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Unequal and unstable: income inequality and bank risk*

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Abstract

We provide evidence that regions in the U.S. with higher income inequality tend to have a riskier banking sector. However, not all banks are more risky, as reflected in a higher dispersion of bank risk. We show how a model based on risk-shifting incentives where banks channel insured deposits into subprime loans can account for both findings. In equilibrium, a competition to risk-shift emerges, leading to a subprime lending boom in which loans to high-risk borrowers carry negative NPVs. Some banks engage in risk-shifting by lending to high-risk subprime borrowers, while the rest specialize in lending to low-risk prime borrowers.

Keywords: Inequality, bank risk, risk-shifting, mortgage credit, banking competition
JEL Classification: G11, G21, G28, G51.

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1 Introduction

Income inequality has been rising in the United States since the 1970s. Over this period, higher earners have captured most of the economic growth in the U.S., while the real income of the bottom 50 percent of the population has stagnated (e.g. Piketty et al., 2018).[1] Another salient trend during this period is the growth of housing finance. That is, banks in the U.S. and elsewhere increasingly rely on mortgage credit as their core line of business as documented by Mian and Sufi (2015) and Jordà et al. (2016). This reliance on mortgage credit, and in particular the emergence of subprime lending, caused many bank failures during the financial crisis of 2008-2009.

Despite the growing interest in both income inequality and bank risk-taking and failure, our understating of whether and how these two phenomena are related remains incomplete. Does income inequality play a role in determining the failure rate of banks in a region? If so, what are the underlying mechanisms?

We address these questions both empirically and theoretically. First, we identify a pattern in the data between the income inequality in a given region in the U.S. and the bank risk in the same region. Second, we propose a general equilibrium model to explain this pattern. The core mechanism is based on Allen and Gale's rational bubble framework (Allen and Gale, 2000) adapted to include income inequality, the housing market, and mortgage credit.

Empirical patterns. We begin by examining the statistical relationship between the level of income inequality in a given metropolitan statistical area (MSA) in the U.S. and different measures of bank risk for these regions for the period 2000 to 2019. The level of income inequality is measured by the Gini coefficient. Bank risk is captured by several measures: the proportion of failed banks per MSA, the average probability of default and the average z-score of the most risky banks per MSA,[2] the average probability of default and the average z-score of all banks per MSA, and the dispersion (standard deviation) of banks' probabilities of default and z-scores per MSA. These measures are calculated for

[1] For studies of the underlying causes of inequality, see David et al. (2013), Goldin and Katz (2009), and Piketty et al. (2014).

[2] Probabilities of default are predicted based on a logit model and explanatory variables commonly used in the literature.

regional banks that operate mainly within a single MSA in the U.S., which is the case for about 90 percent of all banks, and exclude large national banks.

We find robust evidence that the share of failed banks, the average bank risk of the most risky banks, the average bank risk of all banks, and the dispersion of bank risk per MSA is greater in regions with higher income inequality.

Keeley's observation. What mechanism accounts for the patterns in the data? First, more unequal regions may have larger shares of low-income households, which are typically categorized as riskier borrowers. Several papers show how income inequality, household leverage, and household default risk especially among lower-income households, can lead to bank failure. (Mian et al., 2020a; Kumhof et al., 2015; Cairó and Sim, 2018; Rannenberg, 2019). However, banks' risk-taking decisions do not passively follow the risk of their potential borrowers, but instead are endogenously determined, as (Keeley, 1990, p. 1184) notes:

> There is little doubt that increased risk in the economy and declining capital ratios have had a lot to do with the increase in bank [...] failures in recent years. But these developments do not explain why banks [...] allowed bankruptcy risk to increase. After all, depository institutions have considerable control over the riskiness of their asset portfolios and perhaps even more control over their capital ratios.

To account for the empirical patterns - and more broadly to understand how inequality can affect bank risk - one needs a model that considers both household sector risk and banking sector risk separately.

Model preview. We propose a general equilibrium model of bank lending decisions to explain how inequality and bank risk are related in equilibrium. Ex-ante identical banks issue insured deposits and select the riskiness of their loan portfolios. The only source of inefficiency in this model is deposit insurance which can lead to risk-shifting. In our setup, each bank decides whether to specialize in risky or safe lending, what we refer to as *risky banks* and *safe banks.* In equilibrium, all banks will have the same expected profits regardless of their strategy. That is, competition ensures that loan terms to each type of household adjust so that banks engaged in risk-shifting are not more profitable (in expectation) than safe banks.

We embed this banking competition mechanism in a model of mortgage credit based on the *double-trigger* approach to mortgage default, which is common in the literature. The first trigger is negative equity in the house, whereas the second trigger is a low default cost. Following the literature, we assume that low-income borrowers are more likely to draw low default costs than high-income households, which makes the former more likely to default in equilibrium.[3] We close the model by adding a housing production sector. We assume that housing within a region becomes more expensive as the demand for it increases. In this setup, mortgage rates, housing prices and the proportion of risky, and safe banks are all determined in equilibrium and depend on the entire income distribution.

Preview of the results. The model provides a useful framework to examine the relationship between bank risk-taking and income inequality. Specifically, there are two types of borrowers in equilibrium, *prime* and *subprime*, and two types of banks, *safe* and *risky*. The size of each credit segment is obtained in equilibrium. A borrower belongs to the subprime (prime) segment if their income is below (above) a cutoff point. This cutoff increases in the equilibrium price of housing. The equilibrium housing price, in turn, depends on the entire distribution of income because of spillover effects: increased housing demand from the wealthy drives up housing prices for everyone.

Risky banks only lend to subprime borrowers, engage in risk shifting, and fail with positive probability. Safe banks, on the other hand, do not shift risk, only lend to prime borrowers, and always remain solvent. In other words, risky and safe banks' clientele do not overlap in equilibrium. The reason is that a risky bank making a safer loan (i.e., to a prime borrower) creates a surplus that accrues mainly to the taxpayer who backs the deposit insurance guarantee. As a result, in equilibrium, it is privately optimal for those banks choosing to be risky to altogether avoid loans to prime borrowers and focus exclusively on the subprime segment of the mortgage market.

We apply our general equilibrium framework to understand the empirical relation

[3] Lower-income households may experience higher mortgage default rates because of worse income shocks, limited resources, or lack of other funding opportunities. See Foote et al. (2008) and the references therein.

between income inequality and bank risk. Higher inequality pulls more households into the subprime credit segment, leading more banks to specialize in risk shifting. There is an indirect effect, as well: the larger proportion of high-income households - and their increased demand for housing - drive up the price of housing. As a result, lower-income borrowers become more indebted and more likely to default on their mortgage. Thus, households that would be prime borrowers when inequality levels are low can become subprime borrowers when inequality is high. The model's key implication is that banks' risk-shifting incentives interact with income inequality to generate the patterns we observe in the data. If income is distributed uniformly (i.e., there is no inequality), all banks in our setup will have the same failure risk. In other words, bank sorting is a consequence of income inequality.

The sorting of ex-ante identical banks into safe banks and risky banks emerges because banks that shift risk compete to attract higher-risk borrowers by offering low-interest mortgages. In equilibrium, this *competition to risk-shift* implies that loans to subprime borrowers carry negative net present value, and therefore, remain attractive only for risk-shifting banks. In other words, subprime borrowers receive credit at subsidized interest rates, with the deposit insurance agency ultimately bearing the cost. Further, a more dispersed income distribution creates more opportunities for bank specialization into safe and risky. As a result, the dispersion of bank risk and the level of income inequality are positively related in equilibrium. Notably, the competition to risk-shift is a general equilibrium phenomenon that does not emerge in partial equilibrium settings.[4]

The model also implies that inequality will *not* shape bank risk unless risk-shifting is attractive for some banks. We demonstrate this feature by examining equilibrium in a version of the model without deposit insurance, in which the interest offered to the bank's creditors fully reflects the risk of bank default. In this case, all banks remain safe by holding enough capital and limiting their exposure to high-risk borrowers. Moreover, the subprime borrowers no longer receive subsidized credit, and the subprime lending boom does not materialize. In other words, the prevalence of high-risk borrowers is a necessary

[4]The model's prediction that the risky banks issue negative NPV loans is challenging to measure ex-ante. At the same time, there are other manifestations of risk-shifting incentives. Specifically, a risk-shifting bank tends to hold a portfolio that is highly sensitive to house price growth. Such a bank will also issue new loans whose payoff is contingent on house price appreciation (such as deferred amortization mortgages) and highly covariant with the bank's existing loan portfolio. See Landier et al. (2015).

but not a sufficient condition for risky banks - the latter needs a catalyst, i.e. the option to shift risk. This last property of the model reflects *Keeley's observation*, namely that banks can choose their risk level independently from the riskiness of the pool of their potential borrowers.

Related literature. First, we contribute to the growing theoretical literature examining the effect of inequality on bank risk and financial instability more broadly. The underlying reasons for banking instability connected to income inequality can be traced to the political motivation to redistribute (Rajan, 2011), the wealth accumulation preferences of the wealthy (Kumhof et al., 2015), the redistribution through bailouts (Mitkov, 2020), and the saving glut of the rich (Mian et al., 2020b). We expand this literature by identifying (empirically and theoretically) another channel through which inequality can play a role in the banking system's stability.

Second, The *competition to risk-shift* mechanism in our paper is related to the rational bubbles framework of Allen and Gale (2000).[5] In their model, the possibility of risk-shifting leads financial intermediaries protected by limited liability to bid-up the price of risky assets above fundamentals because they can avoid losses in low-payoff states by defaulting. In our model, the competition among risk-shifting banks implies that loans to high-risk borrowers carry negative net present value. In other words, in equilibrium, risky banks pay a premium for risky loans.

Third, our paper belongs to the literature examining how banks risk-shifting incentive can be shaped by government guarantees.[6] For example, Bahaj and Malherbe (2020) study bank capital regulation in the presence of risk-shifting and government guarantees and show that risky banks can optimally choose to fund high-risk negative NPV loans and to avoid low-risk positive NPV loans. Harris et al. (2018) study an environment with borrower heterogeneity and deposit insurance and derive cross-sectional relation between the risk premium of the assets held by financial institutions and show that banks specialize in different risk categories. We complement this literature by examining how banks' risk-shifting incentives interact with the income distribution - a topic that has

[5] See also Rochet (1992), Allen and Gorton (1993), Repullo and Suarez (2004), Harris et al. (2018) and Bahaj and Malherbe (2020).

[6] See Merton (1977), Kareken and Wallace (1978) and Pennacchi (1987) among others.

remained overlooked by this literature.

Outline. The rest of the paper proceeds as follows. Section 2 presents the empirical patterns, and Section 3 introduces the model. Section 4 derives the equilibrium and analyzes its properties. Section 5 applies the model to study how the distribution of income shapes bank risk. Section 6 concludes. Figures and tables of the empirical part as well as all proofs are in the appendix.

2 Empirical patterns

This section explores patterns between measures of income inequality and bank risk. To the best of our knowledge, the existing literature has thus far not studied this relationship. The goal is to document relevant correlations, not necessarily causal relations. The findings from this section serve as the empirical motivation and foundation for the theoretical model in Section 3.

As illustrated in Figure 5, both the level of income inequality (as measured by the Gini coefficient) and the average bank risk (as measured by the share of failed banks) vary geographically across the United States. This variation allows us to explore relationships between both measures.

- Figure 5 around here -

In particular, this section shows the following: *(i)* Higher income inequality is associated with higher bank risk and *(ii)* Higher income inequality is associated with higher dispersion of bank risk. The following paragraphs describe in detail the sample, variables and the analysis that leads to this evidence.

2.1 Preliminary considerations

Relevance of Metropolitan Statistical Areas. In considering the relationship between income inequality and bank risk, it is necessary to define the appropriate and relevant geographic boundaries. In principle, we could consider the data across different countries, metropolitan areas, counties or other geographic boundaries. This study prefers the Metropolitan Statistical Areas (MSA) as defined by the U.S. Office of Management and Budget as its geographic boundaries. An MSA is a geographical region with a relatively high population density at its core and close economic ties throughout the area. An example is the *Washington–Arlington–Alexandria, DC–VA–MD–WV* metropolitan statistical area. The U.S. Census Bureau and the Bureau of Economic Analysis frequently make data on income inequality and local economic conditions available for MSAs.

An MSA is also a relatively good proxy for a banking market. Our data shows that a large fraction of banks operate most of their branches within their respective MSA, most of their deposits come from branches within the MSA, and most of their mortgage loans are also provided to borrowers within the MSA (see Figure 6 for the regional concentration of branches and deposits). Furthermore, banking regulators often define a banking market identically or similarly to an MSA in bank merger assessments (Walter and Wescott, 2008).

- Figure 6 around here -

The role of mortgage loans. The theoretical model that is presented in the following section uses the market for mortgage loans as a key element. Therefore, it is relevant to understand how important mortgage loans are in practice.

Figure 7 illustrates the relative importance of mortgage loans for the banks in our sample. The graph in panel (a) shows that about half of all bank assets are mortgage loans for the average bank. The graph in panel (b) illustrates the relative importance of mortgage loans for banks' non-performing assets. Again, mortgage loans are highly relevant. The main message from both graphs is that the mortgage business is very important for the banks in our sample.

- Figure 7 around here -

2.2 Sample

Our main sample is a cross-sectional dataset that comprises data on bank risk, inequality and economic conditions for 178 Metropolitan Statistical Areas (MSAs) in the U.S. The sample period is 2000 to 2019.

Constructing the final dataset takes several steps. First, we start with annual data of all banks with their headquarters in an MSA.[7] This data comes from banks' call reports, as provided by the FDIC. Second, we exclude large national banks without a specific regional focus (e.g. Bank of America) by restricting the sample to banks that have 50 percent or more of their branches in the MSA where they have their headquarters, which is the case for about 90 percent of all banks. Third, we focus on the larger MSAs where we can observe bank risk of several banks and the corresponding dispersion of bank risk. In particular, we exclude banks from MSAs where less than 5 banks have their headquarters. Finally, banks are removed from our sample if data on income inequality is not available for the MSA where the bank's headquarters is located. These steps result in a final sample of 5,543 banks that are located in 178 MSAs across the U.S. Using this sample, we calculate the averages per MSA for various measures of bank risk, which are described in more detail below.

Data on income inequality and other economic data for each MSA comes from the U.S. Census Bureau and is based on the American Community Survey, which started in 2005.

An overview of all variables is given in Table 2 and summary statistics are shown in Table 3. Table 4 shows the correlations between the main variables of interest. The following section provides a detailed description of each variable.

- Table 2, Table 3 and Table 4 around here -

2.3 Variables description

Income inequality. This study uses the Gini coefficient to measure income inequality for the main analyses. A Gini coefficient of 1 indicates perfect inequality, i.e. one household has all the income and every other household has none. A Gini coefficient of 0 indicates perfect equality, i.e. every household has an equal share of income.

The first year for which the Gini coefficient is available from the U.S. Census Bureau on the MSA level is 2006. Importantly, this measure is based on income data before the financial crisis of 2008 to 2009, such that effects of bank failures and bank risk on income

[7] We do not include branches of foreign chartered institutions or atypical institutions without any mortgage loans on their balance sheet.

inequality during the crisis are excluded. In Section (2.6), Robustness and Extensions, we also explore the role of several alternative measures of income inequality.

Household income. The mean and median household incomes (in USD '000) per MSA are included as control variables. We use these variables from the same year as the first available Gini (2006). The source for this data is the U.S. Census Bureau.

Bank risk. We use several approaches to measure bank risk. First, we use data on bank failures per MSA to calculate the average share of failed banks per MSA. This is the most direct measurement of bank risk. Second, we use measures of bank risk based on banks' predicted probabilities of default. Third, we use measures of bank risk based on banks' z-scores. The reason for using these different approaches is that bank risk is generally difficult to measure, and each of these three approaches has advantages and disadvantages. Altogether, they allow a comprehensive and differentiated analysis about the relationship of income inequality and bank risk.

First, bank failures per MSA is taken as the dependent variable, *Failed_yr_m* (where m stands for mean). The variable is calculated as the long-term average (mean) per MSA of the share of failed banks for each MSA and year.[8] The source for this data is the failed bank list of the *Federal Deposit Insurance Corporation* (FDIC).[9]

Next, we use measures of bank risk that are based on banks' predicted probabilities of default that we predict using a logit model with variables that are frequently used in the literature (see e.g. Cole and White, 2012). Details and regression results of the logit model are provided in the Online Appendix. Based on banks' predicted probabilities of default, several measures of bank risk are calculated on the MSA level:

- The variable *PD_m* captures the average (mean) bank risk per MSA. It is calculated as the long-term average per MSA of the mean of banks' predicted probabilities of default for each MSA and year.

- The variable *PD_90* captures the bank risk of the most risky banks per MSA. It

[8]For example, if 1 out of 10 banks with their headquarters in a given MSA fails in a certain year, the share of failed banks for this MSA and year is 0.1. The variable *Failed_yr_m* reflects the average per MSA for the whole time period.

[9]See https://www.fdic.gov/resources/resolutions/bank-failures/failed-bank-list/.

is calculated as the long-term average per MSA of the 90^{th} percentile of banks' predicted probabilities of default for each MSA and year.[10]

- The variable *PD_sd* is the long-term average per MSA of the standard deviation of banks' predicted probabilities of default for each MSA and year. This measures serves as a proxy for the dispersion of bank risk.

Finally, we use measures of bank risk based on banks' z-scores. This risk measure is also frequently used in the banking literature and reflects bank stability based on data from banks' financial statements (see e.g. Laeven and Levine (2009)). The bank z-score is defined as the natural logarithm of the sum of a bank's return on assets and its core capital ratio, standardized by the standard deviation (8-quarter rolling) of the bank's return on assets, which can be interpreted as the "distance to default". A lower z-score indicates less bank stability.

