Commercial Bank Failures During The Great Recession: The Real (Estate) Story

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Abstract

Cash flow risk from non-household real estate had a more prominent role in precipitating commercial bank failures during the Great Recession than either funding fragility or exposure to household real estate – subprime or otherwise – did. Whereas both failed and survivor banks mispriced real estate risk ex-ante, failed banks' investments suffered both from an excessive focus on sectors with higher aggregate risk and from higher idiosyncratic risk within each sector. The secondary effect of funding fragility is more important for post-2009 failures where funding costs at the time of bank failure were driven by bank-specific solvency risk rather than by aggregate factors unrelated to fundamentals.

Keywords: bank failures, Great Recession, commercial real estate, MBS, risk transfer, funding fragility

JEL Classification: G21, G28, R33

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I. Introduction

A number of large financial institutions – including brokers-dealers, mortgage companies, and insurers – failed during the 2007-2008 funding crisis in the United States. The period immediately following the funding crisis was marked by commercial bank failures that numbered in the hundreds.

Bank failures are not frictionless events. Bank distress can lead to increased risk taking due to the loss of charter value (Keeley (1990)), raise funding costs for non-distressed competitors (Egan, Hortasu and Matvos (2017)), generate severe contractions in credit supply (Ivashina and Scharfstein (2010), Cornett et al. (2011), Antoniades (2016)), and affect real economic activity both in the country where the stress originated (Ashcraft (2005), Calomiris and Mason (2003*a*)) and across borders (Peek and Rosengren (1997), Peek and Rosengren (2000)). Furthermore, bank failures impose significant costs on the resolution authority and the costs can be further compounded by misallocation of failed banks to potential acquirers (Granja, Matvos and Seru (forthcoming)).

Conceptually understanding systematic risk patterns associated with these failures is important. One strand of the literature focuses on agency problems. Laeven and Levine (2009) find that banks with more powerful owners tended to take greater risks during the run-up to the 2007-2008 crisis. Examining the crisis period, Fahlenbrach and Stulz (2011) and Beltratti and Stulz (2012) show that neither better governance nor incentive structures that better aligned the interests of shareholders to those of the management, resulted in better bank performance during the crisis.[1]

Another strand of the literature examines the relation between banks' pre-crisis business models and bank performance during the crisis. Ratnovski and Huang (2009), Beltratti and Stulz (2012), Fahlenbrach, Prilmeier and Stulz (2012) find that banks with more fragile funding structures performed worse during the crisis, Cole and White (2012) find a link between bank failure and exposure to commercial real estate, and DeYoung and Torna (2013) find the composition of banks' sources of income to have also mattered.

This paper builds on the business model literature to provide a comprehensive study of the

[1] Cheng, Hong and Scheinkman (2015) present a challenge to cross-sectional estimates of the impact of compensation policy on firm outcomes, by identifying a causal relation that runs in the reverse direction, from firm risk to managerial pay, as risk-averse managers require more pay to compensate them for working in riskier firms.

relative importance of investment and funding risks in precipitating commercial bank failures during the Great Recession. Importantly, the analysis generates the first micro-level evidence on the operation of risk channels during the crisis.

The analysis proceeds in three stages. The first stage motivates the main analysis by presenting time-series evidence on the evolution of funding and real estate risks, as well as cross-sectional evidence on the evolution of banks' business models during the run-up to the crisis. The second stage relies on the cross-sectional approach employed in the literature on bank risk-taking[2] to jointly identify and rank the main risk-channels proposed in the literature. I empirically test the robustness of the results against a comprehensive set of competing explanations. With the main sources of risk identified, the third stage uses portfolio-level data to reveal how the risk became operational during the crisis.

Although funding risk may have affected bank solvency, a liquidity mechanism involving aggregate funding reversals – of the type discussed in Gorton and Metrick (2012)), Adrian and Shin (2009), Brunnermeier (2009), Brunnermeier and Pedersen (2009), for example – cannot entirely explain commercial bank failures. The FDIC reported 492 commercial bank failures from January 1, 2005 to December 31, 2013. The vast majority of these failures - 462 failures - took place after the last quarter of 2008. That is, during a period when aggregate funding pressures in the banking sector had completely abated.

