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Risky collateral and default probability

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Abstract

We use a novel data set containing all corporate loans throughout the Eurozone to document a series of novel stylized facts on the relationship between collateral and the probability of default. First, we show that the pervasive empirical finding that riskier borrowers pledge collateral is driven by economists' informational disadvantage relative to banks. Accounting for time-varying bank- and firm-specific risk factors produces negative correlations consistent with theory. Second, the relationship between pledging collateral and the probability of default is non-linear. Increasing the ex-ante collateral-to-loan ratio initially lowers the default likelihood but increases it as loans become overcollateralized. Third, this is driven by the riskiness of collateral. We estimate that an increase in the ex-ante collateral-to-loan ratio correlates with greater variance in the underlying collateral's market value after loan origination. We develop a model featuring risk-neutral agents and risky collateral that provides intuition for these empirical patterns. Pledging risky collateral lowers lenders' expected returns in case of default, leading them to demand more collateral to originate a loan but this diminishes a borrower's return when a project is successful leading to less effort and a higher probability of default.

JEL-Codes: D82, G21.

Keywords: collateral, default, moral hazard.

Non-technical summary

Collateral plays a crucial role in modern credit markets by helping lenders manage risks that arise when they know less about borrowers' true financial conditions. Traditional economic theories suggest that pledging collateral—such as property, machinery, or financial assets—reduces the likelihood of default. This is because collateral gives borrowers stronger incentives to repay and compensates lenders if repayment fails. Yet, this paper argues that an often-overlooked dimension of collateral—its own riskiness—can itself shape a firm's probability of default.

Using comprehensive loan-level data from the European Central Bank, covering virtually all commercial loans issued throughout the Eurozone, the study provides a new and detailed look at how collateral affects credit risk. An advantage of the data set is that it records both the initial appraised value of the collateral and its market value at monthly intervals, enabling precise measurement of how collateral values fluctuate over time.

The first set of findings reveals that collateral is far from risk-free. Its value often changes substantially after a loan is made, and these changes depend on how much collateral was initially pledged. Loans that begin with a higher collateral-to-loan ratio—meaning they are more heavily secured—tend to exhibit more volatility in the underlying collateral's value across time. This is true across different types of collateral and regardless of whether the loan eventually defaults. Hence, the paper identifies risky collateral as an intrinsic and measurable feature of secured lending.

The second set of results shows that the relationship between collateral and default probability is not linear but follows a U-shaped pattern. When the amount of collateral increases from low to moderate levels, the probability of default falls, consistent with traditional theories. However, beyond this point, further increases in the collateral-to-loan ratio are associated with higher default probabilities. In other words, very high collateral ratios may make loans riskier, not safer. This surprising result remains robust after accounting for the identity of the bank, borrowing firm, and the collateral type.

To understand this empirical observation, we develop a theoretical model in which an entrepreneur borrows to finance a project that may succeed or fail. The entrepreneur can influence the project's success through effort, but effort is costly and cannot be perfectly observed by the lender—a classic moral hazard problem. The key innovation is that collateral values themselves are allowed to fluctuate. Pledging more collateral increases the expected value of what lenders can recover if the project fails, but it also increases the risk that collateral will lose value. When collateral values are highly uncertain, lenders demand higher returns to protect themselves in bankruptcy. This reduces the entrepreneur's incentive to exert effort and increases the probability of default by lowering their return when a project succeeds. The model thus reproduces the non-monotonic empirical relationship observed in the data.

Our work connects to a strand of literature that views collateral as a tool to solve agency problems, predicting that safer borrowers pledge more collateral to signal their quality. However, empirical evidence has often contradicted this prediction: riskier borrowers are frequently more likely to pledge collateral, and secured loans often exhibit worse repayment outcomes. A methodological contribution of our work is to resolve these seemingly contradictory results. Owing to data limitations, past empirical studies have typically classified loans as either secured or unsecured, ignoring differences in how much collateral is pledged. This approach imposes a linear relationship between collateral and default probability that misses non-linear relationships, such as the one we identify. Moreover, the granularity of the data allows us to pinpoint which confounds bias previous empirical estimates.

The findings carry several policy implications. First, regulators and financial institutions should recognize that collateral risk is a fundamental dimension of credit risk management. Heavily collateralized loans may not always be safer if the underlying collateral is illiquid or its value is volatile and difficult to value. Second, the results highlight the importance of developing better risk-weighting frameworks that account for collateral variability. Finally, understanding how collateral volatility affects credit dynamics is particularly relevant during periods of economic stress, when asset prices fluctuate more sharply and default risks rise.

1 Introduction

Collateral is widely viewed as a contracting device that mitigates asymmetric information problems or agency costs in credit markets. Theory suggests that pledging collateral can alleviate these frictions and reduce the probability that a borrower defaults on loan repayment (Stulz and Johnson (1985), Chan and Thakor (1987), Besanko and Thakor (1987a), Bester (1987), Boot et al. (1991), Aghion and Bolton (1997), Holmstrom and Tirole (1997)). However, empirical studies find mixed evidence (Dennis et al. (2000), Jimenez et al. (2006), Berger et al. (2016), Ioannidou et al. (2022), Collier et al. (2025)). The discrepancy between theory and empirics is potentially due to overlooked characteristics of collateral. In this paper, we explicitly study the riskiness of collateral, which neither theory nor empirics has thus far considered. The distinguishing feature of our paper is that we uncover a novel channel linking collateral to default probability. We begin with the observation that collateral's riskiness increases in the amount pledged. Given that, we show that the relationship between collateral and the probability of default can be positive or negative depending on the amount of collateral.

We use granular credit register data containing the population of corporate loans throughout the Eurozone and document a systematic relationship between collateral riskiness and default probability. Three novel data attributes enable us to go beyond existing research. First, the data uniquely report the underlying asset's nominal value at origination, and its market value at monthly intervals post origination. These features allow us to calculate the collateral-to-loan amount ratio (collateral ratio) at origination and test how it relates to 1) the probability of default, and 2) variance in collateral value. Second, we directly observe the ex ante probability of default that a bank assigns to each borrower, rather than risk proxies. Third, the panel structure of the data, coupled with detailed information on the identity of the borrowing firm, type of collateral, and bank allow us to purge all time-varying borrower-, collateral-, and lender-level threats to identification.

We begin by presenting a series of stylized facts. Collateral can be risky, in the sense that its value can materially change according to the collateral ratio at origination. Estimates show that raising the collateral ratio correlates with greater variance in the underlying collateral's value during the year after loan origination. Importantly, the econometric specifications allow us to identify this effect within an asset class, indicating this result is not driven by cross-collateral variation in default likelihood (Berger et al., 2016). This finding holds irrespective of whether a loan subsequently defaults and for physical and non-physical collateral alike.

Next, we show the collateral ratio is non-monotonically related to the probability of default. For a given face value of debt, increasing the collateral ratio initially reduces the probability of default. However, as a loan becomes increasingly overcollateralized the relationship reverses. Importantly, we obtain this result despite including bank-, collateral- and firm-year fixed effects which purge unobserved heterogeneity.

To reconcile the empirical evidence, we develop a model that establishes a relationship between collateral riskiness and default probability. The framework features risk-neutral lenders, non-contractible borrower effort, and collateral whose value may fluctuate after loan origination. A trade-off exists whereby pledging more collateral raises its expected future value, but also makes it riskier by increasing the probability that it will be worth less than today. When loans are under-collateralized – the face value of debt exceeds the amount of collateral – debtholders obtain all the collateral upon default. Over this range, increasing the amount of collateral pledged increases lenders' expected return in case of default and lowers the face value of debt required to meet their zero-profit condition. A lower debt also increases the entrepreneur's net return when a project succeeds, leading them to exert more effort and lowering the probability of default. In contrast, where a loan is overcollateralized, debtholders' compensation upon default is capped by the face value of debt. While a higher nominal amount of collateral is associated with a higher expected value, the collateral is also riskier which implies lower expected compensation for debtholders upon default. They thus require a higher face value of debt in compensation to extend credit, but this erodes the entrepreneur's net return where the project is successful, and the incentive to exert effort which provokes a higher probability of default. The relationship between the collateral ratio and default probability thus follows a non-monotonic U-shape.