- The variable *Zscore_m* captures the average (mean) bank risk per MSA. It is calculated as the long-term average per MSA of the mean of banks' z-scores for each MSA and year.

- The variable *Zscore_10* captures the bank risk of the most risky banks per MSA. It is calculated as the long-term average per MSA of the 10^{th} percentile of banks' z-scores for each MSA and year (lower z-scores reflect less stability and hence, higher risk).

- The variable *Zscore_sd* is the long-term average per MSA of the standard deviation of banks' z-scores for each MSA and year. It is a proxy for the dispersion of bank risk.

A particular challenge for our measurements of bank risk is that the *Troubled Asset Relief Program* (TARP) supported both solvent and insolvent banks during the financial crisis of 2008 and 2009. In particular, the *Capital Purchase Program*, which was part of TARP, provided capital to 707 financial institutions between October 2008 and December

[10]When there are fewer than 10 banks per MSA in a given year, the variable *PD_90* takes the value of the most risky bank.

2009. Based on the existing evidence from the literature, it would be questionable to classify the financial institutions that received TARP as failed (because they got government support) or as insolvent (because they did not truly fail).[11] To circumvent this ambiguity, the years 2008 and 2009 are excluded from every average measure of bank risk. Hence, *Failed_yr_m* and all other variables that measure bank risk, reflect averages for the years 2000 to 2007 and 2010 to 2019. In a robustness exercise, we also show results for bank risk measures that include the years 2008 and 2009.

2.4 Preliminary graphical evidence

An initial graphical inspection of the relationships between income inequality and different measures of bank risk is shown in Figure 8.

The graphs point to a positive relationship between income inequality and (a) the average share of failed banks per MSA (upper left panel), (b) the average probability of default of the most risky banks per MSA (upper right panel), (c) the average probability of default of all banks per MSA (lower left panel), and (d) the average dispersion of bank risk per MSA, measured as the standard deviation (lower right panel).

- Figure 8 around here -

2.5 Analysis

An ideal experiment to explore the *causal* relationship between income inequality and bank risk is unfortunately not available. This would require a random exogenous shock on income inequality that simultaneously spares bank risk. Hence, the analyses primarily identify correlations, not causal relationships. The model we propose in the next section can generate these relationships as an equilibrium outcome.

[11] On the one hand, Berger and Roman (2015) show that TARP recipients benefitted from a competitive advantage relative to non-TARP recipients, which may have incentivized stable banks to apply for TARP. On the other hand, TARP recipients were subject to certain regulations, such as executive compensation restrictions, which may have incentivized troubled banks to not apply for TARP. Furthermore, a study by Duchin and Sosyura (2012) shows that the likelihood of receiving capital through this program did not only depend on a bank's financial conditions, but also on its political connections. See also Mian et al. (2010); Calomiris and Khan (2015).

Our analysis begins with a simple OLS specification:

$$RISK_j = \alpha + \beta_1 Gini_j + \epsilon_j,$$

where $RISK_j$ represents different measures of bank risk per MSA j. All measures of bank risk are calculated as averages over the sample period. The variable $Gini_j$ is the Gini coefficient of the first year that it is available on the MSA level, i.e. 2006. The average Gini coefficient over the sample period is not used in order to address concerns that bank failures during the financial crisis of 2008 to 2009 may have affected income inequality. We use robust standard errors for the main cross-sectional analysis. In robustness regressions with panel data (MSA and year), we use clustered standard errors on the MSA level.

In further specifications, we include either the mean or median household income of the year 2006 per MSA to control for different levels of income. Note that income inequality is associated with many sociodemographic and economic variables, such as education and the structure of the economy (manufacturing vs. service sector, etc.). Following the literature (see e.g. Kumhof et al. (2015)), the analysis does not control for such variables because the overall relevance of inequality, including its potential sociodemographic and economic drivers, is of primary interest.

Inequality and the share of failed banks. Our first regression results, which are presented in Panel A of Table 5, show a significantly positive relationship between income inequality, measured as Gini coefficients, and the average share of failed banks per MSA. The coefficient of *Gini* is in the range of 0.04 across the three different specifications: without controls (column 1), controlling for mean income (column 2) and controlling for median income (column 3). This means that an MSA a with relatively high Gini of 0.4600 (75th percentile) is associated with a 0.00124 (0.124 percentage points) higher share of failed banks compared with an MSA with a relatively low Gini of 0.4290 (25th percentile).[12] As shown in the descriptive statistics table, the average share of failed banks over the sample period is 0.0030 (0.3 percent). Hence, the difference between the average share of bank failures in MSAs with relatively high and low inequality is economically

[12] The value of 0.00124 comes from multiplying the coefficient of 0.04 with the difference between the Gini at the 75th and the 25th percentiles, i.e. 0.04 $\times$ (0.4600-0.4290)=0.00124.

highly significant.

Inequality and bank risk of the most risky banks. Next, the top percentile of banks' predicted probabilities of default (*PD_90*) and the bottom percentile of banks' z-scores (*Zscore_10*) are used as dependent variables. Both variables reflect the risk of the riskiest banks per MSA. Regression results are shown in Panel B of Table 5. We find a significantly positive relationship between income inequality and bank risk measured as *PD_90* for all three specifications. When using the z-score as a measure of bank risk, the negative coefficients mean that higher income inequality is associated with less bank stability, hence, greater risk. Results are significant for the first specification (column 4), not significant when controlling for mean income (column 5), with a p-value of 0.1178, and again significant when controlling for median income (column 6). Overall, the results confirm the previous results from Panel A that higher income inequality is associated with higher bank risk in the riskiest banks (with the exception of insignificant results in Column (5)).

Inequality and average bank risk. Next, we consider income inequality and average bank risk, *PD_m* and *Zscore_m*. As shown in Panel C of Table 5, we find that income inequality is associated with higher average bank risk per MSA. Interestingly, the coefficients are much lower than in Panel B, where the bank risk of the most risky banks per MSA is the dependent variables. This suggest that income inequality is more relevant for the riskiest banks than for the "average" bank.

Inequality and dispersion of bank risk. Finally, we are interested in whether the dispersion of bank risk is different in MSAs with high and low income inequality. Hence, we use the standard deviation of banks' predicted probabilities of default and the standard deviation of banks' z-scores as dependent variables. Regression results in Panel D of Table 5 show significantly positive relationships between the Gini coefficient and the dispersion of bank risk. Results are statistically significant for every specification.

- Table 5 around here -

Summary of empirical findings. Overall, the main takeaway from this empirical exercise is that income inequality and bank risk are indeed related. We find robust evidence that bank risk and its dispersion are greater in regions that have higher income inequality. While our analysis does not permit us to claim a causal effect from income inequality on bank risk (because income inequality is not exogenous), we believe that the documented positive relationships are an interesting and novel finding that merit further consideration. The next section proposes a stylized model to account for these findings. First, however, we address the question of how robust the empirical results are and present some further results.

2.6 Robustness and Extensions

Several robustness tests and further analyses were conducted. The full results are available in the online appendix, which also includes tables with variable descriptions and descriptive statistics for all new variables (Table OA1 and Table OA2, respectively).

Gini coefficient based on 3-year survey data. As a first robustness check, we use the first available 3-year survey Gini coefficients instead of the first available 1-year survey Gini coefficients, i.e. the 3-year estimate from the 2005-2007 surveys instead of the 1-year estimate from the 2006 survey.[13] As shown in Table OA3 in the online appendix, regression results are qualitatively unchanged compared to our main regression results in Table 5. In particular, the size of the coefficients is similar, and all coefficients are statistically significant on the 1%, 5% and 10% level.

Income share of top 5 percent. Besides the Gini coefficient that we use for our main analyses, there are several alternative measures of income inequality. One popular measure is the share of total income held by the top 1 percent. While this data is not publicly available on the MSA level, the U.S. Census Bureau publishes data on the share of total income held by the top 5 percent. Using this measure, denoted as *Share_top5p* in the analysis, we again find a significantly positive relationship between income inequality and bank risk, as shown in Table OA4 in the online appendix. All coefficients of *Share_top5p*

[13] Note that although 2005 income data is used for the 2005-2007 3-year estimates, the U.S. Census Bureau does not publish a 1-year estimate for 2005 on the MSA level.

are statistically significant on the 1%, 5% and 10% level (with the exception of column 5 in Panel D).

Poverty. One relevant consideration is whether the positive relationship between income inequality and bank risk primarily comes from the share of poor households per MSA. Therefore, we test whether the share of poor households per MSA, denoted as *poverty* in the results table, is also significantly related to bank risk. As Table OA5 shows, we find no significant relationship between poverty and bank risk. Hence, this particular part of the lower tail of the income distribution, which is measured as *poverty*, does not explain the positive relationship between income inequality and bank risk.

Measures of bank risk including the years 2008 and 2009. As discussed at the end of the variables description section, the averages of bank risk variables on the MSA level are all calculated excluding the years 2008 and 2009, because government support through TARP introduces ambiguity (e.g. a bank that received TARP may or may not have failed otherwise). Nevertheless, we also test the relationship between inequality and bank risk for measures of bank risk including the years 2008 and 2009. As shown in Table OA6, the coefficients of every regression are in the same range as for our main analysis in Table 5 (which uses a sample excluding 2008 and 2009). However, the statistical significance is generally weaker, as expected, and four out of 21 coefficients of Gini are not statistically significant.

Panel regressions with clustering on the MSA level. The main regressions that are shown in Table 5 use cross-sectional data on the MSA level. For example, the dependent variable *average bank risk (PD_m)* is calculated in two steps: First, for each MSA and year, we calculate the average probability of default of every bank with its headquarters in the MSA, and second, we calculate the average per MSA over the sample period. The benefit of this approach is that it simplifies the analysis. For robustness, we use the panel dimension of the data (MSA and year), which allows us to control for year fixed effects. Regression results remain qualitatively unchanged (see Table OA7 in the appendix), as shown in Table OA7 in the online appendix.

Predictions of banks' probabilities of default. Finally, note that the online appendix also includes a detailed description of the logit model that we use for predicting banks' probabilities of default.

3 The model

This section proposes a simple model to account for the empirical patterns in the previous section. Our analysis builds on the rational bubbles framework of Allen and Gale (2000) augmented to include income inequality, a housing market, and a mortgage market.

We choose to keep the model simple to highlight the main message in a tractable way. At the end of this paper, Section 5.5 provides a discussion of some of the modeling assumptions and shows that the basic framework is flexible and can be generalized along several relevant dimensions such as *(i)* ex-ante heterogeneous banks, *(ii)* risk-weighted capital, *(iii)* firm sector, and *(iv)* housing speculation. A summary of the model notation is provided at the end of this section in Table 1.

3.1 Households and the housing market

The economy lasts for one period and two dates (0 and 1) and has two types of agents: households and bankers. The distribution of income among the households on date 0 is given by the cumulative distribution function H over the interval $[0, \overline{y}]$.[14]

Demand for housing. Each household with income y demands $n(y)$ units of housing on date 0. We think of a unit of housing as a measurement of an area, e.g., square feet. We assume the demand for housing units is weakly increasing in income $\frac{dn(y)}{dy} \geq 0$. Thus, the households demand $\int_{\underline{y}}^{\overline{y}} n(y)dH(y)$ units of housing on date 0. We denote the price of a unit of housing by P_0. For simplicity, we assume that housing demand is not affected by the housing price. Hence, each household with income y pays $n(y)P_0$ for housing.[15]

[14]Formally, for each $y \in [0, \overline{y}]$ there is a continuum of households with income y. This assumption simplifies the analysis by ensuring banks are atomistic relative to the households.

[15]Equivalently, one can assume that P_0 is the price per unit of quality and that income-y borrowers demand one unit of housing with quality $n(y)$. Both formulations yield equivalent results. A more general specification in which $n(y)$ depends, among other things, on the housing price and the mortgage rates charged by banks yields similar results but at the cost of additional complexity.

Supply of housing. We denote with N the aggregate quantity of housing units produced on date 0. We assume the cost to produce N units of housing is $\phi_H(N)$ where $\phi_H(.)$ is increasing and convex.[16] For concreteness, we assume throughout the analysis that $\phi(N) = c_0 N + c_1 N^2/2$, which implies that the marginal cost to produce one additional unit of housing is $\phi'(N) = c_0 + c_1 N$.

Housing prices. We assume that housing is produced by competitive firms taking housing prices as given. The price per unit of housing on date 0 is equal to $\phi'(N)$. Hence,

$$P_0 = c_0 + c_1 N. \tag{1}$$

The growth rate in the house price between date 0 and date 1 is $g_s = P_{1s}/P_0 - 1$, where P_{1s} is the price per unit of housing on date 1 and s is the state of the economy on date 1. The state on date 1 is either bad $s = B$ with probability q or good $s = G$ with probability $1 - q$. We have $g_B < 0 < g_G$.

3.2 Mortgage loans

The purchase of housing on date 0 is fully financed by a mortgage loan collateralized by the house. Loans are granted on date 0 are repaid on date 1. The outstanding balance on the mortgage on date 1 for a household with income y equals $(1 + r(y))n(y)P_0$, where $r(y)$ is the interest on a mortgage and $n(y)P_0$ is the principal.

On date 1, households have the option of defaulting on their mortgage. Default triggers foreclosure, in which the bank seizes the house, and the household incurs a default cost. The benefit of default is that it cancels the liability on the mortgage when the value of the house is lower than the value of the mortgage: what is referred to as *negative equity in the house*: $(1 + r(y))n(y)P_0 > n(y)P_{1S}$. We follow a reduced-form approach for the cost of default and introduce the index j to distinguish between two households with the same income y but different default costs. Following the literature, we assume that default costs scale proportionally with the house size $n(y)$, an assumption which is not critical

[16] The assumption of increasing cost to produce housing is common in the literature and reflects, among other things, a limited supply of land. See for example Saiz (2010).

for our results.[17] Hence, household j with income y chooses to default on its mortgage if, and only if, the negative equity exceeds the default cost. That is,

$$\underbrace{(1+r(y))n(y)P_0 - n(y)P_0(1+g_s)}_{\text{negative equity}} > \underbrace{n(y)c(j,y)}_{\text{cost of default}}. \tag{2}$$

Rates of default. A default can potentially occur only among households for whom the negative equity in the house exceeds the default cost. We impose that negative equity can occur only in the bad state, which is reflected in the parameter condition $g_G > q/(1-q)$. Each household with income y independently draws a default cost from the distribution $G(.|y)$. The rate of default among income-y in the bad state is denoted $m(y \,|\, P_0, r(y), y)$ and it equals the proportion of households whose cost of default is below the negative equity in the house, that is, $G(P_0(r(y) - g_B) \,|\, y)$. For simplicity, we assume $G(.|y) = U\,[0,\, \beta y]$, where U is the uniform distribution and $\beta > 0$ is a parameter. Hence, we have

$$m(y \,|\, P_0, r(y), y) \equiv \frac{(r(y) - g_B)P_0}{\beta y}. \tag{3}$$

For a fixed amount of negative equity in the house, the default rate decreases in the household's income y. That is, other things being equal, higher-income households have a higher credit quality. In addition, for each y, the rate of default in the bad state increases with the housing price P_0, the interest rate $r(y)$, and the drop in the housing price conditional on the bad state g_B (recall $g_B < 0$).

Our formulation thus captures the *double-trigger theory* of mortgage default. The first trigger is negative equity in the house. The second trigger is a low realization of the default cost. We do not model the different default cost components and instead assume lower-income households are more likely to draw low default costs.

[17] The default cost captures pecuniary and non-pecuniary costs the households would experience in case of default, such as stigma effects, transaction costs, and the foregone benefit of living in the house net of the cost of funds for repaying the mortgage. For example, households must incur additional debt on date 1 to repay their mortgage have a higher cost of funds (and therefore lower default cost) than households can tap their savings. The cost of funds, in turn, is likely to be higher for lower income households. See Foote et al. (2008) and the references therein.

3.3 Banks

There is a continuum of ex-ante identical, risk-neutral bankers indexed by i. The banks can issue capital, deposits, hold storage (i.e., the safe asset) and make mortgage loans. The budget constraint for banker i on date 0 is

$$\alpha_i + l_i = k_i + b_i, \tag{4}$$

where α_i is the amount held in storage, l_i is the amount invested in loans, k_i is equity, and b_i deposits. We assume that deposits are insured by the government (by explicit or implicit guarantees), and banks are subject to a mandatory minimum capital requirement. Specifically, the *maximum leverage ratio* for each bank is $\rho \geq 1$, which implies a bank with a capital of k_i can raise at most $k_i\rho - k_i$ in deposits on date 0.

Cost of funds. Bank i is financed with an amount of capital k_i at a total cost of r_K per unit and an amount of deposits b_i at an opportunity cost of r_D. We assume that

$$r_K = t_K K \qquad \text{and} \qquad r_D = t_D D \tag{5}$$

where $K = \int k_i di$ and $D = \int b_i di$ denotes the aggregate amount of capital and deposits issued by the banking sector on date 0. The deposit market is perfectly competitive. As a result, bank i would set its deposit rate $r_{D,i}$ at a level required for the depositors to recover their opportunity cost of funds r_D in expectation, where r_D is given in (5). Since depositors are insured, they are always either repaid by the bank or by the deposit insurance fund, hence $r_{D,i} = r_D$. If $t_K = t_D = 0$, bank capital and deposits are not scarce, and their opportunity cost of funds equal the return on storage (which is normalized to one). We assume $t_K \geq (\rho - 1)t_D$, which would imply that, in equilibrium, bank capital is a more expensive form of financing than deposits $r_K \geq r_D$.

