Sorting Out the Effect of Credit Supply *

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Abstract

We document that banks that cut lending more during the Great Recession were lending to riskier firms ex-ante. To understand the aggregate implications of this sorting pattern, we build an assignment model in which banks have heterogeneous costs to take on risky loans and firms have different credit risks. In the model, aggregate loan volume depends on the entire distribution of bank holding costs and firm credit risks. We then use our model to recover the change in the distribution of bank holding costs during the Great Recession and quantify its effect on aggregate loan volume.

JEL Codes: G0, G2, G21, G23

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1. Introduction

The financial distress experienced by banks during the Great Recession was associated with a decline in aggregate loan volume and firm output.[1] This shock was not borne uniformly. Notably, Ivashina and Scharfstein (2010) and Chodorow-Reich (2013) show that firms borrowing from banks with higher exposure to securitization markets, such as J.P. Morgan or Lehman Brothers, suffered relatively more during the crisis. Despite these reduced-form findings, little is known on the *aggregate* effect of these shocks on the lending market.

In this paper, we address this gap through a three-step approach. First, we document that these banks with high exposure to securitization markets were lending to riskier firms ex-ante. Second, motivated by this evidence, we build a model of a lending market with heterogeneity in both credit risks and bank holding costs (i.e., the ability of banks to take on credit default risk). In equilibrium, aggregate loan volume depends on the entire distribution of firm credit risks and bank holding costs. Third, we use the model to quantify the relative effect of each distribution in the decline in aggregate loan volume during the Great Recession.

We start by providing evidence of non-random matching between banks and firms during the Great Recession. Based on measures of firm downside risk used in the banking literature, including (1) the borrower loan spread or interest rates, (2) the probability of default implied by its credit rating, and (3) the probability of default implied by the model of Bharath and Shumway (2008), we show that banks that cut lending the most during this period were lending to the riskiest firms ex-ante. The economic magnitudes are large. For instance, a 1 percentage point higher borrower loan spread is associated with a decrease in bank lending growth of 0.66 standard deviations and a t-statistic of 3.58.

We also examine the ex-ante characteristics of the banks that were lending to the riskiest firms. These banks had a lower deposit-to-asset ratio, a closer proximity to Lehman in terms of corporate loan co-syndication, and a higher securitization rate (number of collateralized loan obligations (CLOs) as a fraction of bank loans). Hence, one hypothesis is that these banks were lending to riskier firms because of their higher abilities to securitize. Consistent with this hypothesis, we document that these sorting patterns appear precisely as the securitization market grows (i.e., in

[1] This follows models of the credit supply channel, such as Bernanke and Blinder (1988), Bernanke and Gertler (1989), and Kashyap, Stein, and Wilcox (1993).

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the lead-up to the financial crisis). Relatedly, marketing documents for Lehman during this period pointed to its (perceived) superior ability to package risky loans and to sell them to institutional investors compared to other banks.[2]

To reconcile this sorting evidence, we then develop a competitive one-to-one matching model of a credit market.[3] When there are complementarities between firm riskiness and bank holding cost in the surplus function, firms with greater downside risk borrow from banks with lower holding costs in equilibrium, as in the data. Intuitively, the riskiest firms benefit the most from the banks with lowest per-unit holding costs and thus are willing to pay higher interest to these banks. In contrast, the safest firms with the best credit ratings benefit the least from these banks, and so they match with the banks that have the highest per-unit holding costs and get all the surplus in the relationship.

Our matching model naturally generates credit rationing. Equilibrium in the credit market pins down the marginal firm's ranking (i.e., the default probability cutoff to access the credit market). This characterization can be interpreted from the social planner's perspective. The benefit of lending to the marginal risky firm is the marginal firm's output. Since bringing on an additional risky firm means bringing on a high-holding-cost bank, the cost is the sum of the additional holding cost that each existing bank incurs from lending to riskier firms in equilibrium, which depends on the entire distribution of bank holding costs.

We examine the effect of changes in the distribution of bank characteristics ("credit supply") and firm characteristics ("credit demand") on aggregate loan volume. There is a level effect: an adverse shock that increases the average bank holding cost or the average firm riskiness lowers the aggregate loan volume. There is also a distributional effect: adverse credit supply shocks concentrated on banks with low holding costs tend to have bigger effects on aggregate loan volume relative to shocks concentrated on banks with high holding costs. In this sense, low-holding-cost banks play an essential role in absorbing aggregate risk.

We then take our model to the data, where we focus on a subsample of firms that issue public

[2]See `https://bit.ly/3j0rz9H`. Banks that securitized had a competitive advantage over traditional banks during the years before the Great Recession of 2008 (Nadauld and Weisbach, 2012). While firms could have borrowed from banks with differential exposure to securitization so as to diversify their funding risks during the crisis period, they did not in practice.

[3]Assortative matching or assignment models have been used to study the market for CEOs, underwriters, and venture capitalists (Terviö, 2008; Gabaix and Landier, 2008; Sørensen, 2007; Chang and Hong, 2019).

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debt and borrow from banks. There were roughly 3,100 loans in the pre-crisis period (2005–2007) but only 1,284 loans during the Great Recession or crisis period (2008–2010). We use the Standard and Poor's (S&P) long-term credit rating of firms as our proxy for firm credit risk and then calculate our measure of bank holding cost using the historical default probabilities associated with these credit ratings. We estimate these cross-sectional distributions separately for the 2005–2007 pre-crisis period and the 2008–2010 crisis period.

In general, the default rates of loans and firm default risk are observable, while bank holding costs are not. Nonetheless, under certain assumptions on the surplus function, we can recover the bank holding cost distribution by comparing changes in interest rates to changes in default probabilities as we move across credit ratings. Intuitively, if default probabilities rise rapidly as we move toward firms with worst credit ratings but interest rates do not rise as rapidly, then we infer that it must be that the matching banks for the worst rated firms had much lower holding costs than the banks matched to the better rated firms.

We then take these estimates and use our model to decompose the change in aggregate loan volume into a "credit supply" effect (i.e., the effect of the change in bank characteristics) and a "credit demand" effect (i.e., the effect of the change in firm characteristics). We find that the credit supply effect accounts for two-thirds of the observed drop in the aggregate number of loans during the Great Recession, with the reminder corresponding to the credit demand effect.

Our model is intentionally stylized to focus on the consequences of credit supply shocks in the presence of sorting. We conclude the paper by discussing how one could extend the model to allow for different functional assumptions on the matching surplus function, loan characteristics beyond interest rates, many-to-many matching, and matching frictions.

Literature review. In terms of empirical findings, we contribute to the banking literature by focusing on an under-appreciated dimension of sorting: we show that before the Great Recession, riskier firms tended to borrow from investment banks. Existing work only discusses the effect of size (Berger, Miller, Petersen, Rajan, and Stein, 2005), distance (Petersen and Rajan, 2002; Chen and Song, 2013), and funding (Schwert, 2018). In contrast with our paper, Schwert (2018) describes negative assortative matching between banks and firms: firms with no credit rating (i.e., with no access to the bond market) tend to match with banks with a higher deposit ratio (i.e.,

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safer banks). Our results differ from his in two dimensions. First, our sample includes investment banks, while he only focuses on commercial banks. A large part of the sorting we observe happens between commercial banks and investment banks and within investment banks. Second, we focus on the period leading up to the crisis, while he focuses on the 1987–2012 period. As we discuss in the Online Appendix F, this assortative matching between riskier banks and riskier firms is really a phenomenon starting in the lead-up of the crisis. This suggests that right before the crisis, the ability of riskier banks to offer better terms to riskier firms was more important than firms' concerns that their bank may go under during a crisis.

Our paper also contributes to the literature on the financial drivers of the Great Recession (Ivashina and Scharfstein, 2010; Chodorow-Reich, 2013). This literature uses regressions of firm loans on the health of the banks they are borrowing from to examine the effect of credit supply shocks, which typically requires a random matching assumption after controlling for observable covariates. Our finding of sorting between firms and banks is consistent with Table IV in Chodorow-Reich (2013), who report that the spread of loans issued by the banks that ex-post suffered the most during the crisis was higher than other banks. Relative to this paper, we show that this pattern is pervasive along different measures of firm riskiness—such as leverage, credit rating, and yields on their outstanding bonds—as well as different measures of bank riskiness, such as distance to Lehman or deposit ratio. As such, our results suggest that papers in the literature should also control for interaction terms of lender risk-bearing capacity and borrower riskiness.

Our paper also differs from the estimates of Chodorow-Reich (2013) in another important way. The estimates in his paper are indicative on the ability of firms to substitute across banks. However, it is not necessarily informative on the aggregate effect of bank health on the quantity of lending.[4] In particular, in Online Appendix H, we show that the estimates from firm fixed effects panel regressions can be inversely related to aggregate credit supply effects. Hence, we contribute to the existing literature by examining the effect of this sorting on the *aggregate* effect of credit supply shocks on the credit market. This is possible because we explicitly model the reallocation of banks to firms (in particular, this relates our paper to Darmouni (2020) and Herreno (2019), who examine the aggregate effect on credit supply shocks under a random matching assumption).

[4]See also Jiménez, Mian, Peydró, and Saurina (2019) for another rationale for why firm fixed effects estimates must be adjusted to be interpreted as capturing credit supply effects.

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Roadmap. The rest of our paper proceeds as follows. Section 2 presents our reduced-form evidence for sorting, and Section 3 presents our matching model of the lending market. Section 4 discusses our quantitative exercises, and Section 5 concludes.

2. Empirical Evidence on Sorting

In this section, we present reduced-form evidence of sorting between banks and firms before the Great Recession. Section 2.1 presents the data, and Section 2.2 shows that banks whose health suffered more during the Great Recession were lending to riskier firms ex-ante. Section 2.3 shows that these banks also had a closer relationship with Lehman, a low deposit-to-asset ratio, and a higher securitization intensity.

2.1. Data

DealScan. Our principal source of data is the Thomson Reuters DealScan database. DealScan collects loan-level information on syndicated loans from Securities and Exchange Commission filings, company statements, and media reports. For each loan ("facility"), the data include borrower names, the loan's purpose and type, the loan pricing details, and each bank's role in the agreement (underwriter, agent, adviser, etc.). We only consider the set of lenders marked as lead arrangers for the loan.[5] Following the literature, we exclude loans to financial companies (SIC codes from 6000 to 6500) as well as loans made to non-American companies.

In the rest of this section, we only consider loans issued between the start of 2005 and the second quarter of 2007 ("pre-crisis period"). As in Chodorow-Reich (2013), we consolidate banks to their ultimate parents: we identify 43 distinct banks in activity during this period.

Measures of firm risk. We are interested in borrower characteristics associated with downside or credit risk. Our first measure is the average of the all-in-drawn loan spread, which is the borrower's credit spread over Libor plus annual fees to the lenders. The advantage of this measure is that it is available for almost all loans in our DealScan sample. However, it is not purely a measure of

[5] Following Amiram, Li, and Owens (2020), we identify lead arrangers if the variable lead arranger in DealScan equals "yes." For the remaining 5% of loans without such a flag, we identify lead arrangers as lenders with the role "admin agent," "mandated lead arranger," "arranger," "agent," "syndications agent," or "bookrunner," which are the six most frequent roles associated with the variable lead arranger being equal to "yes."

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a firm's riskiness as it also reflects the lender's ability to hold this risk; that is, it combines the quantity of risk with the price of this risk.[6]

As an additional proxy for a firm's downside risk, we also use the firms' S&P credit rating when available. To obtain it, we first match borrowers to Compustat using the DealScan-Compustat Link from Chava and Roberts (2008). We then merge our match sample with the WRDS Capital IQ database to obtain each firm's S&P long-term issuer credit rating.[7] We convert S&P's letter ratings into default probabilities using the average historical default rate associated with each credit rating (as reported in Appendix Table A1).

As an additional measure of firm riskiness, we also compute firm probabilities of default implied by the Bharath and Shumway (2008) model (BSM). This measure is a simpler version of the probability of default estimated from the model of Merton (1974) but with a similar performance in predicting default rates.[8] While this measure is likely to be noisier than the probability of default implied by S&P ratings, its advantage is that it is available for a larger sample of firms as it can be computed for all firms matched with Compustat/CRSP data (including, in particular, public firms with no outstanding bonds in public markets).

Appendix Table A2 reports summary statistics on each of the loans in our sample, and Appendix Table A3 reports the correlation between our three measures of downside risk. We find that the correlations between the measures of firm riskiness range between 0.3 and 0.7, which motivates our approach of using all of them for robustness. Finally, in Online Appendix D, we show that each of these three measures of downside risk is predictive of negative firm performances during the financial crisis—that is, our measures of ex-ante downside risk are correlated with ex-post performances during the Great Recession.

[6]Indeed, in our model, even though lending rates will be monotonically related to default probabilities, the slope of this relationship will be determined by banks' ability to hold risk.

[7]We use the most recent rating issued by S&P before loan issuance. For less than 1% of observations, multiple ratings are issued within the same day, in which case we take the maximum of ratings.

[8]More precisely, the probability to default from Bharath and Shumway (2008) is given by $\mathcal{N}\left(-\frac{\log\left(\frac{E+D}{D}\right)-(r-\frac{1}{2}\sigma_A^2)}{\sigma_A}\right)$, where $\mathcal{N}$ is the cumulative standard normal distribution function, E is the market capitalization, D is the short-term debt plus half of long-term debt, r is the trailing one-year stock return, and σ_A is asset volatility. See Schwert (2018) for a similar use of Bharath and Shumway (2008)'s distance to default.

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2.2. Firm Riskiness Pre-Crisis and Bank Performance during the Crisis

Sorting test. We are interested in measuring the systematic relationship between a bank's health or performance during the financial crisis and the risk of the firms it was lending to. To do so, we estimate the following model using weighted least squares:

$$Y_j = \alpha + \beta \overline{X}_j + \epsilon_j, \tag{1}$$

where j denotes a bank, $\overline{X}_j$ denotes the average measure of downside risk of its borrowers in the pre-crisis period, and Y_j denotes the bank's performance during the crisis. As in Chodorow-Reich (2013), we use as a measure of a bank's performance the growth of its lending during the financial crisis; that is, $Y_j \equiv L_{j,\text{crisis}}/L_{j,\text{normal}}$, where $L_{j,\text{crisis}}$ denotes the total amount of loans originated by the bank in the nine-month period from October 2008 to June 2009 and $L_{j,\text{normal}}$ denotes the average of the total amount of loans originated from October 2005 to June 2006 and from October 2006 to June 2007.[9] To make it easier to interpret the coefficients in the regression, we normalize this variable so that its standard deviation is one. Finally, we use the number of firms borrowing from each bank as a weight variable.

Panel A in Table 1 reports the result of regressing bank lending growth during the crisis on each of our three measures of firm downside risk. We find that our three measures negatively predict corresponding bank lending growth: the banks that did the worst during the crisis were systematically lending to firms with a higher loan spread, worse credit rating, and higher probability of default. Using borrower loan spread as our measure, we find that a 1 percentage point increase in the average borrower loan spread is associated with a decrease in bank lending growth by 0.66 standard deviations. This is not only a large economic effect but also highly statistically significant, with a t-statistic of 3.58. The R^2 from the regression is 21%, which implies that firms' ex-ante characteristics capture a large fraction of banks' ex-post performances. When we use the probability of default implied by its credit rating, we find that a 1 percentage point increase in the probability of default is associated with a decrease in bank lending growth by 0.27 standard deviations. Finally, a 1 percentage point increase in Bharath and Shumway (2008)'s probability of

[9] That is, we are measuring the bank's performance by comparing the number of loans issued during the financial crisis period with the number of loans issued during the same October to June window in prior years.

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default is associated with a decrease in bank lending growth of 0.14 standard deviations.

Table 1: Firm Riskiness Pre-Crisis and Bank Lending Growth

	β	t-stat	R^2	N
	(1)	(2)	(3)	(4)
Panel A: Bank Lending Growth				
Borrower loan spread	-0.66^{***}	3.58	0.21	43
Borrower default probability (S&P)	-0.27^{***}	3.16	0.20	39
Borrower default probability (BSM)	-0.14^{***}	3.45	0.17	43
Panel B: Bank Lending Growth (Controlling for Firm Characteristics)				
Borrower loan spread	-0.97^{***}	4.25	0.27	42
Borrower default probability (S&P)	-0.31^{**}	2.67	0.16	38
Borrower default probability (BSM)	-0.13^{***}	2.97	0.15	43
Panel B: Bank Lending Growth (Controlling for Firm/Loan Characteristics)				
Borrower loan spread	-1.15^{***}	3.55	0.22	42
Borrower default probability (S&P)	-0.29^{**}	2.35	0.12	38
Borrower default probability (BSM)	-0.12^{***}	3.01	0.15	43

Notes: The table estimates the model

$$Y_j = \alpha + \beta \xi_j + \epsilon_j,$$

where j denotes a bank, Y_j is the bank lending growth from 2006 to 2009 (normalized to have a unit standard deviation), and ξ_j is a bank's average of its borrower downside risk, with or without controlling for a set of firm and loan characteristics. More precisely, Panel A reports the un-adjusted average borrower downside risk, Panel B adjusts for a set of firm characteristics (sales and industry), and Panel C also adjusts for a set of loan characteristics (type, purpose, maturity). Borrower loan spread, borrower probability of default implied by its S&P credit rating, and borrower probability of default implied by the model of Bharath and Shumway (2008) are all in percentage points. Estimation is done with weighted least squares using the number of pre-crisis loans issued by each bank as weights. Estimates for β are in column (1), while the corresponding t-statistics, estimated using robust standard errors, are in column (2) (*** corresponds to a p-value below 0.01).