The severe and extended downturn experienced by real estate markets during the Great Recession aligns well intertemporaly with the timing of bank failures. Two asset bubbles deflated during the crisis: one involving residential real estate (RRE) and a more severe one involving commercial real estate (CRE). This paper argues that while during the run-up to the crisis commercial banks offloaded the risk associated with RRE via active use of the securitization channel (Mian and Sufi (2009), Loutskina and Strahan (2009), Keys et al. (2010), Demyanyk and Van Hemert (2011)), they used their residual balance sheet capacity to fund the growth in CRE markets.

I propose three channels via which stresses in real estate markets could impact banks' financial health. These channels operate via a bank's exposure to real estate risk in each of its (1) illiquid

[2]See, for example, Laeven and Levine (2009), Beltratti and Stulz (2012)

assets, (2) marketable securities, and (3) off-balance sheet credit line portfolios.

During the run-up to the crisis, banks changed their funding structures only marginally but raised their exposure to real estate risk substantially. Importantly, whereas they increased their exposure to non-household real estate borrowers – such as investors in multifamily properties, developers of commercial real estate (CRE) and land development projects – and in the case of large banks also to private-label MBS, they shed their exposure to traditional household real estate products, such as home mortgages and agency MBS. By 2005, banks that ended up failing during the crisis were significantly more exposed to non-household real estate credit – which accounted for roughly half their balance sheet – than survivor banks. These findings point to an aggregate shift of retained risk to non-household real estate credit; with failed banks pursuing this strategy more aggressively.

Cross-sectional estimates, in an initial conditions setting, establish a pecking order of the various drivers of bank failures: exposure to non-household real estate credit was the primary determinant of failures, the effect of funding fragility was of secondary importance, and household real estate's impact was limited to the (marginal) effect of private-label MBS held by large banks. Traditional home mortgages and agency-issued MBS did not impact commercial bank failures during this episode. In short, cash flow risk on the asset side had a more prominent role in precipitating commercial bank failures than funding risk on the liability side did.

The results are robust against a number of competing explanations. More specifically, the effect of non-household real estate risk cannot be explained by shocks in local economic conditions, government interventions, regulatory discretion in placing banks under receivership, non-receivership exits, and the banks' income mix. The results are also robust to controlling for exposure to ABCP conduits, to excluding too-big-to fail banks from the sample, to matching survivor and failed banks on a host of characteristics, to the choice of pre-crisis year, and to the use of a linear estimator.

In the third stage of the analysis, I generate micro-level evidence on the operation of the main risk channels. Although identifying the source of banks' risk-taking in non-household real estate markets extends beyond the scope of this work, I run tests that rule out two plausible explanations, thereby limiting the search space. Specifically, I show that risk-taking in non-household real estate credit is neither a byproduct of a bank's overall risk-taking behaviour nor a byproduct of its risk-taking behaviour in household real estate markets. I then proceed to study how risk became operational during the crisis, by examining the presence of an aggregate component – ie, uniformly affecting all banks per unit of exposure – and an idiosyncratic component – ie, differentially affecting failed banks per unit of exposure.

During the crisis, all real estate loan categories exhibited higher average non-performing loan (NPL) rates than non-real estate ones, regardless of the type of bank investing in the loans. Non-household real estate was the worst performer. Furthermore, in all real estate loan categories, failed banks experienced significantly higher NPL rates than survivor banks. These spreads in NPL rates are particularly pronounced for non-household real estate loans where, after controlling for the influence of local economic conditions, they reach 10 and 12 percentage points for small and large banks, respectively. Differences in NPL rates cannot be explained by the faster pace at which failed banks grew their exposure to real estate loans during the run-up to the crisis.

Interest rate returns show that both failed and survivor banks underpriced real estate risk prior to the crisis. Although failed banks did price their real estate loan portfolios as higher risk than those of survivor banks, at less than 100 basis points the risk spread did not adequately compensate for the significantly higher loan losses they experienced during the crisis.