Our paper relates to two strands of the literature. An emerging body of research explores the pricing implications of collateral in repurchase agreement (repo) markets. Using data from a single hedge fund, Auh and Landoni (2022) show loans secured by lower-quality collateral have higher collateral ratios, and wider spreads over the maturity-matched London Inter-Bank Offered Rate. They also have longer maturity, hinting at rollover concerns for less liquid collateral. Barbiero et al. (2024) document that the liquiditation value of collateral correlates with borrower and collateral risk. Borrowers pay a premium when their default risk is positively correlated with the risk of the collateral that they pledge. Using bank loan data, Luck and Santos (2024) show loan premia vary across different types of collateral. Our paper differs from these articles in two respects. First, we study corporate loans that are key to financing the real economy and provide broad insights using a large data set that contains all commercial and industrial loans throughout the Eurozone economy, one of the largest credit markets in the world which raises the odds that the findings generalize to other contexts. Second, the model we develop provides intuition that ties together the riskiness of pledged collateral and the probability of default. This is a novel finding that departs from existing literature.

A related literature motivates collateral as part of an optimal debt contract to mitigate an effort-moral hazard problem. In this paradigm, pledging collateral improves a borrower's incentive to exert effort, thereby enhancing the likelihood of repayment (Chan and Thakor, 1987; Boot et al., 1991; Aghion and Bolton, 1997; Holmstrom and Tirole, 1997). Adverse selection models predict that safer borrowers within an observationally identical risk pool post more collateral (Bester, 1985; Chan and Thakor, 1987; Besanko and Thakor, 1987a,b). Within both paradigms pledging collateral is generally associated with a lower probability of default. However, a vast body of evidence finds the opposite. Observably riskier borrowers more frequently pledge collateral (Leeth and Scott (1989), Berger and Udell (1995), Dennis et al. (2000)), collateralized loans default more often, and exhibit inferior ex post performance in terms of payments past due and non-accruals (Jimenez and Saurina (2004), Jimenez et al. (2006), Berger et al. (2011, 2016)). Loan risk premiums (loan rates minus the risk-free rate) are also positively correlated with collateral (Berger and Udell (1990), John et al. (2003)).

An econometric thread running through extant empirical articles is that collateral is modelled using a binary variable such that a loan is either secured or unsecured which imposes a linear relationship. However, where the true probability of default-collateral ratio relationship is non-linear, imposing linearity can produce positive correlations if the distribution is sufficiently convex. Moreover, data constraints invariably preclude saturating regressions with the granular fixed effects necessary to eliminate observable and unobservable borrower characteristics, and lender preferences which influence demand for collateral. Our paper makes two methodological contributions to this literature. First, the nature of our data allows us to control for sources of unobserved heterogeneity that is frequently infeasible in less granular data sets. We show that controlling for difficult to observe omitted factors can reconcile the empirical evidence with theories' predictions.[1] A second methodological contribution of our work is to highlight that pledging collateral is non-monotonically related to the probability of default. In contrast with prior research, to our best knowledge, we are the first to identify risky collateral as a determinant of default in credit markets. No other article isolates collateral's riskiness as a driver of how lenders evaluate default likelihood.

The paper is structured as follows. Section 2 outlines the model. In Section 3, we discuss the data set and econometric methods. Section 4 presents and discusses the empirical results while Section 5 presents sensitivity checks. Finally, Section 6 draws conclusions.

2 Model

We consider a two-date economy ($t = 0, 1$) in which all agents are risk-neutral and the risk-free interest rate is normalized to zero. There are two types of agents: entrepreneurs (firms) and lenders. Firms have potentially profitable investment opportunities (projects) but not the funds required for the investment, whereas lenders have unlimited funds but they cannot invest directly. Each project requires a fixed amount of investment of 1. Investment in a project occurs at $t = 0$ and the returns are realized at $t = 1$. A project yields either X (success) or 0 (failure) at $t = 1$. The probability of success p depends on the effort level, $e \in [0, 1]$, chosen by the entrepreneur. For simplicity, we assume that the probability p equals the effort level chosen, $p = e$. The entrepreneur incurs a utility cost from exerting effort which is $\frac{X}{2}e^2$. The firm also has some assets which can be used as collateral (but they cannot be liquidated at $t = 0$). At $t = 1$, the value of collateral will be either C with probability q or 0 with probability $1 - q$. The higher the level of collateral C, the riskier the collateral (lower q), but the expected value of collateral increases with C (i.e., qC increases with C). The distributions of returns of collateral and the new project are independent.

Assumption 1: $X > 4$.

[1] Previous attempts to reconcile the collateral puzzle focus on heterogeneity in the types of collateral across empirical studies (Berger et al., 2016) and lenders' informational advantages (Inderst and Mueller, 2007). Importantly, our tests use collateral- and lender-year fixed effects to account for these influences.

Assumption 1 ensures that the lenders' zero-profit condition can be satisfied even if the collateral available is zero. That is, under Assumption 1, there always exists an equilibrium in which the lenders provide the funds necessary for the investment.

The effort level e chosen by the entrepreneur is her own private information and so cannot be observed by anyone else (moral hazard). The financing contract specifies the amount given from the lender to the entrepreneur (1 unit), the promised repayment (face value of debt) from the entrepreneur to the lender, D, and the (nominal) amount of collateral available, C.

Assumption 2: $qC < 1$ for any $C \leq D$.

The role of Assumption 2 is to ensure that the first-best effort level cannot be achieved when effort is privately chosen. Given the above setting, the net expected return (utility) of the entrepreneur and the expected profit of lenders are given in equations (1) and (2) respectively:

$$U = p(X - D) - (1 - p)q \times \min(C, D) + qC - \frac{X}{2}p^2 \tag{1}$$

$$\Pi = pD + (1 - p)q \times \min(C, D) \tag{2}$$

The Game

Stage 1: Competitive lenders offer financing contracts to the entrepreneur.

Stage 2: Given the terms of the financing contract (and that their effort choice is not observable), the entrepreneur chooses the effort level which maximises her net expected utility.

We look for the subgame perfect Nash equilibria of this game. In any equilibrium, competition among lenders implies that their expected profit is zero.

The Full Information Benchmark

To fix ideas, we start by considering the choice of the entrepreneur in the case her effort choice was observable and verifiable and hence contractible. In this case, we can set the lenders' expected profit equal to zero and substitute equation (2) into equation (1) to obtain the entrepreneur's net expected utility, which is:

$$U = pX + qC - \frac{X}{2}p^2 \tag{3}$$

The entrepreneur will maximise (3) by choosing the effort level p (recall $p = e$). The first-order condition with respect to p is:

$$X - pX = 0 \qquad \Longrightarrow \qquad p^{FB} = 1$$

That is, the full information (first-best) effort level is equal to 1. Thus, under full information, the project would be safe.

Default Probability under Moral Hazard

Now the effort level is not contractible and it is privately chosen by the entrepreneur to maximise her net expected utility after they receive the required funds and the terms of the financing contract have been fixed. This implies that the entrepreneur will maximise equation (1) by choosing p, taking D as given. To simplify the analysis, we consider two cases:

Case 1: $C \leq D$

In this case, $\min(C, D) = C$ and equation (1) can be rewritten as follows:

$$U = p(X - D) - (1 - p)qC + qC - \frac{X}{2}.p^2 \tag{4}$$

The first-order condition with respect to p is:

$$D = (1 - p)X + qC, \tag{5}$$

and the lenders' zero-profit condition becomes:

$$pD + (1 - p)qC = 1. \tag{6}$$

Substituting equation (5) into (6) and solving for p, we obtain:

$$p^* = \frac{X + \sqrt{X^2 - 4X(1 - qC)}}{2X}. \tag{7}$$

From equation (7), it is clear that the effort level (and the success probability) p is strictly increasing in qC. Given that, from equation (6) we can infer that the face value of debt is strictly decreasing in qC. However, qC increases as C increases and q falls. Thus, if $C \leq D$, an increase in the expected value of the collateral leads to a higher success probability (lower default probability) and a lower face value of debt although the collateral becomes riskier.