Management cost. Each banker has a cost of $c(k+b)$ to manage a balance sheet of size $k+b$. This cost is incurred on date 0 before the state $s \in \{G, B\}$ is realized, and it has a fixed and variable component. Specifically,

$$c(k+b) = f + \frac{t}{2}(k+b)^2. \tag{6}$$

where $f > 0$ and $t > 0$. Thus, the cost to manage a bank increases with the size of the bank's balance sheet. This specification would later allow us to pin down the bank size in a tractable way. We think of (6) as capturing the administrative cost of managing a bank (managing employees, branches, evaluating loan applicants). One can also think of the fixed cost f as the banker outside option. We also assume that the banker incurs a fixed default cost of F whenever the bank becomes insolvent. In other words, default is personally costly for the banker.[18]

Portfolio payoffs in the good state. The bank's payoff on date 1 depends on the realization of the state $s \in \{G, B\}$. The probability of the good state is $1-q$, in which case all households repay their mortgage. Thus, one unit invested in mortgage loans to households with income y yields $1 + r(y)$ on date 1, and the payoff on bank i's portfolio is

$$\psi_i(G) = \alpha_i + l_i \int_{\underline{y}}^{\overline{y}} (1 + r(y))\omega_i(y)dy, \tag{7}$$

where $\omega_i(y)$ denotes the weight of bank i's loan portfolio corresponding to income-y households. Let $\omega_i \equiv \{\omega_i(y)\}_{\underline{y}}^{\overline{y}}$ and note that we have $\omega_i(y) \geq 0$ for each y and $\int_{\underline{y}}^{\overline{y}} \omega(y)dy = 1$.

Portfolio payoffs in the bad state. The probability of the bad state is q, in which case a proportion $m(y) \equiv m(y \,|\, P_0, r(y), y)$ of the households with income y default on their mortgage, where $m(y)$ is given in (3). In case of default, the bank forecloses on the house and receives a return of $1 + g_B < 1$ on the loan. Thus, the payoff on bank i's portfolio in that state is

$$\psi_i(B) = \alpha_i + l_i \int_{\underline{y}}^{\overline{y}} \left[(1 - m(y))(1 + r(y)) + m(y)(1 + g_B)\right] \omega_i(y)dy. \tag{8}$$

[18]One can interpret F is as capturing the loss of reputation or losing the private benefit associated with managing the bank. Another way of interpreting the bankruptcy cost is as foregone future profits (i.e., the loss of the bank's franchise).

The above uses the fact that the bank has limited liability, and therefore, the payoff to the equity holders cannot be negative.

Bankers objective. Fix a triple $(r_L,\, r_K,\, r_D)$, where $r_L \equiv \{r(y)\}_{\underline{y}}^{\overline{y}}$ denotes the profile of mortgage interest rates. Banks behave competitively and in the best interest of their equity holders. Specifically, bank i takes as given $(r_L,\, r_K,\, r_D)$ and chooses capital k_i, deposits b_i, loan portfolio $(l_i,\, \omega_i)$, and storage α_i to maximize expected profits

$$\Pi_i = \sum_{s\in\{G,B\}} q_s \max\{\psi_i(s) - b_i(1+r_D),\, 0\} - c(k_i + b_i) - (1+r_K)k_i, \tag{9}$$

subject to the budget constraint in (7), the opportunity cost of deposits and capital in (5), and where $\psi_i(s)$ is the payoff on the bank's portfolio in state $s \in \{G, B\}$ as given in (7) - (8).

Individual bank risk. Each bank can choose whether to become risky or safe through its choice of capital, leverage, storage, and loan portfolio. A bank that remains solvent in both states will be called *safe*. Competition and free-entry imply that, in equilibrium, the expected profit of a safe bank is zero $\Pi^*_{\text{safe}} = 0$. On the other hand, a bank that defaults in the bad state will be called *risky*. Each risky bank fails with probability q, which is the probability of the bad state. Upon default, the banker incurs a cost of F. In equilibrium, the expected profit of each risky banks equals qF, that is, $\Pi^*_{\text{risky}} = qF$.

Table 1: Summary of the model notation

Variable	Description
Economy	
q	Prob. that the state on date 1 is bad, $S = B$
$1 - q$	Prob. that the state on date 1 is good, $S = G$
Households and the housing market	
$y \in [\underline{y}, \overline{y}]]$	Household income on date 0
$H(y)$ and $h(y)$	C.d.f. and p.d.f. of the income distribution on date 0
$n(y)$	Demand for housing units on date 0 for household with income y
P_0	Price per unit of housing on date 0
P_{1S}	Price per unit of housing on date 1 in state $S \in \{G, B\}$
$g_S \equiv P_{1S}/P_0 - 1$	Growth rate in the house price between date 0 and date 1
$n(y)P_0$	Price paid by households with income y for housing
$c_0 + c_1 N$	Marginal cost to produce a unit of housing on date 0
N	Aggregate housing quantity produced on date 0
Mortgage loans	
$n(y)P_0$	Principal of a mortgage loan for households with income y
$r(y)$	Mortgage rate for a household with income y
$n(y)c(j, y)$	Default cost on date 1 for household j with income y
$G(.\vert y) \equiv U[0, \beta y]$	C.d.f. of the default cost for households with income y
$m(y \mid P_0, r(y), y)$	Rate of default of a household with income y
Banks	
k_i	Amount of equity issued by bank i on date 0
b_i	Amount of deposits issued by bank i on date 0
$\rho \equiv \frac{k_i + b_i}{k_i}$	Maximum leverage ratio for each bank
$K = \int k_i di$	Aggregate amount of bank capital
$D = \int b_i di$	Aggregate amount of deposits
$1 + r_K = 1 + t_K K$	Required return on bank capital
$1 + r_D = 1 + t_D D$	Required return on deposits
α_i	Amount invested in storage by bank i
l_i	Amount invested in loans by bank i
$c(k + b) = f + t\frac{(k+b)^2}{2}$	Total cost of managing a bank of size $k + b$
$\omega_i(y)$	Portfolio weight on income-y borrowers for bank i
$\psi_i(G)$	Bank i's portfolio payoff in the good state
$\psi_i(B)$	Bank i's portfolio payoff in the bad state
F	Default cost for the banker

4 Equilibrium outcomes

Before investigating the effect of income inequality on bank risk, we characterize the equilibrium outcome. In our setup, housing prices, mortgage interest rates, and bank risk are all determined in equilibrium and depend on the income distribution. The first main implication of the model is an equilibrium profile of mortgage rates summarized in Proposition 1. This profile is shaped by the competition among banks and their incentive to risk-shift. The second main implication is an equilibrium profile of banking sector risk, summarized in Proposition 2. We show that the proportion of risky banks is closely connected to the income distribution.

4.1 Mortgage interest rates

We proceeds as follows. First, we characterize the equilibrium housing prices and rates of mortgage default. Second, we consider the choices of a bank choosing to be safe. Third, we consider the choices of a bank choosing to be risky. Finally, we derive the equilibrium profile of mortgage interest rates.

Housing prices and rates of default. From (1) the equilibrium price per unit of housing is $P_0 = c_0 + c_1 N$, which implies

$$P_0 = c_0 + c_1 \int_{\underline{y}}^{\overline{y}} n(y) dH(y). \tag{10}$$

The rate of default among income-y households in the bad state is given by (3). Inserting the equilibrium housing price in (3) yields an equilibrium rate of default

$$m(y) \equiv \frac{1}{\beta y} \left[c_0 + c_1 \int_{\underline{y}}^{\overline{y}} n(y) dH(y) \right] (r(y) - g_B), \tag{11}$$

where $r(y)$ is the interest rate on the mortgage loan to income-y household. The expected return on a loan to income-y households is

$$E\left[y \,|\, r(y) \right] \equiv (1-q)(1+r(y)) + q \left[(1-m(y))(1+r(y)) + m(y)(1+g_B) \right]. \tag{12}$$

If the state is good, the loan is repaid in full and the return to the bank is $1 + r(y)$. On the other hand, if the state is bad, the loan is repaid with probability $1 - m(y)$, where $m(y)$ is given in (11).

Undistorted interest rates. Suppose a given safe bank expands its balance sheet by a small amount ϵ and invest in type y loans. Assume this change is small enough so that the bank remains solvent in the bad state (i.e., it remains safe). Since the bank is safe, it internalizes the return of the mortgage loan in each state. The expected return on a loan to income-y household is given in (12). To finance this balance sheet expansion, the bank issues capital Δk at a unit cost of r_K and deposits Δb at a unit cost of r_D (where $\Delta k + \Delta b = \epsilon$). In equilibrium, we have

$$(\Delta k + \Delta b)\, E\left[y \,|\, r(y)\right] - \Delta b(1 + r_D) - \triangle c \leq (1 + r_K)\Delta k, \tag{13}$$

where $\triangle c \equiv c'(k + b)\epsilon$ is the incremental cost the bank incurs from operating a larger balance sheet. The left-hand side of (13) is the incremental gain in the expected payoff to the equity holders. The right-hand side of (13) is the expected return required by equity holders (i.e., their opportunity cost of capital) to put up an additional Δk units of equity. Since the bank is safe, it internalizes the return of the mortgage loan in all states and cares about its expected payoff. Condition (13) implies that the bank cannot increase its expected payoff by expanding its portfolio and lending to income-y households. Given a maximum leverage ratio of ρ, the bank will set $\Delta k = \epsilon/\rho$ and $\Delta b = \epsilon/(1 - \rho)$ where $\Delta k = \epsilon/\rho$ is the minimum amount of new capital necessary to satisfy the bank's leverage constraint (note $\Delta k + \Delta b = \epsilon$). Let $r_u(y)$ denote the interest rate for which (13) holds with equality. That is,

$$E\left[y \,|\, r_u(y)\right] = \frac{1}{\rho}(1 + r_K) + \left(1 - \frac{1}{\rho}\right)(1 + r_D) + c'(k\rho), \tag{14}$$

where $E\left[y \,|\, r_u(y)\right]$ is the expected return on income-y loans defined in (12) and evaluated at $r_u(y)$. We will refer to $r_u(y)$ as the *undistorted interest rate* for income-y households.

Risk shifting interest rates. Next, suppose a given risky bank expands its balance sheet by a marginal amount ϵ, which is financed by issuing capital Δk and debt Δb (such that $\Delta k + \Delta b = \epsilon$). If ϵ is small enough, the bank will continue to be insolvent in the bad state (i.e., it remains risky), and therefore, it only considers its payoff conditional on the good state. Notably, a risky bank will pay the same interest on deposits r_D as a safe bank even though it imposes a cost on the deposit insurance fund in the bad state (since the find must cover the losses incurred by the depositors in the bank). The deposit rate r_D depends on the aggregate amount of deposits used by the banking sector, but not on bank-specific risk. This reflects our assumption that banks have the opportunity to engage in risk-shifting behavior. In equilibrium, we must have

$$(\Delta k + \Delta b)\,(1-q)\,[1 + r(y) - \Delta b(1 + r_D)] - \Delta c \leq (1 + r_K)\Delta k, \tag{15}$$

where $\triangle c \equiv c'(k+b)\epsilon$ is the incremental cost the bank incurs from operating a larger balance sheet. The left-hand side of (15) is the incremental gain in the expected payoff to the bank's equity holders. Since the bank defaults in the bad state, its equity holders only consider the payoff of the loan conditional on the good state. The right-hand side of (15) is the expected return that must be promised to the equity holders to induce them to put up an additional Δk in equity. If (15) holds, a risky bank cannot profitably expand its balance sheet by lending to income-y households. The risky bank would optimally finance this expansion by the maximum leverage possible: $\Delta k = \epsilon/\rho$ and$\Delta b = \epsilon/(1-\rho)$. Let $r_{rs}(y)$ denote the interest rate for which (15) holds with equality. Hence, we have

$$1 + r_{rs}(y) = \frac{1}{1-q}\frac{1}{\rho}(1 + r_K) + \left(1 - \frac{1}{\rho}\right)(1 + r_D) + c'(k\rho). \tag{16}$$

We will refer to $r_{rs}(y)$ as the *risk-shifting interest rate* for income-y households.

Equilibrium mortgage rates. The previous section derived two profiles of interest rates. The undistorted profile in (14) will emerge if all banks are safe. On the other hand, the risk-shifting profile in (16) will emerge if all banks are risky. Ex-ante, each bank can choose whether to be safe or risky and free to operate in any mortgage segment. If both type of banks co-exist in equilibrium, then the expected profit from becoming a safe bank

Π^*_{safe} equals the expected profit from becoming a risky bank $\Pi^*_{\text{risky}} - qF$. This indifference condition has far-reaching implications for the mortgage market. Specifically, competition in the loan market implies that the equilibrium profile of interest rates satisfies

$$r^*(y) = \min \{r_u(y),\, r_{rs}(y)\}. \tag{17}$$

The determination of the equilibrium interest rates in each mortgage segment is illustrated in Figure 1. To understand (17) note that a safe bank will not lend to households with income-y unless the equilibrium mortgage yield in this segment is greater than or equal to $r_u(y)$. Similarly, a risky bank will not lend to households with income y unless the equilibrium interest rate in this mortgage segment is greater than or equal to $r_{rs}(y)$. Consider any given mortgage segment y. For this segment, risky banks have a comparative advantage over safe banks when $r_{rs}(y) < r_u(y)$. On the other hand, safe banks have a comparative advantage over risky banks when $r_{rs}(y) > r_u(y)$. Competition and free-entry into each mortgage segment implies that the equilibrium interest rate $r^*(y)$ is equal to $r_{rs}(y)$ when $r_{rs}(y) < r_u(y)$ and equal to $r_u(y)$ when $r_{rs}(y) > r_u(y)$. Our next result characterizes the equilibrium interest rate that prevails in each mortgage segment.

Proposition 1. ***Equilibrium mortgage interest rates***. *The equilibrium is characterized by an endogenous cutoff $y^* \in \left[\underline{y}, \overline{y}\right]$ such that*

(i) Mortgage loans to households with income $y > y^*$ have an interest rate $r^*(y) = r_u(y)$, where $r_u(y)$ is the undistorted interest rate obtained as the solution to

$$E\left[y \,|\, r_u(y)\right] = \frac{1}{\rho}(1 + r_K) + \left(1 - \frac{1}{\rho}\right)(1 + r_D) + c'(k^*_{\text{safe}}\rho). \tag{18}$$

We refer to households with income $y > y^*$ as prime borrowers.

(ii) Mortgage loans to households with income $y < y^*$ have an interest rate $r^*(y) = r_{rs}$, where r_{rs} is the risk-shifting interest rate given by

$$(1 - q)(1 + r_{rs}) = (1 - q)(1 - \tfrac{1}{\rho})(1 + r_D) + \tfrac{1}{\rho}(1 + r_K) + c'(k^*_{\text{risky}}\rho). \tag{19}$$

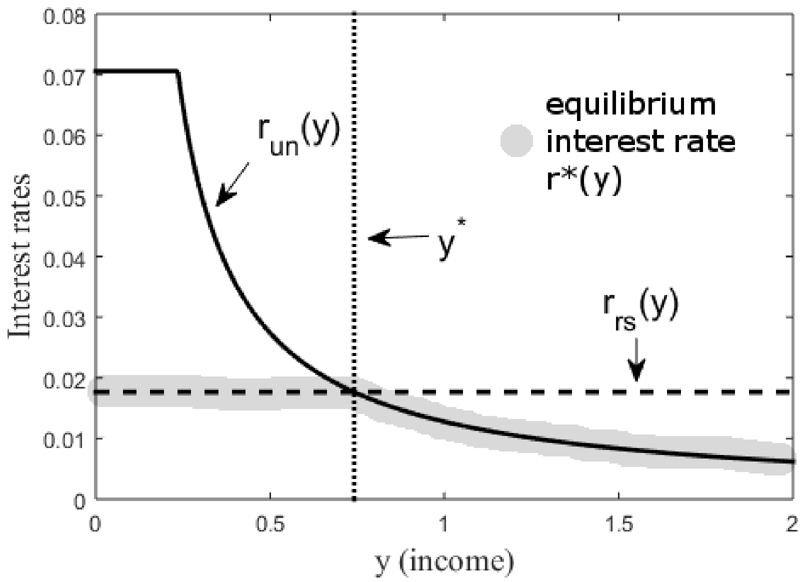
We refer to households with income $y < y^*$ as subprime borrowers.

(iii) The cutoff y^* is determined in equilibrium and equal to

$$y^* = \frac{1}{\beta}\left[c_0 + c_1 \int_{\underline{y}}^{\overline{y}} n(y)dH(y)\right] \frac{(r_{rs} - g_B)^2}{\left(1 + r_{rs} - \left(1 - \frac{1}{\rho}\right)(1 + r_D)\right)}. \tag{20}$$

Proof. See the Appendix. □

Figure 1: Determination of the equilibrium interest rate



The figure shows the determination of the equilibrium cutoff y^* and the resulting profile of equilibrium interest rates $r^*(y)$ for each $y \in [\underline{y}, \overline{y}]$. The undistorted interest rate $r_u(y)$ for each y is given in (14). The risk-shifting interest rate $r_{rs}(y)$ for each y is given in (16). The risk-shifting interest rate is the same for all households $r_{rs} \equiv r_{rs}(y)$. The cutoff y^* is obtained at the intersection of the undistorted and the risk-shifting interest rate $r_u(y^*) = r_{rs}$. The equilibrium interest rate $r^*(y)$ is equal to r_{rs} for each $y < y^*$ and equal to $r_u(y)$ for each $y > y^*$. Households with income $y < y^*$ are called *subprime* borrowers, and households with income $y > y^*$ are called *prime* borrowers. All loans issued to subprime household carry *negative* net present value. In equilibrium, subprime households borrow *only* from risky banks, whereas prime households borrow *only* from safe banks.

The location of the cutoff y^* is endogenous, and it determines the size of the subprime relative to the prime credit segment. If all households have income higher than y^*, that is $\underline{y} > y^*$, there is no subprime credit segment, and all banks are safe. If all households have income less than y^*, that is $\overline{y} < y^*$, there is no prime segment, and all banks are risky.

