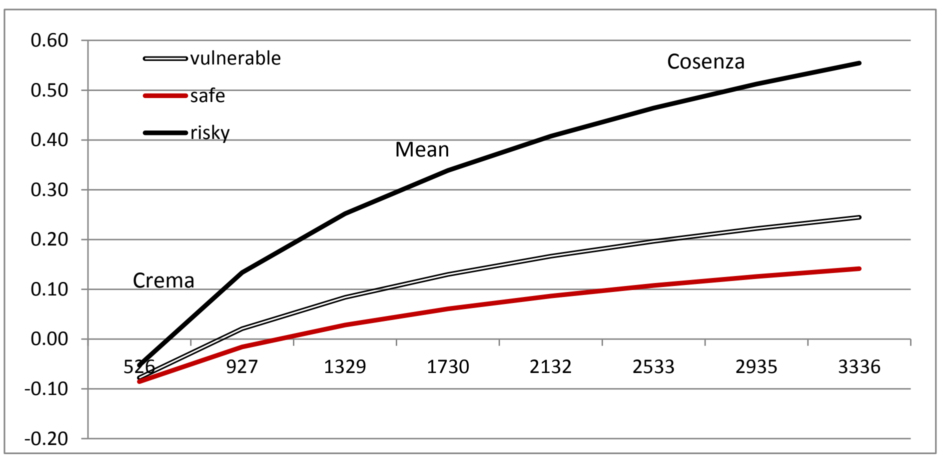

Figure 5: Marginal impacts of banks' bad loans on the likelihood of late payment, safe borrowers

The figure plots the marginal effect of banks' bad loans on the likelihood of late payment (vertical axis), as a function of the duration for the property execution proceedings (horizontal axis, number of days), for safe borrowers, based on estimates in column (1) of Table 8. Dashed lines represent the 95% confidence interval.

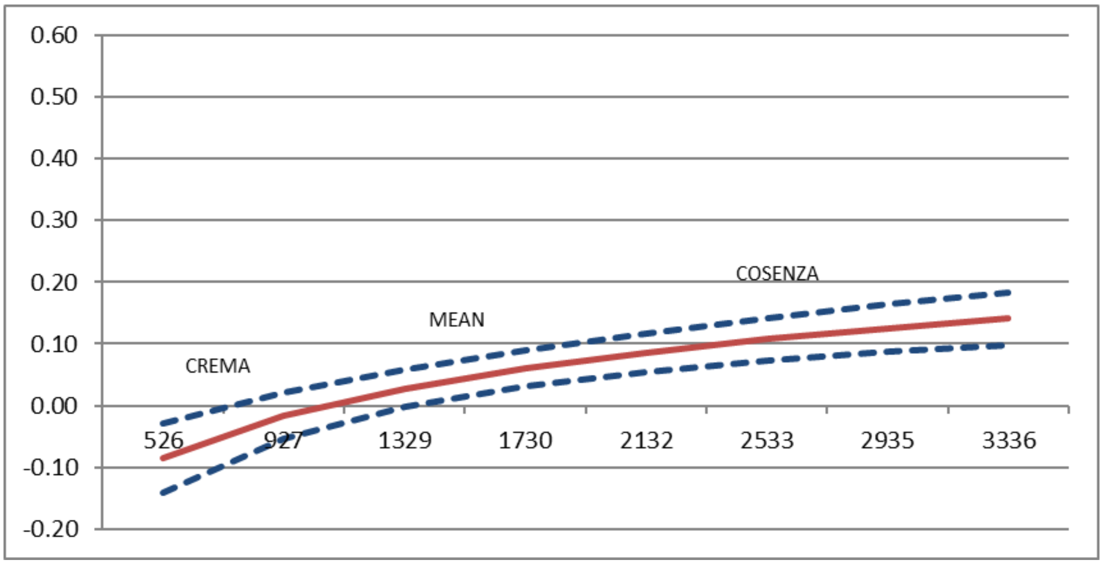

Figure 6: Marginal impacts of exposure to banks' bad loans on firms' overall share of late payments

The figure plots the marginal effect of firms' exposure to its average bank's bad loans on the firms' overall share of late payments (vertical axis), as a function of the duration for the property execution proceedings (horizontal axis, number of days), based on estimates in column (3) of Table 9. Dashed lines represent the 95% confidence interval.