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 higher incidence of failed banks. 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.

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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) 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, tables, and 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 4, 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 4 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 5 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 5 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 6 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 6 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 1 and summary statistics are shown in Table 2. Table 3 shows the correlations between the main variables of interest. The following section provides a detailed description of each variable.

- Table 1, Table 2 and Table 3 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 7.

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 7 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 4, 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. $0.04 \times (0.4600\text{-}0.4290)=0.00124$.

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 4. 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 4, 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 4 show significantly positive relationships between the Gini coefficient and the dispersion of bank risk. Results are statistically significant for every specification.

- Table 4 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 4. 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 4 (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 4 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 A model of inequality and bank risk

In this section, we propose a model to account for the empirical patterns in the previous section. Our analysis is based on the rational bubbles framework of Allen and Gale (2000) adapted to include, income inequality, a housing market and a mortgage market.

3.1 Households

The economy lasts for one period and two dates. The distribution of income among the households on date 0 is characterized by the cumulative distribution function H over the interval $[0, \overline{y}]$.[14] Since we focus on the effect of income inequality, we normalize mean income to one, $\int_0^\infty y dH(y) = 1$.

Each household with income y demands $n(y)$ units of housing, where $\frac{dn(y)}{dy} \geq 0$. That is, the demand for housing is weakly increasing in income.[15] We think of a unit of housing as a measurement of an area, e.g., square feet. We denote the price of a unit of housing by P_0. Hence, each borrower with income y pays $n(y)P_0$ for housing. Equivalently, we can assume that P_0 is the price per unit of quality and that income-y borrowers demand one unit of housing with quality $n(y)$.

3.2 Housing market

The cost to produce one unit of housing is $c_0 + c_1 N$, where c_0 is the fixed cost to produce a unit of housing and $c_1 N$ is the marginal cost that depends on the aggregate housing quantity N that is being produced on date 0. Hence, the cost to produce one unit of housing on date 0 increases with the aggregate quantity of housing units produced on

[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 that banks are atomistic relative to households, but it is not necessary for our results (see Appendix C).

[15] We assume that each household with income y demands a fixed quantity of housing. A more general specification in which the demand for housing depends on the house price and the mortgage rates yields similar results but at the cost of additional complexity.

that date.[16] In equilibrium, the price per unit of housing is equal to the cost to produce one additional unit. Also, by market clearing, the aggregate demand for housing units equals the supply $\int_0^\infty n(y)dH(y) = N$. Hence,

$$\begin{aligned} P_0 &= c_0 + c_1 N \\ &= c_0 + c_1 \int_0^\infty n(y)dH(y). \end{aligned} \tag{1}$$

Thus, the housing price on date 0 depends on the entire distribution of income. The growth rate in the house price between date 0 and date 1 is given by

$$g_S \equiv \frac{P_{1S}}{P_0} - 1$$

where P_{1S} is the price per unit of housing on date 1 which depends on the aggregate state that is either good or bad, $S \in \{G, B\}$. The aggregate state is good with probability $1 - q$ in which case $g_G > 0$ and bad with probability $q \in (0, 1)$ in which case $g_B < 0$. In other words, the growth rate in the housing price is positive in the good aggregate state and negative in the bad aggregate state.

3.3 Mortgages

The purchase of housing is fully financed through a mortgage loan collateralized by the house. Loans are granted on date 0 and repaid on date 1 after the realization of the aggregate state. The outstanding balance on the mortgage on date 1 for a borrower with income y is $R(y)n(y)P_0$ where $R(y) \equiv 1 + r(y)$ is the interest on a mortgage loan and $n(y)P_0$ is the amount of the principle.

Households have the option of defaulting on their mortgage on date 1 after the realization of the aggregate state. 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 commonly referred to as *negative equity in the house*, i.e., $R(y)n(y)P_0 > n(y)P_{1S}$.At the same time, default triggers foreclosure, in which the bank seizes the house, and the borrower incurs a default cost. The default cost captures any pecuniary and non-pecuniary

[16] This is a common assumption in the literature and reflects increasing land prices when the number of produced housing units increases, among other things. See for example Saiz (2010)

cost that the households would experience in case of default.[17] 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 with different default cost.

Household j with income y will choose to default on its mortgage on date 1 if and only if

$$\text{wealth - negative equity} < \text{wealth - cost of default}$$

which is equivalent to

$$\underbrace{n(y)P_0(1+g_S) - R(y)n(y)P_0}_{\text{negative equity}} < -\underbrace{n(y)c_S(j,y)}_{\text{cost of default}}$$

The left-hand-side is the value of repaying the loan when the aggregate state is S. Specifically, household j with income y retains a house whose value is $n(y)P_0(1+g_S)$ and pays $R(y)n(y)P_0$ to the bank. The right-hand side is the (negative) of the cost of default for this particular household. We assume that the default cost scales proportionally with the house size $n(y)$, an assumption which is not critical for our results. Rearranging the above expression and using $R(y) = 1 + r(y)$ yields

$$P_0\left((1+r(y)) - (1+g_B)\right) > c_S(j,y).$$

Thus, mortgage default occurs only among borrowers for whom the negative equity in the house exceeds the default cost. Observe that a borrower with income y has negative equity in the house whenever the interest rate on his mortgage exceeds the growth rate in the house prices between date 0 and date 1, that is, $r(y) > g_S$. To simplify the exposition, we impose the parameter condition $g_G > q/(1-q)$, which implies that all borrowers have positive equity in the house conditional on the good aggregate state, that is, $r(y) < g_G$ for all y. Hence, mortgage defaults (if any) would take place in the bad aggregate state.

Specifically, in the bad aggregate state, each borrower with income y independently draws a default cost from the c.d.f. $G(.|y)$ and chooses to default if and only if his default cost is less than $P_0(r(y) - g_B)$. The proportion of income-y borrowers choosing to default

[17]The default cost can reflect stigma effects, transaction costs, and the foregone benefit of living in the house net of the cost of funds for repaying the mortgage.

is then equal to $G\left(P_0(r(y)-g_B)\,|\,y\right)$. For simplicity, we assume that $G(.|y) = U\left[0,\, \beta y\right]$ where U denotes the uniform distribution and $\beta > 0$ is a parameter. Hence, the rate of default in the bad aggregate state among borrowers with income y is given by

$$G\left[P_0(r(y)-g_B)\,|\,y\right] = \frac{(r(y)-g_B)P_0}{\beta y} \tag{2}$$

For a fixed mortgage rate, the default rate in the bad aggregate state decreases with y. That is, other things being equal, higher-income borrowers have a higher credit quality. In equilibrium, the mortgage rates for different types of borrowers would adjust to reflect their credit quality and the banks' incentives, as we explain below.

Further, for each type of borrower y, the rate of default in the bad state increases with the housing price P_0, the interest rate $r(y)$, and the magnitude of fall in the house price between date 0 and date 1 g_B (recall that $g_B < 0$). Also, note that the rates of default for each type of borrower depends on the entire income distribution through their dependence on the price per-unit of housing P_0.

Our formulation captures the *double-trigger theory* of mortgage defaults. The first trigger is negative equity in the house, as mentioned above. The second trigger is a low realization of the default cost. Moreover, conditional on house price decline, lower-income households are more likely to have a low cost of default, and therefore, more likely to default on their mortgage than higher-income households, other things being equal.[18]

3.4 Banks

There is a continuum of ex-ante identical risk-neutral banks on date 0, each with a fixed endowment (i.e., capital) of $k \in (0, 1)$.[19] We focus on the date 0 decisions of the banks. Each bank can issue deposits, hold a safe asset (i.e., storage) and make mortgage loans. We normalize the return on the safe asset to one and impose a borrowing constraint for each bank

[18] One reason is that the cost of funds is likely to be higher for low-income households, which reduces their default cost. For example, lower-income households may have to incur additional debt to repay their mortgage loan. In contrast, higher-income households can rely on their savings. See Foote et al. (2008) and the references therein.

[19] The assumption of a continuum of banks, each with a fixed endowment of capital, simplifies the exposition. We show in Appendix C that this assumption is not critical for our results.

$$b + k \leq 1. \tag{3}$$

where b is the amount the bank borrows from the depositors on date 0. Hence, the maximum size of each bank's balance sheet is normalized to one and the maximum leverage ratio is $1/k$. Suppose a given bank borrows b by issuing deposits promising to repay $R_D b$ on date 1, where R_D is the gross interest rate on deposits. We assume that deposits are fully insured and for simplicity do not explicitly model how deposit insurance is funded. Because of deposit insurance, the return offered to depositors is equal to the return on the safe asset $R_D^* = 1$. Also, because of deposit insurance, the minimum capital requirement for the banks will be binding in equilibrium, and therefore, each bank borrows $b = 1 - k$. Let $\alpha \in [0, 1]$ denote the amount of the bank's assets invested in the safe asset. On date 0, the bank's budget constraint is

$$\alpha + (1 - \alpha) \int_{\underline{y}}^{\overline{y}} f(y)dy \leq 1 \tag{4}$$

where $(1-\alpha) \int_{y_1}^{y_2} f(y)dy$ is the amount of mortgage loans issued to borrowers with income between y_1 and y_2, and therefore, $(1-\alpha) \int_{\underline{y}}^{\overline{y}} f(y)dy$ is the total amount of mortgage loans issued by the bank. We have $f(y) \geq 0$ for $y \in [0, \bar{y}]$ and $\int_{\underline{y}}^{\overline{y}} f(y) = 1$.

The bank's payoff on date 1 depends on the realization of the aggregate state. The probability of the good aggregate state is $1 - q$, in which case all borrowers repay their mortgage. As a result, one unit invested in mortgage loans to borrowers with income y yields $1 + r(y)$ on date 1 and the payoff to the bank in the good state is

$$\psi_G(\alpha,\, f) \equiv \alpha + (1 - \alpha) \int_{\underline{y}}^{\overline{y}} (1 + r(y))f(y)dy. \tag{5}$$

The probability of the bad aggregate state is q, in which case a proportion $m(y) \equiv G\left[P_0(r(y) - g_B) \,|\, y\right]$ of the borrowers with income y default on their mortgage. In case of default, the bank forecloses on the house and recovers only $1 + g_B < 1$. The bank's payoff in the bad state is

$$\psi_B(\alpha,\, f) \equiv \alpha + (1-\alpha)\int_{\underline{y}}^{\overline{y}} \left[(1-m(y))(1+r(y)) + m(y)(1+g_B)\right] f(y)dy \tag{6}$$

Bank default takes place if the payoff from the bank's portfolio in the bad state is not sufficient to pay the amount promised to the depositors. That is,

$$\underbrace{\psi_B(\alpha,\, f)}_{\text{total cash flow}} < \underbrace{R_D b}_{\text{promised repayment}}, \tag{7}$$

in which case the payoff to the bank is zero. In case of default, the bank's owners incur a default cost of F. For simplicity, we treat the bank's default cost as exogenous.[20] The bank's expected payoff on date 0 is given by

$$(1-q)\left[\psi_G(\alpha,\, f) - R_D b\right] + q \max\left\{\psi_B(\alpha,\, f) - R_D b,\, 0\right\} - k - I_d q F, \tag{8}$$

where I_d is an indicator variable which equals one if the bank defaults in the bad aggregate state and zero otherwise.

On date 0, the bank's problem is to maximize expected profit by choosing (i) how much to borrow from the depositors $b \in [0, 1-k]$, (ii) how much to place in storage $\alpha \in [0,\, k+b]$ and how much to invest in loans $k+b-\alpha$, and (iii) how to allocate its loan portfolio among borrowers with different income levels. When making its portfolio and leverage choices, the bank takes as given (a) its endowment of capital $k \in (0,1)$ and the maximum leverage ratio $1/k$, (b) the profile of mortgage rates $\{r(y)\}_0^{\overline{y}}$, and (c) the return required by depositors R_D.

A summary of the model notation is provided below. Overall, we choose to keep the model simple to highlight the main message in a tractable way. Section 5.6 provides a further discussion 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.

[20] One interpretation of F is as capturing the lost 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).