Finally, if y^* is interior $\underline{y} < y^* < \overline{y}$, the equilibrium features both safe and risky banks. In this case, risky banks will lend exclusively to subprime household since $r_{rs}(y) < r_u(y)$ for each $y < y^*$. At the same time, safe banks will lend exclusively to prime households since $r_{rs}(y) > r_u(y)$ for each $y > y^*$.

Recall from (6) that the cost to manage a bank with balance sheet size $A \equiv k + b$ is $c(A) = f + t(A)^2/2$. The equilibrium amount of capital issued by each safe bank k^*_{safe} and by each risky bank k^*_{risky} equals

$$k^*_{\text{safe}} = \frac{1}{\rho}\sqrt{\frac{2f}{t}} \qquad \text{and} \qquad k^*_{\text{risky}} = \frac{1}{\rho}\sqrt{\frac{2(f+qF)}{t}}. \tag{21}$$

In addition, since bank capital is more expensive than deposits, all banks (safe and risky) will choose to operate at the minimum capital requirement by borrowing $b^*_{\text{safe}} = k^*_{\text{safe}}(\rho-1)$ and $b^*_{\text{risky}} = k^*_{\text{risky}}(\rho-1)$. Thus, the size of each safe bank balance sheet is $A^*_{\text{safe}} = \sqrt{2f/t}$ and the size of each risky bank balance sheet is $A^*_{\text{risky}} = \sqrt{2(f+qF)/t}$.

Negative NPV loans. Proposition 1 has the following implication.

Corollary 1. *Loans to subprime households carry negative net-present value,*

$$E\left[y \,|\, r^*(y)\right] < \frac{1}{\rho}(1+r_K) + \left(1 - \frac{1}{\rho}\right)(1+r_D) + c'\left(k^*_{\text{risky}}\rho\right) \qquad \textit{for } y < y^*. \tag{22}$$

The left-hand side of (22) is the expected return on the mortgage. The right-hand side of (22) is the opportunity cost of equity and debt holders plus the marginal cost for a risky bank of issuing the loan. Once we take into account the cost imposed on the deposit insurance fund, subprime loans carry *negative* net present value.

4.2 Bank risk

Why would any bank issue a loan with a negative net present value? The answer is that these loans will be attractive for risky banks since there is a wedge between the private and the social surplus from subprime loans. Specifically, risky banks default in the bad state, and therefore, do not internalize the payoff of subprime loans in that state. Also, the deposit rate offered by a risky bank will not fully reflect the expected losses to its depositors in the bad state (and, therefore, the cost imposed on the deposit insurance fund). Next, we characterize the proportion of risk banks, the average default probability, and the standard deviation of banks' default probabilities.

Proposition 2. ***Aggregate bank risk***. *The risk profile of the banking sector is characterized as follows:*

(i) In equilibrium, each bank either becomes safe or risky. Safe banks always remain solvent, whereas each risky banks defaults with probability q (the prob. of the bad state).

(ii) Safe banks specialize in lending only to prime households (i.e., with income above y^*) whereas risky banks specialize in lending only to subprime households (i.e., with income below y^*).

(iii) The proportion of risky banks is increasing in the cutoff y^* and is given by

$$f^*_{\text{risky}} = \frac{\int_{\underline{y}}^{y^*} n(y)dH(y)}{\int_{\underline{y}}^{y^*} n(y)dH(y) + \sqrt{1+qF/f}\int_{y^*}^{\overline{y}} n(y)dH(y)}. \tag{23}$$

(iv) The average and the standard deviation of banks' default probabilities are

$$\text{mean} = qf^*_{\text{risky}} \qquad \textit{and} \qquad \text{sd} = q\sqrt{f^*_{\text{risky}}(1-f^*_{\text{risky}})}.$$

Proof. See the Appendix. □

Each safe bank supplies credit only to prime households, and each risky bank supplies credit only to subprime households. The demand for subprime and the demand for prime credit equals

$$d^*_{\text{subprime}} \equiv P^*_0 \int_{\underline{y}}^{y^*} n(y)dH(y) \qquad \text{and} \qquad d^*_{\text{prime}} \equiv P^*_0 \int_{y^*}^{\overline{y}} n(y)dH(y) \tag{24}$$

where P^*_0 and y^* are given in (10) and (20). Since each unit of bank capital is leveraged ρ times the demand for capital from risky and safe banks is $K^*_{\text{risky}} = \frac{1}{\rho}d^*_{\text{subprime}}$ and $K^*_{\text{safe}} = \frac{1}{\rho}d^*_{\text{prime}}$ respectively. The aggregate amount of capital and deposits issued by the banking sector is

$$K^* = \tfrac{1}{\rho}d^*_{\text{subprime}} + \tfrac{1}{\rho}d^*_{\text{prime}} \qquad \text{and} \qquad D^* = (1-\tfrac{1}{\rho})d^*_{\text{subprime}} + (1-\tfrac{1}{\rho})d^*_{\text{prime}} \tag{25}$$

From (5) the equilibrium return on deposits is $1 + r_D^* = 1 + t_D D^*$ and the equilibrium return on capital is $1 + r_K^* = 1 + t_K K^*$. Our assumption $t_K \geq t_D(\rho - 1)$ implies that $r_K^* \geq r_D^*$, and therefore, banks behave optimally by operating at the minimum mandatory capital requirement. Finally, the mass of risky n^*_{risky} and the mass of safe n^*_{safe} banks equals

$$n^*_{\text{risky}} = \frac{K_r^*}{k^*_{\text{risky}}} = \frac{\int_{\underline{y}}^{y^*} P_0^* n(y) dH(y)}{\sqrt{2(f + qF)/t}} \qquad \text{and} \qquad n^*_{\text{safe}} = \frac{K_s^*}{k^*_{\text{safe}}} = \frac{\int_{y^*}^{\overline{y}} P_0^* n(y) dH(y)}{\sqrt{2f/t}}. \quad (26)$$

where k^*_{risky} and k^*_{safe} is the amount of capital issued by each risky and safe bank respectively, given in (21). The proportion of risky banks depends on the distribution of income H, the demand for housing $n(y)$, and the cutoff's location y^*. In the next section, we apply the model to examine the effect of inequality on bank risk.

5 Inequality and bank risk

The model provides a useful laboratory to study the equilibrium effects of income inequality on bank risk. The analysis in this section proceeds as follows.

First, we highlight two novel channels through which inequality can shape bank risk: a direct and an indirect channel. We show that those two channels reinforce each other in some cases, whereas in other cases, they will offset each other.

Second, we show that under a realistic selection of income distributions (i.e., Log-normal or Pareto) and parameter values, the model can account for the empirical patterns. In particular, higher inequality would correspond to a larger proportion of risky banks, higher bank risk on average, and a larger dispersion of bank risk. Thus, the model provides a parsimonious way to understand the data patterns in Section 3.

Third, we show that the model delivers novel predictions on the relation between housing prices, inequality, and bank risk. Specifically, higher income inequality can have an asymmetric effect on bank risk, depending on the elasticity of housing supply.

Fourth, we isolate the fundamental source of bank risk in this environment, namely banks' risk-shifting opportunities. Specifically, suppose risk-shifting is not feasible (meaning that deposit rates fully reflect bank-specific risk). In that case, we show that all banks will be safe, and the income distribution will exert no effect on bank risk. Finally, we argue that the baseline framework is robust to a variety of extensions and generalizations.

5.1 Channels of inequality

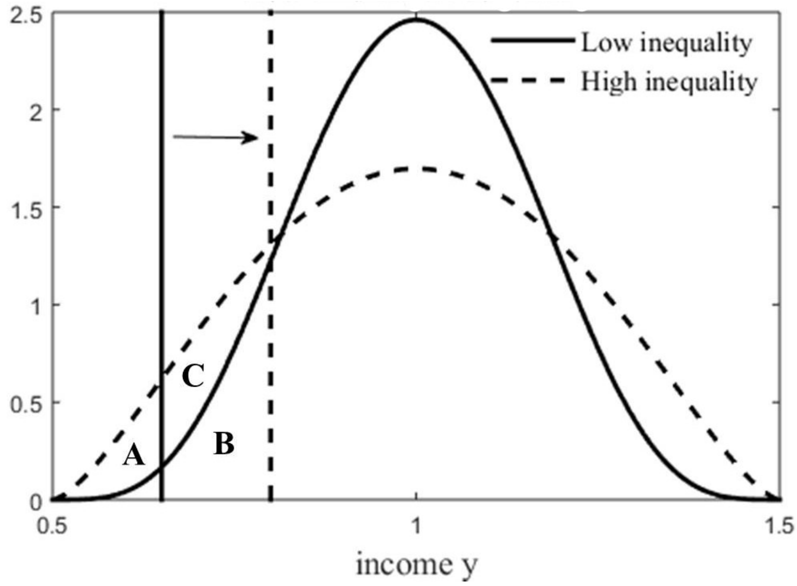
Figure 2 illustrates an economy with low inequality (solid line) and an economy with high inequality (dashed line). The average income for both economies is the same, and higher inequality is represented by a mean-preserving spread of the income distribution. The *direct channel* of inequality, represented by region A on Figure 2, affects the proportion of households with income less than y^*. The *indirect channel* of inequality operates by moving the subprime cutoff y^* and is represented by region B on the same figure. To further characterize the interaction of these channels, recall from (20) that the cutoff y^* is proportional to the equilibrium housing price $P_0^* = c_0 + c_1 \int_{\underline{y}}^{\overline{y}} n(y)dH(y)$. Suppose that the demand for housing is given by

$$n(y) = \left\{ \begin{array}{c} y_{min} \\ \alpha(y - y_{min}) + y_{min} \end{array} \right\} \qquad \text{as} \qquad y \left\{ \begin{array}{c} \leq \\ > \end{array} \right\} y_P, \tag{27}$$

One interpretation of $y_{min} > 0$ is that it represents a poverty line: households with income below y_{min} demand the minimum amount of housing. In this case, $n(y)$ is convex, which implies that a mean-preserving spread of the income distribution would lead to a larger value for the cutoff y^*.[19] As a result, the direct and indirect channels of inequality would tend to magnify each other as illustrated on Figure 2. In this case, higher inequality pulls more households below y^* in addition to pushing up y^*. The overall effect of higher inequality on the proportion of subprime borrowers is determined by combining the two channels. It is represented by regions A (direct effect), B (indirect effect), and C (interaction of direct and indirect effect) on the figure.

[19] An alternative specification is to assume there the government has imposed debt-to-income limits $P_0 n(1+r(y)) \leq \chi y$, where n is the amount of housing demanded by the household and χ is the maximum debt-to-income ratio. The housing demand for income-y household is given by $n(y) = \dfrac{y\chi}{P_0(1+r(y))}$. Using $\dfrac{dr(y)}{dy} \leq 0$ one can show that the function $n(y)$ is (weakly) convex, which will yield the properties illustrated on Figure 2.

Figure 2: Direct and indirect channels of inequality.



The figure shows the direct, indirect, and combined effects of higher income inequality. Higher inequality is represented by a mean-preserving spread of the income distribution. The direct effect pulls more households below the cutoff y^*, making them subprime borrowers (region A). The indirect effect shifts the cutoff's location y^*, in this case, towards a higher point (region B). Finally, the combined effect magnifies the direct and the indirect effect (region C).

5.2 Numerical examples

We next provide numerical examples illustrating how the income distribution shapes bank risk through the interaction of the direct and the indirect channels highlighted in the previous section. These examples help us understand the empirical patterns described in Section 2.

Log-normal distribution. We assume a log-normal distribution for the income of the households. In particular,

$$h(y) = \frac{1}{y\sigma\sqrt{2\pi}} \exp\left[-\frac{(\ln(y)-\mu)^2}{2\sigma^2}\right], \quad y > 0$$

The demand for housing takes the functional form in (27) with the cutoff y_{min} a function of the parameters of the log-normal distribution. We set y_{min} to equal 60 percent of the median income, that is $y_{min} = 0.6 \exp\{\mu\}$, which is a commonly used poverty measure associated with the log-normal distribution.[20] In order to facilitate comparison with the empirical results in Section 2, we capture income inequality with the *Gini coefficient*. For a log-normal distribution $G = 2\Phi(\sigma/\sqrt{2}) - 1$ where Φ is the *c.d.f.* of the standard normal. We fix the mean level of income for all subsequent figures to one and vary the Gini coefficient from 0.35 to 0.55, which corresponds to the range in the data. The mean and the standard deviation of bank default probability are given by

$$q f_{\text{risky}}(G) \quad \text{and} \quad q\sqrt{f_{\text{risky}}(G)(1 - f_{\text{risky}}(G))}$$

where $f_{\text{risky}}(G)$ is the proportion of risky banks corresponding to a given value of the Gini coefficient G. Figure 3(a) shows the proportion of risky banks, Figure 3(b) shows the average bank risk (where bank risk is the probability of bank failure), and Figure 3(c) the standard deviation of bank risk as functions of the Gini coefficient. Overall, the figures match the empirical patterns described in Section 2: higher inequality corresponds to *(i)* a larger proportion of risky banks, *(ii)* higher mean bank risk, and *(iii)* a larger dispersion of bank risk.

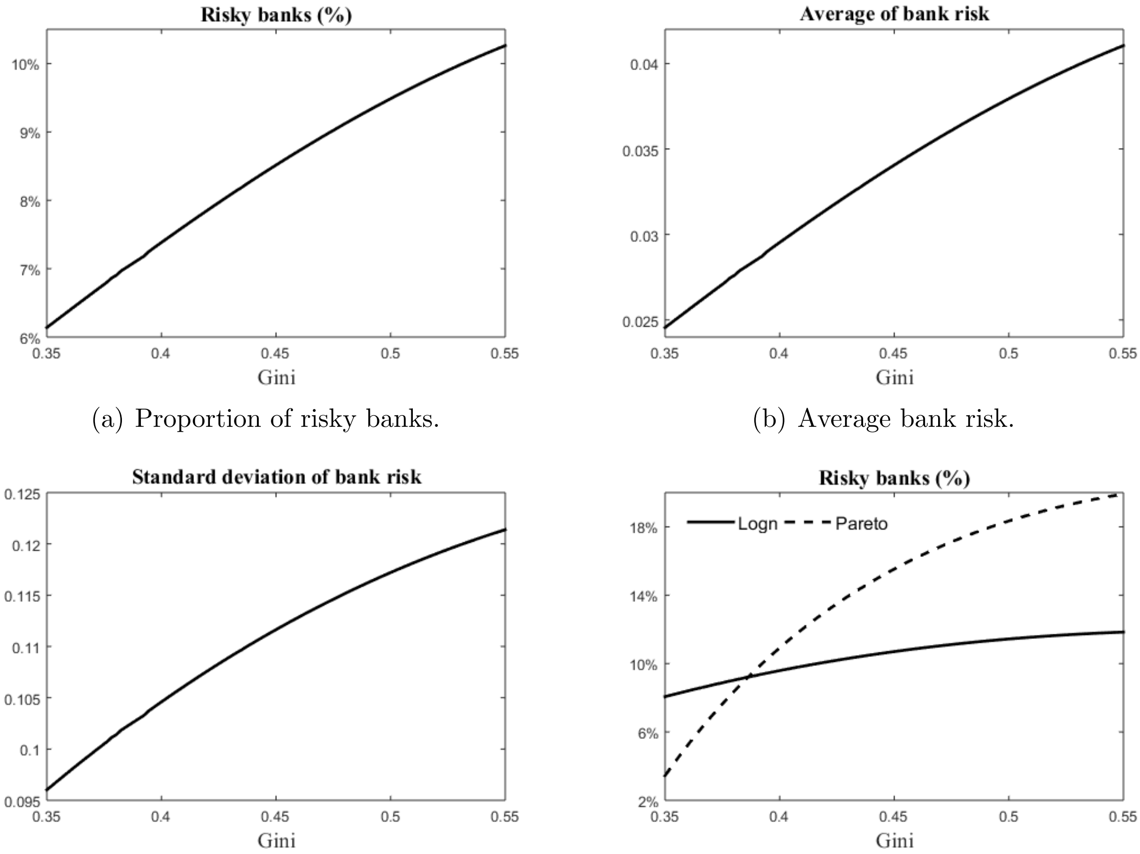
Pareto distribution. We obtain similar qualitative relations when income is Pareto distributed. The density function of a Pareto distributed random variable is given by

$$h_{\text{pareto}}(y) = a y_m^a y^{-a-1}, \quad y > y_m$$

The Gini coefficient of the Pareto distribution equals $1/(2a-1)$. Figure 3(d) shows the relationship between the Gini coefficient and the proportion of risky banks when the distribution of income is Pareto. The main difference relative to the Log-normal distribution is that the equilibrium relation between the Gini and the proportion of risky banks is steeper under the Pareto distribution. That is, the Pareto distribution implies a sharper effect of inequality on bank risk.

[20] The model delivers broadly similar implications for a wide range of specifications for $n(y)$. The remaining parameters of the model are $k = 0.1$, $q = 0.1$, $F = 0.2$, $g_G = 0.2$, $g_B = -0.2$, $c_0 = 0$, $c_1 = 1$, $\alpha = 0$, $\beta = 1$, $t_K = t_D = 0$ and $\gamma = 0$.

Figure 3: Numerical examples.



(a) Proportion of risky banks.

(b) Average bank risk.

(c) Dispersion of bank risk.

(d) Log-normal vs. Pareto.