To visualize this relationship, Figure 1 displays a scatter plot between bank lending growth from 2006 to 2009 on the y-axis and borrower loan spread on the x-axis. The larger circles indicate the number of loans from the bank and hence reflect the bank's size. Investment banks such as Lehman Brothers, Bear Stearns, and Merrill Lynch all drastically decreased lending during the period and were also matched with borrowers with high spreads, that is, high downside risk firms.

Controlling for additional firm characteristics. The relationship we observe between bank performance and the measures of firm downside risk could be a mechanical consequence of some more fundamental sorting pattern not based on risk; for instance, certain banks could lend to smaller firms, which happen to be riskier. To rule out this explanation, we now examine the relationship between bank and firm riskiness after adjusting for other firm and loan characteristics that potentially vary across banks. Firm characteristics available in DealScan are the firm's sales in the previous years as well as its industry (2-digit SIC). Loan characteristics include the loan purpose (acquisition line, corporate purposes, leveraged buyout, real estate, takeover, working

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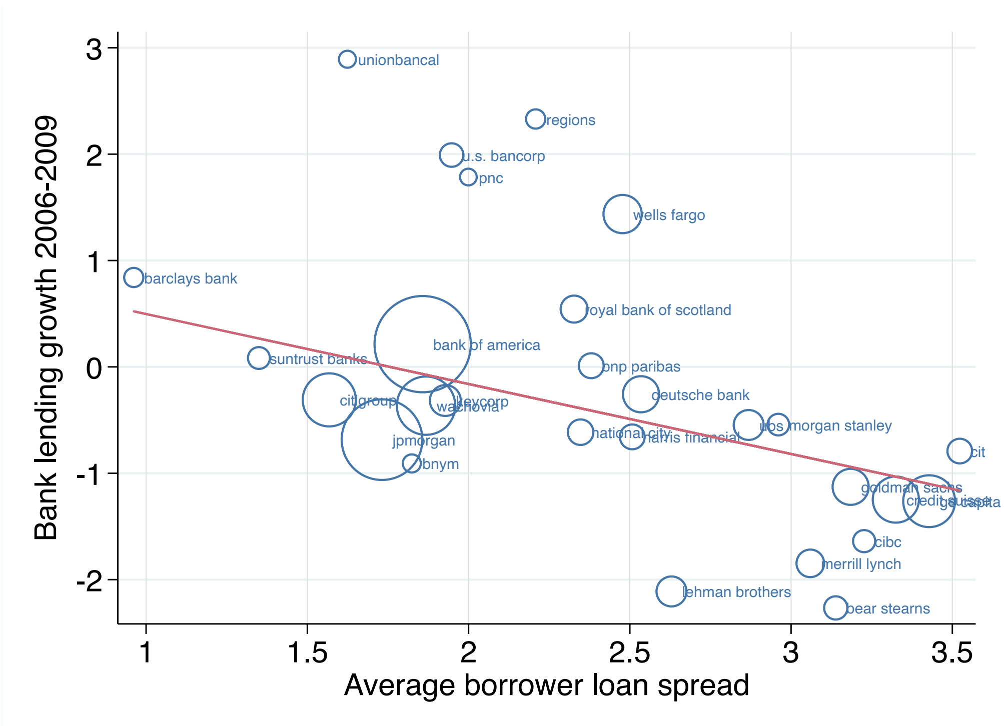

Figure 1: Firm Riskiness Pre-Crisis and Bank Lending Growth 2006–2009

Notes. This figure plots (standardized) bank lending growth over the period 2006–2009 (y-axis) relative to the average spread of its loans issued pre-crisis. The line plots the predicted value from a regression model estimated using weighted least squares (weights are the number of pre-crisis loans). The size of the circle represents the bank-specific weights. For readability, the figure only plots banks with more than 100 loans reported in DealScan during the pre-crisis period.

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capital, corporate purposes, or other), loan type (term loan, term loan a, term loan b, revolver, other), loan amount, and loan maturity.[10]

In a first step, we partial out this set of observable characteristics from firm riskiness to create a constant reference group across banks. More precisely, we run the following regression across all firms in our sample:

$$X_i = \xi_j + b_1 \times \log(\text{Sale}_i) + b_2 \times \log(\text{Sale}_i)^2 + \delta_{\text{industry}_i} + \gamma_{\text{loan purpose}_i} + \zeta_{\text{loan type}_i} + \\ + c_1 \times \text{Loan Maturity}_i + c_2 \times \text{Loan Maturity}_i^2 + e_i, \tag{2}$$

where i denotes a firm and j denotes the bank it is borrowing from. Appendix Table A5 reports the results of this estimation, showing that smaller firms tend to have a higher loan spread and a higher probability of default. Critically, the bank fixed effects, ξ_j, can be seen as a composition-adjusted measure of borrower riskiness at the bank level.

In a second step, we regress a bank's performance on these composition-adjusted measures of borrower riskiness:

$$Y_j = \alpha + \beta \xi_j + \epsilon_j, \tag{3}$$

where, as above, j denotes a bank, Y_j denotes its performance during the financial crisis, and weights are given by the number of loans issued by each bank during the pre-crisis period. The only difference with our original "uncontrolled" specification given in Equation (1) is that the average measure of firm riskiness at the bank level, $\overline{X}_j$, is replaced by our composition-adjusted measure, ξ_j.[11,12] Note that in the particular case in which the set of firm and loans characteristics used to partial out firm riskiness is empty, we obtain the same as our original specification given in Equation (1).

Panel B in Table 1 reports the estimated model after controlling for the set of firm characteristics (industry and size), while Panel C reports the estimated model after controlling for both firm

[10] We top code maturity at 15 years to diminish the impact of outliers.

[11] This two-step procedure is inspired by similar methodologies in the economic literature. In the local labor markets literature, it is used to partial out demographic characteristics that vary across regions (e.g., Suárez Serrato and Zidar, 2016). In the teacher value-added literature, it is used to partial out student characteristics across teachers (e.g., Chetty, Friedman, and Rockoff, 2014)

[12] Formally, this two-step procedure is equivalent to regressing $Y_{j(i)}$ on X_i and a set of additional firm and loan controls, after instrumenting X_i by a set of bank fixed effects.

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and loans characteristics (purpose, type, and maturity).[13] The panels show that the relationship between bank health during the financial crisis and the riskiness of their borrowers pre-crisis is robust to these controls.

Overall, our results suggest strong, positive assortative matching between banks and borrowers. Banks that were particularly hit during the financial crisis were lending to the riskiest firms. One implication is that it is hard to differentiate between the "bank" or credit supply effect and the "firm" or credit risk effect in explaining the negative real effects during the Great Recession associated with risky firms borrowing from hit banks.

2.3. Firm Risk and Bank Characteristics Pre-Crisis

Our evidence above shows that banks lending to riskier firms before the financial crisis did worse during the financial crisis. To better understand this sorting pattern, we now discuss some ex-ante (pre-crisis) characteristics of these banks: we show that banks lending to riskier firms tend to have a close proximity to Lehman, a lower bank deposit-to-asset ratio, and a higher share of securitization. This systematic relationship between bank characteristics and firm characteristics pre-crisis is evidence of a sorting pattern, which will motivate our model below (Section 3). Moreover, these findings cast doubt on the financial crisis literature using these bank characteristics to isolate changes in credit supply (e.g., Ivashina and Scharfstein, 2010 and Chodorow-Reich, 2013). Indeed, our finding that these bank characteristics are systematically correlated with the riskiness of their borrowers suggests that they are also related to changes in credit demand.

Formally, we estimate the same model as above (Equation (3)):

$$Y_j = \alpha + \beta \xi_j + \epsilon_j,$$

where j denotes a bank, ξ_j denotes the average of its borrower riskiness after controlling for a set of firm and loan characteristics (i.e., the bank fixed effects estimated in Equation (2)), and Y_j is one of three bank ex-ante characteristics: distance to Lehman, deposit-to asset-ratio, and securitization intensity. As above, each dependent variable is standardized to have a standard deviation of one.

Panel A of Table 2 reports the results of regressing bank distance to Lehman on our three

[13]We report these two specifications separately since loan characteristics (e.g., loan type) may be a function of a firm's downside risk.

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measures of borrower characteristics. Following Ivashina and Scharfstein (2010), a bank distance to Lehman is defined as the fraction of a bank's syndication portfolio where Lehman Brothers had no lead role. We find that all three measures of borrower downside risk are negatively related to Lehman distance.

Table 2: Firm Riskiness and Bank Ex-Ante Characteristics

	β	t-stat	R^2	N
	(1)	(2)	(3)	(4)
Panel A: Bank Lehman Distance				
Borrower loan spread	-2.59^{***}	3.43	0.43	41
Borrower default probability (S&P)	-0.95^{***}	3.34	0.44	37
Borrower default probability (BSM)	-0.29^{***}	3.59	0.36	42
Panel B: Bank Deposit-to-Asset Ratio				
Borrower loan spread	-2.42^{***}	8.20	0.57	42
Borrower default probability (S&P)	-0.63^{***}	5.68	0.38	38
Borrower default probability (BSM)	-0.23^{***}	7.20	0.42	43
Panel C: Bank Securitization Intensity				
Borrower loan spread	1.23^{**}	2.57	0.33	20
Borrower default probability (S&P)	0.53^{***}	3.15	0.46	20
Borrower default probability (BSM)	0.08^{*}	2.06	0.10	20

Notes: The table estimates the model

$$Y_j = \alpha + \beta\xi_j + \epsilon_j,$$

where j denotes a bank; Y_i is alternatively the bank distance to Lehman (Panel A), deposit-to-asset ratio (Panel B), and securitization intensity (Panel C) (all normalized to have a unit standard deviation); and ξ_j is a bank's average of its borrower downside risk after controlling for a set of firm and loan characteristics. Borrower loan spread, borrower probability of default implied by its credit rating, and borrower probability of default implied by the model of Bharath and Shumway (2008) are all in percentage points. Estimation is done with weighted least squares using the number of pre-crisis loans issued by each bank as weights. Estimates for β are in column (1), while the t-statistics, estimated using robust standard errors, are in column (2) (*** corresponds to a p-value below 0.01).

The correlation is actually even stronger quantitatively than when it comes to predicting bank lending growth in Table 2. Using borrower loan spread, a 1 percentage point increase in the average borrower loan spread is associated with a decrease in Lehman distance by 2.59. The t-statistic is 3.43, and the R^2 is now 43%. Using the borrower probability of default implied by its credit rating, a 1 percentage point increase is associated with a decrease in Lehman distance by 0.95 standard deviations. Similarly, a 1 percentage point increase in the borrower's probability of default implied by Bharath and Shumway (2008) is associated with a decrease in bank lending growth by 0.29 standard deviations.

We then study the correlation between firm risk and the ratio of bank deposits to assets (Chodorow-Reich, 2013).[14] Panel B of Table 2 reports the result of regressing bank deposits on the

[14]We construct this variable using the Federal Reserve FR Y-9C Consolidated Financial Statements for bank

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three measures of firm downside risk. Quantitatively, a 1 percentage point increase in the average borrower loan spread is associated with a decrease in bank deposits by 2.42 standard deviations, with a t-statistic of 8.20 and an R^2 of 57%. Hence, approximately half of the variation in bank deposit-to-asset ratios is related to differences in borrower quality. Similarly, a 1 percentage point increase in the borrower probability of default implied by its S&P credit rating is associated with a decrease in bank deposits by 0.63 standard deviations. Finally, a 1 percentage point increase in the probability of default implied by the model of Bharath and Shumway (2008) is associated with a decrease in bank deposits by 0.23 standard deviations.

Finally, we study the correlation between firm risk and banks' ability to securitize. Indeed, many investment banks such as Lehman, Goldman Sachs, or Bear Stearns were leaders in the securitization of risky corporate loans (Shivdasani and Wang, 2011; Nadauld and Weisbach, 2012). We start from a list of 468 CLOs rated by Moody's during the pre-crisis period (January 2005 to June 2007).[15] For banks in the dataset, we then define the bank securitization intensity as the number of CLOs originated by the bank and rated by Moody's during the pre-crisis period relative to the number of loans issued by the bank during the pre-crisis period.

Panel C of Table 2 reports the result of regressing bank securitization intensity on the three measures of firm downside risk. We find that banks with a higher securitization intensity tend to lend to riskier firms. Quantitatively, a 1 percentage point increase in the average borrower loan spread is associated with an increase in bank securitization by 1.23 standard deviations, with a t-statistic of 2.57 and an R^2 of 33%. Using the borrower probability of default implied by its S&P credit rating, the coefficient is 0.53 with a t-statistic of 3.15. Similarly, a 1 percentage point increase in the probability of default implied by the model of Bharath and Shumway (2008) is associated with an increase in bank securitization intensity by 0.08 standard deviations.

Our finding that banks with a higher securitization intensity were lending to riskier firms before the crisis is consistent with similar findings in the mortgage literature (Keys, Mukherjee, Seru, and Vig, 2010). One rationale is that banks with a higher ability to securitize can offer better pricing terms to riskier firms since they do not need to hold the entire default risk on their balance sheets. For instance, marketing documents for Lehman during this period pointed to their special ability to

holding companies and Bankscope data for foreign holding companies and investment banks.

[15] We thank Taylor Nadauld for sharing the Moody's Enhanced Monitoring Service dataset with us.

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assess and package the riskiest loans compared to other banks. Consistent with the importance of securitization, we show in Online Appendix F that the sorting patterns we document only gradually appears in the 2000s.

In short, our results show that certain banks (e.g., investment banks) were lending to the riskiest firms and they particularly suffered during the crisis.[16] This pattern suggests that understanding the matching between banks and firms is key to understanding the distribution of credit before and during the Great Recession.

3. An Assignment Model of the Credit Market

In this section, we develop a competitive matching model of the credit market in which banks have heterogeneous costs to take on risky loans and firms have different credit risks. Section 3.1 presents the model, Section 3.2 defines the equilibrium, and Section 3.3 examines the effect of changes in the distribution of bank holding costs on loan volume.

3.1. Setup

Credit market. Firms own projects but do not have capital. Banks are endowed with one unit of capital, and they can either offer funding to a firm or earn a net return r_B through other investment opportunities. We refer to r_B as the bank's cost of capital (it corresponds to the value of the bank's outside option).

There is a continuum of heterogeneous firms, indexed by $i \in [0, N^f]$, that differ in their probability of default, denoted $\delta[i]$. A high i denotes a firm with a higher probability of default; that is, firms are ranked by their default probability $\delta'[i] \geq 0$ with $\delta[0] = 0$, where $\delta[\cdot]$ is continuous and differentiable almost everywhere with respect to i.[17] As discussed in Terviö (2008), there is a one-to-one mapping between the function $\delta[\cdot]$ and the cumulative distribution function of default probabilities.[18] Each firm has one project that requires one unit of investment. With probability $1 - \delta[i]$, the project succeeds, in which case it yields a net return $\overline{r}_F[i]$. With probability $\delta[i]$, the

[16] In Online Appendix E, we show that the sorting pattern is not just driven by the difference in lending patterns between investment and commercial banks; it also happens within each bank category.

[17] While the assumption that $\delta[0] = 0$ is not needed for most of our theoretical results, we make it as it simplifies our equations and is going to be satisfied empirically.

[18] More precisely, the cumulative distribution function of default probabilities is given by $F(x) \equiv \delta^{-1}(x/N^f)$ for $0 < x < \delta[N^f]$ and 1 for $x > \delta[N^f]$.

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project fails, in which case it yields a net return $\underline{r}_F[i]$. Finally, $\gamma_F[i] \geq 0$ denotes the value of a firm's outside option. A positive γ_F captures the idea that firms could potentially finance their projects using alternative funding sources (bond, equity, or internal capital).

We make the following two assumptions:

Assumption 1. $r_B > \underline{r}_F[i]$*; that is, the return of the project cannot compensate the opportunity cost of lending if the project fails.*

Assumption 2. *The expected revenue of the project (net of the firm's outside option),* $r_F \equiv (1-\delta[i])\overline{r}_F[i] + \delta[i]\underline{r}_F[i] - \gamma_F[i]$*, is constant across* i*.*

There is also a continuum of heterogeneous risk-neutral banks, indexed by $j \in [0, N]$, that differ in their ability to handle risks, that is, holding costs, denoted $\kappa[j]$. A high j denotes a bank with a lower holding cost; that is, $\kappa'[j] \leq 0$. For instance, a lower holding cost could reflect a higher ability to sell securitized loans to institutional investors. As for firms, we assume that $\kappa[j]$ is continuous and differentiable almost everywhere with respect to j.