Variable	Description
$y \in [\underline{y}, \overline{y}]]$	Income
$H(y)$ and $h(y)$	C.d.f. and p.d.f. of the income distribution
$n(y)$	Demand for housing units by each income y household
P_0	Price per unit of housing on date 0
$1-q$	Probability of the good aggregate state $S = G$
q	Probability of the bad aggregate state $S = B$
P_{1S}	Price per unit of housing on date 1 in state $S \in \{G, B\}$
$g_B \equiv P_{1B}/P_0 - 1 < 0$	Fall in the housing price in the bad aggregate state
$g_G \equiv P_{1G}/P_0 - 1 > 0$	Raise in the housing price in the good aggregate state
c_0	Fixed cost to produce a unit of housing
c_1	Variable cost to produce a unit of housing
$N = \int_0^\infty n(y)dH(y)$	Aggregate housing stock
$n(y)c_S(j, y)$	Default cost for household j with income y in state $S \in \{G, B\}$
$G(.\|y) \equiv U[0, \beta(y)]$	C.d.f. of the default cost for income y households
$\beta(y)$	Maximum default cost for income y households
$R(y) \equiv 1 + r(y)$	Mortgage rate for income y households
k	Bank level of capital
$b \in [0,\, 1-k]$	Bank level of borrowing
$R_D \equiv 1 + r_D$	Deposit rate
α	Fraction of bank's assets invested in storage
$(1-a)f(y)$	Fraction invested in mortgage loans to income y households
F	Banker's non-pecuniary bankruptcy cost

4 Equilibrium outcomes

Equilibrium is a profile of mortgage rates, one for each income level y, such that *(i)* banks choose their leverage and loan portfolios to maximize the expected profits in (8) subject to (3) - (6), *(ii)* the housing price on date 0 is determined by (1) and *(iii)* the default rate for each income level is given by (2). All banks are ex-ante identical and risk-neutral, which implies that the equilibrium expected return on each bank portfolio equals the return on storage.

4.1 Break-even interest rates

We define a reference set of mortgage rates used to characterize the equilibrium outcome. Suppose one unit is invested in mortgage loans to borrowers with income y. The break-even interest rate for these type of borrowers, denoted $r_{be}(y) \equiv R_{be}(y) - 1$, satisfies

$$(1-q) \underbrace{(1+r_{be}(y))}_{\text{return in the good state}} + q\underbrace{[(1-m_{be}(y))(1+r_{be}(y))+m_{be}(y)(1+g_B)]}_{\text{return in the bad state}} = 1. \tag{9}$$

where $m_{be}(y) \equiv G\left(P_0(r_{be}(y) - g_B) \,|\, y\right)$ denotes the rate of default among income y borrowers in the bad state. Notice that if $r(y) = r_{be}(y)$ then loans to borrower with income y carry zero NPV. The break-even interest rate is inversely related to the income of the borrower.

Proposition 1. ***Break-even interest rates***. *We have* $\frac{dr_{be}(y)}{dy} \leq 0$ *for each* $y \in [0, \bar{y}]$.

The profile of break-even interest rates is a useful reference point since they emerge in equilibrium if the banks cannot shift risk. On the other hand, if risk-shifting is an attractive opportunity, the equilibrium profile of mortgage rates is generally different as we show next.

4.2 Bank risk

Suppose a given bank borrows $b \in [0, 1-k]$ in the deposit market. Because of deposit insurance, the return offered to the depositors will not be contingent on the bank's risk and is equal to the return on storage. First, suppose the bank combines $b = 1-k$ with its capital of k and invests a total amount of one in storage or in safe loans (whose expected return in equilibrium equals the return on storage). The bank's payoff from this safe lending strategy is

$$\text{payoff from safe lending} = 1 - b - k. \tag{10}$$

Next, suppose the bank invests 1 in risky loans. Also, suppose the payoff from these loans exceeds b, the amount the bank has promised to repay its depositors, *only* in the good aggregate state. Thus, in the good aggregate state, the bank repays b to its depositors and makes a profit of $R^* - b - k$ where $R^* \equiv 1 + r^*$ is the equilibrium return on the particular portfolio of risky loans selected by the bank. In the bad aggregate state, the entire payoff of the bank's portfolio goes to the depositors, and the bank gets 0. The deposit insurance fund then covers the loss to the depositors. The bank's payoff from this risky lending strategy is

$$\text{payoff from risky lending} = (1 - q)(R^* - b) - k - qF, \tag{11}$$

where F is the bankruptcy cost borne by the banker in the case of default. Thus, any bank choosing to follow the risky lending strategy engages in *risk-shifting* and cares only about the upper part of the returns on its loans.

4.3 Competition to risk-shift

In equilibrium, the bank is indifferent to (i) investing in storage and safe loans or in (ii) risky loans. To ensure that this is the case, the return on the portfolio of risky loans selected by the bank, R^*, adjusts so that the payoff from the safe lending strategy equals the expected payoff from the risky lending strategy. That is,

$$R^* = \frac{1 - qb + qF}{1 - q}. \tag{12}$$

Since all banks are ex-ante identical, in equilibrium, each bank is indifferent to specializing in risk-shifting or safe lending. In other words, the (real) option available to each bank to begin risk-shifting has a value of zero in equilibrium. This competition to risk-shift leads to the following result.

Proposition 2. ***Competition to risk-shift***. *The equilibrium is characterized by an endogenous cutoff $y^* \in [0, \bar{y}]$ given by*

$$y^* \propto \left[c_0 + c_1 \int_0^\infty n(y) dH(y)\right] \frac{(r^* - g_B)^2}{(r^* + k + F)}, \tag{13}$$

and two types of banks, safe and risky, such that the following is true:

(i) all loans to borrowers with income below y^* carry negative NPV to the lender,

(ii) each risky bank lends only to borrowers with income below y^* and

(iii) each safe bank lends only to borrowers with income above y^*.

The equilibrium features risky banks if and only if $y^* > 0$, which will be the case whenever the parameters satisfy the following condition

$$1 - k - F > 1 + g_B.$$

The right-hand side is the fall in the housing price conditional on the bad state $1+g_B < 1$. The left-hand side is the maximum leverage ratio $1 - k$ minus the bankruptcy cost incurred by the banker F. The equilibrium does not feature risk-shifting when either (i) banks are required to hold sufficient minimum capital k, (ii) the cost of bankruptcy borne by the banker F is high enough, or (iii) the fall in the housing price is small $g_B \approx 0$. To focus on the interesting equilibrium, we assume that the above parameter condition is satisfied.

Corollary 1. ***Equilibrium mortgage profile***. *The equilibrium profile of mortgage rates $\{R^*(y)\}_0^{\bar{y}}$ satisfies the following: for each $y < y^*$ we have $R^*(y) = R^* < R_{be}(y)$ where R^* is given in (12) whereas for each $y \geq y^*$ we have $R^*(y) = R_{be}(y)$.*

Figure 1 depicts how the cutoff point y^* is determined. On X-axis is the income of the borrower. The equilibrium mortgage rate corresponding to this type of borrower is on the Y-axis. The cutoff y^* is obtained in equilibrium as the solution to the equation $R_{be}(y^*) = R^*$. The mortgage rate for borrowers with income less than y^* is *below* the corresponding break-even rate $R^*(y) < R_{be}(y)$. In other words, every \$1 invested in mortgage loans to borrowers with $y < y^*$ delivers less than \$1 in expectation to the bank.

4.4 Sorting

Why would any bank issue a loan at a rate that is below the break-even interest rate? The reason is that banks engaged in lending to borrowers with income below y^* default in the bad state, and because of limited liability, only take into account their payoff in the good aggregate state. These banks compete to risk-shift by lowering the interest rate for high-risk borrowers. In equilibrium, this competition drives the interest rate on high-risk loans (i.e., loans to borrowers with income less than y^*) below its corresponding break-even point. This general equilibrium feature of the model is what drives the sorting of banks into safe and risky.[21]

Proposition 3. ***Sorting of banks***. *In equilibrium, ex-ante identical banks specialize in risky lending to subprime-borrowers and become a* risky bank*, or in safe lending to prime borrowers and become a* safe bank*. The proportion of risky banks is given by*

$$f_{\text{risky}} = \frac{\int_0^{y^*} n(y)dH(y)}{\int_0^{\infty} n(y)dH(y)}, \tag{14}$$

where H is the income distribution, $n(y)$ is the per-capita demand for housing, and the proportion of safe banks equals $1 - f_{\text{risky}}$.

Since loans to borrowers with income below y^* carry negative net present value, safe banks will only lend to borrowers with income above this cutoff. Thus, the credit segment for borrowers whose income is below y^* will be served only by risky banks. On the other hand, the credit segment for borrowers with income above y^* will be served only by safe banks. In other words, the equilibrium loan market is segmented, with each bank fully specialized in risky lending to subprime borrowers or safe lending to prime borrowers. Moreover, each bank that is lending to subprime borrowers is also risk-shifting.

The volume of credit in the subprime and the prime credit segments respectively equals

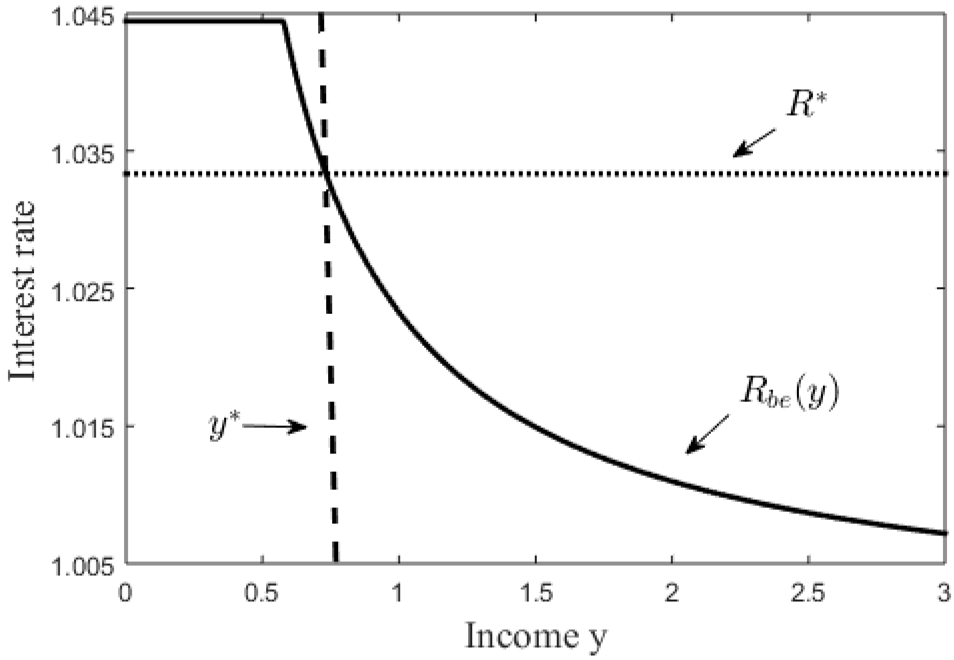
$$d_S \equiv \underbrace{P_0^* \int_0^{y^*} n(y)dH(y)}_{\text{demand for subprime credit}} \qquad \text{and} \qquad d_P \equiv \underbrace{P_0^* \int_{y^*}^{\infty} n(y)dH(y)}_{\text{demand for prime credit}}.$$

The cutoff y^* is endogenous, and it depends on housing and banking market characteristics. For example, low minimum capital ratio k, low bankruptcy cost F, or a higher housing price P_0^* lead to a larger value for y^*. Also, the cutoff y^* depends on the income distribution. The measure of risky and safe banks adjusts to satisfy the demand for subprime and prime credit. The proportion of risky banks equals the measure of risk-shifting

[21] Borrowers with income just above y^* carry credit risk as well, which, however, is not sufficient to attract risk-shifting banks.

banks relative to all banks.

Figure 1: Determination of equilibrium.



5 The effect of inequality on bank risk

We will say that the income distribution $\tilde{H}$ is more *unequal* than the income distribution H if the former is a mean-preserving spread of the latter. Figure 2(a) displays an example of a mean-preserving spread. The solid line represents income distribution with a low level of inequality, and the dashed line represents an income distribution with a high level of inequality. The equilibrium proportion of risky banks associated with the more unequal distribution $\tilde{H}$ is given by

$$\tilde{f}_{\text{risky}} = \frac{\int_0^{\tilde{y}^*} n(y) d\tilde{H}(y)}{\int_0^{\infty} n(y) d\tilde{H}(y)},$$

where $\tilde{y}^*$ is the subprime cutoff corresponding to $\tilde{H}$. That is,

$$\tilde{y}^* \propto \underbrace{\left[c_0 + c_1 \int_0^{\infty} n(y) d\tilde{H}(y)\right]}_{\tilde{P}_0^*} \frac{(r^* - g_B)^2}{(r^* + k + F)}.$$

The overall effect of inequality on bank risk can be decomposed into two channels: direct and indirect.