Analyzing the trajectory of unrealized gains on banks' securities portfolios yields two main findings. First, although the agency-MBS portfolios of failed banks performed worse than those of survivor banks, for both types of banks agency-MBS outperformed the benchmark portfolio of non-MBS securities. Second, regardless of bank type the private-label MBS portfolios performed worse than the non-MBS portfolios but there is no clear evidence of idiosyncratic differences in performance between bank types; the latter is possibly a result of the very small number of banks with significant private-label MBS holdings.

Last, I find that the effect of funding fragility operated primarily through an idiosyncratic channel. Aggregate funding pressures affected the funding costs of both failed and survivor banks only during the early funding phase of the crisis (2007-2008). However, the effect of funding fragility on the probability of bank failure mattered most for the post 2009 failures, ie for failures that took place in the absence of aggregate funding shocks to bank liquidity. Compared to pre-crisis spreads, providers of wholesale funds repriced risk more aggressively during the crisis than providers of core deposits. However, the persistence of a spread in funding costs between failed and survivor banks post 2009 was driven by bank-specific risk rather than by factors unrelated to fundamentals.

The paper synthesizes a detailed picture of the central role of non-household real estate credit in precipitating U.S. commercial bank failures during the Great Recession. The higher risk profile of non-household real estate loans is consistent with general features of these loans. For example, compared to RRE loans, CRE loans are larger and harder to diversify, rely on more complex repayment sources requiring more involved cash flow analysis, are rarely fully amortized with balloon payments of principal often required upon maturity, and face higher barriers to securing alternative financing because of their idiosyncratic features and costly prepayment penalties; arguably, they also face lower disincentives for strategic default (Levitin and Wachter (2013)). Furthermore, the relative illiquid, segmented, and informationally inefficient markets in which CRE assets trade invite a larger role for investor sentiment in valuation (Clayton, Ling and Naranjo (2009)).

Losses on CRE loans can be particularly severe when an aggregate deterioration of conditions in CRE markets leads simultaneously to an increase in strategic defaults and to an industry-wide decrease in the wealth of potential buyers of defaulted assets Brown, Ciochetti and Riddiough (2006). Losses for loan originators may be significantly compounded by firesale discounts driven by a coincidence of shocks to their balance sheets and by holding-period limits.

Research on earlier crisis episodes, points to a link between non-household real estate credit and bank distress. In the early 1990s, Japanese lenders incurred significant losses from their CRE-collateralized loan portfolios, which resulted in a credit crunch within and even outside Japan (Peek and Rosengren (1997), Peek and Rosengren (2000)). Empirical evidence also points to CRE risk as one of the main drivers of the poor performance of the U.S. banking sector in the 1990s (Litan (1992), Boyd and Gertler (1993), Cole and Fenn (2008)).

In the aftermath of the recent 2007-08 funding crisis, references to the non-household real estate sector emerged in public reports examining the failure of specific financial institutions. An important example is the Examiner's Report on the failure of Lehman Brothers that documents the significant role that losses in the bank's CRE portfolio played in its eventual demise.[3]

Nonetheless, scant empirical evidence exists on the drivers of performance of CRE markets during the recent crisis. Duca and Ling (2015) show that CRE markets experienced as deep a downturn as residential mortgage markets did during this episode. The authors attribute price movements in CRE markets to shifts in risk premia that declined in the run-up to the crisis and increased sharply during the crisis. Levitin and Wachter (2013) argue that the boom in CRE markets was partly driven by innovations in commercial mortgage-backed security (CMBS) markets that resulted in traditional investors in CRE markets being outbid by collateralized debt obligation (CDO) packagers with lower underwriting standards.

Similarly, the post-crisis literature on financial intermediation lacks a rigorous examination of systematic patterns of risk-taking in non-household real estate markets. One exception is Cole and White (2012) who find a cross-sectional correlation between commercial real estate investment and the probability of bank failure, in an empirical setting with certain limitations on identification.[4]

I contribute to the literature by producing a more complete analysis of the determinants of bank failures. First I provide aggregate time-series evidence to set the backdrop for the main cross-sectional results on risk-drivers. Second I examine the evolution of banks' pre-crisis business models, and document significant ex-ante shifts that are consistent with the ex-post risk drivers. Third, I examine the relative importance of the various risk drivers, which I identify in a rigorous empirical setting. Fourth, I reject plausible hypotheses about the nature of bank's risk-taking in non-household real estate markets to trace a tighter boundary around its source. Fifth, I use data at the loan product level to show how real estate risk was priced prior to the crisis and how it became operational during the crisis. Similarly, I rely on micro-level data on funding costs to trace the operation of the funding channel during this crisis episode.