Let $C(i, j) = c(\delta[i], \kappa[j])$ denote the cost of holding risk for bank j when lending to firm i. This cost models all the resources bank j spends to make a loan to firm i beyond the cost of capital that is common to all banks, r_B. We assume that $c_\delta > 0$, $c_\kappa > 0$. That is, the holding cost increases with firms' default probability δ and banks' ability κ. We also assume that $c(0, \kappa) = 0$; that is, the cost of holding a firm with zero default probability is zero—this allows us to interpret κ as the bank's ability to hold risk.

We assume that each firm can only, at most, borrow from one bank. Any individual firm i can be matched with a bank j or remain in autarky. That is, we use one-to-one matching to model the relationship between firms and banks. As we will discuss in Section 4.4, the one-to-one relationship can also be interpreted as matching between a single project and a bank manager in an environment where firms have multiple projects and banks have multiple managers.

Within a match, a bank and a firm agree to a debt contract, which specifies an interest rate r. We assume that the project is pledgeable, and thus the bank obtains the value of the project when the firm defaults. Banks understand they will receive $\min\{1 + r, 1 + \underline{r}_F[i]\}$. Given that in equilibrium the interest rate must be larger than r_B, Assumption A1 implies that the bank will receive the interest rate only if the project succeeds. The expected profit of bank j lending to firm

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i at interest rate r is thus equal to

$$W(i,j|r) = (1-\delta[i])r + \delta[i]\underline{r}_F[i] - C(i,j) - r_B.$$

The expected profit of firm i borrowing from bank j (relative to its outside option) at interest rate r is

$$U(i,j|r) = (1-\delta[i])(\overline{r}_F[i] - r) - \gamma_F[i].$$

While a firm's profit does not directly depend on its matching bank j, different banks will charge different interest rates in equilibrium, and thus the distribution of bank ability will affect the firm's profit.

The joint surplus between a matching pair (i,j) is given by

$$s(i,j) \equiv W(i,j|r) + U(i,j|r) = r_F - r_B - C(i,j),$$

which is the net gains of the project $r_F - r_B$ (its expected revenue minus the firm's outside option and the bank's cost of capital) minus the holding cost of the loan $C(i,j)$. It is independent of the loan interest rate r since it only affects how the firm and bank split the surplus—a higher interest rate r means a lower profit for the firm at the benefit of the bank.

3.2. Equilibrium

Our equilibrium concept follows the standard assignment model (Terviö, 2008).[19] The bank's decision can be rewritten as choosing a firm i to maximize its expected profit, taking the firm's equilibrium profit $U[i]$ as given:

$$W[j] = \max_i \{r_F - r_B - C(i,j) - U[i]\}. \tag{4}$$

Conditional on the profit to the firm, lending to a riskier firm means a higher holding cost for a bank, and hence banks prefer to match with safer firms. Since all banks compete for those firms, safer firms must receive a better loan term; that is, $U[i]$ must decrease in i. Banks thus trade off

[19] Equivalently, these models can be understood as bilateral matching models with transferable utility. See more detailed discussion in Chiappori and Salanié (2016).

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between a riskier firm and a higher loan rate. Those lending to the riskier firms are compensated by getting a higher payment, and the matching outcome is then determined by which bank is more willing to absorb firm credit risk.

The matching in general depends on the complementarity between firm riskiness and bank ability in the surplus function, where $s_{12}(i,j) = -C_{12}(i,j)$. When $C_{12}(i,j) < 0$, a bank's ability matters more for a riskier firm in the sense that it can reduce the firm's borrowing cost more and then a bank with a higher ability to hold risk is matched with a riskier firm. Since we observe that riskier firms tend to borrow from banks that are better at securitization (the ones with lower holding costs), we then focus on $C_{12}(i,j) < 0$ (or, equivalently, $c_{\delta\kappa} > 0$) throughout the paper.

Proposition 1. *When $C_{12}(i,j) < 0$, the equilibrium consists of a marginal firm risk rank $i^* \in [0, N)$ and a firm expected profit U defined on $[0, i^*]$ such that*[20]

1. *Firm $i \leq i^*$ matches with bank $j(i) = N - i^* + i$.*
2. *The function U solves*

$$U'[i] = -C_1(i, j(i)), \tag{5}$$

with boundary conditions $U[0] = r_F - r_B$ and $U[i^*] = 0$.

Notice that the marginal risky firm i^* is matched with the best bank $j(i^*) = N$, while the safest firm $i = 0$ is matched with the marginal bank $N - i^*$. Given the sorting outcome $j(i)$, a firm's expected profit $U[i]$ is pinned down so that the first-order condition is satisfied, giving Equation (5). Since we assume that there is an interior solution (footnote 20), the marginal firm's profit (relative to its outside option) must be zero; that is, $U[i^*] = 0$. Similarly, the marginal bank's profit must be zero, and hence its matching firm (i.e., the safest firm) then receives the full surplus of the pair, which gives $U[0] = r_F - r_B$.

Credit rationing. The model naturally generates credit rationing, where some banks might choose not to lend in equilibrium $i^* < N$. This means that not all lending capacity is used, resulting in fewer firms obtaining the loan. The aggregate loan volume in our model is described by the cutoff

[20] We focus on the interior solution where not all banks lend and not all firms borrow; that is, $i^* < \min(N, N^f)$. This happens as long as $N < N^f$ (i.e., banks are scarce relative to firms) and the net gains of the project are small enough; that is, $r_F - r_B < \int_0^N c_\delta(\delta[i], \kappa[i])\delta'[i]di$.

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type i^*, the rank of the riskiest firm getting credit (i.e., the marginal risky firm). Combining the expression for $U'[i]$ with the boundary condition for $U[i^*]$ and $U[0]$ from Proposition 1, we can obtain an equation pinning down the aggregate loan supply, that is, the rank of the marginal firm getting credit i^*:

$$\begin{aligned} r_F - r_B &= U[0] - U[i^*] \\ &= \int_0^{i^*} c_\delta(\delta[i], \kappa[j(i)])\delta'[i]di. \end{aligned} \tag{6}$$

This equation can be interpreted from the social planner's perspective: banks and firms are added to the market until the benefit of adding a marginal bank equates its cost. Indeed, the left-hand side of this equation corresponds to the benefit of adding a marginal bank, which is the surplus of the match between the marginal bank and the safest firm.[21] The right-hand side corresponds to the reallocation cost of adding a marginal bank: existing banks must now lend to slightly riskier firms, which increases their holding costs.

Alternatively, we can rewrite Equation (6) as[22]

$$r_F - r_B - c(\delta[i^*], \kappa[N]) = -\int_0^{i^*} c_\kappa(\delta[i], \kappa[j(i)])\kappa'[j(i)]di. \tag{7}$$

This equation can also be interpreted from the social planner's perspective. The left-hand side corresponds to the benefit of adding a marginal firm, which is the surplus of the match between a marginal firm and the bank with the highest ability to hold risk. The right-hand side captures the reallocation cost of adding this marginal firm: existing firms must now borrow from banks with a slightly lower ability to hold risk.

Observe that if banks were homogeneous (i.e., $\kappa'[i] = 0$), the right-hand side of Equation (7) would be zero; that is, there would be no reallocation cost. In this economy, firms would borrow until the surplus of the match created by the marginal firm is zero (the left-hand size in Equation

[21] Note that because we assumed that the safest firm was riskless, the loan holding cost is zero; that is, $c(\delta[0], \kappa[N - i^*]) = 0$.

[22] We use the fact that

$$c(\delta[i^*], \kappa[N]) = \int_0^{i^*} \frac{dc(\delta[i], \kappa[j(i)])}{di} di = \int_0^{i^*} c_\delta(\delta[i], \kappa[j(i)])\delta'[i]di + \int_0^{i^*} c_\kappa(\delta[i], \kappa[j(i)])\kappa'[j(i)]di.$$

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(7)) is zero. In contrast, in the presence of bank heterogeneity, some firms are excluded from the lending market even though the surplus of matching with the marginal bank is positive.

Finally, note that the reallocation costs appearing in the right-hand side of Equations (6) and (7) are specific to our model with negative sorting. If there was positive sorting (which happens if $c_{\delta\kappa}(\delta[i], \kappa[j]) < 0$), the marginal bank and the marginal firm would always be matched together. Adding them would not affect existing matches.

3.3. Comparative Statics

We now examine formally the effect of changes in bank and firm characteristics on aggregate loan volume.

Level effect. We first discuss the effect of a level shift in bank or firm characteristics on aggregate loan volume. Start from a distribution of bank holding costs $\kappa_0[j]$ at time $t = 0$. We say that banks become worse at holding risk at $t = 1$ when $\kappa_0[j] \leq \kappa_1[j]$ for $j \geq j(i_0^*)$ where i_0^* is the loan volume at time $t = 0$; this corresponds to first-order stochastic dominance. Similarly, we say that firms become riskier when $\delta_0[i] \leq \delta_1[i]$ for $i \leq i_0^*$. The next proposition establishes that the aggregate loan volume decreases when all banks become worse or firms become riskier:

Proposition 2 (Level Effect)**.** *Total loan volume decreases when banks become worse at holding risk, when r_B (banks' cost of capital) increases, when firms become riskier, or when r_F (expected return of a firm's project net of its outside option) decreases.*

Distributional effect. One key implication of our sorting model is that the entire distribution of bank holding costs matters for aggregate outcomes, not just their average. Hence, we now discuss the effect of a mean preserving spread in bank characteristics on aggregate lending.

To simplify our analysis, we now assume that the loan cost function is separable:[23]

Assumption 3. *The loan cost function is separable: $c(\delta, \kappa) = v(\delta)\kappa$.*

The assumption that the surplus function is separable is standard in the matching literature (Gabaix and Landier, 2008). The supplementary assumption that the loan cost function is linear

[23] Note that the initial assumption $c(0, \kappa) = 0$ implies $v(0) = 0$.

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in bank holding cost κ is without loss of generality: κ should be understood as the bank's *effective* holding cost.[24]

Proposition 3 (Distributional Effect)**.** *When $i \to v(\delta[i])$ is convex, total loan volume decreases between $t = 0$ and $t = 1$ when κ_1 stochastically dominates κ_0 at the second-order; that is,*

$$\int_n^N \kappa_0[j]dj \leq \int_n^N \kappa_1[j]dj \text{ for } n \in [N - i_0^*, N],$$

Proposition 3 says that the distribution of credit supply shocks among banks matters for the aggregate change in the loan volume. In particular, this proposition implies that a mean-preserving contraction in bank holding costs decreases total loan volume.[25] In this sense, it implies that banks with lower holding costs are systemically more important.

To understand the intuition for this result, note that under Assumption 3, Equation (6) can be rewritten as

$$r_F - r_B = \int_0^{i^*} \kappa[j(i)] \frac{dv(\delta[i])}{di} di. \tag{8}$$

The right-hand side can be seen as a weighted sum of bank holding costs $\kappa[j(i)]$, where the weights are given by $dv(\delta[i])/di$. If the function $i \to v(\delta[i])$ is convex, then the holding costs of better banks (lower κ) have higher weights than the holding costs of worse banks (higher κ). In this case, a decrease in the dispersion of κ increases the right-hand side of Equation (8). As a result, the equilibrium loan volume i^* must decrease to satisfy Equation (8).

The condition that $i \to v(\delta[i])$ is convex is critical for the result. In our empirical application, we will observe that default probabilities are convex in rankings.[26] Hence, the convexity of $i \to v(\delta[i])$ will hold as long as $\delta \to v(\delta)$ is not too concave — in particular, it holds if the function is $v(\cdot)$ is linear in δ, as we will assume in Assumption 5.

[24]Suppose, for instance, that $c(\delta, \kappa) = v(\delta)f(\kappa)$. Then all of our results would go through after redefining bank holding cost to be $\tilde{\kappa} = f(\kappa)$.

[25]Formally, κ_1 is a mean-preserving contraction of κ_0 if (i) κ_1 stochastically dominates κ_0 at the second order and (ii) κ_1 and κ_0 have the same mean.

[26]See Section 4 and, in particular, Figure 2a.

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4. Taking the Model to the Data

In this section, we analyze the data through the lens of our model. In Section 4.1, we present a methodology to identify the parameters of our model. In Section 4.2, we implement this methodology during the pre-crisis period (2005–2007) and during the crisis period (2008–2010). In Section 4.3, we use these estimates to disentangle the effect of credit demand and credit supply on aggregate loan volume.

4.1. Methodology

Firms' default probabilities can be inferred from their S&P long-term issuer ratings, as in Section 2. Hence, we are left with three objects to identify (i) the distribution of bank holding costs $\kappa[\cdot]$, (ii) the banks' cost of capital r_B, and (iii) the expected revenue from the project (net of the firm's outside option) r_F.

To identify these three objects, we use the three equations characterizing the equilibrium (Proposition 1):

$$\begin{aligned} \text{FOC of bank } j(i) \quad & U'[i] = -c_\delta(\delta[i], \kappa[j(i)])\delta'[i], \\ \text{Lower Boundary Condition} \quad & U[0] = r_F - r_B, \\ \text{Upper Boundary Condition} \quad & U[i^*] = 0. \end{aligned}$$

As discussed above in Section 3, the first equation corresponds to the first-order condition for bank j to match with firm i. The second equation corresponds to the fact that the expected profit of the marginal bank is zero, while the third equation corresponds to the fact that the expected profit of the marginal firm (relative to its outside option) is zero.

Instead of working with the firm's expected profit (relative to its outside option), $U[i]$, it is useful to rewrite these equations in terms of $L[i] \equiv r_F - U[i] = (1 - \delta[i])r[i] + \delta[i]\underline{r}_F[i]$, which

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corresponds to the net expected loan revenue of the bank lending to firm i:

$$\text{FOC of bank } j(i) \quad L'[i] = c_\delta(\delta[i], \kappa[j(i)])\delta'[i],$$
$$\text{Lower Boundary Condition} \quad L[0] = r_B,$$
$$\text{Upper Boundary Condition} \quad L[i^*] = r_F.$$

We need two additional assumptions to identify the model based on this system of equations. The first assumption will allow us to identify $L[\cdot]$ in the data, while the second assumption will allow us to recover $\kappa[j(i)]$ from $c_\delta(\delta[i], \kappa[j(i)]$. We discuss in Appendix C.4 how relaxing these assumptions would affect our estimates.

Assumption 4. *Firms repay the principal in case of default:* $\underline{r}_F[i] = 0$.

This assumption is consistent with empirical evidence of strict seniority of bank debt (Hackbarth, Hennessy, and Leland (2007) derive conditions under which this is optimal for firms).[27] This assumption implies that $L[i] = (1 - \delta[i])r[i]$, meaning we can observe the expected loan revenue $L[i]$ given the loan default probability $\delta[i]$ and its interest rate $r[i]$.

Assumption 5. *The holding cost function takes the form* $c(\delta, \kappa) = \delta\kappa$.

This assumption strengthens Assumption 3, which assumed that the holding cost function was separable in firm default probability and bank holding cost; that is, $c(\delta, \kappa) = v(\delta)\kappa$. Effectively, the new condition adds that $v(\cdot)$ is linear in δ; that is: $v(\delta) = \delta$. While the linearity of $v(\cdot)$ is not critical per se, the point is that we do need to assume a functional form for $v(\cdot)$ to identify κ.

These two assumptions allow us to rewrite the set of equilibrium equations as follows:

$$\text{FOC of bank } j(i) \quad L'[i] = \kappa[j(i)]\delta'[i], \tag{9}$$
$$\text{Lower Boundary Condition} \quad L[0] = r_B, \tag{10}$$
$$\text{Upper Boundary Condition} \quad L[i^*] = r_F, \tag{11}$$

where the left-hand size in each equation is now observable. Hence, the shape of the function L allows us to identify the three main objects of our models: $L[0]$ identifies the bank's cost of capital

[27] A similar assumption is made in the context of bank debt by Hennessy and Whited (2005) and DeAngelo, DeAngelo, and Whited (2011).

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r_B, $L'[i]$ identifies the distribution of the bank's holding costs, and $L[i^*]$ identifies the expected revenue of the project (relative to the firm's outside option) r_F.

We now briefly repeat the intuition behind each of these three equations. Equation (9) reflects the fact that the change in a lender's revenue from matching with a slightly riskier borrower, $L'[i]$, must equal the corresponding increase in its cost, $\kappa[j(i)]\delta'[i]$.[28] This equation allows us to infer banks' holding cost $\kappa[j(i)]$ by looking at the gradient of loan revenue, $L'[i]$, relative to the gradient of default probabilities, $\delta'[i]$. For instance, if we observe that bank loan revenues increase a lot with firm default probabilities, this must mean that matching banks have a hard time absorbing risk.