5.1 Direct channel of inequality

First, there is a *direct channel* which operates by affecting the proportion of households with income below the subprime cutoff y^*. For example, moving from an economy with low inequality to an economy with high inequality can lead to a larger proportion of subprime borrowers relative to the total population as shown on Figure 2(a). Other things being equal, a larger subprime sector leads more banks to specialize in risk-shifting, which leads to a greater subsequent bank failure in the bad aggregate state. In other words, greater income inequality can generate a greater incidence of bank failure. Moreover, *both* the average bank risk and the dispersion of bank risk increases as we move from the economy with low to the economy with high inequality.

5.2 Indirect channel of inequality

Second, there is an *indirect channel* which operates by moving the location of the subprime cutoff from (i.e., from y^* to $\tilde{y}^*$ as shown on Figure 2(a)). The effect of the indirect channel depends on the demand for housing $n(y)$. To illustrate the effect of this channel suppose that the demand for housing takes the form

$$n(y) = \left\{ \begin{array}{c} 0 \\ \alpha y \end{array} \right\} \qquad \text{as} \qquad y \left\{ \begin{array}{c} \leq \\ > \end{array} \right\} y_P, \tag{15}$$

with $\alpha > 0$ and $y_P \geq 0$. This specification assumes that a proportion $H(y_p)$ of the population is excluded from the market for home-ownership due to insufficient resources for down payment or regulatory limits on the payment-to-income ratios.

As illustrated on Figure 2(a), the direct and indirect channels reinforce each other in this case: higher inequality pulls more households below the subprime cutoff in addition to leading to a higher cutoff. To understand why, recall that the equilibrium price of housing is given by $P_0^* = c_0 + c_1 \int_0^\infty n(y) dH(y)$. In this case, a mean-preserving spread of the income distribution H leads to more expensive housing $\tilde{P}_0^* > P_0^*$. That is, the increased demand from the high income households more than offsets the reduced demand from the low income households. Larger P_0^*, in turn, makes home-owners more indebted, and therefore, more likely to default on their mortgage in the bad aggregate state, leading to $\tilde{y}^* > y^*$.

In general, higher inequality can lead to either higher or lower cutoff y^*, depending on the functional form for the demand for housing $n(y)$. For example, suppose that $n(y)$ is concave (i.e., $n(y) = y^{0.5}$ for each y). Then higher income inequality is associated with a lower cutoff y^*. Intuitively, the increased demand for housing from the high income is not enough to offset the reduced demand from the lower income. In this case, the indirect effect of inequality partially mitigates the direct effect.

5.3 Overall effect

The overall effect of inequality on the proportion of risky banks is determined through the interaction of the direct and the indirect effect. The proportion of risky banks can be expressed as

$$f_{\text{risky}} = H\left(y^*\right) \frac{E\left[n(y) \,|\, y < y^*\right]}{E\left[n(y)\right]} = H\left(y^*\right) \sigma_{\text{subp}}$$

The average demand for housing from the subprime borrowers equals $E\left[n(y) \,|\, y < y^*\right]$, whereas the average demand across all borrowers equals $E\left[n(y)\right]$. Thus, σ_{subp} denotes the average housing demand from a subprime borrower relative to the average demand for housing from all borrowers. Note that σ_{subp} depends on the income distribution H, the cutoff y^* and the demand for housing $n(y)$. The effect of a marginal change in the level of inequality on the proportion of risky banks can be decomposed into an indirect and direct effect, that is,

$$\frac{df_{\text{risky}}}{dI} = \underbrace{\frac{dy^*}{dI} h\left(y^*\right) \sigma_{\text{subp}}}_{\text{indirect effect}} + \underbrace{\frac{dH\left(y^*\right)}{dI} \sigma_{\text{subp}} + H\left(y^*\right) \frac{d\sigma_{\text{subp}}}{dI}}_{\text{direct effect}},$$

where I denotes the level of inequality (i.e., higher I corresponds to more unequal distribution). The first component in the above expression is the effect of higher inequality on the cutoff y^*, the second component is the effect on the proportion of households with income below the cutoff, that is, $H(y^*)$, the third component is the effect on the average demand for housing among subprime borrowers relative to the average demand over all borrowers.

5.4 Comparative statics

Next, we provide numerical examples illustrating how the income distribution can shape 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 income distribution. We begin by using a log-normal distribution for the income of the borrowers. Specifically, if the natural logarithm of y is normally distributed with mean μ and variance σ^2 then y is log-normally distributed with a density function:

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

To facilitate comparison with the empirical results in Section 2, we capture income inequality with the Gini coefficient. For a log-normal distribution the Gini coefficient is equal to $2\Phi(\sigma/\sqrt{2}) - 1$ where Φ is the *c.d.f.* of the standard normal.[22] 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 demand for home-ownership is given by

$$n(y) = \begin{Bmatrix} 0 \\ \alpha_0 + \alpha_1 y^{\alpha_2} \end{Bmatrix} \quad \text{as} \quad y \begin{Bmatrix} \leq \\ > \end{Bmatrix} y_P\left(\mu,\, \sigma^2\right),$$

where the cutoff y_P depends on the parameters of the log-normal distribution. We set y_P to equal 60 percent of the median income, $y_P = 0.6\exp\{\mu\}$, which is a commonly used poverty measure associated with the log-normal distribution. It is worth pointing out that similar qualitative results obtain for a wide range of specifications of $n(y)$, both in terms of the cutoff for home-ownership y_P and in terms of the parameters α_0, α_1 and

[22] Since the income distribution is log-normal, holding the mean income fixed and increasing the Gini coefficient corresponds to a mean-preserving spread.

α_2. The remaining parameters of the model are $k = 0.1$, $q = 0.4$, $F = 0.2$, $g_B = -0.4$, $c_0 = 0$, $c_1 = 1$, $\alpha_0 = 0$ and $\alpha_1 = 1$.

Figure 2(b) shows the proportion of risky banks, Figure 2(c) shows the average bank risk (where bank risk is the probability of bank failure), and Figure 2(d) the standard deviation of bank risk as functions of the Gini coefficient. The mean and the standard deviation of bank risk equal

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

where f_{risky} is the proportion of risky banks corresponding to a given value 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. The dispersion of bank risk emerges because some banks specialize in low-risk lending, whereas others specialize in high-risk lending. The supply of credit from risky banks equals the demand for credit originating from subprime borrowers. A more dispersed income distribution (greater inequality) leads to more pronounced sorting and a larger bank risk dispersion.

Pareto income distribution. We obtain similar qualitative relations, namely *(i)* - *(iii)* continue to hold, when income is Pareto distributed. Specifically, 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 $(2a - 1)^{-1}$. Figure 3(a) shows the relation 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 coefficient 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.

For the remaining three panels on the figure, we use a log-normal income distribution.

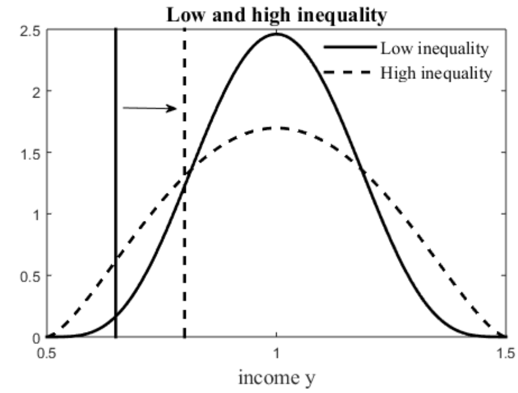
The examples on panels (b) - (d) highlight that the income distribution, the banking sector, and the housing market are closely intertwined.

Home-ownership. Figure 3(b) compares an economy with a low cutoff for home-ownership (where y_P equals 40 percent of the median income) to an economy with a high cutoff for home-ownership (where y_P equals 60 percent of the median income as in the baseline case). The low cutoff is interpreted as lax regulation (i.e., relaxation of loan-to-value or loan-to-income ratios) or stronger home-ownership preferences. For each value of the Gini coefficient, the economy with a low y_P is characterized by a larger proportion of risky banks and also larger dispersion of bank risk. Thus, regions experiencing an increased demand for housing among subprime borrowers will be characterized by a more unstable banking sector.

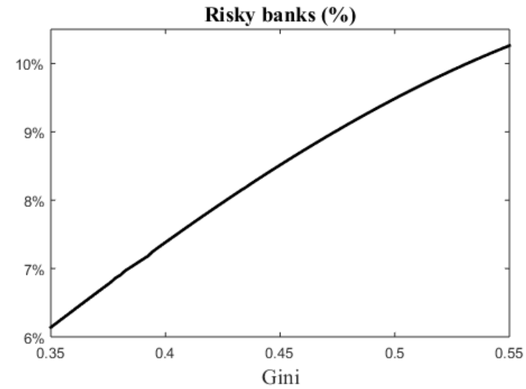
Minimum capital ratios. Figure 3(c) compares an economy with a low mandatory minimum of the capital ratio (solid line) to an economy with a high mandatory minimum of the capital ratio (dashed line). A higher value of the Gini coefficient is associated with a larger proportion of risky banks in both cases. However, the economy with the better-capitalized banks is characterized by a smaller proportion of risky banks for each value of the Gini coefficient. If the minimum capital ratio is sufficiently high, all banks will be safe. Thus, lower capital ratios leads to a more pronounced sorting of banks into safe and risky – especially when the level of inequality is relatively high.

Housing prices. Figure 3(d) shows that the proportion of risky banks is increasing in the probability of the bad state i.e., the probability of housing price decline. The model also implies that for each value of the Gini coefficient, the proportion of risky banks increases with the fall of the house price conditional on the bad state g_B. When the bad state is more likely (or when the fall in the housing price in the bad state is larger), then the banks must charge higher interest rates on their mortgage loans to break-even. High levels of interest rates imply that the equilibrium subprime cutoff y^* goes up, leading more banks to specialize in risk-shifting.

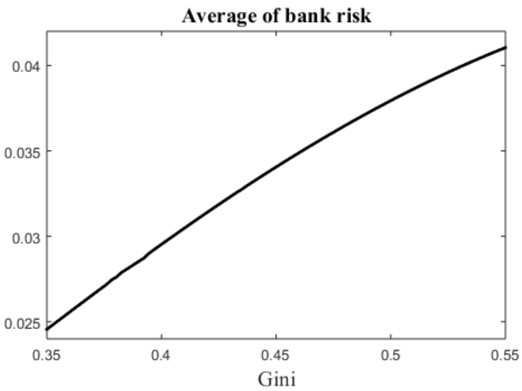
Figure 2: Inequality and bank risk.



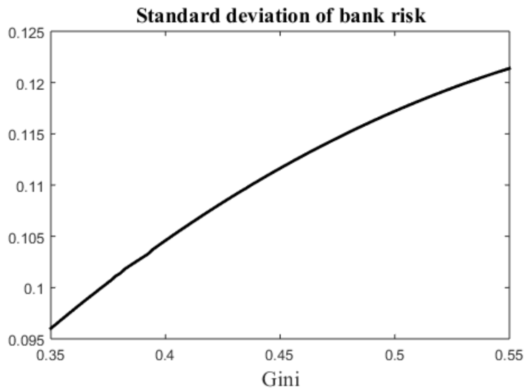
(a) Direct and indirect channels.



(b) Proportion of risky banks.



(c) Average bank risk.



(d) Dispersion of bank risk.