[3]The full report can be found at https://jenner.com/lehman

[4]Cole and White (2012) use data on bank failures in 2009 – and in one robustness test up until the first half of 2010 – and rely on a model to identify would-be failures for subsequent years. This is an important shortcoming because the majority of bank failures took place after 2009. They also do not account for the significant risk exposure stemming from off-balance sheet credit commitments, they infer the direction of effects for MBS risk from a model that does not explicitly control for MBS holdings, they do not convincingly rule out the main competing explanation of shocks to local economic conditions, and their model estimates effects relative to holdings of cash rather than relative to holdings of non-real estate assets within each appropriate portfolio, which is arguably a closer representation of a bank's portfolio allocation process.

II. Data Sources and Time Series Evidence

I obtain the list of failed institutions from FDIC. The FDIC reported 492 bank failures during the period January 1, 2005 to December 31, 2013. The vast majority of these institutions were sold in a bidding process and a small number were liquidated (Granja, Matvos and Seru (forthcoming)). I obtain financial data for banks from the Reports of Condition and Income (call reports) made available online by the Federal Reserve Bank of Chicago. The call reports cover all commercial banks and contain detailed financial information in a number of different schedules. Merging the list of failed banks with the 2005 call reports using the FDIC certificate number as the match key yields a set of 8,541 banks, 405 of which failed.

To achieve a more uniform sample, I drop a number of observations. I first drop thrifts, savings banks, and other institutions that are not classified as commercial banks in the call reports because such banks operate under a different charter and have different business models than commercial banks; this leaves 7,650 commercial banks (384 failed). I then drop small banks with average assets in 2004 less than $50 million and have 5,802 banks (323 failed); banks that entered the sample after 2004, and have 5,634 banks (301 failed); and banks that exited the sample before Dec 31, 2013 without being reported as bank failures by the FDIC (possibly as a result of mergers, parent BHC failure, or changes in reporting requirements)[5] to obtain the final sample that contains 4,320 banks, 301 of which failed between January 1, 2005 and December 31, 2013.

A. Timeline of Bank Failures and Funding Risk

Figure I displays the quarterly timeline of the 301 bank failures in my sample for the period January 1, 2005 to December 31, 2013, which covers a full real estate cycle. The first failure occurred in the last quarter of 2007.[6] Failure rates peaked during 2009-2010, and gradually declined to two bank failures by the fourth quarter of 2013.

[5]In the Appendix, I show that the results still hold if I include non-receivership exits in the sample.

[6]Some smaller non-commercial banks that were dropped from the final sample failed before the fourth quarter of 2007. The general patterns observed in Figure I, however, do not change if I include all banks, commercial and otherwise.

Funding conditions had drastically improved by the time the mass of commercial bank failures started occurring. Figure II shows the time-series variation in the TED spread, a proxy for aggregate funding conditions in the banking sector.[7] That failure rates do not align intertemporaly with the aggregate funding pressures of 2007-2008, suggests that aggregate funding reversals – symptomatic of the broader deterioration of funding conditions that precipitated the crisis (Gorton and Metrick (2012)) – are not likely to have been the primary cause of these failures.

Differences in funding structures and the nature of policy interventions suggest that commercial banks may have not been as exposed to funding risk as brokers-dealers were during the crisis.[8] Commercial banks rely primarily on stable core deposits for funding and to further enhance the resilience of bank deposits, in October 2008 the FDIC deposit insurance limit was raised to $250,000. Furthermore, during the crisis they had access to lender of last resort facilities at the Federal Reserve's discount window and the Term Auction Facility (TAF), which was implemented in December 2007, provided funds to depository institutions against a wide range of collateral in a manner that helped the recipient institutions avoid the "stigma" effect often associated with discount window borrowing.