Equation (10) reflects the fact that in equilibrium, the marginal bank makes zero profit, meaning that its revenue from the loan, $L[0]$, must equal its cost of issuing a loan to a safe firm, r_B. This equation allows us to infer r_B from the interest rate charged to the safest (riskless) firm $L[0] = r[0]$. Equation (11) reflects the fact that in equilibrium, the expected profit of the marginal firm (net of its outside option) is zero, meaning that what the firm expects to pay to its bank, $L[i^*]$, equals the expected revenue of the project (net of the firm's outside option) r_F. This equation allows us to infer r_F from the loan revenue of the bank lending to the riskiest firm $L[i^*] = (1 - \delta[i^*])r[i^*]$.

4.2. Implementation

In this section, we apply our method to identify the distribution of bank holding costs using the DealScan dataset.

Sample construction. We estimate the model in two distinct time periods. The first period ($t = 0$) corresponds to the pre-crisis period discussed in Section 2: it goes from the first quarter of 2005 to the second quarter of 2007 (included). The second period ($t = 1$) corresponds to the crisis period: it goes from the third quarter of 2008 to the fourth quarter of 2010. Because we estimate the model separately in these two time periods, we effectively allow all model parameters to differ from one period to the next, and we index them by t. This includes the functions $\delta_t[\cdot]$ and $\kappa_t[\cdot]$, the

[28]In turn, $L[i] = (1 - \delta[i])r[i]$ implies

$$L'[i] = (1 - \delta[i])r'[i] - r[i]\delta'[i],$$

which says that the marginal bank revenue of lending to a riskier borrower is the sum of two terms. The first term corresponds to the higher payoff if the firm does not default, while the second term corresponds to the higher default probability times the foregone revenue if the firm defaults.

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bank's cost of capital r_{Bt}, the project's payoff (net of the firm's outside option) r_{Ft}, the number of firms N_{ft}, and the number of banks N_t.

In DealScan, we observe 15,962 loans at $t = 0$ (pre-crisis) and 7,805 loans at $t = 1$ (crisis). To identify our model, we must restrict ourselves to the set of firms for which we observe the S&P credit rating (to estimate default probabilities $\delta_t[\cdot]$) as well as loan spreads (to estimate interest rates $r_t[\cdot]$). With these restrictions, the number of loans becomes 3,100 at $t = 0$ (pre-crisis) and 1,284 at $t = 1$ (crisis). Despite this smaller sample, the growth of the number of loans in this subsample is very similar to the growth of the total number of loans in DealScan.[29]

Credit rating bins. In the model, the interest rate is a monotonic function of a firm's probability of default. That is, ranking firms by their default probabilities is the same as ranking them by their interest rate. In the data, however, these two quantities are not exactly the same. As reported in Appendix Table A3, the Spearman's rank correlation between a firm's probability of default and a firm's interest rate is 71%, which reflects the fact that the two distributions are close but not exactly similar. This suggests that in reality, there are other determinants of the interest rate beyond the default probability. A related point is that we only observe credit rating groups, which are coarser than actual default probabilities.

To handle this imperfect matching, we group firms into $K = 5$ credit rating bins, based on the firm credit rating at issuance. More precisely, we construct five bins of credit rating. The first group includes all firms rated between AAA and A− (upper investment grade), the second group includes all firms rated between BBB+ and BBB− (lower investment grade), and the third group includes all firms rated between BB+ and BB− (non-investment grade). The fourth group includes all firms rated between B+ and B− (highly speculative), and the fifth group includes all firms rated CCC+ and below (extremely speculative). These five groups correspond to the five rating classes considered by the National Association of Insurance Commissioners (NAIC).

Table 3 reports the median firm rank i^k, the median default probability δ_t^k, and the median loan interest rate r_t^k within each credit rating bin $k \in \{1, 2, \ldots, K\}$ in each period $t \in \{0, 1\}$. As in Section 2, we compute firms' default probabilities based on their S&P credit ratings at issuance

[29]Still, restricting our sample to firms with a credit rating means that we estimate our model on the subset of firms with a relatively easier access to outside sources of financing (e.g., bond issuance). Changes in default probabilities, $\delta_t[\cdot]$, and project revenue net of firms' outside option, r_{Ft}, may be different for firms without credit ratings, that is, bank-dependent firms (see, e.g., Schwert, 2018).

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(see Table A1 for the mapping between credit ratings and default probabilities). We compute loans' interest rates r as the sum of the (real) average Libor rate during the time period and the all-in-drawn loan spread.[30] We report medians (rather than averages) to help interpret these summary statistics. Indeed, through the lens of the model, the median of a value within a bin can be seen as the value associated with the median firm within the bin; that is, $\delta_t^k = \delta_t[i_t^k]$ and $r_t^k = r_t[i_t^k]$.[31]

Table 3: Estimates for r, L, and κ by Credit Rating Groups

	Rating Groups				
	AAA-A	BBB	BB	B	CCC-C
Panel A: Pre-Crisis (2005-2007)					
Number of loans	245	650	806	1,190	209
Median firm rank i^k	123	570	1,298	2,296	2,996
Median default probability δ^k	0.06	0.28	1.53	7.28	22.67
Median interest rate r^k	1.90	2.20	3.15	3.90	4.40
Expected loan revenue $L = (1 - \delta^k)r^k$	1.90	2.19	3.10	3.62	3.40
Bank holding cost $\kappa^k = (L^k - L^{k-1})/(\delta^k - \delta^{k-1})$		1.34	0.73	0.09	-0.01
		(0.03)	(0.03)	(0.00)	(0.01)
Panel B: Crisis (2008-2010)					
Number of loans	57	293	306	436	192
Median firm rank i^k	29	204	503	874	1,188
Median default probability δ^k	0.06	0.28	0.89	7.28	22.67
Median interest rate r^k	2.01	2.76	3.51	4.26	5.01
Expected loan revenue $L = (1 - \delta^k)r^k$	2.01	2.75	3.48	3.95	3.88
Bank holding cost $\kappa^k = (L^k - L^{k-1})/(\delta^k - \delta^{k-1})$		3.38	1.19	0.07	0.00
		(1.09)	(0.24)	(0.02)	(0.01)

Notes: The table reports the number of loans within each credit rating bin, the median firm rank i_t^k, the median default probability δ_t^k, and the median loan interest rate r_t^k within five credit rating bins corresponding to NAIC ratings from 1 to 5. The first bin includes S&P's credit ratings between AAA and A-, the second bin includes ratings between BBB+ and BBB-, the third bin includes ratings between BB+ and BB-, the fourth bin includes ratings between B+ and B-, and the last bin includes ratings between CCC+ and C.
Based on these estimates, the table also reports the loan revenue within each bin $L_t^k = (1 - \delta_t^k)r_t^k$. Panel A reports these estimates during the pre-crisis period (first quarter of 2005 to second quarter of 2007), while Panel B reports these estimates during the crisis period (third quarter of 2008 to fourth quarter of 2010).
Firm default probability is estimated using its S&P credit ratings at loan issuance (using mapping between letter ratings and implied default probabilities reported in Table A1). The loan interest rate is constructed as the sum of the sum of all-in-drawn loan spread and the three-month Libor rate (deflated by CPI inflation).
The last two rows of each panel reports the estimated bank holding cost as well as its standard error. The bank holding in credit bin $k \geq 2$ is constructed following Equation (12). Bootstrapped standard errors for κ are reported in parentheses.

Default probabilities. Figure 2a plots the median default probability (y-axis) in terms of the median firm rank within each credit bin (x-axis). By construction, we find that default probabilities increase with firm rank i. More interestingly, they appear to be convex in firm rankings: as discussed

[30] We use the three-month Libor rate as this is the benchmark interest rate in the lending market. We convert nominal rates to real rates using the growth of the CPI index during the year.

[31] We obtain a similar interpretation for our estimates of bank holding costs, as discussed below in footnote 34.

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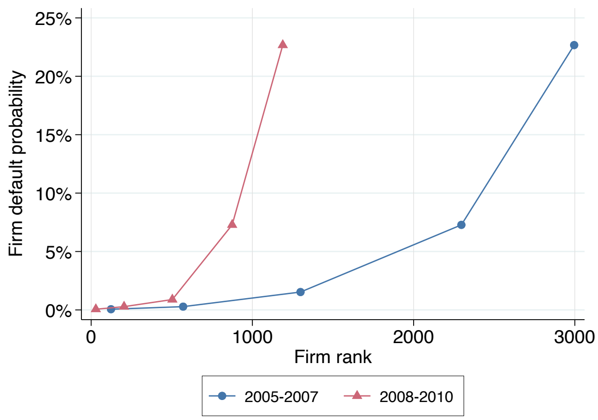
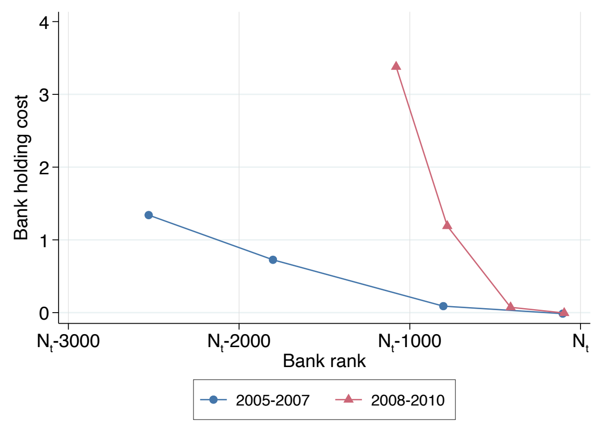


(a) Firm Default Probabilities

(b) Interest Rates

(c) Loan Revenues



(d) Bank Holding Costs

Figure 2: Model-Implied Quantities

Notes: The figures plots, for the pre-crisis and crisis periods, the median default probability δ_t^k (2a), the median loan interest rate r_t^k (2b), and the median expected loan revenue $L_t^k = (1-\delta_t^k)r_t^k$ (2c) within five credit rating bins (y-axis) as a function of the median firm rank i^k within each of these bins (x-axis). Figure 2d plots the bank holding cost κ_t^k as a function of median bank rank $j_t(i_t^k) = N_t - i_t^* + i_t^k$. See the notes of Table 3 for more details on the construction of each variable.

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in Proposition 3, this is a sufficient condition for the heterogeneity in bank holding costs to matter for the aggregate quantities under Assumption 5.

The figure also shows that the distribution of default probabilities rises more quickly during the crisis period ($t = 1$) than in the pre-crisis period ($t = 0$). We show in Appendix C.1 that this is due to two distinct effects: a change in the density of credit ratings among existing firms looking for a loan and a change in the total number of firms looking for a loan.

Interest rates. Figure 2b plots the median interest rates in terms of the median firm rank within each credit bin (x-axis). We find that interest rates rise much more sharply at $t = 1$ than at $t = 0$. This is partly driven by the fact that default probabilities rise more sharply at $t = 1$ relative to $t = 0$ as discussed above. This cannot explain everything, however, as the range of interest rates (maximum versus minimum value) is higher at $t = 1$ than at $t = 0$ (in contrast, the range of default probabilities is the same by construction).

Expected loan revenues. Figure 2c plots the expected loan revenue for each bin, computed as $L_t^k = (1 - \delta_t^k) r_t^k$. As discussed above, the value of L_t at $i = 0$ reflects the bank's cost of capital, r_{Bt}, while the value of L_t at $i = i_t^*$ reflects the firm's expected revenue from the project (net of its outside option), r_{Ft}. In the graph, we see that the value of L_t at the lowest bin, L_t^1, remains approximately constant between $t = 0$ and $t = 1$, around 2%, suggesting that the bank's cost of capital did not change much during the crisis.[32] In contrast, we find that the value of L_t at the highest bin, L_t^K, is higher at $t = 1$ than at $t = 0$. Through the lens of the model, this suggests that the expected revenue of firms' projects (net of their outside options) r_{Ft} has increased from $t = 0$ to $t = 1$. This would explain why the marginal (riskiest) firm is willing to pay more at $t = 1$ relative to $t = 0$ to access the lending market.

Bank holding costs. We then use a discretized version of Equation 9 to compute bank holding costs. More precisely, we compute bank holding costs as the ratio of the difference of loan revenues

[32]More precisely, the fact that interest rates charged to the safest firms remain constant during the time period reflects two compensating forces: the Libor rate decreased by approximately 1% in real terms, while the spread charged to safest firms increased by 1%. Hence, our results suggest a growing wedge between a bank's cost of capital (i.e., its opportunity cost of issuing a loan) and the rate at which it could get funded on the interbank market (i.e., the Libor rate).

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between two consecutive credit rating bins to the difference of their default probabilities; that is,

$$\kappa_t^k \equiv \frac{L_t^k - L_t^{k-1}}{\delta_t^k - \delta_t^{k-1}}, \tag{12}$$

where $k \in \{2, \ldots, K\}$ denotes a credit rating bin, L_t^k denotes the median loan expected value in credit rating bin k, and δ_t^k denotes its median default probabilities.[33] These "discrete" estimates of bank holding costs can be interpreted as the weighted average of banks' individual holding costs between the firm with rank i_t^{k-1} and the firm with rank i_t^k, where the weights are given by $\delta_t'[i]$.[34]

We report the estimates for κ_t^k (as well as bootstrapped standard errors) in Table 3 and Figure 2d (see Appendix C.2 for more details on what drives our estimates for κ_t^k in different bins). One key observation is that κ_t^k decreases with firm rank i_t^k. This result, which is not mechanical, is consistent with the central mechanism of our model: banks with lower holding costs lend to the riskier firms. To understand what drives this finding in the data, remember that we infer the holding cost κ_t from the gradient of the interest rates relative to the gradient of the default rate. The fact that we estimate a high κ_t at high credit rating bins comes from the fact that interest rates increase very rapidly with default risk in this region (i.e., the difference in loan interest rates between credit rating bins A and BBB is much higher than their difference in default probability). The fact that we estimate a low κ_t at low credit rating bins comes from the fact that interest rates do not increase much with default risk in this region (i.e., the difference in loan interest rates between BBB and C is small relative to their differences in default probabilities).

We now compare the estimates for κ_t^k obtained at $t = 0$ (the pre-crisis period) relative to $t = 1$ (the crisis period). We find that across each bin, κ_t^k tends to be higher at $t = 1$ relative to $t = 0$. Empirically, this comes from the fact that, as discussed above, the gradient of interest rates across credit rating bins increases at $t = 1$ relative to $t = 0$. This suggests that banks became less able to hold risk during the financial crisis.

[33] Note that because we estimate κ_t^k as the gradient of L_t^k relative to the gradient of r_t^k, we get $K - 1$ estimates for κ_t^k starting from K estimates for L_t^k and r_t^k within each period $t \in \{0, 1\}$.

[34] Indeed, we have

$$\kappa_t^k \equiv \frac{L_t^k - L_t^{k-1}}{\delta_t^k - \delta_t^{k-1}} = \frac{L_t[i_t^k] - L_t[i_t^{k-1}]}{\delta_t[i_t^k] - \delta_t[i_t^{k-1}]} = \frac{\int_{i_t^{k-1}}^{i_t^k} \delta_t'[i]\kappa_t[j_t(i)]di}{\int_{i_t^{k-1}}^{i_t^k} \delta_t'[i]di}.$$

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Overall, our results suggest that both default probabilities $\delta_t[\cdot]$ and bank holding costs $\kappa_t[\cdot]$ have declined during the crisis. We now use the model to decompose the aggregate loan volume into changes in $\delta_t[\cdot]$ and changes in $\kappa_t[\cdot]$.

4.3. Decomposing the Drop in Aggregate Loan Volume

Definitions. During a given time period, typically both firm and bank characteristics shift, and both affect the aggregate loan supply. Our framework leads to a natural decomposition of the change in loan volume between the two effects in the presence of sorting.

Formally, let $F_t \equiv (r_{Ft}, \delta_t, N_{ft})$ and $B_t \equiv (r_{Bt}, \kappa_t, N_t)$ denote the characteristics of firms and banks at time $t \in \{0, 1\}$. Let $i^*(F, B)$ denote the loan volume given a set of firms' characteristics F and a set of banks' characteristics B. In particular, $i^*(F_0, B_0)$ and $i^*(F_1, B_1)$ correspond to the aggregate loan volumes observed at time $t = 0$ and $t = 1$.

To decompose banks' and firms' impacts, we look at the counterfactual loan volume $i^*(F_1, B_0)$ (resp. $i^*(F_0, B_1)$), which represents the loan volume under pre-crisis characteristics of banks (resp. firms) but post-crisis characteristics of firms (resp. banks).