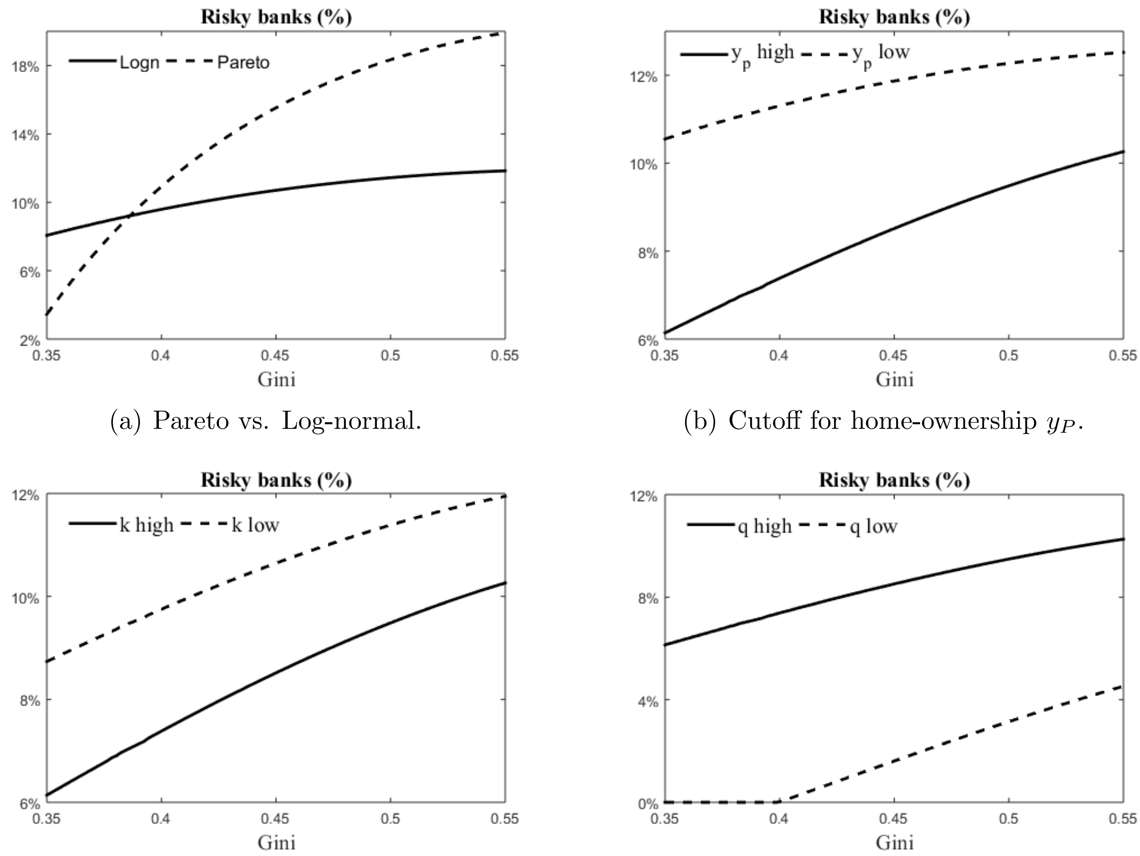
5.5 What if banks cannot risk shift?

In this section, we revisit *Keeley's observation* from the Introduction, why do banks allow their bankruptcy risk to increase in the first place? What happens in this environment if banks cannot risk-shift?

Proposition 4. ***No risk-shifting***. *Suppose that (i) risk-shifting is impossible and (ii) bankers have positive bankruptcy costs. Then all banks will be safe in equilibrium and the distribution of income will have no effect on bank risk.*

The intuition is that a bank weighs the gain from increased risk-taking against the increased likelihood of incurring the bankruptcy costs. If a bank cannot risk-shift, then the interest rate it offers to the depositors must ensure that they break-even in expectation. As a result, risky banks will have a higher cost of funds, which is necessary to compensate

Figure 3: Comparative statics.



(a) Pareto vs. Log-normal.

(b) Cutoff for home-ownership y_P.

(c) Effect of capital k.

(d) Effect of q.

their creditors for the increased probability of losing money. This implies that the expected return on a portfolio of loans for a bank that defaults in the bad aggregate state must exceed the return on storage. This is necessary to compensate the bank for the risk of incurring the bankruptcy cost. However, since all bankers are risk-neutral and ex-ante identical, the expected equilibrium return on each bank's portfolio must equal the return on storage. As a result, in equilibrium, banks do not take excessive risks, unless they can shift risk.[23]

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

5.6 Discussion of modeling assumptions

To highlight the model's central message and show that we can account for the data patterns in a relatively straightforward way, we abstracted from several real-world features of the banking system. However, the basic mechanism is flexible and robust to various generalizations as we argue in this section.

Intensive vs. extensive margins of adjustment. One of the model's implications is that higher income inequality leads to corresponding adjustments among banks, necessary to absorb subprime credit demand. These adjustments, in turn, can be intensive or extensive. (i) The intensive margin: a single risky bank expands to issue loans to all subprime borrowers. (ii) The extensive margin: risky bank's balance sheet size remains fixed, but the number of risky banks adjusts to satisfy subprime credit demand. We have assumed in the baseline model that banks adjust only on the extensive margin. More generally, one would expect a mixed response whereby risky banks become bigger and more numerous. The extent to which (i) or (ii) ends up being the dominant factor depends on the competitive structure (how many banks a given region can support) and the regulatory environment (limits on size and the cost to raise additional capital), among other things. In Appendix C, we show that the model's main implication continues to apply when we allow banks to adjust simultaneously on the intensive margin (by issuing more capital) and on the extensive margin.

Ex-ante heterogeneity among banks. We can allow for ex-ante heterogeneity among banks in lending technologies, implicit or explicit government guarantees, and legacy assets. This modification will not alter the central message of the baseline model. In particular, the competition to risk-shift and banks' sorting into safe and risky would still emerge in equilibrium. At the same time, the equilibrium would exhibit clientele effects that were absent from the baseline framework. For example, banks with riskier legacy assets or banks that are more likely to receive government guarantees will be more prone to specialize in risky lending and engage in risk-shifting practices.

Firms. 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, then the firm sector can 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.[24] 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, the incentive for risk-shifting would be present as long as risk-weights are not fully adjusted to reflect the underlying risks.

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.

[24] There is widespread evidence that deposit insurance premiums do not fully reflect bank risk. See, for example, Kisin and Manela (2016), among others.

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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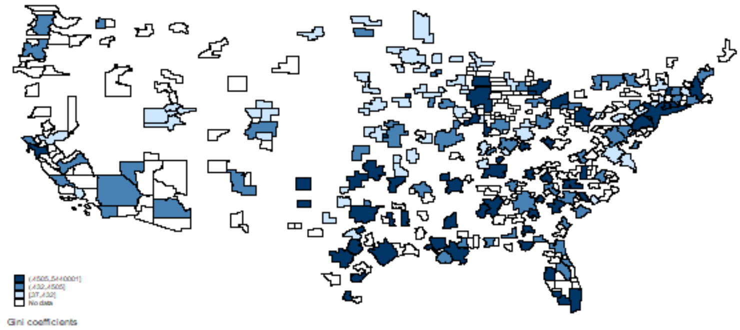
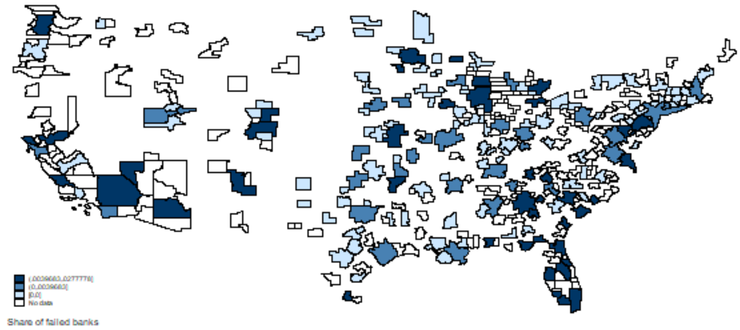
Appendix

A. Figures

Figure 4: Income inequality and bank risk across Metropolitan Statistical Areas



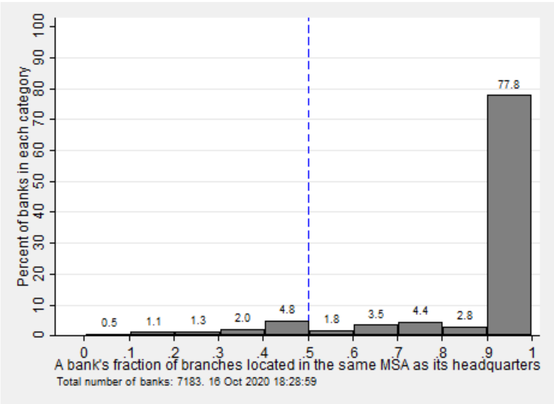
(a) Income inequality (Gini coefficients)



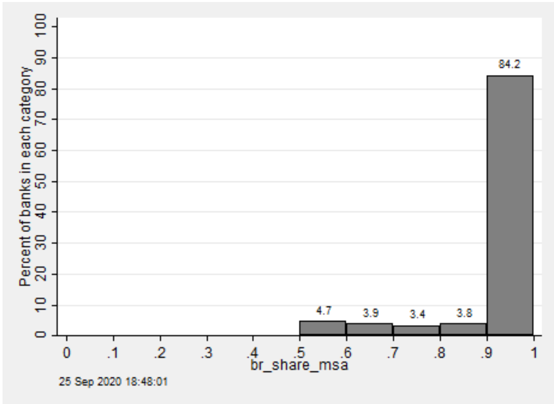
(b) Bank risk (share of failed banks)

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.

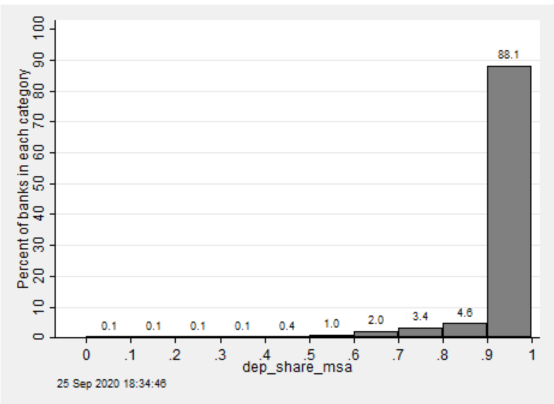
Figure 5: Regional concentration of banks



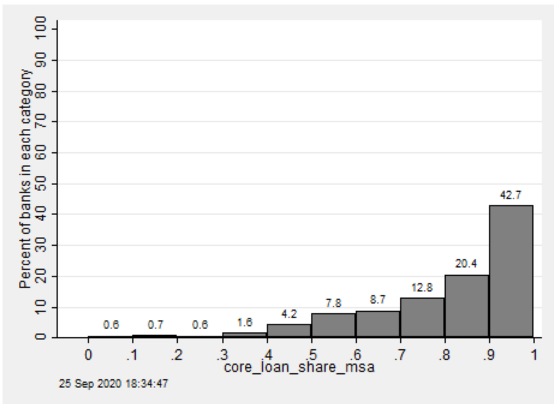
(a) branch concentration of all banks



(b) branch concentration of banks in our sample



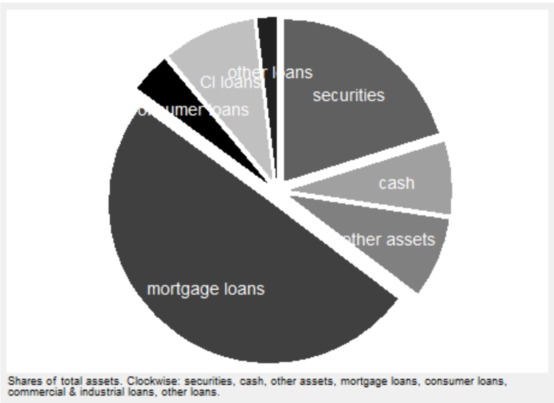
(c) deposit concentration of banks in our sample



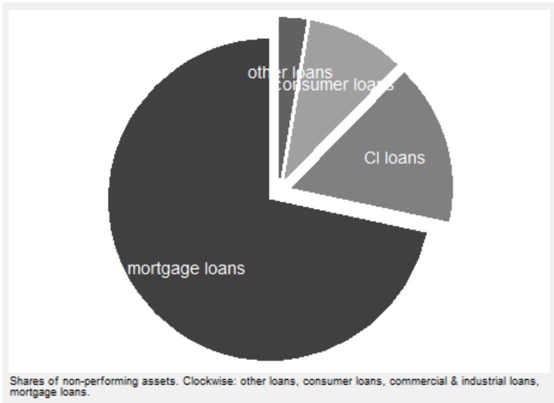
(d) mortgage concentration of banks in our sample

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 6: The role of mortgage loans for banks