B. Evolution of Default Risk

It is instructive to see how default risk evolved across the commercial banking sector during the various phases of the crisis. Figure III shows, separately for the groups of failed and survivor banks, the time series variation in the median z-score, a measure of default risk. The z-score is defined in Equation 1, where $\tilde{ROA}$ is asset returns, with associated mean and standard deviation μ_{ROA} and σ_{ROA}, and CAR is total equity capital divided by total assets.[9] A state of insolvency occurs when $\tilde{ROA} + CAR < 0$. If profits (and hence $\tilde{ROA}$) are normally distributed then the z-score is inversely

[7] Tracking the LIBOR-OIS spread paints a very similar picture of the evolution of aggregate funding pressures.

[8] For example, the 2007 annual report of Lehman Brothers shows that repurchase agreements accounted for 26% of its balance sheet. The corresponding exposure for Citibank N.A. was 0.88%.

[9] For each quarter, the mean and standard deviation of asset returns are taken over the 16 quarters up to and including that quarter. For each year, I plot the median z-score for all quarters for all banks in each group. I aggregate over the four quarters to avoid over-interpreting variation in the z-score resulting from seasonal variation in ROA. I plot the median because the z-score is highly skewed. The observed time trends remain unchanged if I plot the natural logarithm of the z-score instead.

related to the probability of insolvency (Roy (1952)).

$$zscore = \frac{\mu_{ROA} + CAR}{\sigma_{ROA}} \tag{1}$$

Variation in the z-score of survivor banks tracks aggregate levels of bank distress, free of idiosyncratic shocks that may have affected failed banks only. The z-score of survivor banks grows until 2007, but then enters a period of decline, with a significant drop in 2009 and signs of recovery emerging in 2012. This pattern suggests that default risk in the banking sector was not solely driven by factors idiosyncratic to failed institutions, but was at least partly due to aggregate shocks that also affected institutions that survived the crisis. Importantly, this aggregate factor enters in full force after 2008.

Idiosyncratic risk is also present during the run-up to the crisis. Failed banks enter the crisis with a lower median z-score than survivor banks. In unreported analysis, I find that this pre-crisis difference is primarily driven by the volatility of asset returns rather than by differences in profitability and equity buffers. Failed banks' distance to default shortens significantly in 2008, a trend that continues at an accelerating pace as the crisis progresses.

C. Evolution of Real Estate Risk

The collapse of real estate prices generated a persistent shock that adversely impacted bank balance sheets even after aggregate funding pressures in the banking sector had abated. Figure IV shows the quarterly evolution of two real estate indices. The dashed line represents the S&P/Case-Shiller U.S. National Home Price Index that measures shifts in the total value of all existing single-family housing stock in the U.S. The solid line represents the National Association of Real Estate Investment Trusts FTSE NAREIT All Equity REITs Index. The index spans the commercial real estate space across the U.S. and contains all tax-qualified real estate investment trusts (REITs) with more than 50 percent of total assets in qualifying real estate assets other than mortgages secured by real property that also meet minimum size and liquidity criteria.

Real estate prices dipped during the financial crisis and recovered more slowly than funding markets did. Sights of a recovery in residential real estate emerged late in 2012, and growth resumed by 2013. CRE prices recovered faster but went through a significantly more volatile cycle.

Though suggestive, aggregate-level fluctuations do not convincingly identify the main drivers of bank failures. In the remainder of the paper, I rely on the use of bank-level data to empirically identify these mechanisms.

III. Empirical Methodology

Bank failure is essentially an "initial conditions" problem. A bank's pre-crisis business model determines its exposure to various risk factors, which in turn determines the probability that the bank transitions to a state of failure once the risk materializes during a crisis.

A commercial bank's business model can broadly be described by three components: (a) assets, (b) liabilities, and (c) off-balance sheet commitments. The combined performance of these three components determines the bank's profitability, which in turn determines its overall financial health via its impact on bank capital.