We then define the credit supply effect ϕ^S as

$$\phi^S \equiv \frac{1/2\,(i^*(F_0, B_0) - i^*(F_0, B_1)) + 1/2\,(i^*(F_1, B_0) - i^*(F_1, B_1))}{i^*(F_0, B_0) - i^*(F_1, B_1)}. \tag{13}$$

The denominator represents the total change in loan volume across periods, where both firm characteristics and bank holding costs have changed. The first (resp. second) term in the numerator is the counterfactual change in the loan volume due to the change in bank characteristics, holding firm characteristics fixed at time $t = 1$ (resp. $t = 0$). Note that these two terms generally differ as the effect of changing bank characteristics potentially depends on the set of firm characteristics. The numerator is defined as the average effect of these counterfactual changes. By definition, if all bank characteristics remain the same (i.e., $B_0 = B_1$), then $\phi^S = 0$; that is, there is no credit supply effect.

By symmetry, the credit demand effect can be defined as

$$\phi^D \equiv \frac{1/2\,(i^*(F_0, B_0) - i^*(F_1, B_0)) + 1/2\,(i^*(F_0, B_1) - i^*(F_1, B_1))}{i^*(F_0, B_0) - i^*(F_1, B_1)} = 1 - \phi^S. \tag{14}$$

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While the credit supply effect ϕ^S represents the contribution of changes in bank characteristics for aggregate loan volume, the credit demand effect ϕ^D represents the contribution of changes in firm characteristics.

Methodology. As shown in Equations (13) and (14), computing the credit demand and credit supply effects, ϕ^D and ϕ^S, requires us to compute four loan volumes: $i^*(F_0, B_0)$, $i^*(F_1, B_1)$, $i^*(F_0, B_1)$, and $i^*(F_1, B_0)$. The first two quantities correspond to the loan volumes under two actual equilibria, (F_0, B_0) and (F_1, B_1), which are directly observed at $t = 0$ and $t = 1$. In contrast, the last two quantities correspond to the loan volumes in two counterfactual worlds, (F_0, B_1) and (F_1, B_0), which are not observed.

We now discuss how we construct the aggregate loan volumes in these two counterfactual equilibria. We first use our discrete estimates for $\{\delta_t^k\}_{k=1}^K$ and $\{\kappa_t^k\}_{k=2}^K$ from Section 4.2 to specify the full (continuous) distributions $\delta_t[\cdot]$ and $\kappa_t[\cdot]$ for $t \in \{0, 1\}$. More precisely, we interpolate in between our estimates by assuming that both default probabilities and bank holding costs are piecewise linear and continuous in between the median ranks within each credit rating bin $\{i_t^k\}_{k=1}^K$. We extrapolate beyond our estimates by assuming that default probabilities for inactive firms $(i > i_t^*)$ and bank holding costs for inactive banks $(j < j_t(i_t^*))$ are equal to the default probability of the riskiest active firm $(i = i_t^*)$ and to the holding cost of the worst active bank $(j = j_t(i_t^*))$, respectively. We give more details on the construction of these distributions in Appendix C.3.

Equipped with the estimated functions $\delta_t[\cdot]$ and $\kappa_t[\cdot]$, we compute the counterfactual aggregate loan volume $i^*(F_0, B_1)$ as the number i^* solving the following equation:

$$r_{F0} - r_{B1} = \int_0^{i^*} \kappa_1 \left[N_1 - i^* + i\right] \delta_0'[i] di. \tag{15}$$

Figure 3 illustrates the construction of $i^*(F_0, B_1)$. For firm i, the figure plots its default probability at $t = 0$, $\delta_0[i]$, the holding cost of the bank it borrows from at $t = 0$, $\kappa_0[N_0 - i_0^* + i]$, and the holding cost of the bank it would borrow from if the distribution of bank characteristics shifted to the one at $t = 1$, $\kappa_1[N_1 - i^*(F_0, B_1) + i]$. Note that the distribution of bank holding costs worsens from period $t = 0$ to $t = 1$, implying that fewer firms can borrow under B_1 than under B_0; that is, $i^*(F_0, B_1) < i^*(F_0, B_0)$.

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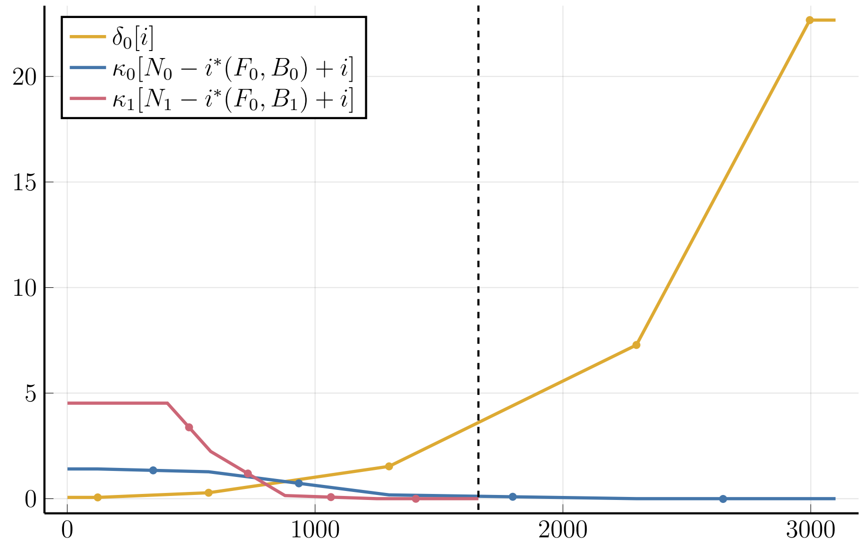

Figure 3: Actual (F_0, B_0) and Counterfactual (F_0, B_1) Equilibria

Notes: The figure plots the riskiness $\delta_0[i]$ of firm i at time $t = 0$ (orange line), the holding cost of its matching bank $\kappa_0[N_0 - i^*(F_0, B_0) + i]$ at time $t = 0$ (blue line), and the holding cost of its matching bank in the counterfactual world in which bank characteristics shift to the ones at $t = 1$; that is, $\kappa_1[N_1 - i^*(F_0, B_1) + i]$ (red line). The functions are obtained by interpolating linearly following the methodology described in Appendix C.3 (the discrete estimates from Table 3 are represented by dots). The vertical dashed line represents the counterfactual loan volume $i^*(F_0, B_1)$, computed using (15).

Similarly, we compute the counterfactual aggregate loan volume $i^*(F_1, B_0)$ as the number i^* solving the following equation:

$$r_{F1} - r_{B0} = \int_0^{i^*} \kappa_0 \left[N_0 - i^* + i\right] \delta_1'[i] di.$$

Result. As discussed above, the aggregate loan volumes under (F_0, B_0) and under (F_1, B_1) are simply given by the aggregate loan volumes at $t = 0$ and $t = 1$, which gives $i^*(F_0, B_0) = 3,100$ and $i^*(F_1, B_1) = 1,284$. After applying the methodology discussed above, we obtain that the two counterfactual aggregate loan volumes are $i^*(F_0, B_1) = 1,659$ and $i^*(F_1, B_0) = 2,187$.

Note that the improvement of banks' characteristics from B_0 to B_1 results in a lower impact under F_1 than under F_0; that is,

$$\underbrace{i^*(F_1, B_0) - i^*(F_1, B_1)}_{2{,}187-1{,}284} < \underbrace{i^*(F_0, B_0) - i^*(F_0, B_1)}_{3{,}100-1{,}659}.$$

The difference between the two numbers justifies our approach of defining the credit supply effect as the average between these two effects. Intuitively, the difference comes from the fact that a given

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improvement in credit supply has more impact when borrowing firms are safer.

Combining these estimates, we get that the credit supply effect is $\phi^S = 65\%$, while the credit demand effect is $\phi^D = 35\%$.[35] Hence, these results suggest that roughly two-thirds of the decline in loan volume is due to a decline in credit supply, while one-third is due to a decline in credit demand.

4.4. Discussion

Identifying our parameters (and disentangling between credit and demand effects) required a certain number of assumptions. We now briefly discuss the effect of relaxing these assumptions on our results and consider a few extensions of the model to make it more realistic (see Appendix C for a more thorough discussion).

Relaxing Assumptions 4 and 5. We required two specific assumptions to recover bank holding costs in the data: Assumption 4 assumed a particular recovery rate in case of default, while Assumption 5 assumed that the loan cost holding function was linear with respect to default probability. We discuss in Appendix C.4 what our estimates recover in case these assumptions are not satisfied, and we formalize the condition under which our procedure over- or under-estimates the heterogeneity of bank holding costs in the data.

Loan characteristics. In the baseline model, all loans have the same structure. In reality, loans differ with respect to their amounts, maturities, and other characteristics (e.g., type and purpose). To account for this heterogeneity, we re-estimate bank holding costs κ after controlling for loan interest rates for a set of loan characteristics available in DealScan. As discussed in Section C.4.3, we find that controlling for this set of characteristics does not change our results quantitatively.

Many-to-many matching. Our baseline model focuses on one-to-one matching. However, it can also be directly extended to an environment with many-to-many relationships, provided that profits are separable with respect to different loans.

[35] More precisely, substituting our estimates for $i^*(F_0, B_0)$, $i^*(F_0, B_1)$, $i^*(F_1, B_0)$, and $i^*(F_1, B_1)$ in Equation (13) gives

$$\phi^S = \frac{1/2\,(3,100 - 1,659) + 1/2\,(2,187 - 1,284)}{3,100 - 1,284} \approx 65\%.$$

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Assume that each bank j has $m(j)$ measure of managers, where each manager can lend 1 to a firm. Managers make their loan decisions separately but share the same bank-specific risk capacity $\kappa[j]$. Each firm i, on the other hand, has $l(i)$. Projects have the same independent payoffs but share the same firm-specific default probability $\delta[i]$. The baseline model can then be reinterpreted as matching between each manager and each project. The only difference is that the underlying distribution of κ and δ accounts for the capacity distribution $m(j)$ and $l(i)$: specifically, the measure of projects with a default probability lower than $\delta[i]$ is $\int_0^i l(\tilde{i})d\tilde{i}$, while the measure of managers with a holding cost higher than $\kappa[j]$ is $\int_0^j m(\tilde{j})d\tilde{j}$.

Matching frictions. Our baseline model assumes frictionless matching. In reality, there is suggestive evidence that the reallocation of firms to banks takes time after a shock to the financial sector. Along these lines, Ivashina and Scharfstein (2010) and Chodorow-Reich (2013) document that firms borrowing from banks exposed to the securitization markets were more likely to exit the lending market during the Great Recession.[36]

We now discuss what would happen if the reallocation of firms to banks takes time between $t = 0$ and $t = 1$. When their banks are hit, we assume that firms can only rematch with probability $\lambda \in [0, 1]$. With probability $1 - \lambda$, these firms lose access to refinancing. In general, we refer to hit banks as the ones with extremely high holding costs and are thus no longer active. This specification captures that $1 - \lambda$ of these firms lose their loans whenever their borrowing banks are hit. In other words, some safer firms that could have refinanced are now exogenously removed out of the market due to the sticky relationship.[37]

This notion of sticky relationships effectively makes surviving firms riskier since an inflow of infra-marginal firms will try to replace the firms removed from the lending market. Nevertheless, conditional on firms that can reallocate or rematch, the equilibrium characterization and thus our methodology remains the same. In particular, given that firms' riskiness is observable, our estimate of the bank holding cost distribution remains the same. In other words, since sticky relationships

[36] Note, however, that this empirical fact could be rationalized by our frictionless model since in our model these firms are riskier to begin with. On a related note, our sorting model can also rationalize why the same firms keep borrowing from the same banks even though this empirical fact is often interpreted in the literature as evidence of frictions (e.g., Chodorow-Reich, 2013).

[37] For simplicity, we further assume that all the shocks here are unexpected. One could extend the model for expected shocks. In the case that the types and shocks are i.i.d, the matching outcome remains the same. More generally, the specification of shocks and persistence of types could, however, then affect the matching outcomes as what matters is the expected surplus of the relationship.

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will effectively decrease the demand for lending at $t = 1$, it will be part of our credit demand effect.

5. Conclusion

We show in this paper that in the years before the Great Recessions, investment banks were lending to riskier firms. We find that this sorting arises naturally in a competitive matching model of a credit market where banks with low holding costs lend to risky firms. We also find that this sorting affects the overall loan volume as well as its response to credit supply shocks. We then use our model to assess the importance of a shift in the distribution of credit supply. We implement our approach using available data on loan interest rates and historical default rates from credit ratings.

Our model can be applied to other time periods and markets. For instance, in Online Appendix G, we find that bank holding costs are lower in the 2002–2004 period than the pre-2000s period, consistent with the rise of the securitization market in the 2000s. Finally, while we focus on the bank lending market, our model could also be applied to the market for private equity or venture capital. In particular, one could use a similar methodology to decompose the well-documented time-series fluctuations of funding in these markets into supply versus demand effects.

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Appendices

A. Appendix for Section 2

This appendix contains a set of tables that complement our empirical results discussed in Section 2. Table A1 reports the mapping between S&P letter ratings and the corresponding (historical) default rates over the 1981–2008 period. Table A2 reports summary statistics for loans (DealScan "facilities") and banks over the pre-crisis period (i.e., from January 2005 to June 2007). Table A3 reports the cross-correlation between our three measures of firm riskiness; they range between 0.28 and 0.5. We also report the "rank" correlation, which compares the ranking of firms with respect to each of these three measures, and they range between 0.5 and 0.71.

Similarly, Table A4 reports the cross-correlation of bank characteristics. All the characteristics are related but not perfectly so, as they capture different aspects of bank lending policy. Table A5 reports the result of regressing each of our three measures of firm riskiness on a set of firm and loan characteristics. The table shows, for instance, that smaller firms tend to have a higher loan spread and a higher probability of default.

Table A1: Mapping between S&P Ratings and Default Probabilities

S&P Rating	NAIC Designation	Default Probability
AAA	1	0.00
AA+	1	0.00
AA	1	0.02
AA-	1	0.03
A+	1	0.05
A	1	0.06
A-	1	0.08
BBB+	2	0.16
BBB	2	0.28
BBB-	2	0.28
BB+	3	0.68
BB	3	0.89
BB-	3	1.53
B+	4	2.44
B	4	7.28
B-	4	9.97
CCC to C	5	22.67

Notes: This table reports the yearly default rate (in percentage) within each S&P credit rating over the 1981–2008 period. Data are from "Understanding S&P Global Ratings' Rating Definitions," June 3, 2009.

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Table A2: Summary Statistics

Variable	Count	Mean	S.D.	p10	p50	p90
Panel A: Loans						
Number of lead arrangers	14,966	1.30	0.49	1.00	1.00	2.00
Loan maturity (Years)	14,286	4.47	1.86	1.83	5.00	7.00
Loan amount	14,966	0.26	0.65	0.01	0.09	0.60
Loan spread	12,782	2.29	1.51	0.62	2.00	3.75
Firm default probability (S&P)	3,127	3.05	4.46	0.16	1.53	7.28
Firm default probability (BSM)	3,855	2.52	12.46	0.00	0.00	0.16
Firm sales	9,216	5.27	47.79	0.07	0.60	7.70
Panel B: Banks						
Bank lending growth	43	-0.52	0.30	-0.87	-0.59	-0.07
Bank Lehman distance	42	0.01	0.01	0.00	0.01	0.02
Bank deposit to asset ratio	43	0.42	0.25	0.03	0.47	0.68
Bank securitization intensity	20	0.05	0.06	0.01	0.04	0.14
Investment bank dummy	43	0.51	0.51	0.00	1.00	1.00

Notes: Panel A reports summary statistics on loans (DealScan "facilities") issued from January 2005 to June 2007. Loan maturity is in years, and loan amount and firm sales are in billions of dollars. Loan spread, firm default, probabilities are in percentages. Panel B reports bank-level characteristics over the same time period.

Table A3: Correlation between Measures of Firm Riskiness

Variables	Loan Spread	Default Prob. (S&P)	Default Prob. (BSM)
Panel A: Pearson's Correlation			
Loan spread	1.00		
Default probability (S&P)	0.45	1.00	
Default probability (BSM)	0.28	0.48	1.00
Panel B: Spearman's Rank Correlation			
Loan spread	1.00		
Default probability (S&P)	0.71	1.00	
Default probability (BSM)	0.50	0.59	1.00

Notes: This table reports cross-correlation between our three measures of firm riskiness. Panel A reports the standard Pearson's product-moment correlation, that is, the ratio between the covariance and the squared product of variances. Panel B reports the Spearman's rank correlation, that is, the ratio between the covariance of ranks and the squared product of their variances.

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Table A4: Correlation between Bank Characteristics

Variables	Lending Growth	Lehman Distance	Deposit Ratio	CLO Intensity
Panel A: Pearson's Correlation				
Lending growth	1.00			
Lehman distance	0.39	1.00		
Deposit ratio	0.47	0.58	1.00	
CLO intensity	−0.56	−0.80	−0.70	1.00
Panel B: Spearman's Rank Correlation				
Lending growth	1.00			
Lehman distance	0.42	1.00		
Deposit ratio	0.49	0.56	1.00	
CLO intensity	−0.65	−0.83	−0.81	1.00

Notes: This table reports cross-correlation between bank characteristics. Panel A reports the standard Pearson's product-moment correlation, that is, the ratio between the covariance and the squared product of variances. Panel B reports the Spearman's rank correlation, that is, the ratio between the covariance of ranks and the squared product of their variances.