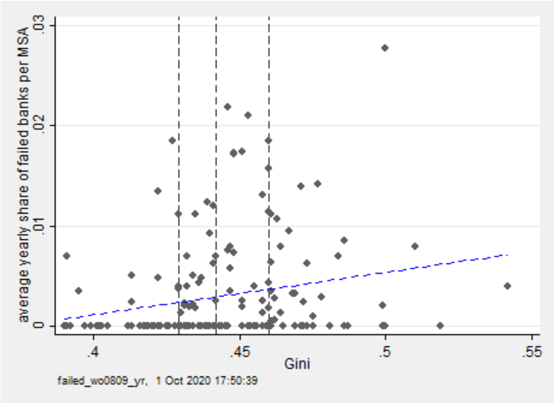
(a) shares of total bank assets



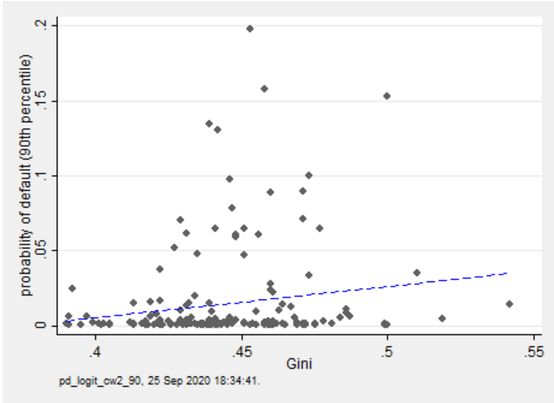
(b) shares non-performing assets

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

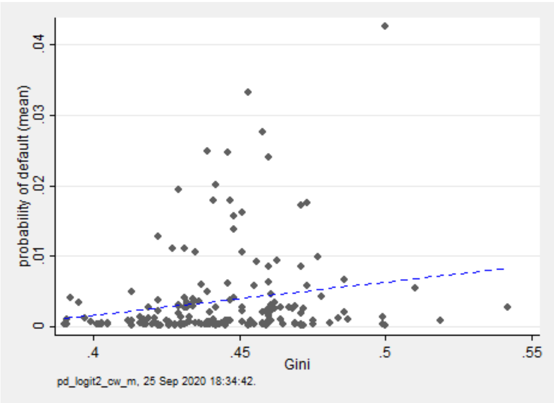
Figure 7: First graphical evidence



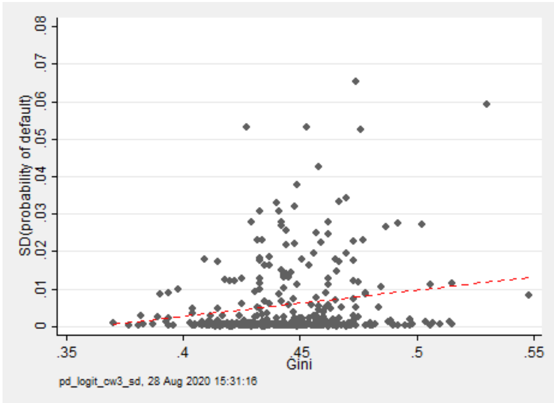
(a) shares of failed banks per MSA



(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 1: Variable description

Variable name	Description
Bank characteristics	
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	**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	**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. Calculations are based on FDIC data.
Banking market characteristics on the MSA level	
Failed_yr_m	**Share of bank failures.** This variable is calculated as the average (mean) yearly share 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. Calculations are 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. Calculations are based on FDIC data.
PD_sd	**Dispersion of bank risk:** We use the long-term average standard deviation of banks' predicted probabilities of default for each MSA and year to represent dispersion of bank risk per MSA. Calculations are 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. Calculations are 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. Calculations are based on FDIC data.
Zscore_sd	**Dispersion of bank risk:** We use the long-term average standard deviation of banks' z-scores for each MSA and year to represent dispersion of bank risk per MSA. Calculations are 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	
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 of 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, 2008 American Community Survey (Table B19083). Note: We use this variable from the year 2006 because this is the first year it is available on the MSA level.
Mean_income	**Mean household income.** The variable is given in USD '000. Source: U.S. Census Bureau, 2005 American Community Survey (Table DP03). Note: We use this variable from the year 2005 because this is the first year it is available on the MSA level.
Med_income	**Median household income.** The variable is given in USD '000. Source: U.S. Census Bureau, 2005 American Community Survey (Table DP03). Note: We use this variable from the year 2005 because this is the first year it is available on the MSA level.

Table 2: 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 yr_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 3: Cross-correlation table

Variables	Gini	Mean income	Med income	Failed_yr	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_yr_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 4: Main regression results: MSA-level cross-sectional data

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

Panel A: Share of failed banks

	(1)	(2)	(3)
	Failed_yr_m	Failed_yr_m	Failed_yr_m
Gini	0.0423***	0.0370**	0.0459***
	(0.0081)	(0.0172)	(0.0068)
Mean_income		0.0001*	
		(0.0891)	
Med_income			0.0001*
			(0.0799)
Obs.	178	178	178
Adj. R2	0.0372	0.0532	0.0503

gini_1y_06, failed_wo0809_yr_m, 19 Oct 2020 13:28:58

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
Gini	0.2080**	0.1956**	0.2155**	-3.1783**	-2.4850	-3.6418**
	(0.0176)	(0.0235)	(0.0176)	(0.0334)	(0.1178)	(0.0147)
Mean_income		0.0002			-0.0091***	
		(0.5285)			(0.0060)	
Med_income			0.0002			-0.0115***
			(0.5657)			(0.0082)
Obs.	178	178	178	178	178	178
Adj. R2	0.0221	0.0195	0.0188	0.0251	0.0649	0.0599

gini_1y_06, pd_logit_cw2_90/ ln_zscore_10, 19 Oct 2020 13:28:58

Panel C: Average bank risk

	(1)	(2)	(3)	(4)	(5)	(6)
	PD_m	PD_m	PD_m	Zscore_m	Zscore_m	Zscore_m
Gini	0.0471**	0.0406**	0.0513**	-2.1759**	-1.6883*	-2.4943***
	(0.0317)	(0.0470)	(0.0293)	(0.0180)	(0.0771)	(0.0074)
Mean_income		0.0001			-0.0064***	
		(0.1558)			(0.0042)	
Med_income			0.0001			-0.0079***
			(0.1402)			(0.0054)
Obs.	178	178	178	178	178	178
Adj. R2	0.0284	0.0428	0.0396	0.0250	0.0670	0.0599

gini_1y_06, pd_logit_cw2_m/ ln_zscore_m, 19 Oct 2020 13:28:59

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
Gini	0.1067***	0.0877**	0.1197***	1.2380**	0.9420*	1.4426***
	(0.0067)	(0.0249)	(0.0060)	(0.0198)	(0.0822)	(0.0048)
Mean_income		0.0002**			0.0039***	
		(0.0439)			(0.0004)	
Med_income			0.0003**			0.0051***
			(0.0289)			(0.0004)
Obs.	178	178	178	178	178	178
Adj. R2	0.0333	0.0661	0.0635	0.0320	0.0931	0.0901

gini_1y_06, pd_logit_cw2_cv/ ln_zscore_cv, 19 Oct 2020 13:28:59

C. The cost of bank capital

In the baseline version of the model, each bank's capital level was fixed at k. This section shows how to relax this assumption by analyzing a version of the model in which bank capital is privately costly. Specifically, a bank that raises k units of capital must pay an issuance cost of $c(k)$, where $c(0) = 0$, $c' > 0$ and $c'' > 0$ for $k \geq 0$. This modeling approach follows Admati et al. (2018) and others by incorporating various agency costs in a reduced form. A bank that raises k units of capital can invest up to $k\rho$ in mortgage loans, where ρ denotes the maximum leverage ratio. The expected profit of a safe bank is then given by

$$\pi_S = \rho k_S \left[\gamma^* - b_S(k)\right] - k_S(1 + c(k_S))$$

where γ^* is the expected return on the safe bank's portfolio, k_S is the safe bank's capital level and $b_S(k) \in [0,\, \rho k_S]$ is the amount the safe bank borrows from the depositors. At the same time, the expected profit of a risky bank is given by

$$\pi_R = (1 - q)\left[\rho k_R R^* - b_R(k)\right] - k_R(1 + c(k_R))$$

where $R^*$is the return on the risky bank's portfolio conditional on the good aggregate state, k_R is the risky bank's capital level and $b_R(k) \in [0,\, \rho k_R]$ is the amount the risky bank borrows from the depositors. For simplicity, we set the bankruptcy cost of the banker to equal zero $F = 0$. The same result obtains when the bankruptcy cost is proportional to the bank's assets.

Banks take R^* and γ^* as given and choose their portfolio, capital level and leverage ratio to maximize their expected profits. The optimal capital level for a risky (safe) bank satisfies $d\pi_R^*/dk_R = 0$ ($d\pi_S^*/dk_S = 0$). Since deposits are insured, and bank capital is costly, a bank that raises k units of capital chooses to operate at the maximum leverage ratio of ρ, and therefore borrows $b_i(k) \equiv \rho k - k$ for $i \in \{R, S\}$. In equilibrium, yields on safe and risky loans would adjust so that all types of banks make zero expected profits $\pi_i^* = 0$ for $i \in \{R, S\}$. It is then relatively straightforward to show that each type of bank chooses the same capital level $k^* = k_i^*$. Moreover, the equilibrium is characterized by Propositions 2. In particular, *(i)* risky banks specialize and lend only to borrowers with income below y^*, *(ii)* safe banks lend only to borrowers with income above this cutoff, and *(iii)* loans to borrowers with income below y^* carry negative net present value. In other words, bank sorting remains a feature of the equilibrium outcome.

A continuum of banks is also not critical for our results on banks' sorting. Specifically, suppose that n banks Bertrand compete by setting their loan rate for each borrower type, and there is free entry into each credit segment. That is, all credit segments are perfectly contestable. Then the equilibrium number of risky n_R^* and safe n_S^* banks respectively is given by

$$n_R^* = \frac{1}{\rho k^*} P_0^* \int_0^{y^*} n(y) dH(y) \qquad \text{and} \qquad n_S^* = \frac{1}{\rho k^*} P_0^* \int_{y^*}^{\bar{y}} n(y) dH(y)$$

The issuance cost $c(k)$ affects the optimal level of capital k^*, and hence, the number of safe and risky banks necessary to satisfy the demand for credit in each segment. However, the relative proportion of risky $n_R^*/(n_R^* + n_S^*)$ and safe $n_S^*/(n_R^* + n_S^*)$ banks would not change and continues to be characterized by Proposition 3.

D. Proofs

Proof of Proposition 1.

Proof. For each income level $y \in [0, \bar{y}]$ the solution of the equation in (9) can be characterized as follows *(i)* $R_{be}(y) = 1$ iff $G(\omega(y) \,|\, y) = 0$, *(ii)* $R_{be}(y) \in \left(1, \frac{1-q(1+g_B)}{1-q}\right)$ iff $G(\omega(y) \,|\, y) \in (0,1)$ and *(iii)* $R_{be}(y) = \frac{1-q(1+g_B)}{1-q}$ iff $G(\omega(y) \,|\, y) = 1$ where $\omega(y) = n(y)P_0 \left(R_{be}(y) - (1+g_B)\right)$ is the negative equity in the house in the bad state for income-y borrowers. So, consider another borrower with income $y + \epsilon$ where $\epsilon > 0$. An increase in the income from y to $y + \epsilon$ holding $R_{be}(y)$ fixed will lead to a loan of $n(y+\epsilon)P_0$, and therefore, a required repayment of $n(y+\epsilon)P_0 R_{be}(y)$ where $n(y+\epsilon) > n(y)$. Applying (**??**) we have

$$G\left(n(y+\epsilon)P_0\left(R_{be}(y) - (1+g_B)\right) \,|\, y+\epsilon\right) \leq G\left(n(y)P_0\left(R_{be}(y) - (1+g_B)\right) \,|\, y\right)$$

for all y and $\epsilon > 0$ which implies $R_{be}(y+\epsilon) \leq R_{be}(y)$. Moreover, $R_{be}(y+\epsilon) < R_{be}(y)$ whenever $R_{be}(y) \in \left(1, \frac{1-q(1+g_B)}{1-q}\right)$. That is, the break-even interest rate is non-decreasing in the income of the borrower. The break-even mortgage profile has a useful property: for each $y \in [0, \bar{y}]$ and each $R \leq R_{be}(y)$ we have

$$(1-q)R + q\psi\left(R \,|\, y\right) \leq (1-q)R_{be}(y) + q\psi\left(R_{be}(y) \,|\, y\right) = 1$$

That is, setting an interest rate below the corresponding break-even level leads to a negative net present value loan. The last condition will be satisfied whenever $R_{be}(y)$ for each $y \in [0, \bar{y}]$ corresponds to the smallest of all possible solutions of (9). □

Proof of Proposition 2.