Intuitively, if the amount of collateral is less than the face value of debt ($C \leq D$), the full amount of collateral will be transferred to debtholders in case of default. Thus, the higher the (expected) value of collateral, the higher the compensation for debtholders when the investment fails and so the lower the face value of debt required to satisfy their zero-profit condition. The lower the face value of debt, the higher the entrepreneur's net return in case of success, which incentivizes the entrepreneur to exert more effort, resulting in a lower default probability.

Case 2: $C > D$

In this case, $\min(C, D) = D$, and equation 1 becomes:

$$U = p(X - D) - (1 - p)qD + qC - \frac{X}{2}p^2. \tag{8}$$

The first-order condition with respect to p can be written as:

$$D = \frac{(1 - p)X}{1 - q}, \tag{9}$$

and the lenders' zero-profit condition becomes:

$$pD + (1 - p)qD = 1. \tag{10}$$

Substituting equation (9) into (10) and solving for p, we obtain:

$$p^* = \frac{(1-2q)X + \sqrt{[(1-2q)X]^2 - 4X(1-q)[1-(q(X+1))]}}{2(1-q)X}. \tag{11}$$

It can be shown (see Appendix A for a proof) that p is strictly increasing in q. That is, as q falls and so the value of the collateral increases (both C and qC), the success probability falls (the default probability increases). Then, equation (10) implies that the face value of debt increases as q falls (see Appendix B for a graphical proof).

The intuition for this result is as follows: if the amount of collateral is higher than the face value of debt ($C > D$), the amount of collateral which will be transferred to debtholders in case of default is equal to the face value of debt. However, a higher (nominal) amount of collateral is associated with higher expected collateral value but also higher risk. Because the debtholders' compensation in case of default is capped by the face value of debt, the higher the collateral risk the lower the expected compensation for debtholders in default. Hence, the riskier the collateral (despite having higher expected value), the higher the face value of debt necessary to meet the debtholders' zero-profit condition. This implies that the entrepreneur' net return in case of success will be lower which, in turn, leads to a lower effort level and a higher default probability.

The proposition below summarises these results:

Proposition: i) If $C \leq D$, an increase in collateral leads to a lower default probability, ii) If $C > D$, an increase in collateral leads to a higher default probability.

Empirical Implications. In this section, we summarize our empirically testable hypotheses:

Hypothesis 1: If the collateral ratio is low, an increase in collateral ratio leads to a fall in the default probability.

Hypothesis 2: If the collateral ratio is high, an increase in collateral ratio leads to an increase in the default probability.

Hypothesis 3: The higher the collateral ratio, the riskier the collateral.

In words, if collateral is relatively scarce and safe, an increase in its expected value relaxes the entrepreneur's effort moral hazard constraint and results in a higher effort choice which, in turn, leads to a higher success (or lower default) probability. If collateral is relatively abundant and risky, an increase in its expected value and riskiness results in a lower effort level and a higher default probability.

3 Data and Methods

We test the model's predictions using granular credit register information on individual bank loans in the euro area. Each national central bank within the Eurosystem collects harmonised data on each banks' corporate loan and reports this to the European Central Bank (ECB). The ECB collates the information across countries and makes the data available through the AnaCredit database.[2]

Each observation constitutes a unique loan for which we observe lender (bank identifier), borrower (firm identifier, country location, zip code, employees, industry), and loan characteristics at the point of origination and at the reporting reference date. The loan attributes include the origination date, type of credit (overdraft, revolving credit, credit lines, term loans, repurchase agreements and other loans), outstanding balance, interest rate and date of maturity. AnaCredit began collecting data in September, 2018, and our sample contains loans originated between January 2019 to December 2023, although we remove all loans originated between January 2020 and December 2021 to ensure neither the COVID-19 pandemic nor the concomitant government loan guarantee schemes prejudice the findings.

At the point of origination, we observe, 1) whether a loan is secured by collateral, 2) if so, the type of underlying asset (property, equipment, buildings, securities etc.), 3) the monetary value of the pledged collateral, and 4) the estimated probability of default over the next 12 months the bank assigns a borrower.[3] We define the collateral ratio (CR) as the ratio of the collateral value to loan amount at origination. A novel element of the data is that we can track the post

[2]Further details on AnaCredit are available from `https://www.ecb.europa.eu/stats/money_credit_banking/anacredit/html/index.en.html`.

[3]Across the Eurosystem, banks assign each borrower an ex-ante estimated probability of default (PD), reflecting the likelihood that the borrower will fail to meet scheduled repayments within a one-year horizon. This assessment is made at the firm-year level, meaning each lender attributes a PD to a specific borrower for a given year. Only banks that employ internal rating-based models calculate PDs for their clients. In AnaCredit, over 60% of loans are associated with a borrower-level PD.

origination market value of the collateral underlying each loan on a monthly frequency. Using this information, we calculate σMV, the variance of the collateral's value during the 12 months after loan origination.

[Insert Table 1]   [Insert Table 2]

Table 1 defines each variable in the data set while Table 2 presents summary statistics. The sample contains approximately 14.1 million observations, of which 43% are unsecured (Figure 1, left side panel). The mean collateral ratio is 1.43 indicating that the average loan is over collateralized.

Among secured loans there exists considerably heterogeneity in the collateral ratio. The right panel of Figure 1 shows the modal collateral ratio is 1, with more than 26% of equally collateralized loans. 21% of loans are under collateralized whereas 52% have collateral ratios above 1. High collateral ratios are common with 20% of loans secured using collateral that is worth at least 2.5 times as much as the face value of debt. There is clear variation in collateral ratios across countries. For example, Figure 2 shows the average loan in Austria, Germany, Lithuania, Luxembourg, Malta, the Netherlands and Portugal has a collateral ratio less than 1. In all other countries the collateral ratio ranges between 1 and 2, except for Belgium where the average exceeds 2. These patterns may reflect banks' risk preferences, the availability of different types of collateral, and industrial composition. Most industries in Figure 3 have an average collateral ratio between 1 and 2, although firms operating in the construction and public administration and defence sectors typically post less collateral than the loan amount.

Figure 4 illustrates the most common assets firms use to secure credit. Among secured loans, offices are pledged as collateral in approximately 27% of cases with other financial guarantees posted 25% of the time. Commercial and residential real estate account for 11% and 8% of collateral, respectively, while other physical collateral, such as equipment and machinery, is used to secure 6% of loans. Loans, deposits, trade receivables, equities and securities are less commonly pledged, accounting for between 1% and 3% of observations in the data set. The least common forms of collateral are insurance, derivatives and gold which each represent a nominal share.

[Insert Figure 1]   [Insert Figure 2]   [Insert Figure 3]   [Insert Figure 4]

The mean probability of default banks assign is 9.84%, although the median value is 1.26% indicating this variable is positively skewed. On average, the collateral underlying a loan appreciates in value by 2% during the year following origination. However, at the 25$^{\text{th}}$ percentile of the distribution collateral depreciates by 26% whereas at the 75$^{\text{th}}$ percentile there is no change relative to its ex ante value. The average loan has a maturity of 7.79 years, an outstanding balance of €11.43 (ln), and is secured by 1.96 assets.[4]

3.1 Empirical Model

We take the model's predictions to the data using panel data estimators saturated with several fixed effects terms. Specifically, to establish correlations between the collateral ratio and the probability of default, and to identify whether the relationship is non-monotonic, we estimate

$$PD_{lbfct} = \beta CR_{lbfct} + \gamma CR^2_{lbfct} + \delta X_{lbfct} + \varphi_{bt} + \varphi_{ft} + \varphi_{ct} + \varepsilon_{lbfct}, \tag{12}$$

where PD_{lbfct} is the estimated probability of default assigned by bank b on loan l to borrowing firm f at time t, secured using collateral of type c; CR_{lbfct} is the collateral ratio which we also include as a squared term to capture potential non-linear associations; X_{lbfct} denotes a vector of loan-level control variables; ε_{lbfct} represents the error term.[5]

Our econometric strategy relies on a series of fixed effects to purge confounds. φ_{bt} represent bank $\times$ year fixed effects that capture all time-varying bank-level determinants of the probability of default. Similarly, φ_{ft} are firm $\times$ year fixed effects which eliminate time-varying firm-level drivers of default likelihood. The empirical model also includes collateral $\times$ year fixed effects, φ_{ct}, to rule out time-varying heterogeneity in the probability of default across different types of collateral. We cluster the standard errors at the bank level.