5.3 Effect of housing supply elasticity

Note that the proportion of risky banks does not only depend on the income distribution, but also on several other factors as stated in Proposition 2. Specifically, the cutoff y^* increases with the equilibrium housing price P_0^*. The equilibrium housing price, in turn, is given by $P_0^* = c_0 + c_1 \int_{\underline{y}}^{\overline{y}} n(y)dH(y)$. Note that the housing price is positively related to the parameter c_1, which controls the variable cost to produce a housing unit. We will say that the supply of housing is inelastic (elastic) when c_1 is high (when c_1 is low). Thus, the cutoff's equilibrium value y^* is inversely related to the housing supply elasticity. Figure 4 displays the equilibrium proportion of risky banks as a function of c_1. The solid line is based on a log-normal income distribution with a mean equal to 1 and a Gini coefficient equal to 0.3. The dashed line is based on a log-normal income distribution with a mean equal to 1 and a Gini coefficient equal to 0.5. The figure highlights the interaction between the elasticity of housing supply and the relationship between income inequality and the proportion of risky banks. The proportion of risky banks is positively associated with c_1, and hence, negatively associated with the housing supply elasticity. If c_1 is relatively high, higher inequality will push more households into the prime segment leading to fewer risky banks. On the other hand, if c_1 is relatively low, higher inequality will push more households into the subprime segment leading to more risky banks.

The preceding discussion has three implications. First, other things being equal, regions with more inelastic housing supply will be characterized by a larger proportion of risky banks. Second, if housing supply is relatively elastic, then the equilibrium cutoff generally falls in the range where inequality and bank risk are positively associated. Third, if housing supply is very inelastic, however, then the previous relation does not hold, and inequality and bank risk will be negatively associated. We consider the third implication as less relevant in practice, but an interesting theoretical possibility.

5.4 What if banks cannot risk-shift?

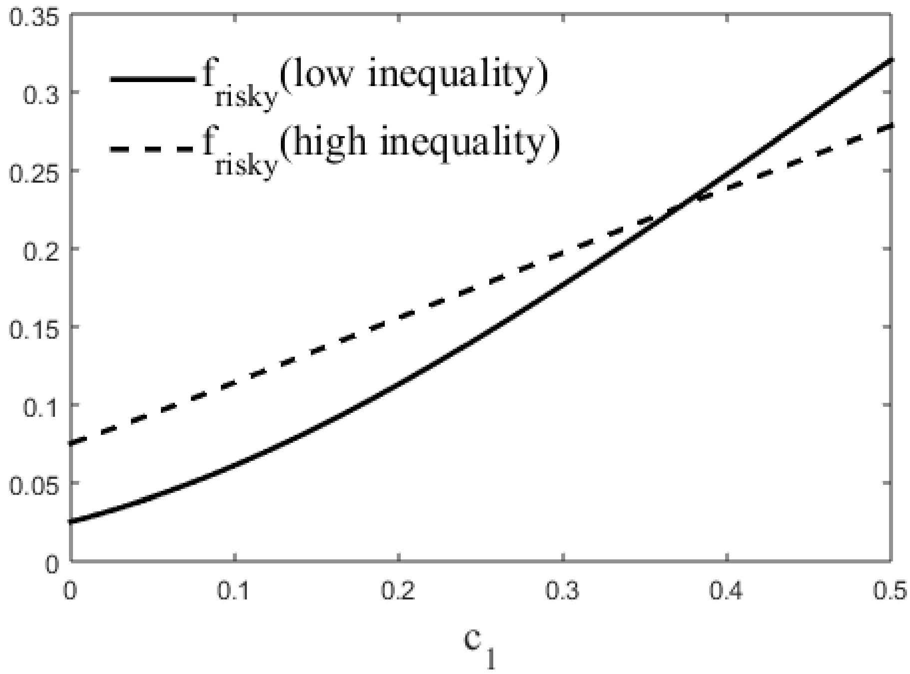
Next, we revisit *Keeley's observation* from the Introduction, namely, why do banks allow their default risk to increase in the first place? In order to study this question, we switch off the risk-shifting channel. We say that risk-shifting is not feasible when the deposit rate set by any given bank fully reflects its bank-specific risk.

Proposition 3. ***Risk shifting is not feasible***. *Suppose that (i) each banker incur a default cost of $F > 0$ upon bank default and (ii) risk-shifting is not feasible. Then, the mortgage interest rate for each y is undistorted (that is $r^*(y) = r_u(y)$), and all banks will be safe. Hence, the distribution of income has no effect on bank risk when the banks cannot risk-shift.*

Proof. See the Appendix. □

If risk-shifting is not feasible, then a bank choosing to be risky must fully compensate its depositors (or the deposit insurance fund, in case of bank-specific risk-premiums) for their expected loss. This implies that the only way for a risky bank to recoup its expected

Figure 4: The effect of housing supply elasticity



The figure shows the equilibrium proportion of risky banks as a function of the elasticity of housing supply. A higher value of c_1 corresponds to a less elastic housing supply. The solid line is based on a log-normal income distribution with a mean equal to 1 and a Gini coefficient equal to 0.3. The dashed line is based on a log-normal income distribution with a mean equal to 1 and a Gini coefficient equal to 0.5. For this particular example, the economy with higher inequality is characterized by a greater (smaller) proportion of risky banks when c_1 is below (above) about 0.4.

default cost of qF is to set its lending rates higher than the lending rates in safe banks. In other words, risky banks will be at a competitive disadvantage compared to safe banks and unable to attract borrowers. The bankers anticipate that they will be unable to recoup their default cost, and therefore, choose to operate a safe bank. In other words, bank failure will not emerge in this setup unless the banks can engage in risk-shifting.[21] Proposition 3 allows us to isolate the fundamental source of bank risk in this setup, namely risk-shifting.

5.5 Discussion

To highlight the model's central message and show that we can account for the data patterns relatively straightforwardly, we abstracted from several real-world features of

[21] However, this does not mean that banks reject risky loans. Banks continue to provide risky loans, but only to the degree that their capital is sufficient to buffer against bankruptcy in the bad state.

the banking system. However, the primary mechanism is flexible and robust to various generalizations, as we argue in this section.

Ex-ante heterogeneity among banks. The baseline model abstracted from the firm sector. Augmenting the model with firms is relatively straightforward. In this case, risky banks would issue subprime mortgage credit and also finance relatively risky firms. At the same time, safe banks would give out prime mortgage credit and finance relatively safe firms. Thus, the firm sector provides another dimension for bank specialization while not fundamentally altering the relation between income inequality and bank risk. Specifically, holding the firm sector fixed the association between the income distribution and bank risk continues to hold: higher inequality pushes more banks to specialize in risk-shifting. Simultaneously, if inequality and overall firm risk are positively (negatively) associated, the firm sector would magnify (mitigate) the relation between inequality and bank risk.

Risk-weighted capital. The baseline model assumes for simplicity that banks do not pay a premium on deposit insurance. As long as the deposit insurance premium does not fully reflect the bank's risk, the scope for risk-shifting remains. There is widespread evidence that deposit insurance premiums do not fully reflect bank risk. See, for example, Kisin and Manela (2016), among others. Similarly, we assumed that banks are subject to an overall minimum capital requirement while abstracting from explicitly modeling risk-weights on different asset classes (i.e., subprime vs. prime loans). Analogously to deposit insurance, risk-shifting incentives would be present as long as risk-weights are not fully adjusted to reflect bank-specific risk.

Housing speculation. Studies have shown that the speculative mortgage segment was an integral and potentially destabilizing part of the mortgage market(Adelino et al., 2016). Augmenting the model with housing speculation amplifies the effect of inequality on bank risk. The reason is that under plausible specifications, the demand for risky mortgages would originate from high-income housing speculators in addition to low-income subprime borrowers, thus creating more pronounced risk-shifting incentives for the banks. Similarly, assuming that banks can offer a menu of mortgage contracts (in terms of down payments or sensitivity to housing price appreciation) will not fundamentally alter the model's central message. Instead, it will add another dimension of bank specialization since risk-shifting banks would design their mortgages to maximize payoffs conditional on surviving.

6 Conclusion

We documented novel empirical patterns, namely that regions in the U.S. with higher income inequality tend to have a larger proportion of failed banks and a higher risk of bank failure. We also find that not every bank in more unequal regions is taking more risk, as reflected in a higher dispersion of bank failure risk.

To account for these patterns, we proposed a general equilibrium model based on competition and risk-shifting incentives. The core idea is that the option to risk-shift has an equilibrium value of zero when all banks are ex-ante identical and can control their failure risk through their portfolio and leverage decisions. This observation has far-reaching consequences for the effect of inequality on bank risk. Specifically, we showed that the equilibrium implies two types of banks, safe and risky, and two types of borrowers, prime and subprime. A subprime (prime) borrower has income (below) above an endogenous cutoff point.

In equilibrium, banks are ex-ante indifferent between specializing in risk-shifting (and thus becoming risky) and remaining safe. Moreover, risky banks lend only to subprime borrowers, whereas safe banks lend only to prime borrowers. That is, their clientele does not overlap. This sorting outcome emerges because the competition to risk-shift among risky banks drives the interest rate they charge to subprime borrowers to a level that is below its break-even point. Consequently, subprime loans carry negative net present value, leaving them attractive only to risk-shifting banks, whereas safe banks avoid this market segment and focus on prime borrowers.

The proportion of risky banks within a region adjusts to satisfy the demand for subprime credit relative to prime credit demand. Moving from an economy with low inequality to one with high inequality has a direct effect by pulling more households below the subprime cutoff and an indirect impact by shifting the cutoff's location. This outcome can lead to a subprime lending boom and create excessive bank risk and lead to subsequent bank failure. Under reasonable choice of parameter values, the model predicts that higher inequality is associated with (i) a higher incidence of failed banks, (ii) a greater average risk of bank failure, and (iii) a larger dispersion of bank failure risk. These equilibrium predictions arise in a banking model based on standard ingredients in which the only friction is deposit insurance.

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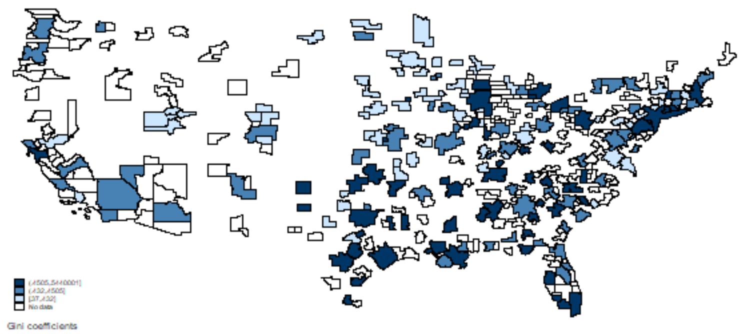
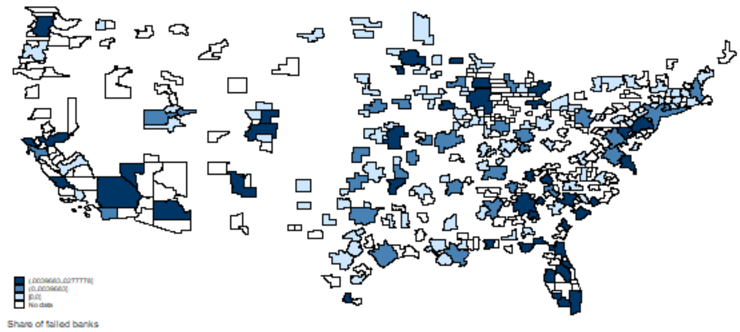
Appendix

A. Figures

Figure 5: Income inequality and bank risk across Metropolitan Statistical Areas



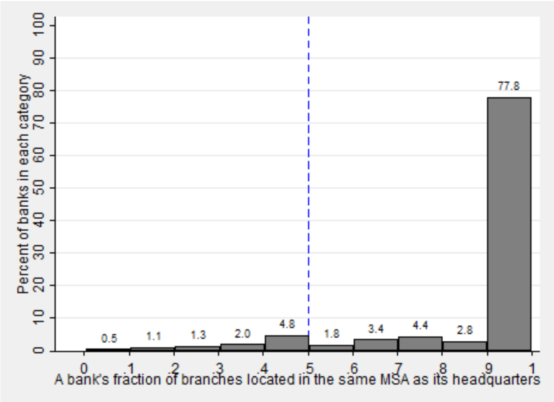
(a) Income inequality (Gini coefficients)



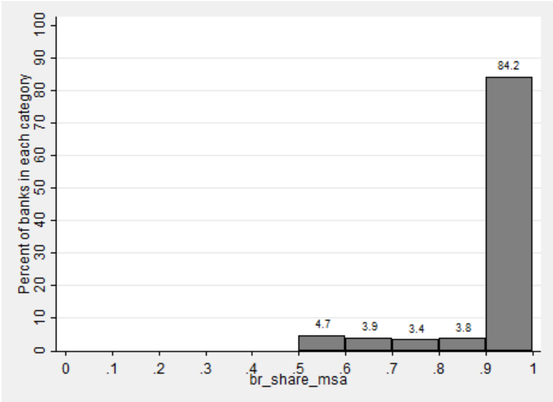
(b) Bank risk (share of failed banks)

The upper panel shows the Gini coefficients per MSA for the year 2006 (source: U.S. Census Bureau/ American Community Survey). Darker colors represent higher values, i.e. higher inequality. The lower panel shows a measure of bank risk, i.e. the share of failed banks over the full sample period 2000 to 2019. Darker colors represent higher values, i.e. higher bank risk. No data on the Gini coefficient is available for MSAs that are colored white.

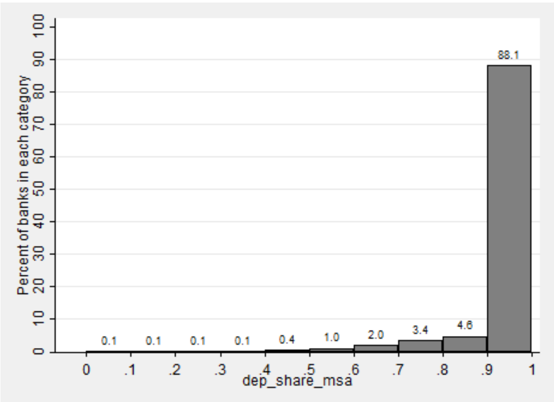
Figure 6: Regional concentration of banks



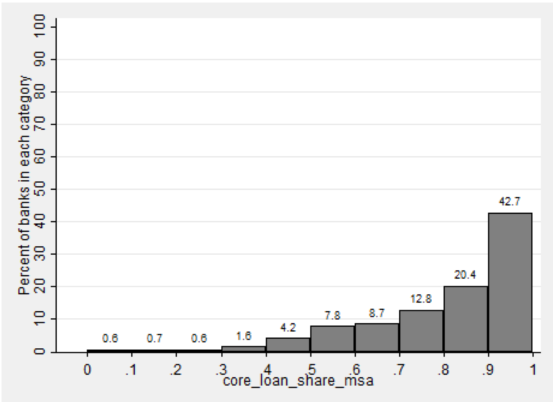
(a) branch concentration of all banks



(b) branch concentration of banks in our sample



(c) deposit concentration of banks in our sample



(d) mortgage concentration of banks in our sample

This figure shows in panel (a) the share of branches of each bank that are located in the same MSA as the bank's headquarters in the year 2000, what we refer to as *branch concentration*. For our main sample that is used for the regressions, we focus on banks with a branch concentration of 50% or more (panel b), which includes all banks to the right of the horizontal line in panel (a). The idea of this requirement is to exclude large national banks, such as Bank of America, from the sample. Panel (c) and panel (d) show the deposit concentration and the mortgage concentration, respectively, for banks in our sample.

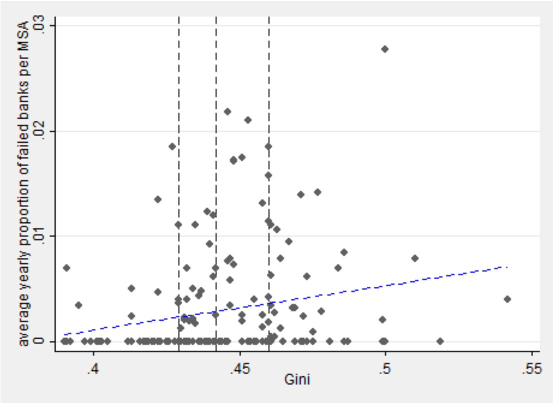
Figure 7: The role of mortgage loans for banks

(a) shares of total bank assets

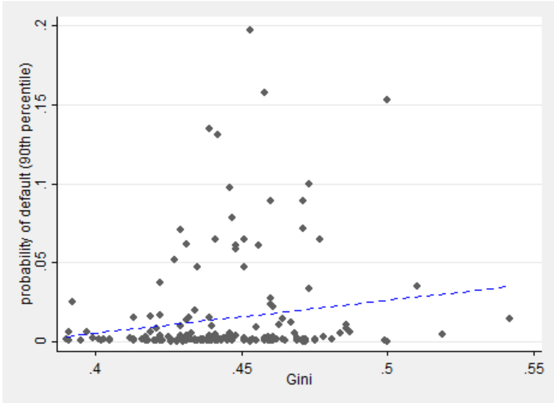
(b) shares non-performing assets

This figure shows the shares of total bank assets (left) and the shares of non-performing assets (right).