Proof. Suppose that the mortgage profile is given by $R^*(y) = R^*$ for $y < y^*$ and $R^*(y) = R_{be}(y)$ where R^* is defined in (12) and where the cutoff y^* solves $R_{be}(y^*) = R^*$. We show that for this mortgage profile *(i)* borrowers with income $y < y^*$ obtain credit only from risky banks, *(ii)* borrowers with income $y > y^*$ obtain credit only form safe banks and *(iii)* all banks (safe and risky) make zero profits.

We begin by showing that safe banks make zero profits and strictly prefer to lend only to borrowers with income greater than or equal to y^*. The objective of a safe bank is to maximize its expected payoff (since it remains solvent in both states), which implies that safe banks will not lend to borrowers with $y < y^*$. The reason is simple: since $R^*(y) < R_{be}(y)$ for each $y < y^*$ a loan to borrowers whose income is below y^* carries a negative NPV. As a result, safe banks strictly prefer to hold the safe asset (i.e. storage) or to lend to borrowers with income above y^* rather than to borrowers with income below the cutoff y^*. So, consider a safe bank with a portfolio consisting of loans only to borrowers with $y \geq y^*$. That is, with a portfolio $f_s(y \,|\, y^*) = 0$ for $y \leq y^*$ and $f_s(y \,|\, y^*) \geq 0$ for $y > y^*$ with $\int_0^{\bar{y}} f_s(y \,|\, y^*)\, dy = 1$. Since the bank is safe it remains solvent in the bad state$\psi_B(0, f_s) \geq b$, and therefore does not incur the default cost F. In addition, since $R^*(y) = R_{be}(y)$ for each $y > y^*$, each loan carries zero NPV and the expected profit for a safe bank is zero:

$$(1-q)\psi_G(\alpha_s, f_s) + q\psi_B(\alpha_s, f_s) - (b+k) = 0.$$

Next, we show that risky banks make zero profits and strictly prefer to lend only to borrowers with income less than or equal to y^*. The objective of a risky bank is to maximize its payoff conditional on the good aggregate state (since it defaults in the bad state). Hence, each risky bank strictly prefers to lend at the highest possible interest rate. The profile $\{R^*(y)\}_0^{\bar{y}}$ implies that the maximum interest rate is R^* which applies to each borrower with income less than or equal to y^*. Therefore, a risky bank only lends to borrowers with income below y^*. So, consider a portfolio consisting of loans only to borrowers with $y < y^*$. That is, $f_r\,(y\,|\,y^*) \geq 0$ for $y < y^*$ and $f_r\,(y\,|\,y^*) = 0$ for $y \geq y^*$ with $\int_0^{\bar{y}} f_r\,(y\,|\,y^*)\,dy = 1$. Since $R^* = R_{be}\,(y^*)$ for each $y < y^*$ we have $\psi\,(R^*\,|\,y) \leq \psi\,(R^*\,|\,y^*)$ for each $y < y^*$.

We show that any portfolio consisting of loan only to borrowers with $y \leq y^*$ leads to bank default in the bad state. Specifically, for $y = y^*$ we have $R^* = R_{be}\,(y^*)$. Using (12) this implies that $\psi\,(R^*\,|\,y^*) = 1 - k - F$ where $F \geq 0$ is the non-pecuniary bankruptcy cost. Applying (**??**) it follows that $\psi\,(R^*\,|\,y) < 1 - k - F$ for each $y < y^*$.This last condition implies

$$\psi_B\,(\alpha_r,\, f_r) = \int_0^{y^*} \psi\,(R^*\,|\,y)\, f_r\,(y\,|\,y^*)\,dy < 1 - k,$$

and therefore the bank defaults in the bad aggregate state. Since the bank defaults in the bad state, it incurs the bankruptcy cost F with probability q. The payoff for the bank in the good state is $\psi_G\,(\alpha_r,\, f_r) = \int_0^{y^*} R^* f_r\,(y\,|\,y^*)\,dy$ which implies that the expected payoff for this risky bank is equal to zero:

$$(1 - q)\,(\psi_G\,(\alpha_r,\, f_r) - b) - qF - k = 0$$

We have shown that safe and risky banks have the same expected profits equal to zero. Hence, each bank is indifferent between specializing in being safe or risky. The competition to risk-shift pushes down interest rate to borrowers with income below y^* until risky banks make zero profits. In equilibrium, risky and safe banks co-exist when the cutoff y^* is interior $0 < y^* < \bar{y}$. Note that y^* is interior if and only if $1 < R^* < \frac{1-q(1+g_B)}{1-q}$ which is equivalent to the following condition on the parameters $1 - k - F > 1 + g_B$. Moreover, since $R_{be}(y)$ is decreasing in y the cutoff, when it exist, is unique apart from non-generic cases.

Finally, we show that $\{R^*(y)\}_0^{\bar{y}}$ is the only profile of mortgage rates consistent with equilibrium. First, we must have $R(y) \leq R_{be}(y)$ for each $y \in [0,\, \bar{y}]$. That is, competition and free-entry implies that that there are no loans with strictly positive NPV in equilibrium. Second, risky banks will not lend to a given borrower unless the interest rate is greater than or equal to R^*. The reason is that lending at an interest below R^* will not allow risky banks to break-even in expectation (i.e. make zero profits). This implies that risky banks will not lend to borrowers with income above y^* since $R^*(y) < R^*$ for each $y > y^*$. Third, the interest rate for each borrower with income below y^* must be the same and equal to R^*. An interest rate which is greater than R^* would imply that risky banks make positive profits, which cannot be sustained in equilibrium. □

Proof of Proposition 3.

Proof. First, we construct portfolios for risky and safe banks. Second, we show that these portfolios are consistent with equilibrium: the credit market for each income level clears and all banks make zero profits. Third, we use these portfolios and credit market clearing to derive the proportion of risky and the proportion of safe banks.

First, the interest rate for all borrowers with income below y^* is equal to R^*. Hence, each risky banks is indifferent on how to allocate its portfolio among these borrowers as long as it lends only to $y < y^*$. Let $\nu^* \equiv \int_0^{y^*} P_0^* n(y)h(y)dy$ and consider the following portfolio $b_r = 1 - k$, $\alpha_r = 0$ and

$$f_r\,(y\,|\,y^*) = \tfrac{1}{\nu^*} P_0^* n(y)h(y)$$

for $y \leq y^*$and $f_r\,(y\,|\,y^*) = 0$ for $y > y^*$. That is, the bank forms portfolio of loans only to borrowers with income $y < y^*$. Note: $f_r\,(y\,|\,y^*) \geq 0$ for each $y \in [0, \bar{y}]$ and $\alpha_r + (1 - \alpha_r) \int_0^{\bar{y}} f_r\,(y\,|\,y^*)\,dy = 1$. Applying Proposition 2, each bank holding such a portfolio defaults in the bad state (i.e. it is indeed risky) and makes zero profits.

Second, since the interest rate for each borrower with income above y^* is equal to its corresponding break-even value, each safe bank is indifferent on how to allocate its portfolio among these type of borrowers, as long as it lends only to $y \geq y^*$. So, consider the portfolio $b_s = 1 - k$, $\alpha_s = 0$ and

$$f_s\left(y\,|\,y^*\right) = \tfrac{1}{\nu^*}P_0^* n(y)h(y)$$

for $y > y^*$and $f_s\left(y\,|\,y^*\right) = 0$ for $y \leq y^*$. That is, the bank forms portfolio of loans only to borrowers with income $y > y^*$. Note: $f_s\left(y\,|\,y^*\right) \geq 0$ for each $y \in [0, \bar{y}]$ and $\alpha_s + (1-\alpha_s)\int_0^{\bar{y}} f_s\left(y\,|\,y^*\right) dy = 1$.

If a bank holding such a portfolio is safe, it must remain solvent in the bad state. We assume that $\int_0^{\bar{y}} \psi\left(R_{be}(y)\,|\,y\right) f_s\left(y\,|0\right) dy \geq 1 - k$. In words: a bank which lends to each borrower in proportion to his credit demand remains solvent in the bad aggregate state. This assumption is not necessary, but it simplifies the analysis since it implies that for any y^*, a bank holding the portfolio f_s is safe. . Specifically, for any $\epsilon > 0$ we have $f_s\left(y\,|\,\epsilon\right) = 0 \leq f_s\left(y\,|0\right)$ for $y \leq \epsilon$ and $f_s\left(y\,|\,\epsilon\right) > f_s\left(y\,|0\right)$ for $y > \epsilon$. This implies that the c.d.f. $F_s\left(z\,|\,\epsilon\right) \equiv \int_0^z f_s\left(y\,|\,\epsilon\right) dy$ dominates the c.d.f. $F_s\left(z\,|\,0\right) \equiv \int_0^z f_s\left(y\,|\,0\right) dy$ in the first-order stochastic sense. Then, since $\psi\left(R_{be}(y)\,|\,y\right)$ is non-decreasing in y it follows that

$$\int_0^{\bar{y}} \psi\left(R_{be}(y)\,|\,y\right) f_s\left(y\,|\epsilon\right) dy \geq \int_0^{\bar{y}} \psi\left(R_{be}(y)\,|\,y\right) f_s\left(y\,|0\right) dy \geq 1 - k.$$

Hence, a bank which lends only to borrowers with income greater than or equal to $y^* \in [0,\ \bar{y}]$ is safe. Moreover, since safe banks issue only zero NPV loans, they make zero profits.

The number of risky banks adjust to satisfy the demand for credit among borrowers with income $y \leq y^*$ i.e. $\int_0^{y^*} P_0^* n(y)\mu h(y)dy = k_r$. Similarly, the number of risky banks adjust to satisfy the demand for credit among borrowers with income $y > y^*$ i.e. $\int_{y^*}^{\bar{y}} P_0^* n(y)\mu h(y)dy = k_s$. In other words, each bank has one unit of funds and therefore k_r banks are necessary to satisfy the demand for subprime credit and k_s banks are necessary to satisfy the demand for prime credit. Note that for each $z \in [0,\ y^*]$ the demand for credit in the subprime segment is equal to the supply of credit by risky banks

$$\int_0^z P_0^* n(y)\mu h(y)dy = k_r \int_0^z f_r(y)dy.$$

The left-hand side is the demand for credit among borrowers with income between 0 and z. The right-hand side is the supply of credit to borrowers with income between 0 and

z. Similarly each $z \in [y^*, \bar{y}]$ the demand for credit in the prime segment is equal to the supply of credit by safe banks

$$\int_{y^*}^{z} P_0^* n(y)\mu h(y)dy = k_s \int_{y^*}^{z} f_r(y)dy.$$

Finally, the proportion of risky banks is equal to $f_r = k_r/(k_r + k_s)$ which yields the expression in (14). The mean qf_r and the standard deviation of bank risk $q\sqrt{f_r(1-f_r)}$ then follow immediately. □

Proof of Proposition 4.

Proof. Suppose risk-shifting is not possible. We must show that bank default is not consistent with equilibrium. We proceed by contradiction by fixing a profile of mortgage interest rates and assuming that there is a bank which defaults in the bad state. We then show that the expected payoff for such a risky bank is strictly less than zero which is not consistent with equilibrium.

So, fix a profile of mortgage rates $\{R(y)\}_0^{\bar{y}}$ and suppose that a bank with a portfolio (α, f, b) becomes insolvent in the bad aggregate state $\psi_B(\alpha, f) < b$ where ψ_G is given in (6). We will show that the expected net payoff for this bank is less than zero. First, since the bank defaults in the bad aggregate state it must pay the bankruptcy costs F. The expected payoff for this risky bank is $(1-q)(\psi_G - R_D b) - qF - k$ where its payoff in the good state ψ_G is given in (5).