A bank becomes insolvent when its capital buffers are depleted. Bank capital reflects the net book worth of the bank, and it can be modeled as obeying the law of motion shown in Equation 2. For each bank i in time period t, capital in the next period is equal to the stock of capital the bank enters the current period with, plus net adjustments resulting from the performance of each asset, liability, and off-balance sheet exposure, indexed a, l, f, respectively, with stock levels denoted by $Asset_{ait}$, $Liability_{lit}$, and Off_{fit}, and corresponding nominal net returns R^{asset}_{ait}, $R^{liability}_{lit}$, and R^{off}_{fit}. The stock of capital may also be affected by other observable factors and unobservable idiosyncratic shocks, denoted by $Other_{xit}$ and ϵ_{it} respectively, and by aggregate shocks denoted by κ_t.

$$\begin{aligned} Capital_{it+1} = Capital_{it} &+ \sum_a (Asset_{ait} \cdot R^{asset}_{ait}) + \sum_l (Liability_{lit} \cdot R^{liability}_{lit}) \\ &+ \sum_f (Off_{fit} \cdot R^{off}_{fit}) + \sum_x Other_{xit} + \kappa_t + \epsilon_{it} \end{aligned} \tag{2}$$

Using contemporaneous financial variables to fit a model of bank failure during the crisis – a survival duration model, for example – would introduce simultaneity bias in the estimates.[10] Banks actively manage their business models in response to changing economic and financial conditions and such adjustments are also informed by the banks' internal assessment of their own default risk.

To address this concern, the approach typically employed in the literature involves using cross-sectional variation in banks' pre-crisis business models to explain cross-sectional differences in bank performance during the crisis (see, for example, Laeven and Levine (2009), Fahlenbrach and Stulz (2011), Beltratti and Stulz (2012)). I employ a similar approach in this paper.

I choose 2005 as the base pre-crisis year and for each bank I average the values of control and explanatory variables over the four quarters of 2005. I estimate the probit model shown in Equation 3, where $Fail_i$ is a binary indicator variable which takes the value of 1 if bank i was placed under FDIC receivership during 2006-2013,[11] $I(.)$ is the indicator function, and W_i is defined in Equation 4. Note that Equation 4 is a simple two-period version of Equation 2.

$$Fail_i = I(W_i < 0) \tag{3}$$

$$\begin{aligned} W_i = \beta^C \cdot Capital_i + \sum_a \beta_a^A \cdot Asset_{ai} + \sum_l \beta_l^L \cdot Liability_{li} \\ + \sum_f \beta_f^F \cdot Off_{fi} + \sum_x \beta_x^X \cdot Other_{xi} + \kappa + \epsilon_i \end{aligned} \tag{4}$$

The empirical estimation rests on the assumption that cross-sectional differences in the banks' pre-crisis business models are not driven by adjustments made in anticipation of the severe stresses that the sector would experience during the crisis. This assumption is grounded on the following empirical evidence: (1) 2005 was followed by one more year of rapid credit expansion, (2) the first aggregate strains in the real estate and funding markets were experienced in 2006 and 2007 respectively, and (3) in my sample there were no commercial bank failures until the last quarter of 2007. Furthermore, Cheng, Raina and Xiong (2014) find little evidence that in 2004-2006 midlevel

[10] In a panel setting, this source of bias would be exacerbated by the inclusion of bank fixed effects that would remove cross-sectional variation and rely entirely on potentially endogenous within-bank variation for identification.

[11] I choose 2013 as the end period because residential real estate markets resumed growth roughly during that year.

managers in securitized finance were aware of the impending crash of the U.S. housing bubble. The paper's main findings are robust to using either 2004 or 2006 as the base year.

I split banks into two size buckets using a $1 billion threshold applied to the average total assets of each bank for 2004. Bank size is the dimension most likely to sort out major differences in important unobservables across banks,[12] and this split allows me to examine whether the paper's main findings are consistent across size categories.

IV. Baseline Business Model

The baseline specification includes a key set of variables that describe the bank's pre-crisis business model, including its exposure to funding risk. This model does not explicitly account for the bank's exposure to real estate risk. Table I provides definitions.

The model is motivated by the CAMEL indicators employed by bank supervisors to assess the financial health of banks. The acronym stands for (C)apital adequacy, (A)sset quality, (M)anagement capability, (E)arnings, and (L)iquidity.

I first decompose the bank's funding structure into broad categories normally considered in the literature. I use the bank's equity capital ratio as a measure of capital adequacy (Berger and Bouwman (2013))[13] and the ratio of core-deposits to assets as a measure of funding stability (Cornett et al. (2011), Berger and Bouwman (2013)). The coefficients for these variables should be read in relation to the omitted category of non-core (wholesale) funding.