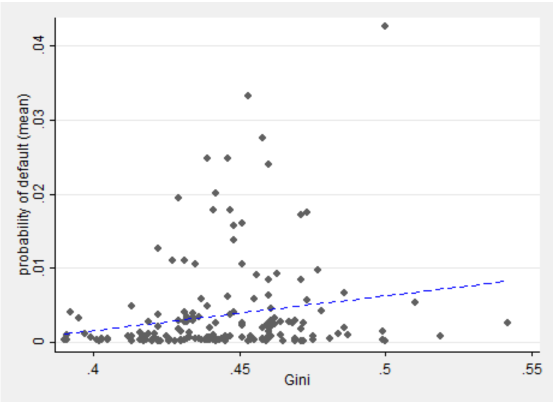
Figure 8: First graphical evidence



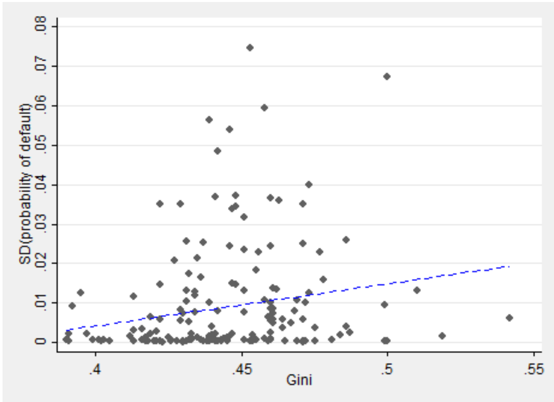
(a) shares of failed banks per MSA



(b) most risky banks per MSA (PD_90)



(c) average bank risk per MSA (PD_m)



(d) dispersion of bank risk per MSA (PD_sd)

This figure shows the relationship between income inequality (Gini coefficient) and different measures of bank risk per MSA.

B. Main Tables

Table 2: Variable description

Variable name	Description
Bank characteristics: panel data for each bank and year	
Failed_yr	**Bank failure.** A dummy variable with a value of 1 if the bank failed in year t, and 0 otherwise. Source: FDIC failed bank list.
PD_yr	**Predicted probability of default.** The predicted probabilities of default are based on a logit model with bank failures and several explanatory variables that are frequently used in the literature for such models (equity ratio, return on assets, non-performing assets, etc.). Details are provided in the Online Appendix.
Zscore_yr	**Z-score.** The natural logarithm of the sum of a bank's equity ratio and its return on assets, standardized by the standard deviation of return on assets using a rolling 8-quarter window. Source: Own calculations based on FDIC data.
Banking market characteristics on the MSA level: cross-sectional data for each MSA	
Failed_m	**Proportion of bank failures.** This variable is calculated as the average (mean) yearly proportion of bank failures.
PD_m	**Average bank risk:** The long-term average per MSA of the mean of banks' predicted probabilities of default for each MSA and year. Source: Own calculations based on FDIC data.
PD_90	**Bank risk of most risky banks:** The long-term average per MSA of the 90th-percentile of banks' predicted probabilities of default for each MSA and year. Source: Own calculations based on FDIC data.
PD_sd	**Dispersion of bank risk:** We use the long-term average standard deviation of banks's predicted probabilities of default for each MSA and year to represent dispersion of bank risk per MSA. Source: Own calculations based on the standard deviation of bank risk and the mean bank risk per MSA.
Zscore_m	**Average bank risk:** The long-term average per MSA of the mean of banks' z-scores for each MSA and year. Source: Own calculations based on FDIC data.
Zscore_10	**Bank risk of most risky banks:** The long-term average per MSA of the 10th-percentile of banks' z-scores for each MSA and year. Source: Own calculations based on FDIC data.
Zscore_sd	**Dispersion of bank risk:** We use the long-term average standard deviation of banks's z-scores for each MSA and year to represent dispersion of bank risk per MSA. Source: Own calculations based on the standard deviation of bank risk and the mean bank risk per MSA.
Inequality measures and further economic characteristics on the MSA level: cross-sectional data for each MSA	
Gini	**Gini coefficient.** The Gini coefficient is defined as "the difference between the Lorenz curve (the observed cumulative income distribution) and the notion of a perfectly equal income distribution." A measure of 1 indicates perfect inequality, i.e., one household having all the income and rest having none. A gini measure of 0 indicates perfect equality, i.e., all households having an equal share of income. Source: U.S. Census Bureau, 2006 American Community Survey (Table B19083). Note: We use this variable from the year 2006 because this is the first year when it is available on the MSA level.
Mean_income	**Mean household income.** The variable is stated in USD 000. Source: U.S. Census Bureau, 2006 American Community Survey (Table DP03). Note: We use this variable from the year 2006 because this is the first year when the Gini is available on the MSA level.
Med_income	**Median household income.** The variable is stated in USD 000. Source: U.S. Census Bureau, 2006 American Community Survey (Table DP03). Note: We use this variable from the year 2006 because this is the first year when the Gini is available on the MSA level.

Table 3: Descriptive statistics

	Obs.	**Mean**	**SD**	**Min**	**P10**	**P50**	**P90**	**Max**
Gini	178	0.4421	0.0261	0.3630	0.4110	0.4400	0.4750	0.5440
Mean_income	178	61.6576	10.9862	40.7990	50.3950	58.9515	74.4720	124.6650
Med_income	178	47.3233	8.0766	28.6600	37.6020	45.9445	56.9530	78.9780
Failed_m	178	0.0030	0.0052	0.0000	0.0000	0.0000	0.0111	0.0278
PD_m	178	0.0037	0.0065	0.0001	0.0002	0.0009	0.0110	0.0426
PD_90	178	0.0147	0.0319	0.0004	0.0007	0.0016	0.0609	0.1974
PD_sd	178	0.0089	0.0138	0.0002	0.0003	0.0022	0.0260	0.0747
Zscore_m	178	4.1554	0.3175	3.2730	3.7434	4.1950	4.5426	4.8579
Zscore_10	178	2.8705	0.4628	1.6744	2.2576	2.8777	3.4871	4.1142
Zscore_sd	178	0.9350	0.1629	0.5522	0.7310	0.9072	1.1420	1.3210

Table 4: Cross-correlation table

Variables	Gini	Mean income	Med income	Failed_m	PD_m	PD_90	PD_sd	Zscore_m	Zscore_10	Zscore_sd
Gini	1.000									
Mean_income	0.146	1.000								
Med_income	-0.109	0.943	1.000							
Failed_m	0.225	0.180	0.108	1.000						
PD_m	0.228	0.171	0.105	0.807	1.000					
PD_90	0.197	0.083	0.026	0.709	0.950	1.000				
PD_sd	0.224	0.226	0.161	0.791	0.962	0.907	1.000			
Zscore_m	-0.173	-0.245	-0.176	-0.563	-0.544	-0.477	-0.553	1.000		
Zscore_10	-0.166	-0.239	-0.176	-0.546	-0.520	-0.466	-0.549	0.825	1.000	
Zscore_sd	0.168	0.287	0.224	0.375	0.342	0.284	0.418	-0.353	-0.752	1.000

Table 5: Main regression results: MSA-level cross-sectional data

This table shows regression results for the empirical model presented in Section 2. See Table 2 for a detailed explanation of every variable, and Table 3 for descriptive statistics. All regressions include a constant (not reported). Standard errors are reported in parentheses. The ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively.

Panel A: Share of failed banks

	(1) Failed_m	(2) Failed_m	(3) Failed_m
Gini	0.0423***	0.0370**	0.0459***
	(0.0158)	(0.0154)	(0.0167)
Mean_income		0.0001*	
		(0.0000)	
Med_income			0.0001*
			(0.0001)
Obs.	178	178	178
Adj. R2	0.0372	0.0532	0.0503

Panel B: Bank risk of most risky banks

	(1) PD_90	(2) PD_90	(3) PD_90	(4) Zscore_10	(5) Zscore_10	(6) Zscore_10
Gini	0.2080**	0.1956**	0.2155**	-3.1783**	-2.4850	-3.6418**
	(0.0868)	(0.0856)	(0.0899)	(1.4823)	(1.5811)	(1.4774)
Mean_income		0.0002			-0.0091***	
		(0.0003)			(0.0033)	
Med_income			0.0002			-0.0115***
			(0.0003)			(0.0043)
Obs.	178	178	178	178	178	178
Adj. R2	0.0221	0.0195	0.0188	0.0251	0.0649	0.0599

Panel C: Average bank risk

	(1) PD_m	(2) PD_m	(3) PD_m	(4) Zscore_m	(5) Zscore_m	(6) Zscore_m
Gini	0.0471**	0.0406**	0.0513**	-2.1759**	-1.6883*	-2.4943***
	(0.0218)	(0.0203)	(0.0234)	(0.9109)	(0.9495)	(0.9198)
Mean_income		0.0001			-0.0064***	
		(0.0001)			(0.0022)	
Med_income			0.0001			-0.0079***
			(0.0001)			(0.0028)
Obs.	178	178	178	178	178	178
Adj. R2	0.0284	0.0428	0.0396	0.0250	0.0670	0.0599

Panel D: Dispersion of bank risk (average standard deviation per MSA)

	(1) PD_sd	(2) PD_sd	(3) PD_sd	(4) Zscore_sd	(5) Zscore_sd	(6) Zscore_sd
Gini	0.1067***	0.0877**	0.1197***	1.2380**	0.9420*	1.4426***
	(0.0389)	(0.0388)	(0.0430)	(0.5264)	(0.5388)	(0.5054)
Mean_income		0.0002**			0.0039***	
		(0.0001)			(0.0011)	
Med_income			0.0003**			0.0051***
			(0.0001)			(0.0014)
Obs.	178	178	178	178	178	178
Adj. R2	0.0333	0.0661	0.0635	0.0320	0.0931	0.0901

C. Proofs

Proof of Proposition 1.

Proof. The discussion in the text establishes that the equilibrium profile of interest rates is given by (17), namely $r^*(y) = r_{rs}(y)$ for $y < y^*$ and $r^*(y) = r_u(y)$ for $y > y^*$ where $r_{rs}(y)$ is given in (16) and $r_u(y)$ is given in (14). The cutoff y^* is then obtained at the intersection of the undistorted and the risk-shifting interest rate: $r_u(y^*) = r_{rs}$. It remains to show that the cutoff y^* is given by (20). Suppose a household with income y obtains a loan at an interest rate r. The return on this loan in the bad state is

$$\psi(r, y) \equiv (1 - m(y, r))(1 + r) + m(y, r)(1 + g_B)$$

where $m(y, r) = \min\{P_0(r - g_B)/\beta y,\, 1\}$ is the rate of default among income-y households in the bad state. By combining (14) and (16) it follows that the cutoff y^* must satisfy

$$\psi(r_{rs}, y^*) = (1 - \tfrac{1}{\rho})(1 + r_D).$$

The left-hand side is the expected return from a loan to income-y^* household in the bad state. The right-hand side is the return offered to the depositors. The above states that a loan to an income-y^* household has an expected return in the bad state equal to the return promised to the depositors. Expressing $m(y, r)$ in terms of P_0 and r_{rs} and rearranging yields

$$\psi(r_{rs}, y^*) = (1 + r_{rs}) - \min\left\{\tfrac{P_0^*}{\beta y^*}(r_{rs} - g_B),\, 1\right\}(r_{rs} - g_b) = (1 - \tfrac{1}{\rho})(1 + r_D).$$

This equation can be solved for y^* yielding the expression for the cutoff in (20). A sufficient condition for the existence of the cutoff is $(1 - \frac{1}{\rho})(1 + r_D) > 1 + g_B$. Notice that for each $y < y^*$, we have $\psi(r_{rs}, y) < (1 - \frac{1}{\rho})(1 + r_D)$. Therefore, a bank lending exclusively to households with income less than y^* is a risky bank since it becomes insolvent in the bad state. On the other hand, for each $y > y^*$ we have $\psi(r_{rs}, y) > (1 - \frac{1}{\rho})(1 + r_D)$. Hence, any bank lending exclusively to households with income higher than y^* is a safe bank since it remains solvent in the bad state. □

Proof of Proposition 2.

Proof. The discussion in the text establishes that the proportion of risky banks is given in (23) provided that (i) all banks borrow to the maximum allowed leverage ratio ρ, (ii) the amount of capital issued by safe banks k^*_{safe} is given by the first expression in (21), and (iii) and the amount of capital issued by risky banks k^*_{risky} is given by the second component in (21). Here we show that (i) - (ii) are indeed the case.

To begin, fix a triple (r^*, r_K, r_D), where $r^* = \{r^*(y)\}$ for each y is the equilibrium profile of mortgage interest rates. The expected payoff of a safe bank is

$$(b_s + k_s) \int_{\underline{y}}^{\overline{y}} E\left[y \,|\, r^*(y)\right] \omega_s(y) dy - b_s(1 + r_D) - k_s(1 + r_K) - c(k_s + b_s)$$

where k_s, $b_s$and ω_s denotes the capital, deposits, and loan-portfolio chosen by safe banks. We assume that safe banks operate at the maximum leverage ratio ρ, and later verify this assumption. Substituting for $b_s = k_s(\rho - 1)$, the expected payoff of a safe bank can be expressed as

$$k_s\rho \left\{ \int_{\underline{y}}^{\overline{y}} E\left[y \,|\, r^*(y)\right] \omega_s(y) dy - (1 - \frac{1}{\rho})(1 + r_D) - \frac{1}{\rho}(1 + r_K) \right\} - c(k_s\rho)$$

If in equilibrium, safe banks lend to income-y households (that is, $\omega^*_s(y) > 0$), then

$$E\left[y \,|\, r^*(y)\right] = (1 - \frac{1}{\rho})(1 + r_D) - \frac{1}{\rho}(1 + r_K) + c'(k^*_{\text{safe}}\rho),$$

where k^*_{safe} is the equilibrium level of capital issued by safe banks. Otherwise, a safe bank can strictly increase its payoff by either increasing (if the above is positive) or decreasing (if the above is negative) its exposure to income-y households. Next, define

$$\Pi^*_{\text{safe}} \equiv \int_{\underline{y}}^{\overline{y}} E\left[y \,|\, r^*(y)\right] \omega_s(y) dy - (1 - \frac{1}{\rho})(1 + r_D) - \frac{1}{\rho}(1 + r_K) = c'(k^*_{\text{safe}}\rho).$$

Safe banks take Π^*_{safe} as given and choose their capital to maximize their expected profits.

That is,

$$\max_k k\rho\Pi^*_{\text{safe}} - f - \frac{t}{2}(k\rho)^2$$

The solution is $k^*_{\text{safe}} = \Pi^*_{\text{safe}}/\rho t$. Moreover, since $\Pi^*_{\text{safe}} = c'(k^*_{\text{safe}}\rho)$, we have $k^*_{\text{safe}} = c'(k^*_{\text{safe}}\rho)/\rho t$, and therefore, each safe bank is best-responding by choosing k^*_{safe} when the others are also choosing k^*_{safe}. The free-entry condition implies that Π^*_{safe} adjust so that the expected profit for safe banks equal zero. That is, $\Pi^*_{\text{safe}} = \sqrt{2ft}$, which yields the expression in (21), namely $k^*_{\text{risky}} = (1/\rho)\sqrt{2f/t}$. Next, the expected payoff for a risky bank is

$$(b_r + k_r)(1-q)\left\{\int_{\underline{y}}^{\overline{y}} E\left[y\,|\,r^*(y)\right]\omega_r(y)dy - b_r(1+r_D)\right\} - k_r(1+r_K) - c(k_r+b_r) - qF$$

where k_r, $b_r$and ω_r denotes the capital, deposits, and loan-portfolio chosen by risky banks and qF is the expected cost of default. Similar to safe banks, we assume and later verify that risky banks borrow $b_r = k_r(\rho-1)$. Substituting for b_r in terms of k_r in the above expression and rearranging yields

$$k_r\rho\left\{(1-q)\left[\int_{\underline{y}}^{\overline{y}}(1+r^*(y))\omega_r(y)dy - (1-q)(1-\frac{1}{\rho})(1+r_D)\right] - \frac{1}{\rho}(1+r_K)\right\} - c(k_r\rho) - qF$$

In equilibrium, if $\omega^*_r(y) > 0$ then the loan to income-y households has an expected payoff in the good state of

$$(1-q)\left(1+r^*(y)\right) = \frac{1}{\rho}(1+r_K) + (1-q)(1-\frac{1}{\rho})(1+r_D) + c(k^*_{\text{risky}}\rho)$$

where k^*_{risky} is the common capital level for risky banks. Hence, we have

$$\Pi^*_{\text{risky}} \equiv (1-q)\left[\int_{\underline{y}}^{\overline{y}}(1+r^*(y))\omega_r(y)dy - (1-q)(1-\frac{1}{\rho})(1+r_D)\right] - \frac{1}{\rho}(1+r_K) = c(k^*_{\text{risky}}\rho)$$

Risky banks take Π^*_{risky} as given and choose their capital to maximize their expected profits. That is,

$$\max_k k\rho\Pi^*_{\text{risky}} - f - \frac{t}{2}(k\rho)^2 - qF$$

The solution sets $k^*_{\text{risky}} = \Pi^*_{\text{risky}}/\rho t$. Since $\Pi^*_{\text{risky}} = c'(k^*_{\text{risky}}\rho)$, we have $k^*_{\text{risky}} = c'(k^*_{\text{risky}}\rho)/\rho t$, and therefore, each risky bank is best-responding by choosing k^*_{risky} when the other risky banks set k^*_{risky}. The free-entry condition then implies that Π^*_{risky} adjust so that the expected profit for safe banks equal zero. That is, $\Pi^*_{\text{risky}} = \sqrt{2(f + qF)t}$, which yields the expression in (21), namely $k^*_{\text{risky}} = (1/\rho)\sqrt{2(f + qF)/t}$.