Since risk-shifting is not possible R_D adjust to ensure the depositors break-even in expectation. That is, $(1-q)R_D b + q\psi_B = b$. With probability $1-q$ the state is good and the depositors receive the promised amount bR_D, where R_D is the gross deposit rate offered by this bank. On the other hand, with probability q the state is bad and the depositors receive ψ_B which is less than bR_D. Using the expression for R_D, the expected profit for the bank becomes is

$$\int_0^{\bar{y}} \left[(1-q)R(y) + q\psi\left(R(y)\,|\,y\right)\right] f(y)dy - qF - (b+k)$$

From Proposition 1 we know that $R(y) \leq R_{be}(y)$ which implies that each loan carries non-positive NPV: $(1-q)R(y) + q\psi\left(R(y)\,|\,y\right) \leq 1$. Since each loan carries non-positive

NPV and $F_{\cdot} > 0$ it follows that the expected profit for the bank is negative. Hence, the bank strictly prefers to hold storage, which is not consistent with equilibrium. Hence, when risk-shifting is not possible, equilibrium default does not occur among banks with strictly positive franchise values. □

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 on the MSA level	
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).
Ratio_0520	**Income ratio 05:20.** We calculate this variable as the ratio of the mean income of the top 5 percent and the mean income of the bottom 20 percent. Source: U.S. Census Bureau, 1-year estimate from 2006 (the first year when this 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).

Table OA2: Descriptive statistics

	Obs.	**Mean**	**SD**	**Min**	**P10**	**P50**	**P90**	**Max**
	Obs	Mean	SD	Min	P10	Median	P90	Max
PDL m	327	0.0040	0.0064	-0.0140	-0.0024	0.0028	0.0123	0.0267
Zscore m	327	4.1037	0.4145	1.9024	3.5807	4.1403	4.5956	5.2594

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 1 for a detailed explanation of every variable, and Table 2 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_yr	(2) Failed_yr	(3) Failed_yr
Gini07	0.0500**	0.0442**	0.0532***
	(0.0107)	(0.0195)	(0.0100)
Mean income		0.0001*	
		(0.0887)	
Med income			0.0001*
			(0.0742)
Constant	-0.0192**	-0.0210**	-0.0248**
	(0.0241)	(0.0234)	(0.0145)
Obs.	178	178	178
Adj. R2	0.0442	0.0593	0.0570

gini_3y_07, failed_wo0809_yr_m, 24 Sep 2020 18:11:20

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
Gini07	0.2177**	0.2044*	0.2240**	-3.7398**	-2.9869*	-4.1571***
	(0.0456)	(0.0511)	(0.0466)	(0.0169)	(0.0788)	(0.0093)
Mean income		0.0002			-0.0088***	
		(0.5125)			(0.0075)	
Med income			0.0002			-0.0113***
			(0.5776)			(0.0094)
Constant	-0.0820*	-0.0860*	-0.0932*	4.5318***	4.7591***	5.2689***
	(0.0826)	(0.0850)	(0.0949)	(0.0000)	(0.0000)	(0.0000)
Obs.	178	178	178	178	178	178
Adj. R2	0.0197	0.0170	0.0160	0.0299	0.0687	0.0642

gini_3y_07, pd_logit_cw2_90/ ln_zscore_10, 24 Sep 2020 18:11:21

Panel C: Average bank risk

	(1) PD_m	(2) PD_m	(3) PD_m	(4) Zscore_m	(5) Zscore_m	(6) Zscore_m
Gini07	0.0551*	0.0481*	0.0587*	-2.3221**	-1.8026*	-2.5971**
	(0.0538)	(0.0702)	(0.0514)	(0.0228)	(0.0898)	(0.0120)
Mean income		0.0001			-0.0061***	
		(0.1511)			(0.0052)	
Med income			0.0001			-0.0074***
			(0.1389)			(0.0078)
Constant	-0.0208*	-0.0229*	-0.0273*	5.1870***	5.3438***	5.6728***
	(0.0945)	(0.0913)	(0.0720)	(0.0000)	(0.0000)	(0.0000)
Obs.	178	178	178	178	178	178
Adj. R2	0.0332	0.0465	0.0432	0.0235	0.0628	0.0547

gini_3y_07, pd_logit_cw2_m/ ln_zscore_m, 24 Sep 2020 18:11:21

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
Gini07	0.1205**	0.1002**	0.1319**	1.5173***	1.2028**	1.6999***
	(0.0106)	(0.0301)	(0.0108)	(0.0046)	(0.0359)	(0.0017)
Mean income		0.0002**			0.0037***	
		(0.0416)			(0.0008)	
Med income			0.0003**			0.0049***
			(0.0292)			(0.0006)
Constant	-0.0446**	-0.0507**	-0.0647**	0.2609	0.1659	-0.0615
	(0.0296)	(0.0320)	(0.0148)	(0.2696)	(0.5022)	(0.7989)
Obs.	178	178	178	178	178	178
Adj. R2	0.0358	0.0667	0.0635	0.0416	0.0986	0.0976

gini_3y_07, pd_logit_cw2_cv/ ln_zscore_cv, 24 Sep 2020 18:11:22

Table OA4: Income share of top 5 percent

This table shows regression results for the empirical model presented in Section 2. See Table 1 for a detailed explanation of every variable, and Table 2 for descriptive statistics. P-values 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_yr_m	Failed_yr_m	Failed_yr_m
shares_top5	0.0006***	0.0006***	0.0006***
	(0.0043)	(0.0092)	(0.0052)
Mean_income		0.0001	
		(0.1831)	
Med_income			0.0001
			(0.1697)
Obs.	178	178	178
Adj. R2	0.0612	0.0671	0.0664

shares_top5_1y_06, failed_wo0809_yr_m, 29 Sep 2020 11:58:28

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
shares_top5	0.0031**	0.0029**	0.0030**	-0.0475***	-0.0362*	-0.0460**
	(0.0158)	(0.0155)	(0.0160)	(0.0091)	(0.0723)	(0.0146)
Mean income		0.0001			-0.0081**	
		(0.7266)			(0.0172)	
Med income			0.0001			-0.0096**
			(0.8083)			(0.0307)
Constant	-0.0484*	-0.0512*	-0.0516*	3.8499***	4.1319***	4.2856***
	(0.0529)	(0.0767)	(0.0958)	(0.0000)	(0.0000)	(0.0000)
Obs.	178	178	178	178	178	178
Adj. R2	0.0360	0.0313	0.0309	0.0421	0.0725	0.0654

shares_top5_1y_06, pd_logit_cw2_90/ ln_zscore_10, 24 Sep 2020 18:19:34

Panel C: Average bank risk

	(1)	(2)	(3)	(4)	(5)	(6)
	PD_m	PD_m	PD_m	Zscore_m	Zscore_m	Zscore_m
shares_top5	0.0007**	0.0006**	0.0007**	-0.0410***	-0.0339***	-0.0400***
	(0.0297)	(0.0379)	(0.0329)	(0.0004)	(0.0057)	(0.0008)
Mean income		0.0001			-0.0050**	
		(0.2058)			(0.0242)	
Med income			0.0001			-0.0062**
			(0.2201)			(0.0258)
Constant	-0.0107*	-0.0131*	-0.0141*	5.0000***	5.1755***	5.2845***
	(0.0929)	(0.0925)	(0.0806)	(0.0000)	(0.0000)	(0.0000)
Obs.	178	178	178	178	178	178
Adj. R2	0.0462	0.0537	0.0496	0.0698	0.0940	0.0906

shares_top5_1y_06, pd_logit_cw2_m/ ln_zscore_m, 24 Sep 2020 18:19:34

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
shares_top5	0.0016***	0.0013**	0.0016***	0.0149**	0.0098	0.0142**
	(0.0041)	(0.0145)	(0.0068)	(0.0191)	(0.1467)	(0.0243)
Mean income		0.0002*			0.0036***	
		(0.0699)			(0.0010)	
Med income			0.0003*			0.0043***
			(0.0560)			(0.0035)
Constant	-0.0242**	-0.0315**	-0.0357**	0.6281***	0.5015***	0.4330***
	(0.0290)	(0.0279)	(0.0162)	(0.0000)	(0.0002)	(0.0013)
Obs.	178	178	178	178	178	178
Adj. R2	0.0558	0.0772	0.0728	0.0322	0.0850	0.0732

shares_top5_1y_06, pd_logit_cw2_cv/ ln_zscore_cv, 24 Sep 2020 18:19:35

Table OA5: Poverty

This table shows regression results for the empirical model presented in Section 2. See Table 1 for a detailed explanation of every variable, and Table 2 for descriptive statistics. P-values are 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	0.0423***		0.0506**
	(0.0081)		(0.0131)
poverty		-0.0000	-0.0002
		(0.8929)	(0.2956)
Obs.	178	175	175
Adj. R2	0.0372	-0.0057	0.0406

gini_1y_06, failed_wo0809_yr_m, 19 Oct 2020 13:29:03

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**		0.2134*	-3.1783**		-3.7732**
	(0.0176)		(0.0581)	(0.0334)		(0.0174)
poverty		0.0005	-0.0001		0.0035	0.0140
		(0.5827)	(0.8938)		(0.7436)	(0.2226)
Obs.	178	175	175	178	175	175
Adj. R2	0.0221	-0.0033	0.0157	0.0251	-0.0051	0.0264

gini_1y_06, pd_logit_cw2_90/ ln_zscore_10, 19 Oct 2020 13:29:04

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**		0.0560*	-2.1759**		-2.6644***
	(0.0317)		(0.0556)	(0.0180)		(0.0089)
poverty		-0.0000	-0.0002		0.0023	0.0097
		(0.8763)	(0.3968)		(0.7223)	(0.1816)
Obs.	178	175	175	178	175	175
Adj. R2	0.0284	-0.0056	0.0294	0.0250	-0.0051	0.0284

gini_1y_06, pd_logit_cw2_m/ ln_zscore_m, 19 Oct 2020 13:29:04

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***		0.1345***	1.2380**		1.7194***
	(0.0067)		(0.0080)	(0.0198)		(0.0018)
poverty		-0.0002	-0.0006		-0.0054	-0.0102**
		(0.5632)	(0.1636)		(0.1596)	(0.0152)
Obs.	178	175	175	178	175	175
Adj. R2	0.0333	-0.0035	0.0433	0.0320	0.0076	0.0639

gini_1y_06, pd_logit_cw2_cv/ ln_zscore_cv, 19 Oct 2020 13:29:05

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 1 for a detailed explanation of every variable, and Table 2 for descriptive statistics. P-values are reported in parentheses. The ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively.

Panel A: Bank failures

	(1) Failed_yr	(2) Failed_yr	(3) Failed_yr
Gini	0.0393	0.0292	0.0460*
	(0.1207)	(0.2125)	(0.0890)
Mean income		0.0001**	
		(0.0332)	
Med income			0.0002**
			(0.0202)
Constant	-0.0136	-0.0173	-0.0244*
	(0.2178)	(0.1604)	(0.0784)
Obs.	179	179	179
Adj. R2	0.0167	0.0572	0.0508

gini_1y_06, failed_wo0809_yr_m, 24 Sep 2020 18:32:07

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	0.1779**	0.1568*	0.1915**	-3.2912**	-2.4876	-3.8402**
	(0.0477)	(0.0846)	(0.0368)	(0.0307)	(0.1286)	(0.0113)
Mean income		0.0003			-0.0105***	
		(0.3200)			(0.0031)	
Med income			0.0003			-0.0136***
			(0.3525)			(0.0036)
Constant	-0.0610	-0.0687*	-0.0830*	4.2424***	4.5338***	5.1319***
	(0.1165)	(0.0916)	(0.0713)	(0.0000)	(0.0000)	(0.0000)
Obs.	179	179	179	179	179	179
Adj. R2	0.0127	0.0152	0.0137	0.0247	0.0753	0.0711

gini_1y_06, pd_logit_cw2_90/ ln_zscore_10, 24 Sep 2020 18:32:07

Panel C: Average bank risk

	(1) PD_m	(2) PD_m	(3) PD_m	(4) Zscore_m	(5) Zscore_m	(6) Zscore_m
Gini	0.0414*	0.0325	0.0474**	-2.3295**	-1.7673*	-2.7040***
	(0.0627)	(0.1268)	(0.0460)	(0.0164)	(0.0817)	(0.0064)
Mean income		0.0001*			-0.0074***	
		(0.0638)			(0.0024)	
Med income			0.0001*			-0.0093***
			(0.0533)			(0.0024)
Constant	-0.0137	-0.0169	-0.0233*	5.1276***	5.3315***	5.7343***
	(0.1559)	(0.1162)	(0.0572)	(0.0000)	(0.0000)	(0.0000)
Obs.	179	179	179	179	179	179
Adj. R2	0.0174	0.0452	0.0410	0.0256	0.0765	0.0697

gini_1y_06, pd_logit_cw2_m/ ln_zscore_m, 24 Sep 2020 18:32:08

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	0.0960**	0.0702*	0.1138**	1.2636**	0.9445*	1.4875***
	(0.0191)	(0.0916)	(0.0123)	(0.0168)	(0.0799)	(0.0032)
Mean income		0.0003**			0.0042***	
		(0.0121)			(0.0002)	
Med income			0.0004***			0.0056***
			(0.0064)			(0.0002)
Constant	-0.0318*	-0.0411*	-0.0605**	0.3926*	0.2768	0.0298
	(0.0745)	(0.0517)	(0.0110)	(0.0929)	(0.2268)	(0.8938)
Obs.	179	179	179	179	179	179
Adj. R2	0.0214	0.0766	0.0728	0.0308	0.0973	0.0955

gini_1y_06, pd_logit_cw2_cv/ ln_zscore_cv, 24 Sep 2020 18:32:08

Table OA7: Panel/ measures of bank risk - clustering on MSA level

This table shows regression results for the empirical model presented in Section 2. See Table 1 for a detailed explanation of every variable, and Table 2 for descriptive statistics. P-values are reported in parentheses. The ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively.