The model predicts that the ex post riskiness of the underlying collateral's market value is linearly related to the initial collateral ratio. We capture collateral riskiness using the variance in its value during the 12 months after loan origination. In these tests, we estimate

$$\sigma MV_{lbfct} = \beta CR_{lbfct} + \delta X_{lbfct} + \varphi_{bt} + \varphi_{ft} + \varphi_{ct} + \varepsilon_{lbfct}, \tag{13}$$

[4]Figure 1.B in the online Appendix displays the coverage of the data, in terms of the number of banks operating in each country. Banks are mostly concentrated in Germany, France, Italy and Spain.

[5]It is worth noticing that while the PDs do not vary across loans within the same borrower, CR does.

where all variables are defined as in equation (12) except σMV_{lbfct} is the variance in the collateral's value between origination and 12 months afterwards. As the theory linearly relates collateral riskiness to the collateral ratio, equation (13) does not include quadratic terms.

4 Results

In this section, we begin by studying the collateral puzzle and then evaluate the model's predictions on how collateral ratios influence the probability of default and collateral riskiness.

4.1 The Collateral Puzzle and Non-Monotonicity

A voluminous body of research finds a positive association between pledging collateral and proxies for the probability of default. We establish whether the same pattern holds in our data by using the extant literature's methodology: a linear estimator with a dummy variable indicating whether a loan is collateralized of any amount. We estimate:

$$PD_{lbfct} = \beta Collateral_{lbfct} + \delta X_{lbfct} + \varphi_{b[t]} + \varphi_{f[t]} + \varphi_{ct} + \varepsilon_{lbfct}, \tag{14}$$

where all variables are defined in equation (12) except $Collateral_{lbfct}$ is a dummy variable equal to 1 if a loan is secured by collateral of any amount, 0 otherwise. φ_b, φ_f, and φ_t denote bank (or bank×quarter), firm (or firm×quarter), and year fixed effects, respectively.

[Insert Table 3]

Column 1 in Table 3 presents the results. Consistent with the findings of prior research, the collateral dummy variable's coefficient estimate is positive and significant. Economically, this indicates that firms pledging collateral are, on average, associated with a 1.31 percentage point higher probability of default compared with those borrowing on an unsecured basis. For the average firm in the sample, this corresponds to roughly a 13.3% higher probability of default. The maturity, loan amount and protections coefficient estimates are insignificant.

Across columns 2 to 4 of the table we attempt to understand the source of the collateral puzzle. We find that including bank×year or firm×year fixed effects sequentially in columns 2 and 3 renders the collateral dummy coefficient estimate insignificant. However, column 4 shows that when we include both sets of fixed effects in the estimating equation, firms pledging collateral have significantly lower probabilities of default. Accounting for difficult to observe time-varying bank and firm characteristics is thus important in deciphering how posting collateral influences a bank's perception of a borrower's propensity to repay loan obligations.

An advantage of our data over existing research is that we can observe the value of collateral rather than a simple collateralization indicator. This allows us to go beyond extant research to establish the curvature of the relationship between the collateral ratio and the probability of default. Column 5 replicates the preceding test using the collateral ratio in place of the collateral dummy variable in equation (14). Despite including the vector of time-varying fixed effects, we find a 10 percentage point increase in the collateral ratio reduces firms' probability of default by 0.4 percentage points. The coefficient estimate is significant at the 10% level. The results in column 6 show the effect is robust to controlling for collateral×year fixed effects that remove any collateral-specific confounds that change over time.[6]

[Insert Figure 5]

Next, we test the theoretical model's prediction that the relationship between collateral ratios and the probability of default is non-linear. Estimates in column 7 show the probability of default is a convex function of the collateral ratio. Pledging more collateral to secure a loan initially decreases the probability of default, but the relationship subsequently reverses and becomes positive. Both the linear and quadratic collateral ratio point estimates are significant at the 1% level. Consistent with the model's prediction that collateral ratios are positively related to the probability of default among overcollateralized loans, the turning point in the relationship is located at a collateral ratio of approximately 2.8. Figure 5 presents a graphical depiction of the non-monotonic relationship with 95% confidence intervals that do not cross the origin, indicating the effect sizes are significantly different from zero. Finally, outliers are unlikely to drive the inferences as we conservatively restrict the sample to observations with a CR value of at most 5. Nevertheless, in column 8 we test the robustness of the findings to using a sample containing loans with a maximum CR value of 2.5. Despite this change, the results remain intact.

[6] In Table 1.B in the online Appendix, we replace firm×year fixed effects with industry×location×size×year fixed effects to allow the inclusion of single bank-relationships in the estimation. The results are in line with the baseline.

In the model, the probability of default depends on the expected value of collateral (qC) and the face value of debt (D). The turning point in the relationship can therefore be above one (i.e. where $C = D$) because the probability that collateral depreciates (q) is below 1 for most assets. The empirical results are thus consistent with realistic model parameter configurations.

These tests provide two important insights that reconcile the contradictory empirical evidence surrounding the relationship between collateral and default likelihood. First, establishing robust correlations between these variables requires granular data sets that previous research typically does not have access to. Saturating the estimating equation with high-level fixed effects is also essential to obviate the influence of confounding factors. Second, a methodological contribution is to demonstrate that measuring collateralization using ratios rather than a dummy variable produces very different results. The positive correlation between collateral and default found in extant research may be driven by linear estimators not accounting for a non-linear data generating process.

Among the control variables, we find that firms borrowing with longer maturities tend to have significantly higher probabilities of default, although the coefficient estimate is only significant when conditioning on firm×year fixed effects. Firms borrowing larger loan amounts are typically positively correlated with the probability of default while pledging a greater number of assets as collateral (protections) is associated with a significantly higher probability of default. This is an important finding since it implies that loans are riskier as firms pledge more assets to secure a loan.

4.2 Collateral Riskiness

One of the model's predictions is that collateral becomes riskier as the collateral ratio increases. We test this hypothesis by estimating equation (13) using the variance in the collateral's value during the twelve months after loan origination as the dependent variable.

[Insert Table 4]

Estimates in Table 4 show the assets underlying loans with higher collateral ratios are indeed riskier. Column 1 provides the results using the entire sample. We find a 10 percentage point increase in the collateral ratio is associated with a significant 3.88% increase in the variance of the underlying collateral's market value during the year after loan origination.[7] The result is consistent with the theoretical model's prediction that for a given loan amount, pledging more collateral is associated with riskier collateral in the sense that its future market value is more uncertain.

Throughout the remainder of Table 4, we conduct validation checks in various subsamples. In column 2, we report estimates from a sample where we again conservatively restrict the sample to observations with a CR value of 2.5 or less. The magnitude of the collateral ratio coefficient estimate increases to 0.5645 and remains significant at the 5% level.

A key question is whether collateral riskiness is a general phenomenon, or if riskiness exists only among loans that default. We therefore estimate equation (12) using sub-samples containing loans that do and do not default in columns 3 and 4, respectively. In both specifications we find the collateral ratio coefficient estimate is positive, comparable in economic magnitude and significant. The patterns we detect thus appear to hold across all loans, and are not driven by loans that subsequently default.