Table A5: Relationship between Firm Characteristics and Firm Riskiness

	Loan Spread	Default Probability (S&P)	Default Probability (BSM)
	(1)	(2)	(3)
Log sales	0.18*	−1.83	−7.63
	(1.88)	(−0.92)	(−1.20)
Log sales^2	−0.01***	0.03	0.17
	(−4.69)	(0.59)	(1.11)
Loan maturity (Years)	−0.06***	−0.28	0.46
	(−2.88)	(−1.29)	(0.81)
Loan maturity^2 (Years)	0.01***	0.00	−0.07
	(4.58)	(0.09)	(−0.93)
Industry (F-stat)	10***	5,886***	666***
Loan purpose (F-stat)	51***	1***	2**
Loan type (F-stat)	380***	6***	5***
R^2 (within)	0.34	0.22	0.16
N Loans	7906	2709	3501
N Banks	42	38	43

Notes: This table estimates the model

$$X_i = \xi_{j(i)} + b_1 \times \log(\text{Sale}_i) + b_2 \times \log(\text{Sale}_i)^2 + \delta_{\text{industry}_i} + \gamma_{\text{loan purpose}_i} + \zeta_{\text{loan type}_i} + + c_1 \times \text{Loan Maturity}_i + c_2 \times \text{Loan Maturity}_i^2 + e_i,$$

where X_i is alternatively the interest rate on the loan (column (1)), the probability of default implied by the firm's S&P rating (column (2)), or the probability of default implied by the model of Bharath and Shumway (2008) (column (3)). Industry is measured using two-digit SIC codes. The row R^2 (within) reports the R^2 of the regression net of the bank fixed effects. Estimation is done with OLS, and t-statistics, estimated using standard errors clustered at the bank and firm level, are in parentheses.

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B. Appendix for Section 3

B.1. Proofs

Proof of Proposition 1. From Equation (4), by monotone comparative statics, if $C_{12}(i,j) < 0$, then $j(i)$ increases with i. That is, a higher j (bank with a lower holding cost) will choose a higher i (riskier firms). Hence, given any marginal type i^*, the market-clearing condition thus implies that $j(i) = N - i^* + i$, where the riskiest firm is matched with the best bank $j(i^*) = N$. Last, given any equilibrium profit $U(i)$ and matching outcome $j(i)$, it must satisfy Equation (5), which is the first-order condition from banks' optimization problem. □

Proof of Proposition 2. Let i_0^* be the loan supply at $t = 0$ (under κ_0) and i_1^* be the loan supply at $t = 1$ (under κ_1). Market clearing at $t = 0$ implies

$$r_F - r_B = \int_0^{i_0^*} c_\delta(\delta[i], \kappa_0[j(i)])\delta'[i]di.$$

The fact that $\kappa_0[j] \leq \kappa_1[j]$ gives

$$r_F - r_B \leq \int_0^{i_0^*} c_\delta(\delta[i], \kappa_1[j(i)])\delta'[i]di$$

since $c_\kappa \geq 0$ and $c_{\delta\kappa} \geq 0$.

Since $i^* \to \int_0^{i^*} c_\delta(\delta[i], \kappa_1[j(i)])\delta'[i]di$ is an increasing function, we get that $i_1^* \leq i_0^*$. Therefore, total loan volume decreases when banks are worse at holding risk. A similar derivation would give that total loan volume decreases when firms are riskier or when $r_F - r_B$ is higher. □

Proof of Proposition 3. Market clearing at $t = 0$ implies

$$\begin{aligned} r_F - r_B &= \int_0^{i_0^*} \frac{dv(\delta[i])}{di}\kappa_0[j(i)]di \\ &= \int_0^{i_0^*} \frac{dv(\delta[i])}{di} d\left(\int_{i_0^*}^{i} \kappa_0[j(i')]di'\right). \end{aligned}$$

Integrating by parts gives

$$\begin{aligned} r_F - r_B &= -\frac{dv(\delta[i])}{di}\Big|_{i=0} \int_{i_0^*}^{0} \kappa_0[j(i')]di' - \int_0^{i_0^*} \frac{d^2v(\delta[i])}{di^2}\left(\int_{i_0^*}^{i} \kappa_0[j(i')]di'\right) di \\ &= \frac{dv(\delta[i])}{di}\Big|_{i=0} \int_0^{i_0^*} \kappa_0[j(i')]di' + \int_0^{i_0^*} \frac{d^2v(\delta[i])}{di^2}\left(\int_{i}^{i_0^*} \kappa_0[j(i')]di'\right) di \\ &= \frac{dv(\delta[i])}{di}\Big|_{i=0} \int_{N-i_0^*}^{N} \kappa_0[j]dj + \int_0^{i_0^*} \frac{d^2v(\delta[i])}{di^2}\left(\int_{N-i_0^*+i}^{N} \kappa_0[j]dj\right) di. \end{aligned}$$

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Note that we have both $\frac{dv(\delta[i])}{di}\Big|_{i=0} \geq 0$ and $\frac{d^2v(\delta[i])}{di^2} \geq 0$.

The assumption that $\int_n^N \kappa_0[j]dj \leq \int_n^N \kappa_1[j]dj$ for $n \in [N - i_0^*, N]$ gives:

$$r_F - r_B \leq \frac{dv(\delta[i])}{di}\Big|_{i=0} \int_{N-i_0^*}^{N} \kappa_1[j]dj + \int_0^{i_0^*} \frac{d^2v(\delta[i])}{di^2} \left(\int_{N-i_0^*+i}^{N} \kappa_1[j]dj \right) di.$$

Integrating by parts gives:

$$r_F - r_B \leq \int_0^{i_0^*} \frac{dv(\delta[i])}{di} \kappa_1[j(i)]di.$$

As in Proposition 3, this allows us to conclude that $i_1^* \leq i_0^*$; that is, total loan volume decreases when the distribution of bank holding costs becomes less spread out. □

C. Appendix for Section 4

C.1. Decomposing the Change in Default Probabilities

As discussed in Section 4.2, the change in the default probability function $\delta[\cdot]$ between $t = 0$ and $t = 1$ could be driven by two distinct forces: a change in the density of default probabilities within these firms between $t = 0$ and $t = 1$ (a change in credit quality) and a change in the total number of firms looking for a loan (a change in credit quantity).

To see this formally, note that we have $\delta_t[i] = F_t^{-1}(i/N_t^f)$, where $F_t(\cdot)$ denotes the cumulative distribution function of default probabilities at time t and N_t^f denotes the number of firms looking for a loan at time t. This equation suggests that changes in $\delta[\cdot]$ can be decomposed into a term due to changes in $F_t(\cdot)$ and changes in N_t^f as follows:

$$\begin{aligned} \delta_1[i] - \delta_0[i] &= F_1^{-1}\left(\frac{i}{N_1^f}\right) - F_0^{-1}\left(\frac{i}{N_0^f}\right) \\ &= \underbrace{F_1^{-1}\left(\frac{i}{N_0^f}\right) - F_0^{-1}\left(\frac{i}{N_0^f}\right)}_{\text{Change in Credit Quality}} + \underbrace{F_1^{-1}\left(\frac{i}{N_1^f}\right) - F_1^{-1}\left(\frac{i}{N_0^f}\right)}_{\text{Change in Credit Quantity}}. \end{aligned} \tag{16}$$

The first term corresponds to the effect of the change in $F_t(\cdot)$ (credit quality), while the second term corresponds to the effect of the change in N_t^f (credit quantity). This accounting framework decomposes the change in $\delta_t[\cdot]$ into these two effects by introducing an intermediate quantity, $F_1^{-1}(i/N_0^f)$, which corresponds to the counterfactual $\delta_1[\cdot]$ if the only thing that changed between $t = 0$ and $t = 1$ was the density of credit rating for firms looking for loans (i.e., a change in $F_t(\cdot)$ holding fixed N_t^f). However, this counterfactual function is hard to construct as we do not observe N_t^f, the total number of firms looking for a loan (as we do not observe firms that do not get a match).

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We now present a potential way to implement this decomposition. The idea is use as a proxy for $F_1^{-1}\left(i/N_0^f\right)$ the ranking function of default probabilities at time $t=1$ of firms borrowing at $t=0$. This approach recovers $F_1^{-1}\left(i/N_0^f\right)$ under the assumption that the density of default probabilities in the set of firms looking for loans at time 1 is the same as the density of default probabilities at $t=1$ for firms looking to borrow at time $t=0$ (and that no firm experiences an improvement in credit between $t=0$ and $t=1$).

Figure A1 plots the result. The blue line plots $\delta_0[\cdot]$, while the red line plots $\delta_1[\cdot]$ (as in Figure 2a). The key difference is the addition of a dashed blue line, which corresponds to the default probabilities at $t=1$ of firms that were borrowing at $t=0$, that is, our proxy for $F_1^{-1}\left(i/N_0^f\right)$. Under the two assumptions discussed above, the gap between the dashed blue line and the solid blue line reflects the effect of the change in credit quality (i.e., the first term in (16)), while the difference between the blue dashed line and the red line corresponds to the effect of the change in credit quantity (i.e., the second term in (16)).

Visually, we find that both effects play a role. Still, there is a larger gap between the dashed blue line and the solid red line than between the dashed blue line and the solid blue line. This observation suggests that the drop in credit quantity plays a larger role than the worsening of credit quality in explaining the overall change in the observed default probabilities between $t=0$ and $t=1$.

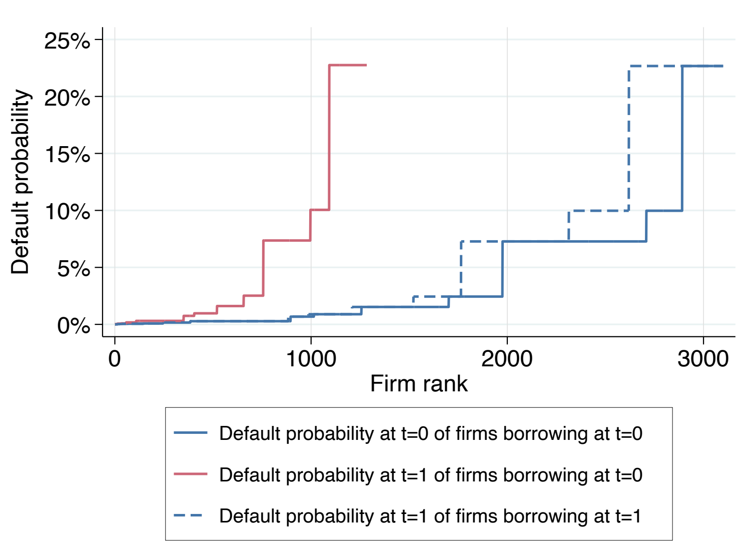

Figure A1: Decomposing the Change in Default Probabilities

C.2. Decomposing Our Identification of Bank Holding Costs

We now provide more details about what drives our identification for $\{\kappa_t^k\}_{k=2}^K$ for $t\in\{0,1\}$. We start by decomposing the difference in loan revenue across two consecutive credit rating bins, $L_t^k - L_t^{k-1}$. As in footnote 28, the difference in L_t^k can be decomposed into a term due to the

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difference in interest rates and a term due to the differences in default probabilities:

$$\begin{aligned}\underbrace{L_t^k - L_t^{k-1}}_{\Delta L_t} &= (1-\delta_t^k)r_t^k - (1-\delta_t^{k-1})r_t^{k-1} \\ &= \underbrace{(1-\delta_t^k)(r_t^k - r_t^{k-1})}_{(1-\delta_t)\Delta r_t} \quad \underbrace{-r_t^{k-1}(\delta_t^k - \delta_t^{k-1})}_{-r_t\Delta\delta_t}. \end{aligned} \tag{17}$$

In other words, the difference in the revenue of a loan between two credit rating bins is the sum of two terms: the first term corresponds to the higher payoff if the firm does not default, while the second term corresponds to the higher default probability times the foregone revenue if the firm defaults.

Dividing Equation (17) by the difference in default probabilities gives us a corresponding decomposition for κ_t^k:

$$\begin{aligned}\kappa_t^k &\equiv \frac{L_t^k - L_t^{k-1}}{\delta_t^k - \delta_t^{k-1}} \\ &= \underbrace{(1-\delta_t^k)\frac{r_t^k - r_t^{k-1}}{\delta_t^k - \delta_t^{k-1}}}_{(1-\delta_t)\Delta r_t/\Delta\delta_t} \quad \underbrace{-r_t^{k-1}}_{-r_t}. \end{aligned} \tag{18}$$

We report all of these decompositions at time $t \in \{0,1\}$ in Table A6. Overall, we find that most of our inference on bank holding costs is driven by the first term, that is, by the gradient of interest rates with respect to default probabilities.

C.3. Constructing the Counterfactual

We now describe how we construct the full (continuous) distributions $\delta_t[\cdot]$ and $\kappa_t[\cdot]$ from the discrete set of estimates $\{\delta_t^k\}_{k=1}^K$ and $\{\kappa_t^k\}_{k=2}^K$ estimated in Section 4.2. We assume the default probability function $\delta_t[\cdot]$ is piecewise linear in between $\{0, i_t^1, i_t^2, \ldots, i_t^K, N_t^f\}$, where i_t^k denotes the median rank in bin k at time t. Hence, the function $\delta_t[\cdot]$ is obtained by interpolating linearly between the points $\delta_t[0] = 0, \delta_t[i_t^1] = \delta_t^1, \ldots, \delta[i_t^K] = \delta_t^K$, where δ_t^k denotes the median firm default probability in bin k at time t. Finally, we assume that $\delta_t[i] = \delta_t^K$ for $i > i^K$.

Similarly, we assume that the bank holding cost function $\kappa_t[\cdot]$ is piecewise linear in between $\{0, j_t(i_t^1), j_t(i_t^2), \ldots, j_t(i_t^K), N_t\}$. Under this assumption, our discretized estimate κ_t^k can be seen as the average bank holding cost between i_t^{k-1} and i_t^k; that is,[38]

$$\kappa_t^k = \frac{\kappa_t[j_t(i_t^{k-1})] + \kappa_t[j_t(i_t^k)]}{2} \quad \text{for } 2 \le k \le K. \tag{19}$$

Empirically, as seen in the last column of Table 3, we find that $\kappa_t^K = 0$ for $t \in \{0,1\}$. A natural

[38] This is a special case of the result discussed in footnote 34.

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Table A6: Details on Estimating Bank Holding Costs by Credit Rating Groups

	Rating Groups				
	AAA-A	BBB	BB	B	CCC-C
Panel A: Pre-Crisis (2005-2007)					
$\delta^k - \delta^{k-1}$		0.22	1.25	5.75	15.39
$r^k - r^{k-1}$		0.30	0.95	0.75	0.50
$L^k - L^{k-1}$		0.29	0.91	0.51	-0.21
First term $(1-\delta^k)(r^k - r^{k-1})$		0.30	0.94	0.70	0.39
Second term $-r^{k-1}(\delta^k - \delta^{k-1})$		0.00	-0.03	-0.18	-0.60
$\kappa^k = (L^k - L^{k-1})/(\delta^k - \delta^{k-1})$		1.34	0.73	0.09	-0.01
First term $(1-\delta^k)(r^k - r^{k-1})/(\delta^k - \delta^{k-1})$		1.36	0.75	0.12	0.03
Second term $-r^{k-1}$		-0.02	-0.02	-0.03	-0.04
Panel B: Crisis (2008-2010)					
$\delta^k - \delta^{k-1}$		0.22	0.61	6.39	15.39
$r^k - r^{k-1}$		0.75	0.75	0.75	0.75
$L^k - L^{k-1}$		0.74	0.73	0.47	-0.08
First term $(1-\delta^k)(r^k - r^{k-1})$		0.75	0.74	0.70	0.58
Second term $-r^{k-1}(\delta^k - \delta^{k-1})$		0.00	-0.02	-0.22	-0.66
$\kappa^k = (L^k - L^{k-1})/(\delta^k - \delta^{k-1})$		3.38	1.19	0.07	0.00
First term $(1-\delta^k)(r^k - r^{k-1})/(\delta^k - \delta^{k-1})$		3.40	1.22	0.11	0.04
Second term $-r^{k-1}$		-0.02	-0.03	-0.04	-0.04

Notes: The table completes Table 3 in the main text by computing intermediary quantities used to compute the sequence of bank holding costs $\{\kappa_t^k\}_{k=2}^{\infty}$. Panel A reports these estimates during the pre-crisis period (first quarter of 2005 to second quarter of 2007), while Panel B reports these estimates during the crisis period (third quarter of 2008 to fourth quarter of 2010). Within each panel, the first row reports the gradient of default probabilities $\delta_t^k - \delta_t^{k-1}$, where δ_t^k denotes the median default probability in bin k at time t. The second row reports the gradient of interest rates $r_t^k - r_t^{k-1}$, where r_t^k denotes the median interest rate in bin k at time t. The next three rows report the gradient of loan revenue, $L_t^k - L_t^{k-1}$, where $L_t^k = (1-\delta_t^k)r_t^k$ denotes the loan revenue in bin k at time t as well as its decomposition into two terms: $(1-\delta_t^k)(r_t^k - r_t^{k-1})$ and $-r_t^{k-1}(\delta_t^k - \delta_t^{k-1})$, as defined in Equation (17). Finally, the remaining three rows report the estimated bank holding costs, $\kappa_t^k = (L_t^k - L_t^{k-1})/(\delta_t^k - \delta_t^{k-1})$, as well as its decomposition into two terms: $(1-\delta_t^k)(r_t^k - r_t^{k-1})/(\delta_t^k - \delta_t^{k-1})$ and $-r_t^{k-1}$, as defined in Equation (18).