The aggregate volume of subprime credit is $d^*_{\text{subprime}} = \int_{\underline{y}}^{y^*} P^*_0 n(y)dH(y)$ and the aggregate volume of prime credit is $d^*_{\text{prime}} = \int_{y^*}^{\overline{y}} P^*_0 n(y)dH(y)$. Since each unit of capital is leveraged ρ times, the aggregate amount of capital issued by all banks (safe and risky) is

$$K^* = \frac{1}{\rho} d^*_{\text{subprime}} + \frac{1}{\rho} d^*_{\text{prime}}$$

The first component is the amount of capital issued by risky banks and the second component is the amount for capital issued by safe banks. Similarly, the aggregate amount of deposits issued by all banks is

$$D^* = \left(1 - \frac{1}{\rho}\right) d^*_{\text{subprime}} + \left(1 - \frac{1}{\rho}\right) d^*_{\text{prime}}$$

The first component is the amount of deposits issued by risky banks and the second component is the amount of deposits issued by safe banks. Note that $K^* + D^* = \int_{y^*}^{\overline{y}} P^*_0 n(y)dH(y)$. The mass of risky and safe banks can then be obtained from

$$n^*_{\text{risky}} = \frac{d^*_{\text{subprime}}}{k^*_{\text{risky}}} \qquad \text{and} \qquad n^*_{\text{safe}} = \frac{d^*_{\text{prime}}}{k^*_{\text{safe}}}.$$

Using the optimal choices of k^*_{risky} and k^*_{safe} derived above, the proportion of risk banks $f^*_{\text{risky}} = n^*_{\text{risky}}/(n^*_{\text{risky}} + n^*_{\text{safe}})$ is then given in (23). The loan portfolio for risky banks is $\omega^*_r(y) = P_0 n(y)/d^*_{\text{subprime}}$ for $y < y^*$ and $\omega^*_r(y) = 0$ for $y > y^*$. Note that $\omega^*_r(y) \geq 0$ for each y and $\int_{\underline{y}}^{\overline{y}} \omega^*_r(y)dy = 1$. Moreover, for each $z < y^*$, the demand for subprime credit equals the supply.

$$\int_{\underline{y}}^{z} P^*_0 n(y)dH(y) = n^*_{\text{risky}} k^*_{\text{risky}} \rho \int_{\underline{y}}^{z} \omega^*_r(y)dy.$$

The loan portfolio for safe banks is $\omega^*_s(y) = 0$ for $y < y^*$ and $\omega^*_s(y) = P_0 n(y)/d^*_{\text{prime}}$ for

$y > y^*$. Note that for each $z > y^*$, the demand for prime credit equals the supply.

$$\int_{y^*}^{z} P_0^* n(y) dH(y) = n_{\text{safe}}^* k_{\text{safe}}^* \rho \int_{y^*}^{z} \omega_s^*(y) dy.$$

Finally, from (5), in equilibrium, the required return on capital and deposits is

$$r_K^* = t_K K^* \qquad \text{and} \qquad r_D^* = t_D D^*$$

Our assumption $t_k \geq (\rho - 1)t_D$ implies that capital is at least as expensive as deposits $r_K^* \geq r_D^*$, and therefore, banks are behaving optimally by operating at the minimum capital requirement as we initially assumed. □

Proof of Proposition 3.

Proof. Since in equilibrium deposits are a cheaper source of funds than capital, all banks operate at the minimum capital requirement $b = k(\rho - 1)$. In equilibrium, the expected payoff for a risky bank must recoup its expected default cost. That is,

$$k_r \rho (1-q) \left\{ \int_{\underline{y}}^{\overline{y}} (1 + r^*(y)) \omega_r(y) dy - \left(1 - \frac{1}{\rho}\right)(1 + r_{D,r}) - \frac{1}{\rho}(1 + r_K) \right\} - c(\rho k_r) = qF$$

where $r_{D,r}$ is the interest rate on deposits set by risky banks. Since risk-shifting is not feasible, the interest on deposits $r_{D,r}$ adjust so that the bank's depositors break-even in expectation. That is,

$$(1-q)(1 + r_{D,r}) + q \int_{\underline{y}}^{\overline{y}} \left[(1 - m^*(y))(1 + r^*(y)) + m^*(y)(1 + g_B)\right] \omega_r(y) dy = 1 + r_D,$$

where r_D is the opportunity cost of funds for the depositors and $m^*(y)$ is the rate of default among income-y households in the bad state. Combining the participation constraint of the depositors in risky banks with the zero-profit condition implies

$$\int_{\underline{y}}^{\overline{y}} E\left[y \mid r^*(y)\right] \omega_r(y) dy = \left(1 - \frac{1}{\rho}\right)(1 + r_D) + \frac{1}{\rho}(1 + r_K) + \frac{c(\rho k_r) + qF}{\rho k_r}$$

At the same time, for a safe bank we have

$$\int_{\underline{y}}^{\overline{y}} E\left[y \,|\, r^*(y)\right] \omega_s(y)dy = \left(1 - \frac{1}{\rho}\right)(1 + r_D) + \frac{1}{\rho}(1 + r_K) + \frac{c(\rho k_s)}{\rho k_s}$$

As an implication, risky banks will issue more capital $k_r > k_s$ and operate a larger balance sheet $k_r\rho > k_s\rho$ than safe banks to recoup their expected default cost of qF. Since $c(.)$ is convex, $k_r > k_s$, and $F > 0$ we have

$$\int_{\underline{y}}^{\overline{y}} E\left[y \,|\, r^*(y)\right] \omega_r(y)dy > \int_{\underline{y}}^{\overline{y}} E\left[y \,|\, r^*(y)\right] \omega_s(y)dy$$

That is, the expected payoff risky bank's portfolio ω_r must be strictly greater than the expected payoff of a safe bank's portfolio ω_s. This will be necessary to compensate the risky bank for paying the default cost F with probability q. Next, consider another bank which invests a fraction $\epsilon > 0$ in the risky bank portfolio and $1 - \epsilon$ in safe banks portfolio $\omega = \epsilon\omega_r + (1 - \epsilon)\omega_s$. For ϵ small enough, this bank is safe (and therefore will not incur the default cost F) and earns an expected payoff greater than the other safe banks. However, this situation is not consistent with equilibrium, and therefore, our assumption that there exist a risky bank cannot be true. Hence, if risk-shifting is not possible, then all banks must be safe. $\square$

Online Appendix

This additional material is for online publication only.

Part I. Several tables that provide robustness test for our main results as well as additional results.

- Descriptives
  - I Description of new variables
  - II Descriptive statistics of new variables
- Alternative measures of inequality and other economic conditions
  - III Gini coefficient based on 3-year survey data (2005 to 2007)
  - IV Income share of top 5 percent
  - V Poverty
- Alternative measures of bank risk
  - VI Measures of bank risk including the years 2008 and 2009 (i.e., the years when government assistance through TARP took place, which are excluded otherwise)
- Panel regressions (MSA and year level)
  - VII Measures of bank risk – clustering on MSA level

Part II. A detailed description of our prediction of banks' probabilities of default (PD).

Part I: Robustness regressions

Table OA1: Variable description

Variable name	Description
Inequality measures and further economic characteristics: cross-sectional data for each MSA	
Gini_3y	**Gini coefficient based on 3-year survey data (2005 to 2007).** Source: U.S. Census Bureau, 2005 to 2007 3-year estimates from the American Community Survey 2007 (the first year when 3-year estimates are available).
Mean_income_3y	**Mean household income based on 3-year survey data (2005 to 2007).** The variable is stated in USD 000. Source: U.S. Census Bureau, 2005 to 2007 3-year estimates from the American Community Survey 2007 (the first year when 3-year estimates are available).
Med_income_3y	**Median household income based on 3-year survey data (2005 to 2007).** The variable is stated in USD 000. Source: U.S. Census Bureau, 2005 to 2007 3-year estimates from the American Community Survey 2007 (the first year when 3-year estimates are available).
Poverty_share	**Poverty_share.** The measure is defined as the "percentage of families and people whose income in the past 12 months is below the poverty level - 18 years and over". Source: U.S. Census Bureau, 1-year estimate from 2006 (the first year when the Gini coefficient and other income data is available on MSA level).
Share_top5p	**Income share of top 5 percent.** Source: U.S. Census Bureau, 1-year estimate from 2006 (the first year when this data is available).
Banking market characteristics: cross-sectional data for each MSA (based on banks' headquarters locations)	
For robustness regressions, the following variables are calculated based on all years from 2000 to 2019, including the years of the financial crisis 2008 and 2009, which are excluded for the calculation of the variables in the main analysis, because government support during the financial crisis such as TARP may distort the variables.	
Failed_0809_m	**Proportion of bank failures.** This variable is calculated as the average (mean) yearly proportion of bank failures.
PD_0809_m	**Average bank risk:** The long-term average per MSA of the mean of banks' predicted probabilities of default for each MSA and year. Source: Own calculations based on FDIC data.
PD_0809_90	**Bank risk of most risky banks:** The long-term average per MSA of the 90th-percentile of banks' predicted probabilities of default for each MSA and year. Source: Own calculations based on FDIC data.
PD_0809_sd	**Dispersion of bank risk:** We use the long-term average standard deviation of banks's predicted probabilities of default for each MSA and year to represent dispersion of bank risk per MSA. Source: Own calculations based on the standard deviation of bank risk and the mean bank risk per MSA.
Zscore_0809_m	**Average bank risk:** The long-term average per MSA of the mean of banks' z-scores for each MSA and year. Source: Own calculations based on FDIC data.
Zscore_0809_10	**Bank risk of most risky banks:** The long-term average per MSA of the 10th-percentile of banks' z-scores for each MSA and year. Source: Own calculations based on FDIC data.
Zscore_0809_sd	**Dispersion of bank risk:** We use the long-term average standard deviation of banks's z-scores for each MSA and year to represent dispersion of bank risk per MSA. Source: Own calculations based on the standard deviation of bank risk and the mean bank risk per MSA.
Banking market characteristics: panel data for each MSA and year (based on banks' headquarters locations)	
Failed_yr_m	**Proportion of bank failures.** This variable is calculated as the proportion of bank failures for each MSA and year.
PD_yr_m	**Average bank risk:** The mean of banks' predicted probabilities of default for each MSA and year. Source: Own calculations based on FDIC data.
PD_yr_90	**Bank risk of most risky banks:** The 90th-percentile of banks' predicted probabilities of default for each MSA and year. Source: Own calculations based on FDIC data.
PD_yr_sd	**Dispersion of bank risk:** We use the standard deviation of banks's predicted probabilities of default for each MSA and year to represent dispersion of bank risk for each MSA and year. Source: Own calculations based on the standard deviation of bank risk and the mean bank risk per MSA.
Zscore_yr_m	**Average bank risk:** The mean of banks' z-scores for each MSA and year. Source: Own calculations based on FDIC data.
Zscore_yr_10	**Bank risk of most risky banks:** The 10th-percentile of banks' z-scores for each MSA and year. Source: Own calculations based on FDIC data.
Zscore_yr_sd	**Dispersion of bank risk:** We use the standard deviation of banks's z-scores for each MSA and year to represent dispersion of bank risk per MSA and year. Source: Own calculations based on the standard deviation of bank risk and the mean bank risk per MSA.

Table OA2: Descriptive statistics

	Obs.	**Mean**	**SD**	**Min**	**P25**	**P50**	**P75**	**Max**
Gini_3y	178	0.4442	0.0233	0.3820	0.4290	0.4435	0.4600	0.5400
Mean_income 3y	178	63.8251	11.1943	41.3830	57.1610	61.4865	69.0010	127.7820
Med_income 3y	178	48.8698	8.1825	28.3280	43.5820	47.1160	53.5640	81.1630
Poverty_share	175	11.8886	3.4740	6.1000	9.7000	11.5000	13.5000	30.8000
Share_top5	178	20.6045	2.1218	15.9000	19.3000	20.5000	21.8000	29.9000
Failed_0809_m	179	0.0039	0.0067	0.0000	0.0000	0.0000	0.0056	0.0480
PD_0809_m	179	0.0047	0.0069	0.0003	0.0008	0.0020	0.0048	0.0419
PD_0809_90	179	0.0180	0.0334	0.0006	0.0020	0.0042	0.0138	0.2089
PD_0809_sd	179	0.0109	0.0149	0.0003	0.0010	0.0042	0.0155	0.0777
Zscore_0809_m	179	4.0930	0.3358	3.1246	3.9170	4.1190	4.3031	4.8117
Zscore_0809_10	179	2.7807	0.4813	1.4861	2.5043	2.8203	3.1216	4.1142
Zscore_0809_sd	179	0.9538	0.1687	0.5522	0.8270	0.9292	1.0774	1.5602
Failed_yr_m	3,169	0.0030	0.0193	0.0000	0.0000	0.0000	0.0000	0.3333
PD_yr_m	3,169	0.0037	0.0169	0.0000	0.0002	0.0003	0.0007	0.2620
PD_yr_90	3,169	0.0146	0.0817	0.0000	0.0004	0.0008	0.0018	0.9940
PD_yr_10	3,169	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0022
PD_yr_sd	3,169	0.0089	0.0372	0.0000	0.0002	0.0004	0.0012	0.4229
Zscore_yr_m	3,169	4.1551	0.5157	0.9535	3.8899	4.2004	4.4848	5.5461
Zscore_yr_10	3,169	2.8661	0.9291	-2.7257	2.4162	2.9771	3.4915	5.0787
Zscore_yr_sd	3,169	0.9366	0.3462	0.0193	0.7123	0.9005	1.1238	3.6194

Table OA3: Gini coefficient based on 3-year survey data (2005 to 2007)

This table shows regression results for the empirical model presented in Section 2. See Table 2 (main text) and Table OA1 (this online appendix) for an explanation of every variable, and Table 3 (main text) and Table OA2 (this online appendix) for descriptive statistics. All regressions include a constant (not reported). Standard errors are reported in parentheses. The ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively.

Panel A: Bank failures

	(1) Failed_m	(2) Failed_m	(3) Failed_m
Gini_3y	0.0500**	0.0442**	0.0532***
	(0.0194)	(0.0187)	(0.0204)
Mean_income_3y		0.0001*	
		(0.0000)	
Med_income_3y			0.0001*
			(0.0000)
Obs.	178	178	178
Adj. R2	0.0442	0.0593	0.0570

Panel B: Bank risk of most risky banks

	(1) PD_90	(2) PD_90	(3) PD_90	(4) Zscore_10	(5) Zscore_10	(6) Zscore_10
Gini_3y	0.2177**	0.2044*	0.2240**	-3.7398**	-2.9869*	-4.1571***
	(0.1081)	(0.1040)	(0.1118)	(1.5499)	(1.6891)	(1.5801)
Mean_income_3y		0.0002			-0.0088***	
		(0.0002)			(0.0033)	
Med_income_3y			0.0002			-0.0113***
			(0.0003)			(0.0043)
Obs.	178	178	178	178	178	178
Adj. R2	0.0197	0.0170	0.0160	0.0299	0.0687	0.0642

Panel C: Average bank risk

	(1) PD_m	(2) PD_m	(3) PD_m	(4) Zscore_m	(5) Zscore_m	(6) Zscore_m
Gini_3y	0.0551*	0.0481*	0.0587*	-2.3221**	-1.8026*	-2.5971**
	(0.0284)	(0.0264)	(0.0299)	(1.0106)	(1.0565)	(1.0235)
Mean_income_3y		0.0001			-0.0061***	
		(0.0001)			(0.0021)	
Med_income_3y			0.0001			-0.0074***
			(0.0001)			(0.0028)
Obs.	178	178	178	178	178	178
Adj. R2	0.0332	0.0465	0.0432	0.0235	0.0628	0.0547

Panel D: Dispersion of bank risk (average standard deviation per MSA)

	(1) PD_sd	(2) PD_sd	(3) PD_sd	(4) Zscore_sd	(5) Zscore_sd	(6) Zscore_sd
Gini_3y	0.1205**	0.1002**	0.1319**	1.5173***	1.2028**	1.6999***
	(0.0467)	(0.0458)	(0.0512)	(0.5286)	(0.5688)	(0.5331)
Mean_income_3y		0.0002**			0.0037***	
		(0.0001)			(0.0011)	
Med_income_3y			0.0003**			0.0049***
			(0.0001)			(0.0014)
Obs.	178	178	178	178	178	178
Adj. R2	0.0358	0.0667	0.0635	0.0416	0.0986	0.0976

Table OA4: Income share of top 5 percent

This table shows regression results for the empirical model presented in Section 2. See Table 2 (main text) and Table OA1 (this online appendix) for an explanation of every variable, and Table 3 (main text) and Table OA2 (this online appendix) for descriptive statistics. All regressions include a constant (not reported). Standard errors are reported in parentheses. The ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively.

Panel A: Bank failures

	(1) Failed_m	(2) Failed_m	(3) Failed_m
Share_top5	0.0006***	0.0006***	0.0006***
	(0.0002)	(0.0002)	(0.0002)
Mean_income		0.0001	
		(0.0000)	
Med_income			0.0001
			(0.0000)
Obs.	178	178	178
Adj. R2	0.0612	0.0671	0.0664

Panel B: Bank risk of most risky banks

	(1) PD_90	(2) PD_90	(3) PD_90	(4) Zscore_10	(5) Zscore_10	(6) Zscore_10
Share_top5	0.0031**	0.0030**	0.0031**	-0.0475***	-0.0347*	-0.0466**
	(0.0013)	(0.0012)	(0.0013)	(0.0180)	(0.0203)	(0.0185)
Mean_income		0.0001			-0.0080**	
		(0.0003)			(0.0034)	
Med_income			0.0001			-0.0098**
			(0.0003)			(0.0045)
Obs.	178	178	178	178	178	178
Adj. R2	0.0360	0.0310	0.0310	0.0421	0.0696	0.0662

Panel C: Average bank risk

	(1) PD_m	(2) PD_m	(3) PD_m	(4) Zscore_m	(5) Zscore_m	(6) Zscore_m
Share_top5	0.0007**	0.0006**	0.0007**	-0.0410***	-0.0328***	-0.0404***
	(0.0003)	(0.0003)	(0.0003)	(0.0113)	(0.0122)	(0.0117)
Mean_income		0.0001			-0.0051**	
		(0.0001)			(0.0023)	
Med_income			0.0001			-0.0067**
			(0.0001)			(0.0028)
Obs.	178	178	178	178	178	178
Adj. R2	0.0462	0.0520	0.0507	0.0698	0.0930	0.0937

Panel D: Dispersion of bank risk (average standard deviation per MSA)

	(1) PD_sd	(2) PD_sd	(3) PD_sd	(4) Zscore_sd	(5) Zscore_sd	(6) Zscore_sd
Share_top5	0.0016***	0.0013**	0.0016***	0.0149**	0.0089	0.0145**
	(0.0006)	(0.0005)	(0.0006)	(0.0063)	(0.0068)	(0.0062)
Mean_income		0.0002*			0.0037***	
		(0.0001)			(0.0011)	
Med_income			0.0003*			0.0044***
			(0.0001)			(0.0015)
Obs.	178	178	178	178	178	178
Adj. R2	0.0558	0.0755	0.0749	0.0322	0.0842	0.0754

Table OA5: Poverty

This table shows regression results for the empirical model presented in Section 2. See Table 2 (main text) and Table OA1 (this online appendix) for an explanation of every variable, and Table 3 (main text) and Table OA2 (this online appendix) for descriptive statistics. All regressions include a constant (not reported). Standard errors are reported in parentheses. The ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively.