Borrowers pledge both tangible and intangible assets to secure credit. We therefore test the validity of our findings by splitting the sample between loans secured by physical (property, equipment, buildings etc.) and non-physical (securities, deposits, other financial collateral etc.) collateral. It appears unlikely that time-varying shocks to the value of different asset classes drive the baseline findings given we saturate the regressions with collateral $\times$ year fixed effects. The results in columns 5 and 6 show significantly positive associations between the collateral ratio and the variance of the assets' market value irrespective of the type of pledged collateral. The parameter estimate is somewhat larger when restricting the sample to physical collateral, although the difference in economic magnitudes between specifications is modest. This suggests that similar collateral riskiness dynamics exist irrespective of what type of assets are used to secure credit.

5 Robustness Tests

The empirical tests rely on a battery of granular time-varying fixed effects to eliminate potential confounds. Placebo tests provide another window into whether the baseline findings reflect

[7] The economic magnitude is calculated as $10 \times (e^{0.3279} - 1) = 3.88\%$

other observable or unobservable forces. Lenders should only incorporate collateral ratios into their probability of default assessment where it influences their expected profits. If a lender is not exposed to losses in case of default, the collateral ratio should remain an insignificant determinant of the probability of default. For example, where a loan has a full credit risk guarantee, such as from the government, the lender faces zero (or negligible) losses in case of default and the riskiness of the collateral is irrelevant. In such a sample, the collateral ratio coefficient estimate will only be significant if the collateral ratio systematically correlates with an omitted variable that is unaccounted for in equation (12). If this is the case, the coefficient estimate in the placebo sample should strongly resemble that in the baseline sample, both in economic and statistical significance.

[Insert Table 5]

AnaCredit contains observations of loans with a full credit risk guarantee. For this exercise, we consider only loans where the guarantor is the government or a third party other than the debtor. While the main sample does not include these observations, we use this placebo group to estimate equations (12) and (13). Table 5 presents the results. In column 1, both the linear and quadratic collateral ratio coefficient estimates are insignificant. This is also the case in column 2 when we use the variance of the collateral's value as the dependent variable. It therefore appears unlikely that we misattribute the collateral ratio effects to omitted variables.

Next, we undertake a variety of sensitivity checks to rule out potential confounding effects. Does the collateral ratio affect whether a lender renegotiates loan conditions terms with a borrower to avoid default? This seems unlikely as the probability of default is set at the point of loan origination, but such a mechanism would attenuate the effect of collateral ratios. We examine this conjecture by estimating equation (12) using a dummy equal to 1 if a loan is subsequently renegotiated, 0 otherwise. Column 1 of Table 6 reports the results showing both the linear and quadratic collateral ratio terms' coefficients are insignificant.

[Insert Table 6]

In the remainder of Table 6 we perform a series of tests by excluding different types of loans that may confound the inferences. For example, securitization allows lenders to pass credit risk to loan purchasers which may erode their ex-ante screening incentives and diminish the role of collateral. Similarly, within a syndicate a lender may behave differently because it shares losses upon default. Lenders are potentially exposed to greater credit risk where a loan is non-recourse or subordinated. Discrepancies in the remaining time to maturity (mismatches) between a loan and its collateral can pose significant risks for lenders. This is of particular concern to banks when the loan's residual maturity exceeds that of the collateral, as the loan may transition from being secured to unsecured during its term. International lending is complicated by distance which inhibits monitoring borrowers. We also exclude floating rate observations to ensure monetary policy changes do not drive the inferences. Finally, we restrict the sample to single-bank borrowers—excluding firms with multiple banking relationships—to ensure results are not confounded by lender competition. Columns 2 to 9 show the findings are robust to sequentially removing each of these categories from the sample.

[Insert Table 7]

A concern may be that our findings reflect the riskiness of a borrowing firm, rather than the collateral it pledges. To account for this, we exploit a feature of our data which captures firm-level riskiness at the loan-level using the ratio of accumulated impairments to loan amount and the number of past due days.[8] Column 1 in Table 7 reports estimates of equation (12) that include the impairment ratio as an additional covariate. Whereas higher impairment ratios are significantly positively correlated with the probability of default, the baseline finding endures. This is also the case in column 2 where we include the past due indicator to capture another source of risk. The remainder of Table 7 reports equivalent specifications that test whether the collateral riskiness effects reflect firm-specific risks. Estimates of of equation (13) continue to document a significantly positive relationship between the collateral ratio and the underlying collateral's post-origination market value variance.

6 Conclusions

This paper establishes for the first time that the riskiness of collateral correlates with the probability that a borrower defaults. Using a novel data set of corporate loans we empirically document

[8]The firm-specific riskiness variables we use evolve across time such that we can identify the parameter estimates through variation between loans to the same firm that are originated at different times.

that higher collateral ratios, 1) are associated with a bank assigning a significantly higher probability of default to a borrower, and 2) as collateral ratios increase the assets securing a loan become riskier in the sense that they are substantially more likely to depreciate in value during the year following loan origination. These insights constitute first evidence that the riskiness of collateral itself can explain borrower's propensity to default.

A second contribution of our work is to document that the collateral ratio-probability of default relationship is non-monotonic. Specifically, for a given loan amount pledging more collateral initially reduces the odds of a borrower default, but among overcollateralized loans the relationship becomes positive. We develop a simple model featuring moral hazard that draws these observations together. As a borrower exhausts their safest assets, they pledge riskier ones. As the collateral ratio increases, so too does the riskiness of the collateral. This exposes lenders to potential losses in case of default because only a fraction of the posted collateral is available upon liquidation. They therefore demand borrowers post more collateral to secure a loan to increase their expected returns in case of default. However, this reduces the borrowing firm's return where a project is successful and erodes their incentive to exert effort resulting in a higher probability of default.

A vast empirical literature has produced evidence that is typically at odds with theory's predictions on how collateral shapes credit markets. Whereas models find that posting collateral reduces the odds of borrower default, applied studies often find the opposite. A methodological contribution of our paper is to provide insights that reconcile this 'collateral puzzle'. Extant studies frequently lack data on the value of collateral pledged to secure a loan and instead rely on indicator variables to infer whether collateral is present. The granularity of our data also allows us to account for unobservable firm, and bank, characteristics. Accounting for this and how collateral is measured produces markedly different inferences. Furthermore, we find the relationship between collateral and the probability of default is non-monotonic. Failing to account for the convexity of the distribution can also produce positive correlations between collateral and the odds of default.

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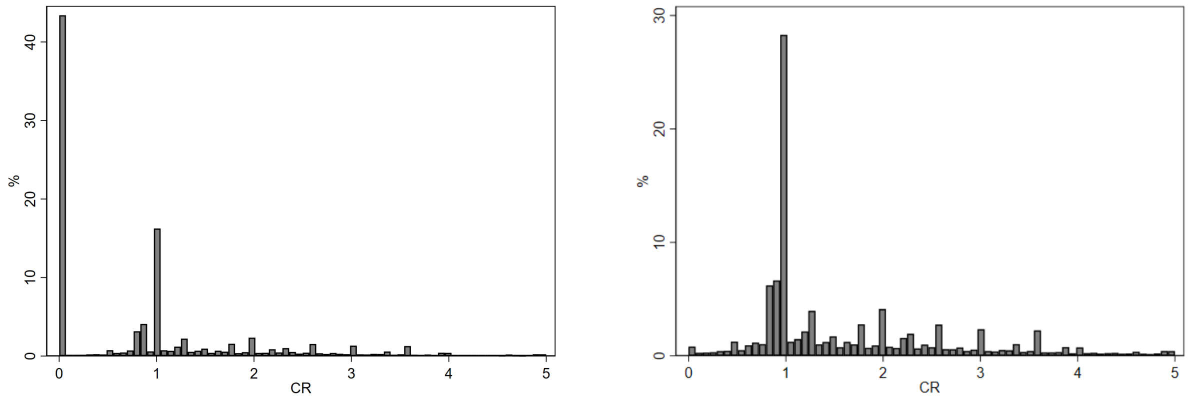
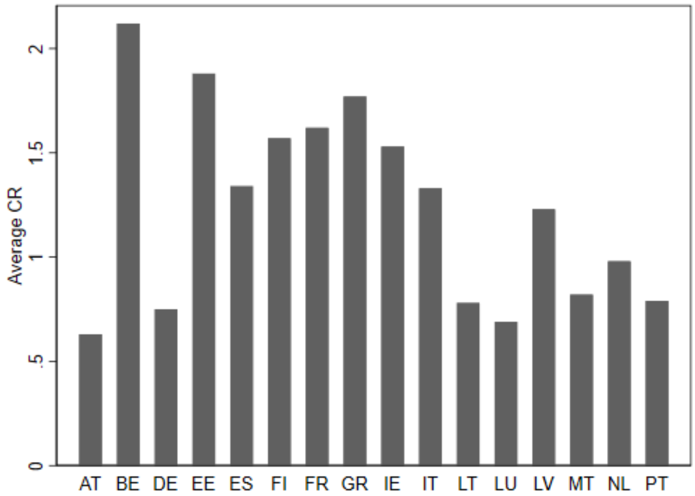
Figures