Panel A: Bank failures

	(1) Failed_yr	(2) Failed_yr	(3) Failed_yr
Gini	0.0395***	0.0337**	0.0426***
	(0.0077)	(0.0217)	(0.0063)
Mean income		0.0001*	
		(0.0822)	
Med income			0.0001*
			(0.0738)
Year FE	Yes	Yes	Yes
No. of MSAs	178	178	178
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

gini_1y_06, failed_wo0809_yr_m, 19 Oct 2020 13:29:06

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	0.1958**	0.1850**	0.2011**	-2.6546*	-1.8364	-3.1002**
	(0.0155)	(0.0235)	(0.0148)	(0.0629)	(0.2161)	(0.0288)
Mean income		0.0001			-0.0099***	
		(0.5954)			(0.0016)	
Med income			0.0002			-0.0130***
			(0.6331)			(0.0014)
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

gini_1y_06, pd_logit_cw2_90/ ln_zscore_10, 19 Oct 2020 13:29:07

Panel C: Average bank risk

	(1) PD_m	(2) PD_m	(3) PD_m	(4) Zscore_m	(5) Zscore_m	(6) Zscore_m
Gini	0.0436**	0.0371**	0.0470**	-1.9260**	-1.3833	-2.2119**
	(0.0266)	(0.0473)	(0.0245)	(0.0301)	(0.1343)	(0.0128)
Mean income		0.0001			-0.0066***	
		(0.1626)			(0.0024)	
Med income			0.0001			-0.0083***
			(0.1487)			(0.0028)
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

gini_1y_06, pd_logit_cw2_m/ ln_zscore_m, 19 Oct 2020 13:29:08

Panel D: Dispersion of bank risk (coefficient of variation) per MSA

	(1) PD_sd	(2) PD_sd	(3) PD_sd	(4) Zscore_sd	(5) Zscore_sd	(6) Zscore_sd
Gini	0.1008***	0.0807**	0.1118***	1.1164**	0.7706	1.3089***
	(0.0061)	(0.0303)	(0.0058)	(0.0319)	(0.1320)	(0.0077)
Mean income		0.0002**			0.0042***	
		(0.0441)			(0.0001)	
Med income			0.0003**			0.0056***
			(0.0289)			(0.0000)
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

gini_1y_06, pd_logit_cw2_cv/ ln_zscore_cv, 19 Oct 2020 13:29:10

Part II: Predictions of banks' probabilities of default[25]

Data The data sources that we use for the prediction of the banks' default probabilities are the *Federal Deposit Insurance Corporation* (FDIC) for all bank financial data and information about bank failures.[26] The sample includes yearly data on 11,484 U.S. banks from 2000 to 2018, which results in a total of 150,856 observations. 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. See Table OA8 for a description of all variables.

The number of bank failures for this sample is 571. 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.

Model We predict banks' probabilities of default (PD) using the following linear probability model:[27]

$$\begin{aligned} Fail_{i,t} = \tau_t \times \gamma_s &+ \beta_1 AGE_{i,t-1} + \beta_2 CIR_{i,t-1} + \beta_3 COI_{i,t-1} + \beta_4 EQ_{i,t-1} \\ &+ \beta_5 FOR_{i,t-1} + \beta_6 IENC_{i,t-1} + \beta_7 LIQ_{i,t-1} + \beta_8 LOA_{i,t-1} + \beta_9 NPA_{i,t-1} \\ &+ \beta_{10} RE_{i,t-1} + \beta_{11} ROA_{i,t-1} + \beta_{12} SIZE_{i,t-1} + \epsilon_{i,t}. \end{aligned}$$

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. The variables $\tau_t \times \gamma_s$ cover year-state fixed effects to capture developments over time in the different U.S. states. In line with the literature, we choose the first lag of all right-hand-side variables.

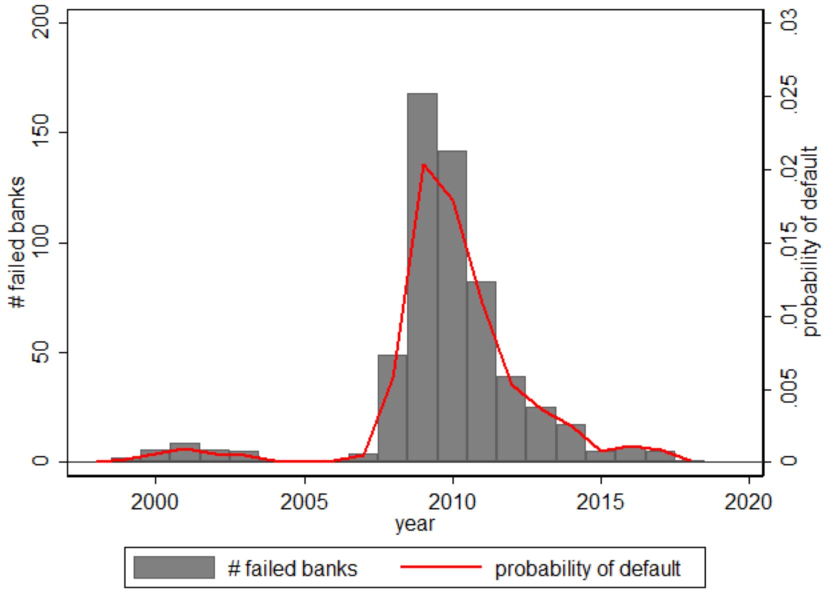
[25] This section is similar to a section in the Online Appendix of the paper *Natural Disasters and Bank Stability* by Noth and Schüwer (SAFE Working Paper, 2018).

[26] 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/).

[27] A linear probability model allows us to include year-state fixed effects. With a nonlinear probability model, the introduction of many fixed effects leads to i) practical problems because the presence of many variables makes the estimation much more difficult, and ii) the incidental parameters problem (Greene et al., 2002; Fernandez-Val, 2009).

Results Regression results of the probability model are shown in Table OA9. Figure OA1 illustrates the banks' average predicted probabilities of default per year, which increase significantly during the 2008 financial crisis. Predicted probabilities of default (PD) are then used as a measure of bank risk for the regressions in the main part of this paper.

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 ell as the banks' average predicted probabilities of default (own predictions, as described in this section).

Table OA8: Predictions of default probabilities/ variable description

Variable name	Description
AGE	**Age:** Banks' age as the natural logarithm of the quarterly distance to each bank's date of establishment. Source: FDIC ($\ln(qtr - birthqtr)$).
CIR	**Cost-to-income ratio:** The ratio of banks' total cost to income. Source: FDIC ($nonix/(nim + nonii)$).
COI	**Commercial and industrial loan ratio:** The ratio of banks' commercial and industrial loans to total assets. Source: FDIC ($lnci/asset$).
EQ	**Equity ratio:** The ratio of total equity to total assets. Source: FDIC ($eqv/100$).
FAIL	**Bank failure:** Bank failures come from the FDIC's *failed bank list* (transaction types PA, PI, PO, PI). Source: FDIC (https://www.fdic.gov/bank/individual/failed/). To account for public bailouts, we include "technical" bank failures if a bank's sum of equity and reserves is lower than half of its non-performing assets (see, Cole and White, 2010).
FOR	**Foreclosure ratio:** The ratio of a bank's other real estate owned, which is not directly related to its business and consists largely of foreclosed property, to total assets. Source: FDIC ($ore/asset$).
IENC	**Income earned, not collected on loans:** The ratio of banks' income not collected on loans to total assets. Source: FDIC ($oaienc/asset$).
LIQ	**Liquidity:** The ratio of difference between federal funds purchased and sold to total assets. Source: FDIC ($(frepp - frepo)/asset$).
LOA	**Gross loan ratio:** The ratio of banks' gross loans to total assets. Source: FDIC ($lnlsgr/asset$).
NPA	**Non-performing assets ratio:** The sum of loans past due 30-90+ days but still accruing interest and nonaccrual loans, scaled by total assets. Source: FDIC ($(p9asset + p3asset + naasset)/asset$).
RE	**Real estate loan ratio:** The ratio of banks' real estate loans to total assets. Source: FDIC ($lnre/asset$).
ROA	**Return on assets:** Net income as a percentage of average total assets. Source: FDIC ($roa/100$).
SIZE	**Bank size:** The natural logarithm of banks' total assets. Source: FDIC ($\ln(asset)$).

Table OA9: Predictions of default probabilities

Notes: The column shows results of the linear probability model. See Table OA8 for a detailed description of all variables. Standard errors are clustered at the bank level. ***, ** and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
		failed_yr	failed_yr
L.eqv100	-0.1662***	-0.0263***	-0.0268***
	(0.0000)	(0.0000)	(0.0000)
L.roa100	-0.0415***	-0.2141***	-0.1954***
	(0.0000)	(0.0000)	(0.0000)
L.lnatres_asset	0.0160	0.3489***	0.3707***
	(0.2540)	(0.0023)	(0.0019)
L.npao_asset	0.0264***	0.5994***	0.5965***
	(0.0000)	(0.0000)	(0.0000)
L.securities_asset	-0.0084***	0.0063***	0.0077***
	(0.0000)	(0.0000)	(0.0000)
L.bro_asset	0.0028**	0.0303***	0.0269***
	(0.0222)	(0.0000)	(0.0000)
L.ln_asset	-0.0002	0.0005***	0.0007***
	(0.2074)	(0.0002)	(0.0001)
L.cash_assets	-0.0020	0.0143***	0.0158***
	(0.4384)	(0.0000)	(0.0000)
L.intan_asset	0.1094***	0.0389***	0.0295**
	(0.0000)	(0.0024)	(0.0201)
L.lnreres_asset	-0.0029*	-0.0151***	-0.0146***
	(0.0611)	(0.0000)	(0.0000)
L.lnremult_asset	0.0084***	0.0108*	0.0013
	(0.0038)	(0.0589)	(0.8118)
L.lnrecons_asset	0.0112***	0.0467***	0.0457***
	(0.0000)	(0.0000)	(0.0000)
L.lnrenres_asset	-0.0041**	-0.0235***	-0.0264***
	(0.0130)	(0.0000)	(0.0000)
L.CI loans_assets	0.0043*	-0.0175***	-0.0130***
	(0.0679)	(0.0000)	(0.0000)
L.consumer loans_assets	-0.0144***	-0.0355***	-0.0321***
	(0.0021)	(0.0000)	(0.0000)
Year × State FE	Yes		
Clustering	Bank level		
Unique banks	11492		
Failed banks	564		
Obs.	141,720	154,466	154,466
No. of cluster		11,492	11,492
Adj. R2		0.1028	0.1110

Timestamp: 28 Sep 2020 11:20:22