Panel A: Bank failures

	(1)	(2)	(3)
	Failed_m	Failed_m	Failed_m
Share_top5	0.0006***		0.0006***
	(0.0002)		(0.0002)
Poverty_share		-0.0000	-0.0000
		(0.0001)	(0.0001)
Obs.	178	175	175
Adj. R2	0.0612	-0.0057	0.0572

Panel B: Bank risk of most risky banks

	(1)	(2)	(3)	(4)	(5)	(6)
	PD_90	PD_90	PD_90	Zscore_10	Zscore_10	Zscore_10
Share_top5	0.0031**		0.0030**	-0.0475***		-0.0476***
	(0.0013)		(0.0013)	(0.0180)		(0.0180)
Poverty_share		0.0005	0.0003		0.0035	0.0055
		(0.0008)	(0.0009)		(0.0105)	(0.0105)
Obs.	178	175	175	178	175	175
Adj. R2	0.0360	-0.0033	0.0317	0.0421	-0.0051	0.0378

Panel C: Average bank risk

	(1)	(2)	(3)	(4)	(5)	(6)
	PD_m	PD_m	PD_m	Zscore_m	Zscore_m	Zscore_m
Share_top5	0.0007**		0.0007**	-0.0410***		-0.0413***
	(0.0003)		(0.0003)	(0.0113)		(0.0114)
Poverty_share		-0.0000	-0.0001		0.0023	0.0041
		(0.0002)	(0.0002)		(0.0065)	(0.0065)
Obs.	178	175	175	178	175	175
Adj. R2	0.0462	-0.0056	0.0416	0.0698	-0.0051	0.0667

Panel D: Dispersion of bank risk (average standard deviation per MSA)

	(1)	(2)	(3)	(4)	(5)	(6)
	PD_sd	PD_sd	PD_sd	Zscore_sd	Zscore_sd	Zscore_sd
Share_top5	0.0016***		0.0016***	0.0149**		0.0155**
	(0.0006)		(0.0006)	(0.0063)		(0.0062)
Poverty_share		-0.0002	-0.0003		-0.0054	-0.0061
		(0.0003)	(0.0003)		(0.0038)	(0.0038)
Obs.	178	175	175	178	175	175
Adj. R2	0.0558	-0.0035	0.0548	0.0322	0.0076	0.0434

Table OA6: Measures of bank risk – including 2008 and 2009 (government assistance through TARP)

This table shows regression results for the empirical model presented in Section 2. See Table 2 (main text) and Table OA1 (this online appendix) for an explanation of every variable, and Table 3 (main text) and Table OA2 (this online appendix) for descriptive statistics. All regressions include a constant (not reported). Standard errors are reported in parentheses. The ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively.

Panel A: Bank failures

	(1)	(2)	(3)
	Failed_0809_m	Failed_0809_m	Failed_0809_m
Gini	0.0393	0.0292	0.0460*
	(0.0252)	(0.0233)	(0.0269)
Mean_income		0.0001**	
		(0.0001)	
Med_income			0.0002**
			(0.0001)
Obs.	179	179	179
Adj. R2	0.0167	0.0572	0.0508

Panel B: Bank risk of most risky banks

	(1)	(2)	(3)	(4)	(5)	(6)
	PD_0809_90	PD_0809_90	PD_0809_90	Zscore_0809_10	Zscore_0809_10	Zscore_0809_10
Gini	0.1779**	0.1568*	0.1915**	-3.2912**	-2.4876	-3.8402**
	(0.0892)	(0.0904)	(0.0910)	(1.5110)	(1.6294)	(1.4996)
Mean_income		0.0003			-0.0105***	
		(0.0003)			(0.0035)	
Med_income			0.0003			-0.0136***
			(0.0004)			(0.0046)
Obs.	179	179	179	179	179	179
Adj. R2	0.0127	0.0152	0.0137	0.0247	0.0753	0.0711

Panel C: Average bank risk

	(1)	(2)	(3)	(4)	(5)	(6)
	PD_0809_m	PD_0809_m	PD_0809_m	Zscore_0809_m	Zscore_0809_m	Zscore_0809_m
Gini	0.0414*	0.0325	0.0474**	-2.3295**	-1.7673*	-2.7040***
	(0.0221)	(0.0212)	(0.0236)	(0.9612)	(1.0095)	(0.9807)
Mean_income		0.0001*			-0.0074***	
		(0.0001)			(0.0024)	
Med_income			0.0001*			-0.0093***
			(0.0001)			(0.0030)
Obs.	179	179	179	179	179	179
Adj. R2	0.0174	0.0452	0.0410	0.0256	0.0765	0.0697

Panel D: Dispersion of bank risk (average standard deviation per MSA)

	(1)	(2)	(3)	(4)	(5)	(6)
	PD_0809_sd	PD_0809_sd	PD_0809_sd	Zscore_0809_sd	Zscore_0809_sd	Zscore_0809_sd
Gini	0.0960**	0.0702*	0.1138**	1.2636**	0.9445*	1.4875***
	(0.0406)	(0.0414)	(0.0450)	(0.5234)	(0.5362)	(0.4982)
Mean_income		0.0003**			0.0042***	
		(0.0001)			(0.0011)	
Med_income			0.0004***			0.0056***
			(0.0002)			(0.0015)
Obs.	179	179	179	179	179	179
Adj. R2	0.0214	0.0766	0.0728	0.0308	0.0973	0.0955

Table OA7: Panel

This table shows regression results for the empirical model presented in Section **??**, but uses panel data (for each MSA and year) instead of cross-sectional data (long-term averages for each MSA). See Table 2 (main text) and Table OA1 (this online appendix) for an explanation of every variable, and Table 3 (main text) and Table OA2 (this online appendix) for descriptive statistics. All regressions include a constant (not reported). Standard errors are clustered on MSA level and reported in parentheses. The ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively.

Panel A: Bank failures

	(1) Failed_yr_m	(2) Failed_yr_m	(3) Failed_yr_m
Gini	0.0395***	0.0337**	0.0426***
	(0.0147)	(0.0146)	(0.0154)
Mean income		0.0001*	
		(0.0000)	
Med income			0.0001*
			(0.0000)
Year FE	Yes	Yes	Yes
Obs.	3,169	3,169	3,169
No clusters	178	178	178
Adj. R2	0.0760	0.0772	0.0770
Within R2	0.0029	0.0045	0.0044

Panel B: Bank risk of most risky banks

	(1) PD_yr_90	(2) PD_yr_90	(3) PD_yr_90	(4) Zscore_yr_10	(5) Zscore_yr_10	(6) Zscore_yr_10
Gini	0.1958**	0.1850**	0.2011**	-2.6546*	-1.8364	-3.1002**
	(0.0802)	(0.0810)	(0.0817)	(1.4184)	(1.4794)	(1.4062)
Mean income		0.0001			-0.0099***	
		(0.0002)			(0.0031)	
Med income			0.0002			-0.0130***
			(0.0003)			(0.0040)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3,169	3,169	3,169	3,169	3,169	3,169
R2	0.0947	0.0950	0.0949	0.1832	0.1961	0.1954
Within R2	0.0040	0.0043	0.0043	0.0063	0.0221	0.0211

Panel C: Average bank risk

	(1) PD_yr_m	(2) PD_yr_m	(3) PD_yr_m	(4) Zscore_yr_m	(5) Zscore_yr_m	(6) Zscore_yr_m
Gini	0.0436**	0.0371**	0.0470**	-1.9260**	-1.3833	-2.2119**
	(0.0195)	(0.0186)	(0.0207)	(0.8810)	(0.9196)	(0.8794)
Mean income		0.0001			-0.0066***	
		(0.0001)			(0.0021)	
Med income			0.0001			-0.0083***
			(0.0001)			(0.0028)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3,169	3,169	3,169	3,169	3,169	3,169
R2	0.1337	0.1362	0.1359	0.2646	0.2831	0.2809
Within R2	0.0049	0.0077	0.0073	0.0120	0.0368	0.0338

Panel D: Dispersion of bank risk (average standard deviation) per MSA

	(1) PD_yr_sd	(2) PD_yr_sd	(3) PD_yr_sd	(4) Zscore_yr_sd	(5) Zscore_yr_sd	(6) Zscore_yr_sd
Gini	0.1008***	0.0807**	0.1118***	1.1164**	0.7706	1.3089***
	(0.0363)	(0.0370)	(0.0400)	(0.5161)	(0.5092)	(0.4852)
Mean income		0.0002**			0.0042***	
		(0.0001)			(0.0010)	
Med income			0.0003**			0.0056***
			(0.0001)			(0.0013)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3,169	3,169	3,169	3,169	3,169	3,169
R2	0.1609	0.1658	0.1655	0.1042	0.1209	0.1206
Within R2	0.0055	0.0113	0.0111	0.0073	0.0258	0.0255

Part II: Predictions of banks' probabilities of default

Data. The prediction of banks' default probabilities is based on financial data and information about bank failures, which is both provided by the *Federal Deposit Insurance Corporation* (FDIC).[22] For our sample, we require that a bank has its headquarters anywhere in the contiguous United States and has non-missing information for all variables we use in the analysis. The sample includes yearly data on 11,492 U.S. banks and a total of 141,720 observations over the period 2000 to 2019. See Table OA8 for a description of all variables.

The number of bank failures for this sample is 564. It includes final bank failures (e.g., Washington Mutual Bank) as well as assistance transactions (e.g., in the case of Bank of America and Citigroup), as provided by the FDIC's *Bank Failures and Assistance Data* list.

A particular challenge is how to deal with the years 2008 and 2009 of the financial crisis, when both solvent and insolvent banks were supported through the *Troubled Asset Relief Program* (TARP), as also discussed in Section **??** of the main text. Based on the existing evidence from the literature, it would be questionable to classify the financial institutions that received TARP as failed (see footnote 11 in the main text for further information and references.). In order to circumvent this ambiguity, we exclude observations from 2008 and 2009 of banks that received TARP during this time.

Model. Following the literature (e.g., Cole and White, 2012), we predict banks' probabilities of default (PD) based on a logistic regression model, where the dependent variable $Fail_{i,t}$ is a binary variable with a value of one if bank i fails in year t, and zero otherwise. We use the first lag of all explanatory variables, which include banks' equity (EQ), return on assets (ROA), loan and leases loss allowance (ALL), non-performing assets (NPA), securities (SC), brokered deposits (BD), bank size ($SIZE$), liquidity ($CASH$), Goodwill and other intangibles ($INTAN$), real estate 1–4 Family residential property ($RERES$), real estate multifamily (5 or more) residential property ($REMUL$), real estate construction & development loans ($RECON$), real estate nonfarm nonresidential

[22] See the webpage *FDIC Bank Data & Statistics* (https://www.fdic.gov/bank/statistical/) and the webpage *Failed Banks* (https://www.fdic.gov/bank/individual/failed/).

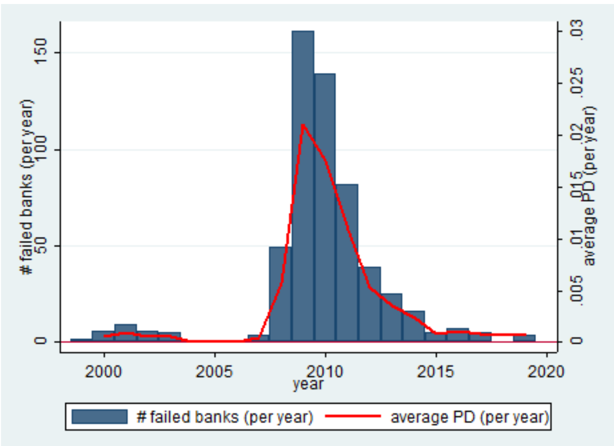
mortgages (*RENRES*), commercial and industrial loans (*CI*), consumer loans (*CON*), as well as a dummy for each year. All variables (except FAIL and SIZE) are expressed as a decimal fraction of total assets.

Results Regression results of the logistic regression model are shown in Table OA9. The coefficients in the table represent the marginal effect of a change in the relevant explanatory variable, when all variables are evaluated at their means.

For the interpretation of results, note that the fraction of failed banks over the sample period is 0.0040. Hence, on average, 4 out of 1,000 banks failed each year. Overall, the reported results have the expected signs and significance. For example, higher capital (EQ) and higher profitability (ROA) is associated with a significantly lower probability of failure. Higher fractions of non-performing assets (NPA), intangible assets (INTAN) and real estate construction & development loans (RECON) are among the factors that are associated with a significantly higher probability of failure. The model explains about 60% of the variability in the dependent variable, as measured by the pseudo-R2 statistic.

The actual number of failed banks as well as the banks' average predicted probabilities of default per year are illustrated in Figure OA1.

Figure OA1: Failed banks and probabilities of default



This figure shows the number of failed banks (source: *Bank Failures and Assistance Data* from the FDIC webpage) as well as the banks' average predicted probabilities of default (own predictions, as described in this section).

Table OA8: Variable description (predictions of default probabilities)

All variables (except FAIL and SIZE) are expressed as a decimal fraction of total assets.

Variable name	Description
FAIL	**Bank failure:** The dependent variable FAIL is binary. Bank failures come from the FDIC's *failed bank list*. Source: FDIC (https://www.fdic.gov/bank/individual/failed/).
EQ	**Equity:** The ratio of total equity to total assets. Source: FDIC ($eqv/100$).
ROA	**Return on assets:** Net income as a decimal fraction of total assets. Source: FDIC ($roa/100$).
ALL	**Loan and leases loss allowance:** The ratio of loan and leases loss allowances to total assets. Source: FDIC ($lnatres/asset$).
NPA	**Non-performing assets:** The sum of loans past due 30-90 days but still accruing interest, loans past due 90+ days but still accruing interest, and nonaccrual loans, scaled by total assets. Source: FDIC ($(p3asset + p9asset + naasset)/asset$).
SC	**Securities:** The ratio of total securities to total assets. Source: FDIC ($sc/asset$).
BD	**Brokered Deposits:** The ratio of brokered deposits to total assets. Source: FDIC ($bro/asset$).
SIZE	**Bank size:** The natural logarithm of banks' total assets. Source: FDIC ($\ln(asset)$).
CASH	**Cash & Balances due from depository institutions:** The ratio of cash and balances due from depository institutions to total assets. Source: FDIC ($chbal/asset$).
INTAN	**Goodwill and other intangibles:** The ratio of goodwill and other intangibles to total assets. Source: FDIC ($intan/asset$).
RERES	**Real Estate 1–4 Family residential property:** The ratio of loans secured by 1-4 family residential properties to total assets.Source: FDIC ($lnreres/asset$).
REMUL	**Real Estate Multifamily (5 or more) residential property:** The ratio of multifamily (5 or more) residential property loans secured by real estate to total assets. Source: FDIC ($lnremult/asset$).
RECON	**Real Estate Construction & Development Loans:** The ratio of construction and land development loans secured by real estate to total assets. Source: FDIC ($lnrecons/asset$).
RENRES	**Real Estate Nonfarm Nonresidential Mortgages:** The ratio of nonresidential loans, excluding farm loans, primarily secured by real estate to total assets. Source: FDIC ($lnrenres/asset$).
CI	**Commercial and industrial loans:** The ratio of commercial and industrial loans to total assets. Source: FDIC ($lnci/asset$).
CON	**Consumer Loans:** The ratio of consumer loans to total assets. Source: FDIC ($lncon/asset$).

Table OA9: Predictions of default probabilities

The column shows results of a logistic regression model to explain bank failures, where the dependent variable $Fail_{i,t}$ is a binary variable with a value of one if bank i fails in year t, and zero otherwise. We use the first lag of all explanatory variables. See Table OA8 for a detailed description of all variables. The sample period is 2000 to 2019 (excluding observations from 2008 and 2009 of banks that received TARP during this time). The total number of banks is 11,492, and the total number of bank failures is 564. The coefficients in the table show the marginal effect of a change in the relevant variable, when all variables are evaluated at their means. Standard errors are shown in parentheses. ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively.

	Marginal Effects
L.EQ	-0.0041***
	(0.0007)
L.ROA	-0.0010***
	(0.0003)
L.ALL	0.0004
	(0.0004)
L.NPA	0.0007***
	(0.0001)
L.SC	-0.0002***
	(0.0001)
L.BD	0.0001**
	(0.0000)
L.SIZE	-0.0000
	(0.0000)
L.CASH	-0.0000
	(0.0001)
L.INTAN	0.0027***
	(0.0006)
L.RERES	-0.0001*
	(0.0000)
L.REMULT	0.0002**
	(0.0001)
L.RECONS	0.0003***
	(0.0001)
L.RENRES	-0.0001**
	(0.0000)
L.CI	0.0001*
	(0.0001)
L.CON	-0.0004***
	(0.0001)
Unique banks	11,491
Failed banks	564
Obs.	141,720
Pseudo-R2	0.60