Figure 1: CR distribution



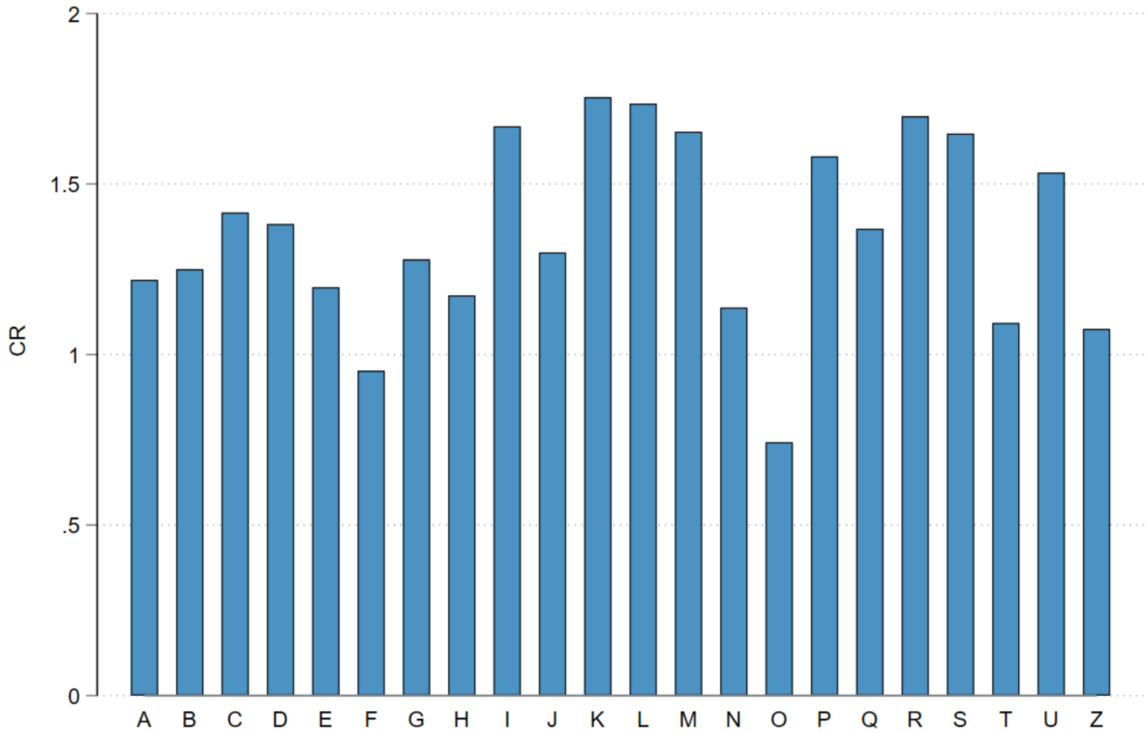
Notes: The graph reports the distribution of the collateral-to-loan ratio within the sample. A value of 0 indicates no collateral is pledged to secure a loan. The y-axis shows the percentage of observations with a given collateral-to-loan ratio.

Figure 2: Collateral-to-Loan Ratio Distribution across Countries



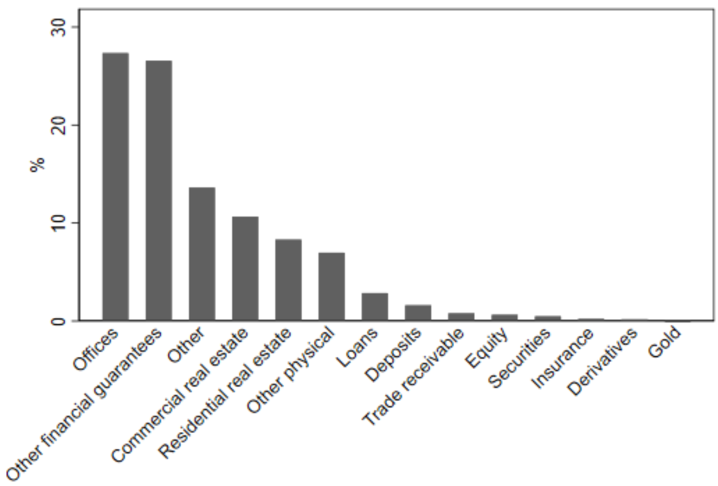
Notes: The graph reports the distribution of the average collateral-to-loan ratio across countries. Country labels are abbreviated as follow: AT (Austria); BE (Belgium); DE (Germany); EE (Estonia); ES (Spain); FI (Finland); FR (France); GR (Greece); IE (Ireland); IT (Italy); LT (Lithuania); LU (Luxembourg); LV (Latvia); MT (Malta); NL (The Netherlands) and PT (Portugal).

Figure 3: Collateral Ratio Distribution across Industries



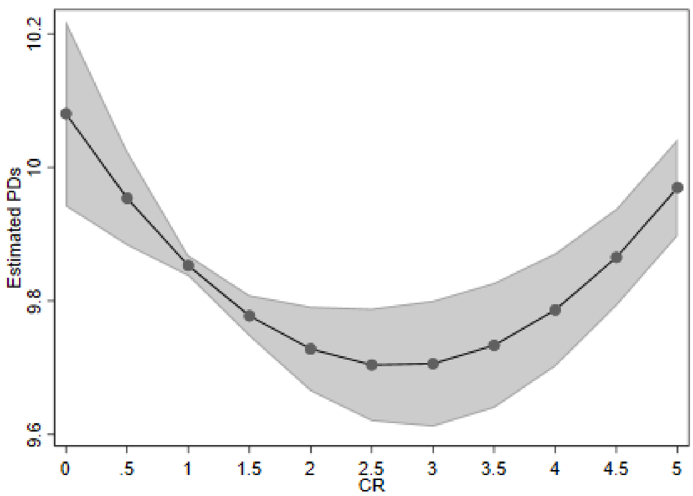
Notes: The graph reports the distribution of the collateral-to-loan ratio across industries. Sectors definitions: A (Agriculture, forestry and fishing); B (Mining and quarrying); C (Manufacturing); D (Electricity, gas, steam and air conditioning supply); E (Water supply; sewerage; waste management and remediation activities); F (Construction); G (Wholesale and retail trade; repair of motor vehicles and motorcycles); H (Transporting and storage); I (Accommodation and food service activities); J (Information and communication); K (Financial and insurance activities); L (Real estate activities); M (Professional, scientific and technical activities); N (Administrative and support service activities); O (Public administration and defence; compulsory social security); P (Education); Q (Human health and social work activities); R (Arts, entertainment and recreation); S (Other services activities); T (Activities of households as employers; undifferentiated goods - and services - producing activities of households for own use); T (Activities of extraterritorial organisations and bodies); Z (Others)

Figure 4: Share by collateral type



Notes: The graph reports the share by collateral type within the sample. More collaterals can be pledged against the same instrument.