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assumption is that bank holding costs are (weakly) positive. Combined with the fact that the function $\kappa_t[\cdot]$ is (weakly) decreasing in j, this allows us to conclude that $\kappa_t[j] = 0$ for $j \geq j(i_t^{K-1})$. We then use Equation (19) to solve for $\kappa_t[j_t(i^k)]$ recursively from $k = K-2$ to $k = 1$. Interpolating linearly between these points gives us the full (continuous) distribution $\kappa_t[\cdot]$ from $j_t(i_t^1)$ to N_t. Finally, we assume that $\kappa_t[\cdot]$ is constant between $j = 0$ and $j = j_t(i_t^1)$; that is, $\kappa_t[j] = \kappa_t[j_t(i_t^1)]$ for $0 \leq j \leq j_t(i^1)$. This is a conservative assumption on bank holding costs for $j \leq j_t(i^1)$ as $\kappa_t[\cdot]$ is (weakly) decreasing in j.

C.4. Extensions

C.4.1. Relaxing Assumption 4

Assumption 4 assumes that firms repay the principal in case of default; that is, $\underline{r}_F[i] = 0$. Yet in practice, collateral requirements and liquidation payoffs vary, with some loans unsecured, some secured by cash flows, and others secured by assets. We now discuss how our estimates will change by allowing a more general repayment; that is, $\underline{r}_F[i] = f(\delta[i])$.

In this case, loan expected revenue $L[\cdot]$ is

$$L[i] = (1 - \delta[i])r[i] + \delta[i]f(\delta[i]),$$

where the first term, $\hat{L}[i] = 1 - \delta[i])r[i]$, corresponds to our baseline estimate. Hence, bank holding cost $\kappa[\cdot]$ is

$$\kappa[j(i)] = \frac{L'[i]}{\delta'[i]} = \frac{\hat{L}'[i]}{\delta'[i]} + f(\delta[i]) + \delta[i]f'(\delta[i]), \tag{20}$$

where the first term, $\hat{\kappa}[j] \equiv \frac{\hat{L}'[i]}{\delta'[i]}$, corresponds to our baseline estimate. Hence, a different estimate for the recovery rate would translate of our estimates for κ.

Consider, in particular, the case in which $f(\cdot)$ is constant (i.e., the recovery rate across is the same across all firms). In this case, the true $\kappa[\cdot]$ is simply a translation of our estimated κ. In particular, the difference in our baseline estimates between $t = 0$ and $t = 1$ still recovers the actual change in $\kappa[\cdot]$ between the two periods.

More generally, consider the case $f(\delta) = -\ell\delta^\phi$ with $\phi \geq 0$. In this case, $f(\delta[i]) + \delta[i]f'(\delta[i]) = -\ell(1+\phi)\delta^\phi$, and so Equation (20) implies

$$\kappa_1[j] - \kappa_0[j] = \hat{\kappa}_1[j] - \hat{\kappa}_0[j] - \ell(1+\phi)\left(\delta_1[i_1(j)]^\phi - \delta_0[i_0(j)]^\phi\right).$$

The first term corresponds to our baseline-estimated change in bank holding cost. The second term depends on the change in the recovery rate of the loan across periods and is driven by two forces: the change in firm default probabilities $\delta_t[\cdot]$ and the change in the matching function $i_t(j)$.

From Figure 2, $\delta_0[i_0(j)] = \delta_0[j - N_0 + i_0^*]$ is given by the blue line in Figure 2(a), and $\delta_1[i_1(j)] = \delta_1[j - N_1 + i_1^*]$ can be understood as a parallel shift of the red line to the right by $(i_0^* - i_1^*)$. Thus,

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one can see that, empirically, banks at the top of the distribution remain effectively matched with the same type of firms. For example, the highest ranked bank is lending to $\delta_1[i_1^*]$ ($\delta_2[i_2^*]$) before (after) crisis, and thus $\delta_1[i_1(j)] \approx \delta_0[i_0(j)]$. On the other hand, banks (conditional on being active) at the lower ranks are essentially lending to the safer firms. For example, the marginal bank at period 1 (i.e., $N_1 - j = i_1^*$) is matched to $\delta_0[i_0^* - i_1^*]$ (and $\delta_1[0]$) before (after) crisis. In other words, they are effectively lending to weakly safer firms at $t = 1$; that is, $\delta_1[i_1(j)] \leq \delta_0[i_0(j)]$.

Overall, this discussion suggests that when $\phi > 0$, we accurately recover the change in bank holding costs at the top of the distribution, but we underestimate the change in holding costs for the banks at bottom, as the default probability of their matching firms effectively decreased during the crisis.

C.4.2. Relaxing Assumption 5

In Assumption 4, we assumed that the cost holding function was separable in default probability δ and bank holding cost κ; that is, $c(\delta, \kappa) = v(\delta)\kappa$. To map our model to the data, we had to strengthen this assumption by assuming that the cost holding function was linear in default probability; that is, $v(\delta) = \delta$. We now discuss how our estimates change if the linearity assumption (Assumption 5) is not satisfied.

Under this more general assumption, our baseline estimate for κ, denoted $\hat{\kappa}$, actually identifies

$$\hat{\kappa}[j(i)] = \frac{L'[i]}{\delta'[i]} = v'(\delta[i])\kappa[j(i)].$$

If v is convex ($v'(\delta[i])$ is high when $\kappa[j(i)]$ is low), our linearity assumption would lead us to underestimate the heterogeneity in κ. Symmetrically, if v is concave ($v'(\delta[i])$ is low when $\kappa[j(i)]$ is low), our linearity assumption would lead us to overestimate the heterogeneity in κ.

Note, however, that taking the ratio of our estimated κ^k reported in Table 3 between $t = 1$ and $t = 0$ does correctly recover the ratio of actual κ between $t = 0$ and $t = 1$. Indeed, for a given default probability δ^k, denote i_t^k the ranking of a firm with a default probability δ^k at time t. We have

$$\frac{\hat{\kappa}_1[j(i_1^k)]}{\hat{\kappa}_0[j(i_0^k)]} = \frac{L_1'[i_1^k]/\delta_1'[i_1^k]}{L'[i_0^k]/\delta'[i_0^k]} = \frac{v'(\delta[i_1^k])\kappa[j(i_1^k)]}{v'(\delta[i_0^k])\kappa[j(i_0^k)]} = \frac{\kappa_1[j(i_1^k)]}{\kappa_0[j(i_0^k)]}$$

since $\delta[i_0^k] = \delta[i_1^k] = \delta^k$.

C.4.3. Adjusting for Loan Characteristics

In the baseline model, all loans have the same structure. However, in reality, loans differ with respect to their amounts, maturities, and other characteristics. To account for this heterogeneity, we now re-conduct our model estimation after controlling for loan interest rates with respect to these loan characteristics.

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More precisely, similarly to Section 2, we residualize interest rates with respect to loan characteristics by running regressions of the form

$$r_i = \xi_{kt} + b_1 \times \log(\text{Loan Amount}_i) + b_2 \times \log(\text{Loan Amount}_i)^2 + \delta_{\text{industry}_i} + \gamma_{\text{loan purpose}_i} + \zeta_{\text{loan type}_i} + \\ + c_1 \times \text{Loan Maturity}_i + c_2 \times \text{Loan Maturity}_i^2 + e_i,$$

where i denotes a loan, k denotes its credit rating, and t denotes the period it was issued. Note that the specification includes credit rating bins times period fixed effects (ξ_{kt}), meaning that we purely estimate the effect of loan characteristics on interest rates *within each credit rating and period bin.* Our measure of residualized interest rates is then $\hat{\xi}_{kt} + \hat{e}_i + \overline{r_i}$, where $\overline{r_i}$ denotes the average interest rate in our sample. It can be seen as the interest rate loan i would get if its characteristic were the same as the average characteristic in our sample.

Table A7 reports the median residualized interest rate within each credit rating bin. Following the same methodology as the one described in Section 4.2, the table also reports associated loan expected revenue, L, and bank holding cost, κ, both computed using residualized interest rates. In particular, κ is now estimated from the gradient of loan expected revenue between two consecutive credit rating bins *holding constant loan characteristics across the two bins* relative to the gradient of default probabilities.

Figure A2 plots the obtained estimates for r and κ and compares them with the ones obtained with un-realized interest rates (i.e., the baseline estimates plotted in Figure 2). The two plots are similar—the key difference is that the slope of the residualized interest rates with respect to default probabilities is a bit smaller at $t = 0$, and, accordingly, the distribution of bank holding costs is a bit lower. Overall, these results suggest that our estimates for κ are robust to controlling for different loan characteristics.

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Table A7: Estimates for r, L, and κ after Controlling for Loan Characteristics

	Rating Groups				
	AAA-A	BBB	BB	B	CCC-C
Panel A: 2005-2007					
Number of loans	244	647	799	1,159	204
Median firm rank i^k	122	568	1,291	2,270	2,951
Median default probability δ^k	0.06	0.28	1.53	7.28	22.67
Median interest rate r^k	2.36	2.60	3.22	3.75	4.25
Expected loan revenue $L = (1 - \delta^k)r^k$	2.36	2.60	3.17	3.48	3.29
Bank holding cost $\kappa^k = (L^k - L^{k-1})/(\delta^k - \delta^{k-1})$		1.06	0.46	0.05	-0.01
		(0.03)	(0.00)	(0.00)	(0.00)
Panel B: 2008-2010					
Number of loans	57	291	304	430	189
Median firm rank i^k	29	203	500	867	1,177
Median default probability δ^k	0.06	0.28	0.89	7.28	22.67
Median interest rate r^k	2.26	3.08	3.59	4.29	4.94
Expected loan revenue $L = (1 - \delta^k)r^k$	2.26	3.07	3.56	3.98	3.82
Bank holding cost $\kappa^k = (L^k - L^{k-1})/(\delta^k - \delta^{k-1})$		3.71	0.80	0.07	-0.01
		(1.07)	(0.26)	(0.02)	(0.01)

Notes: The table reports the number of loans, the median firm rank i_t^k, the median default probability δ_t^k, the median *residualized* loan interest rate r_t^k, and the median residualized expected loan revenue L_t^k within five credit rating bins corresponding to NAIC ratings from 1 to 5. Panel A reports these estimates during the pre-crisis period $t = 0$ (first quarter of 2005 to second quarter of 2007), while Panel B reports these estimates during the crisis period $t = 1$ (third quarter of 2008 to fourth quarter of 2010).

Firm default probability is estimated using its S&P credit ratings at loan issuance (using mapping between letter ratings and implied default probabilities reported in Table A1). To construct residualized interest rates (i.e., interest rates adjusted for firm and loan characteristics), we first run a regression on the loan spread on firm and loan characteristics in these two periods:

$$\text{spread}_{it} = a + b_1 \times \log(\text{Sale}_{it}) + b_2 \times \log(\text{Sale}_i)^2 + \delta_{\text{industry}_{it}} + \gamma_{\text{loan purpose}_{it}} + \zeta_{\text{loan type}_{it}} + + c_1 \times \text{Loan Maturity}_{it} + c_2 \times \text{Loan Maturity}_{it}^2 + e_{it},$$

where i denotes a firm borrowing at time t (we use the same set of firm and loan characteristics as in (2)). We then construct residualized loan spreads as $\overline{\text{spread}}_i + \hat{e}_i$, where $\overline{\text{spread}}_i$ corresponds to the mean of spreads in our sample and $\hat{e}_i$ corresponds to the residuals estimated in the regression above. We finally get the interest rate by adding the Libor rate at loan issuance. We then construct the residualized loan revenue as $(1 - \delta)r$, where r denotes the residualized interest rate. Note that the sample size is slightly smaller than that in Table OA3 in the Online Appendix since we focus on loans where none of the controls are missing.

Finally, the last two rows of each panel reports the estimated bank holding cost as well as its standard error. The estimated bank holding cost in credit bin k is estimated as the ratio between ΔL (the difference between the median residualized loan revenue in credit bin k and the one in credit bin $k-1$) and $\Delta\delta$ (the difference between the median default probability in credit bin k and the one in credit bin $k-1$). Bootstrapped standard errors for κ are reported in parentheses (they correspond to the standard deviation of the estimates for κ obtained by drawing firm samples within each credit rating bin).

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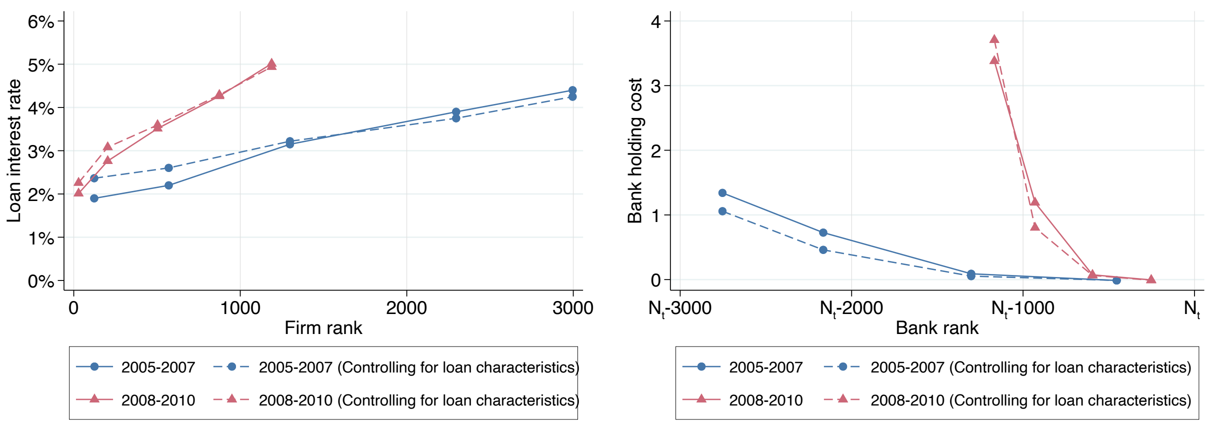

(a) Interest Rates

(b) Bank Holding Costs

Figure A2: Model-Implied Quantities after Controlling for Firm and Loan Characteristics

Notes: Figure A2a plots, for the pre-crisis (2005–2007) and the crisis (2008–2010) periods, the median interest rate (solid line) and the median residualized interest rate (dashed line) within five credit rating bins (y-axis). Interest rates are plotted as a function of the median firm rank i within each of these bins (x-axis). Figure A2b plots the bank holding cost estimated using interest rates (solid line) versus the one estimated using residualized interest rates (dashed line) as a function of the median bank rank within each of these bins. See the notes of Table A7 for more details on the construction of each variable.

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Online Appendices (not for publication)

D. Firm Riskiness and Economic Performances

In this section, we show that our three firm downside risk measures are negatively related to firm performance during the financial crisis. To show this, we run regressions of the form

$$\log\left(\frac{K_{i,2009}}{K_{i,2007}}\right) = \alpha + \beta X_{i,2007} + \gamma \log\left(\frac{K_{i,2007}}{K_{i,2005}}\right) + \epsilon_i,$$

where i denotes a firm, $X_{i,2007}$ denotes one of the three borrower measures of risk in 2007, and K_i denotes installed capital.[39] We winsorize the logarithmic two-year growth of capital at the 1st and 99th percentile. Additionally, we also run this specification with bank fixed effects (where the bank corresponds to the lead arrangers in the last loan issued in the pre-crisis period) to take out any effect due to changes in bank credit supply.