Figure 5: Collateral Ratio and Default Probability



Notes: The graph plot the estimated PD at different levels of CR. The solid dark grey line indicates the point estimates, whilst the shaded light grey confidence intervals at the 95% level.

Tables

Table 1: Variable Descriptions

Variable	Description
Probability of default	The ex-ante probability of default assigned by bank b to firm f
Collateral dummy	A dummy variable equal to 1 if loan l to firm f is secured by collateral, 0 otherwise
CR	The ex-ante ratio of collateral's nominal value to the loan amount for loan l to firm f
σ Collateral	The variance of the underlying collateral's market value for loan l to firm f between origination and one year
Interest rate	The interest rate on loan l to firm f at the point of origination
Maturity	Time until maturity of loan l to firm f in days, measured in natural logarithms
Amount	The loan amount for loan l to firm f, measured in natural logarithms
Protections	The number of assets pledged as collateral underlying loan l to firm f

Notes: This table defines of each variable used in the empirical analysis. For brevity we suppress the variables' subscripts.

Table 2: Descriptive Statistics

Variable	Observations	Mean	σ	Percentile 1^{st}	25^{th}	50^{th}	75^{th}	99^{th}
Probability of default	6,139,801	9.84	23.91	0.00	0.40	1.26	4.44	100.00
Collateral dummy	14,146,488	0.64	0.47	0.00	0.00	1.00	1.00	1.00
CR	6,139,801	1.43	1.09	0.00	0.90	1.00	2.00	4.72
σ Collateral	6,061,383	0.02	0.97	-1.00	-0.26	0.00	0.00	6.54
Maturity	6,139,801	7.79	0.92	4.49	7.50	7.84	8.46	9.30
Amount	6,139,801	11.43	1.43	8.29	10.44	11.40	12.25	15.42
Protections	6,139,801	1.96	2.72	1.00	1.00	1.00	2.00	8.00

Notes: This table reports post estimation summary statistics based on equation (12). For ΔMV the descriptive statistics is based on equation (13). Variable definitions are provided in Table 1. σ denotes a variable's standard deviation.

Table 3: Collateral and Default Probability

	1	2	3	4	5	6	7	8
Dependent variable: probability of default								
Collateral	0.0131***	0.0088	-0.0029	-0.0010**				
	(0.005)	(0.006)	(0.002)	(0.000)				
CR					-0.0004*	-0.0005*	-0.0028***	-0.0050***
					(0.000)	(0.000)	(0.001)	(0.001)
CR^2							0.0005***	0.0014***
							(0.000)	(0.000)
Maturity	0.0021	0.0083	0.0019***	0.0014***	0.0013***	0.0015***	0.0015***	0.0012**
	(0.002)	(0.005)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Amount	-0.0011	-0.0109***	0.0001	0.0003*	0.0003	0.0004*	0.0005**	0.0005*
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Protections	0.0007	0.0039***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bank FE	Yes	No	No	No	No	No	No	No
Firm FE	Yes	No	No	No	No	No	No	No
Year FE	Yes	No	No	No	No	No	No	No
Bank × Year FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes
Firm × Year FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Collateral × Year FE	No	No	No	No	No	Yes	Yes	Yes
Observations	14,146,488	14,910,434	11,378,229	11,378,226	11,378,226	6,139,801	6,139,801	4,750,974
R-squared	0.702	0.095	0.946	0.950	0.950	0.947	0.947	0.948

Notes: This table presents estimates of equation (12). The dependent variable is the probability of default. Variable definitions are provided in Table 1. The standard errors are clustered by bank and the corresponding t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4: Collateral Riskiness

	1	2	3	4	5	6
Sample	All	CR <2.5	Default status		Collateral	
			Yes	No	Physical	Non-physical
Dependent variable: σ Market value						
CR	0.3279**	0.5645**	0.4205**	0.3228**	0.5260***	0.4472**
	(0.126)	(0.222)	(0.173)	(0.125)	(0.061)	(0.198)
Maturity	-0.4608***	-0.3262**	-0.4067	-0.4695***	0.1528	-0.5493***
	(0.162)	(0.142)	(0.423)	(0.163)	(0.419)	(0.130)
Amount	1.8936***	1.8886***	1.9315***	1.8921***	1.6708***	1.8756***
	(0.128)	(0.101)	(0.125)	(0.130)	(0.147)	(0.038)
Protections	0.0773**	0.0836**	0.0888	0.0776**	0.0458	0.0902
	(0.032)	(0.035)	(0.079)	(0.031)	(0.033)	(0.061)
Firm × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Collateral × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,414,907	2,559,150	150,494	3,244,405	1,266,119	1,820,398
R-squared	0.77	0.78	0.78	0.77	0.67	0.72

Notes: This table presents estimates of equation (13). Variable definitions are provided in Table 1. The standard errors are clustered by bank and are reported in parentheses. Physical collateral denotes material assets (for example, commercial property). Non-physical collateral indicates intangible assets (for example, patents). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5: Placebo Tests

	1	2
Dependent variable:	PD	σ Market value
CR	0.0000	-0.0006
	(0.000)	(0.000)
CR^2	-0.0000	
	(0.000)	
Maturity	0.0006	0.0541*
	(0.001)	(0.031)
Amount	0.0004*	-0.0352**
	(0.000)	(0.017)
Protections	0.0003**	0.0144**
	(0.000)	(0.007)
Bank × Year FE	Yes	Yes
Firm × Year FE	Yes	Yes
Collateral × Year FE	Yes	Yes
Observations	1,527,983	1,500,162
R-squared	0.947	0.911

Notes: This table presents estimates of equation (12). The dependent variable is the probability of default. Variable definitions are provided in Table 1. The standard errors are clustered by bank and the corresponding t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 6: Robustness Tests

	1	2	3	4	5	6	7	8	9
Sample excludes		Securitized	Syndicated	Non-recourse	Subordinated	Mismatches	Cross-border	Floating	Multiple bank
Dependent variable	Renegotiated	Probability of default							
CR	0.0003	-0.0029***	-0.0028***	-0.0025***	-0.0029***	-0.0029***	-0.0030***	-0.0017**	-0.0389**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.015)
CR^2	-0.0001	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***	0.0003***	0.0067**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
Maturity	-0.0006	0.0015***	0.0015***	0.0007**	0.0015***	0.0013***	0.0016***	0.0013***	0.0029
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)
Amount	0.0001	0.0005*	0.0005*	0.0004*	0.0005**	0.0005**	0.0005*	0.0004	-0.0037**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Protections	-0.0001	0.0003***	0.0002***	0.0003***	0.0003***	0.0002***	0.0003***	0.0002*	0.0048***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Collateral × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	605,625	5,966,610	6,114,334	5,189,996	6,095,479	5,661,369	5,548,460	4,296,202	2,158,749
R-squared	0.97	0.94	0.94	0.94	0.94	0.94	0.94	0.95	0.30

Notes: This table presents estimates of equation (12). Variable definitions are provided in Table 1. The standard errors are clustered by bank and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 7: Controlling for Firm Riskiness

	1	2	3	4
Dependent variable	Probability of default		σ Market value	
CR	-0.0032***	-0.0031***	0.3293**	0.3291**
	(0.001)	(0.001)	(0.126)	(0.126)
CR^2	0.0006***	0.0006***		
	(0.000)	(0.000)		
Maturity	0.0013*	0.0015*	-0.4632***	-0.4643***
	(0.001)	(0.001)	(0.163)	(0.164)
Amount	0.0004	0.0004	1.8959***	1.8961***
	(0.000)	(0.000)	(0.128)	(0.128)
Protections	0.0002***	0.0002***	0.0773**	0.0773**
	(0.000)	(0.000)	(0.032)	(0.032)
Impairment ratio	0.0029***	0.0028***	-0.0238***	-0.0237***
	(0.000)	(0.000)	(0.008)	(0.008)
Past due		0.0001***		-0.0002
		(0.000)		(0.000)
Observations	6,139,801	6,139,038	3,414,907	3,414,362
R-squared	0.94	0.95	0.76	0.77
Firm × Year FE	Yes	Yes	Yes	Yes
Bank × Year FE	Yes	Yes	Yes	Yes
Collateral × Year FE	Yes	Yes	Yes	Yes

Notes: This table presents estimates of equation (12). Variable definitions are provided in Table 1. The standard errors are clustered by bank and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Online Appendix

A Proofs

We provide a proof that p^* in equation (11) is strictly increasing in q.

Substituting (9) into (10), we obtain the following quadratic equation which we denote by $f(p)$:

$$f(p) = (1-q)Xp^2 - (1-2q)Xp + [1 - q(X+1)] \tag{15}$$

We know that

$$\frac{\partial f}{\partial p}(p = p^*)\frac{dp^*}{dq} + \frac{\partial f}{\partial q} = 0.$$

Also, $\frac{\partial f}{\partial p}(p = p^*) > 0$, since $(1-q)X > 0$ for any $q < 1$ and p^* is the higher of the two roots which solve $f(p) = 0$.

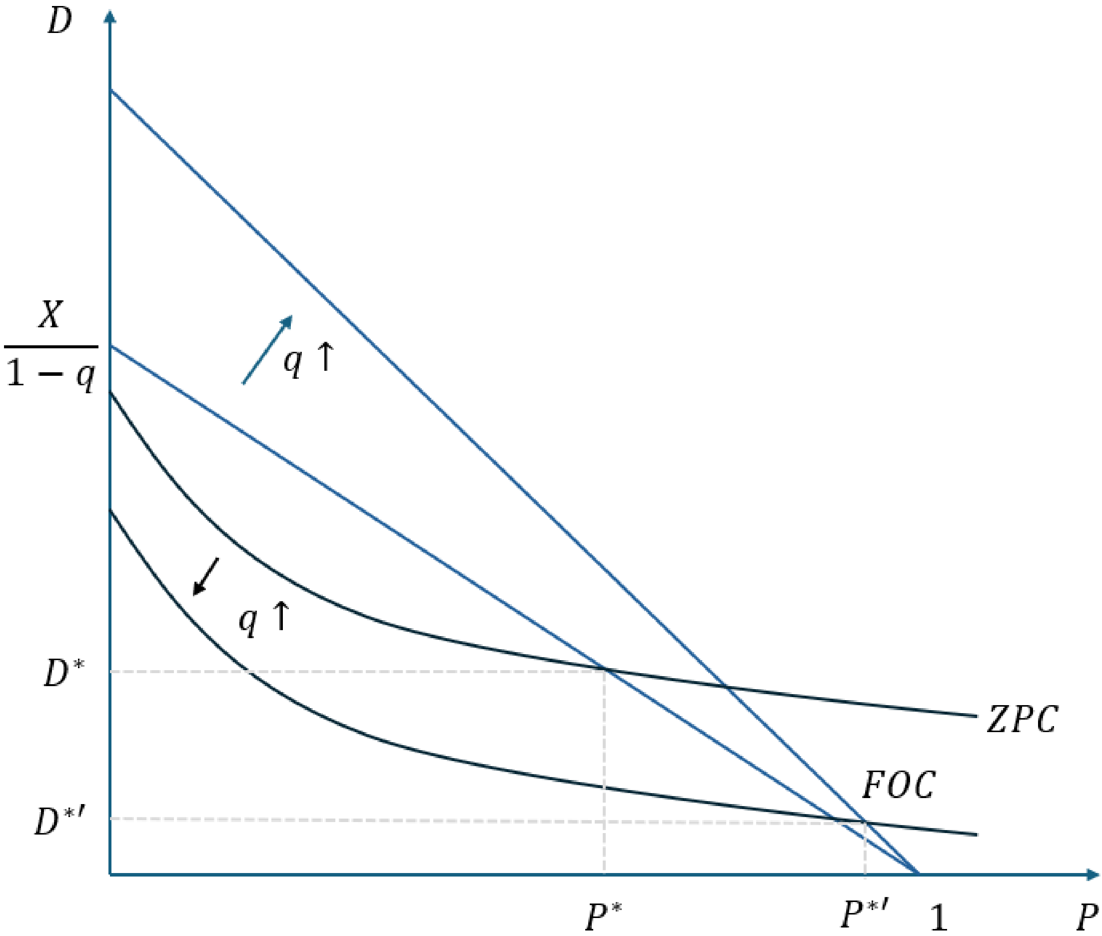
$$\frac{\partial f}{\partial q} = -X(p^2) + 2Xp - (X+1) = -(1-p)^2X - 1 < 0$$

Therefore, $\frac{dp^*}{dq} > 0$

B Graphical Proof

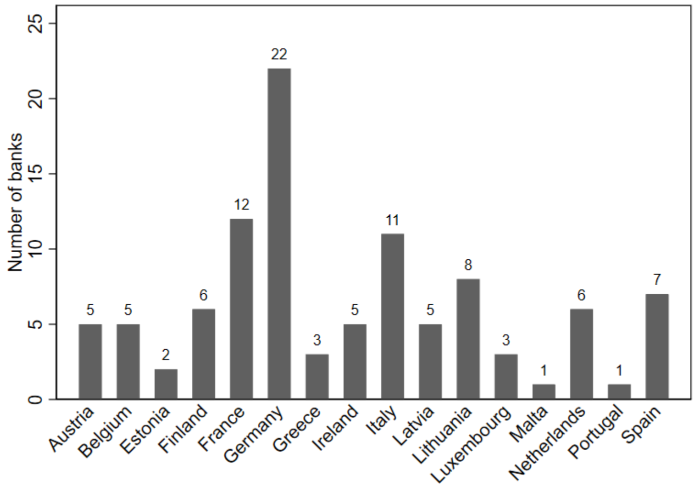
Case 2: $C > D$

The equilibrium levels of the endogenous variables P and D are determined by conditions (9) and (10). Below, we depict these two equations in the (D, P)-space and graphically explore how a change in q affects both variables.



As q increases from q to q', P rises from P^* to $P^{*\prime}$, while D falls from D^* to $D^{*\prime}$.

Figure 1.B: Number of banks by country



Notes: The graph reports the number of banks entering the estimation by country.

Table 1.B: Collateral and Default Probability

	1	2	3	4	5	6	7
Dependent variable: probability of default							
Collateral dummy	0.0110**	-0.0021	0.0088	-0.0007			
	(0.004)	(0.002)	(0.006)	(0.001)			
CR					-0.0031*	-0.0051**	-0.0252***
					(0.002)	(0.002)	(0.009)
CR^2							0.0045***
							(0.002)
Maturity	0.0076*	0.0092**	0.0083	0.0083*	0.0086*	0.0044	0.0040
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)
Amount	-0.0047**	-0.0043***	-0.0109***	-0.0037***	-0.0035***	-0.0050***	-0.0047***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Protections	0.0021***	0.0020***	0.0039***	0.0019***	0.0026***	0.0029***	0.0028***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Bank FE	Yes	No	No	No	No	No	No
ILS FE	Yes	No	No	No	No	No	No
Year FE	Yes	No	No	No	No	No	No
ILS × Year FE	No	Yes	No	Yes	Yes	Yes	Yes
Bank × Year FE	No	No	Yes	Yes	Yes	Yes	Yes
Collateral × Year FE	No	No	No	No	No	Yes	Yes
Observations	14,466,270	13,671,587	14,910,434	13,671,583	13,671,583	8,423,962	8,423,962
R-squared	0.42	0.54	0.09	0.56	0.56	0.53	0.53

Notes: This table presents estimates of equation (12). Variable definitions are provided in Table 1. The standard errors are clustered by bank and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

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The views expressed are those of the authors and do not necessarily reflect those of the ECB or the Eurosystem.

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