Table OA1: Firm Riskiness and Firm Performance during the Financial Crisis

	Capital Growth 2007–2009					
	(1)	(2)	(3)	(4)	(5)	(6)
Loan Spread	-.047***	-.044***				
	(-4.4)	(-3.7)				
Default Probability (S&P)			-.0086**	-.0066		
			(-2.6)	(-1.7)		
Default Probability (BSM)					-.0039***	-.0037***
					(-6.1)	(-6.9)
Capital Growth 05-07	.1***	.1***	.067**	.074**	.096***	.11***
	(3)	(2.9)	(2.4)	(2.3)	(4.1)	(4.1)
Bank FE	No	Yes	No	Yes	No	Yes
R^2	.031	.057	.02	.056	.021	.056
N	1482	1476	793	786	1291	1285

Notes: This table estimates the model

$$\log\left(\frac{K_{i,2009}}{K_{i,2007}}\right) = \alpha + \beta X_i + \gamma \log\left(\frac{K_{i,2007}}{K_{i,2005}}\right) + \epsilon_i,$$

where i denotes a firm and X_i is alternatively its loan spread in columns (1) and (2), probability of default implied by its S&P rating in columns (3) and (4), and probability of default implied by the Bharath and Shumway (2008) model in columns (5) and (6). The specification is estimated using bank fixed effects in columns (2), (4), and (6). The estimation is done with OLS with standard errors clustered at firm and bank levels. t-statistics are in parentheses (*** corresponds to a p-value below 0.01)

Table OA1 reports the results. Column (1) shows that the borrower loan spread from the DealScan universe is negatively correlated with borrower capital growth from 2007 to 2009. A 1 percentage point increase in the loan spread (or in bond spread for public firms) is approximately associated with a 2.6% decrease in the capital growth. Column (2) adds bank fixed effects and

[39] We measure capital as net property plant and equipment in Compustat (`ppent`).

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shows that for the firms in the portfolio of the same bank, borrower loan spread predicts a lower CAPX growth over the financial crisis period. Note that the coefficients of interest are very similar in columns (1) and (2).

In columns (3) and (4), our independent variable of interest is borrower probability of default implied by their S&P credit rating. Note that because not all firms have an S&P rating, the number of observations drops relative to the previous specification (940 in columns (3) and (4) compared to 1,711 in columns (1) and (2)). We get that a 1 percentage point increase in the probability of default is associated with a 0.8% decrease in capital growth. We obtain identical point estimates in column (3) without bank fixed effects and in column (4) with bank fixed effects.

Columns (5) and (6) show that a 1 percentage point increase in the probability of default, computed using the model of Bharath and Shumway (2008), is associated with a 0.4% decrease in capital growth during the financial crisis. The sample here is almost similar to the DealScan sample absent the data lost in the merger between DealScan and Compustat. Hence, regardless of our exact measure of borrower downside risk, we get robustly similar results that risky borrowers reduce their investment during the financial crisis relative to less risky ones.

The findings in Table OA1 can, to a large extent, be anticipated from findings in earlier papers. For instance, Greenwood and Hanson (2013) find that aggregate corporate debt issuance is positively correlated with aggregate credit risk appetite. They also find that credit risk appetite was extremely high before the financial crisis and fell substantially during it. Still, these findings are significant as they show that regressing firm outcomes on one of the bank characteristics discussed in Section 2 (bank health, distance to Lehman, deposit-to-asset ratio, securitization intensity) suffers from an omitted variable bias: firm riskiness is correlated with each of these bank characteristics and directly affected firm outcomes during the financial crisis.

E. Sorting within Bank Type

One important characteristic of banks lending to the riskiest firms before the crisis is that they were typically investment banks as opposed to commercial banks (see Figure 1). Hence, one natural question is whether the sorting pattern we document also happens within bank category. To answer this question, we re-estimate our sorting regressions from Section 2 after adding a dummy variable for bank category.

Formally, we estimate the following model:

$$Y_j = 1_{\text{investment bank}_j} + \beta \xi_j + \epsilon_j,$$

where j denotes a bank, $1_{\text{investment bank}_j}$ is a dummy variable equal to one (resp. zero) if the bank is an investment bank or a foreign bank (resp. commercial bank), and ξ_j measures the average riskiness of firms borrowing from bank j, as defined in Equation (2). Hence, the key difference with Equation (3) is that we add a dummy for bank category (investment versus commercial banks),

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which allows us to examine the sorting patterns within bank category.

Table OA2 reports the results. We find roughly similar coefficients relative to the baseline model (as reported in Tables 1 and 2), although some coefficients are no longer significant. Overall, we conclude that bank category does not fully explain the sorting pattern: there is still some residual sorting between firms and banks within these bank categories.[40]

Table OA2: Firm Riskiness and Bank Ex-Ante Characteristics within Bank Type

	β	t-stat	R^2	N
	(1)	(2)	(3)	(4)
Panel A: Bank Lending Growth				
Borrower loan spread	-0.74	1.12	0.24	42
Borrower default probability (S&P)	-0.19	1.22	0.14	38
Borrower default probability (BSM)	-0.10^{**}	2.28	0.17	43
Panel B: Bank Lehman Distance				
Borrower loan spread	-1.86^{**}	2.38	0.45	41
Borrower default probability (S&P)	-0.71^{***}	2.83	0.50	37
Borrower default probability (BSM)	-0.21^{**}	2.44	0.50	42
Panel C: Bank Deposit Ratio				
Borrower loan spread	-1.21^{**}	2.40	0.67	42
Borrower default probability (S&P)	-0.27^{**}	2.20	0.60	38
Borrower default probability (BSM)	-0.15^{***}	4.49	0.65	43
Panel D: Bank CLO Intensity				
Borrower loan spread	0.83	1.40	0.35	20
Borrower default probability (S&P)	0.48^{**}	2.42	0.47	20
Borrower default probability (BSM)	0.02	0.57	0.29	20

Notes: This table estimates the model

$$Y_j = 1_{\text{investment bank}_j} + \beta \xi_j + \epsilon_j,$$

where j denotes a bank, Y_i is alternatively the bank distance to Lehman (Panel A), deposit-to-asset ratio (Panel B), and securitization intensity (Panel C) (all normalized to have a unit standard deviation); and ξ_j is a bank's average of its borrower downside risk after controlling for a set of firm and loan characteristics. Borrower loan spread, borrower probability of default implied by its credit rating, and borrower probability of default implied by the model of Bharath and Shumway (2008) are all in percentage points. Estimation is done with weighted least squares, where weights are given by the number of pre-crisis loans issued by each bank. Estimates for β are in column (1), while the t-statistics, estimated using robust standard errors, are in column (2) (*** corresponds to a p-value below 0.01).

F. Sorting over Time

In the main text, we document a strong sorting pattern between banks and firms before the financial crisis. One natural question is if this sorting is constant over time or if it is a specific characteristic of the pre-crisis period. To examine this question, we need to focus on bank characteristics that are directly comparable over time. Hence, we restrict ourselves to the deposit-to-asset ratio (as other bank characteristics such as Lehman distance or securitization intensity are specific to the pre-crisis period).

[40] In unreported regressions, we find that most of the residual sorting pattern happens within investment banks rather than within commercial banks.

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Hence, we run the following regression model using weighted least squares:

$$\text{Deposit-to-Asset Ratio}_{jt} = \alpha + \beta_t \overline{X}_{jt} + \epsilon_{jt},$$

where j denotes a bank, t denotes a two-year period, and $\overline{X}_{jt}$ denotes the average riskiness of all firms to which bank j issues a loan in this two-year period. As in Table 1, firm riskiness is measured as loan spread, default probability implied by the S&P rating, and default probability implied by the model of Bharath and Shumway (2008). Weights are the number of loans issued by each bank during the time period.

Figure OA1 plots the result. What is apparent is that sorting really starts in the 2000s and becomes more and more important up to the financial crisis. This pattern is consistent with the idea that this rising sorting pattern is related to the growing ability of certain banks to securitize their loans.

(a) Loan Spread (b) Default Probability (S&P) (c) Default Probability (BSM)

Figure OA1: Regressing Bank Deposit-to-Asset Ratios on Average Borrower Characteristics over Time

Notes: This figure plots the estimate of β_t and its 95% confidence interval (in the dashed line, using robust standard errors) for the regression model

$$\text{Deposit-to-Asset Ratio}_{jt} = \alpha + \beta_t \overline{X}_{jt} + \epsilon_{jt},$$

where j denotes a bank, t denotes a two-year period, and $\overline{X}_{jt}$ denotes the average riskiness of all firms to which bank j issues a loan in this two-year period. The regression is estimated using weighted least squares, where weights are given by the number of bank loans issued by each bank during the time period. Standard errors are clustered at the bank level.

G. The Pre-Securitization Period

In the main text, we estimate the model on two periods: a pre-crisis period (2005–2007) and a crisis period (2008–2010). We now also estimate the model on a period that predates both of them, which can be seen as a "pre-securitization" period, denoted by $t = -1$. By analogy with the pre-crisis period, we define this period as the period going from the first quarter of 2002 to the second quarter of 2004 (included).

As in Table 3, Table OA3 reports the median of δ, r, L, and the implied κ within each of our five credit rating bins. Figure OA3 plots these estimates and compares them to the ones obtained in the pre-crisis and crisis periods. The number of loans during this pre-securitization period $t = -1$

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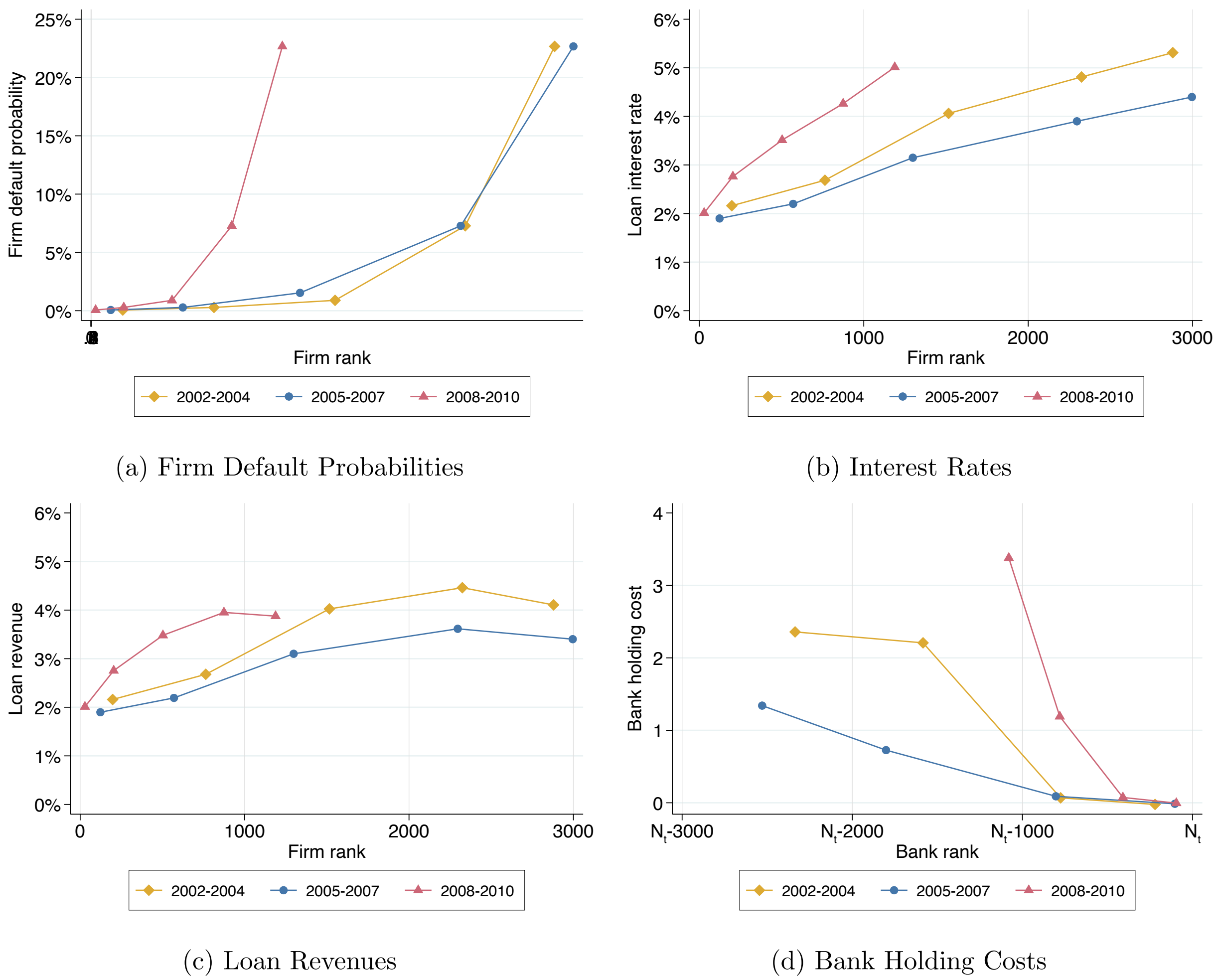
is $i^*_{-1} = 3,008$, which is a bit lower than the number of loans during the pre-crisis period $t = 0$, which is $i^*_0 = 3,100$. Importantly, we find that bank holding costs, as inferred by the gradient of loan spreads relative to default probabilities, tend to be higher in the 2002–2004 period relative to the 2005–2007 period. This is consistent with the idea that the development of the securitization market in between the two time periods reduced banks' holding costs.



(a) Firm Default Probabilities

(b) Interest Rates

(c) Loan Revenues

(d) Bank Holding Costs

Figure OA2: Model-Implied Quantities (Including the 2002–2004 Period)

Notes: The figure reports the same quantities as Figure 2 but adds estimates for the "pre-securitization" period going from 2002 to 2004.

H. Discrepancy between Panel Regression Estimates and Aggregate Effects

A popular empirical design in the bank lending channel literature is to regress firm loans on the health of the banks they are borrowing from. Researchers often interpret the magnitude of the estimated coefficient as a measure of the size of the credit supply effect. In this section we discuss

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Table OA3: Estimated Bank Holding Costs in 2002–2004

	Rating Groups				
	AAA-A	BBB	BB	B	CCC-C
Number of loans	394	739	765	852	258
Median firm rank i^k	197	764	1,516	2,324	2,879
Median default probability δ^k	0.06	0.28	0.89	7.28	22.67
Median interest rate r^k	2.16	2.69	4.06	4.81	5.31
Expected loan revenue $L = (1-\delta^k)r^k$	2.16	2.68	4.03	4.46	4.11
Bank holding cost $\kappa^k = (L^k - L^{k-1})/(\delta^k - \delta^{k-1})$		2.36	2.21	0.07	-0.02
		(0.10)	(0.40)	(0.01)	(0.01)

Notes: The table reports the same quantities as Table 2, but it now estimates them for the "pre-securitization" period going from 2002 to 2004.

the disconnect between the two concepts in the context of our model. To explicitly compare our approach to the popular firm fixed effects estimator used in the literature (Khwaja and Mian, 2008), we propose an extended environment of our baseline model where each firm needs \$2 and each bank can lend \$1 to a firm. In this simple setup, a firm can obtain \$2 of loans (\$1 from each bank) or zero loans otherwise if and only if $i \leq i_t^*$.

Suppose that due to some credit supply shock (e.g., changes in the distribution of bank holding costs $\kappa[\cdot]$), loan volume declines between $t = 0$ and $t = 1$, with the rank of the marginal firm decreasing from i_0^* to $i_1^* < i_0^*$. The model predicts that the riskier firms with ranking $i \in [i_1^*, i_0^*]$ will be driven out of the market, independent of whether they were borrowing from a hit bank or not.

For these set of firms being driven out of the credit market, an econometrician regressing the change in the loan of these firms on whether or not their lender is hit, using firm fixed effects, would obtain zero; that is, $\beta_{out}^{FE} = 0$.[41] On the other hand, firms above the cutoff can secure funding by reallocating to other banks. For these firms, the estimated coefficient in a firm fixed effects regression would give $\beta_{ref}^{FE} = 2$.

Overall, the firm fixed effects estimator in the literature can be understood as the average of β_{out}^{FE} and β_{rf}^{FE}:

$$\beta^{FE}(\mu) = (1-\mu)\beta_{ref}^{FE} + \mu\beta_{out}^{FE},$$

where μ denotes the weight on firms driven out of the market, conditional on them having one hit bank. A larger drop in the credit supply thus means a higher measure of firms that would be driven out of the market, implying a higher weight on β_{out}^{FE} and therefore a lower β^{FE}. Hence, in this particular setup, the strength of the aggregate credit supply effect is inversely related to the magnitude of the fixed effects estimate.

[41] Specifically, for those firms, the change in the loan between firm i and bank j yields $\Delta L_{i,j} = -1 \; \forall j \in \{H, N\}$, where $j = H$ if and only if the bank is hit. The estimator solves $\left(\Delta L_{i,j} - \Delta \bar{L}_i\right) = \beta^{FE}(e_{i,j} - \bar{e}_i)$ where $e_{i,j} = -1$ if and only if the lending bank is hit $j \in H$; $\Delta \bar{L}_i$ and $\bar{e}_i$ denote the average change in the loan supply and exposure for firm i. For those firms, $\beta^{FE} = 0$ as $\Delta L_{i,j} = -1$ and $\Delta \bar{L}_i = -1$.

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Finally, consider an extreme case where a given fraction of banks becomes bankrupt and is replaced with new banks with the same holding cost as the original banks. Since there is effectively no change in the aggregate distribution of risk capacity, the aggregate supply effect is zero. However, the fixed effects estimator is highest as it purely captures the refinance/substitution effects.

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