To account for the liquidity of a bank's assets, I decompose its asset structure into three categories: money market instruments, marketable securities, and other illiquid assets. Estimated effects for these variables should be interpreted in relation to the omitted asset category of cash (includes reserves), which is the most liquid and least risky asset on the balance sheet.

Motivated by the literature on drawdown risk, I also include the ratio of unused lines of credit to total assets.[14] Studies show that banks experienced a rapid increase in drawdowns during the

[12]See Allen and Saunders (1986) for differences in the costs faced in the federal funds market, Kashyap and Stein (2000) for differences in the strength of the bank lending channel of transmission of monetary policy.

[13]The results remain unchanged if I use the Tier 1 leverage ratio, or the Tier 1 risk-based capital ratio.

[14]I exclude commitments associated with credit cards to avoid skewing the distribution of this variable towards the

crisis (Ivashina and Scharfstein (2010), Campello et al. (2011), Acharya and Mora (2015)). Such drawdowns may have significantly increased a bank's asset risk. Dwyer, Zhang and Zhao (2011) show that riskier borrowers tend to utilize a larger portion of their credit lines, and that defaulted firms draw down more of their lines than non-defaulted ones do, doing so more heavily as they approach default.

The ratio of NPLs to total loans measures asset quality.[15] I proxy for managerial quality with the bank efficiency ratio that measures the bank's ability to turn non-financial resources into income.[16] To control for earnings, I include the return on average assets. More profitable banks should be better placed to absorb losses, by rebuilding their equity buffers from retained earnings. However, to the extent that high asset returns during the upturn of the cycle may be reflecting high cash flow risk, they could be associated with a higher probability of failure during the downturn.

Last, I include a dummy variable indicating whether the bank is member of a bank holding company (BHC) and the natural logarithm of total assets. BHC membership may help a bank absorb shocks through the activation of internal capital markets (Campello (2002)). Asset size can proxy for a number of unobservables, such as opacity and "too big to fail" effects, but the direction of its net effect is not clear a priori.

A. Pre-crisis Trends and Cross-Sectional Differences

Table II displays difference-in-means tests for the 2001 and 2005 levels of variables describing the banks' baseline business models. All variables are winsorized at the 1% and 99% levels.

During the run-up to the crisis banks' funding fragility increased marginally. Reliance on core-deposit funding declined by 1.5 and 0.9 percentage points, respectively for small and large banks. Equity capital declined by 0.4 percentage points across small banks and increased by 0.6 percentage points for large banks. These figures imply an increase of reliance on wholesale sources of funds by 1.9 percentage points for small banks, and by a mere 0.3 percentage points for large banks.

few large credit card issuers in the sample.

[15]I define NPLs as loans past due 90 days or more and still accruing plus loans not accruing, to mitigate the effect of managerial discretion in reporting losses.

[16]The ratio decreases in the presence of unproductive overhead, but could also decrease because of higher expenditures associated with relationship-based banking activities.

Large banks are significantly less reliant on core deposits as a source of funding than small banks.

Investment-related shifts are more marked. Banks drew down their liquid asset buffers – cash, money market instruments, and, in the case of smaller banks, securities – while increasing their investments in illiquid assets. Exposure to illiquid assets increased by 3.1 and 1.4 percentage points, respectively for small and large banks.

Off-balance sheet exposure to credit commitments also increased during this period, by 2.5 and 3.2 percentage points, respectively for small and large banks.

Failed and survivor banks entered the crisis with business models that differed in a number of parameters. Table III displays difference-in-means tests for the means of the pre-crisis (2005) distributions of control variables for failed and survivor banks.

Consistently across size categories, failed banks are less likely to be members of a BHC, rely less on core-deposit funding, and hold less cash. Failed banks also have thinner capital buffers, invest more in money market instruments, hold smaller securities portfolios and more illiquid assets; these differences, however, are statistically significant only in the subsample of small banks.

Interestingly, on metrics of performance such as the return on assets, efficiency, and NPL rates, survivor banks do not outperform failed banks prior to the crisis.

B. Probit Estimates

To identify the independent effect of each variable on the probability of failure, I estimate the binary probit model described earlier in Equation 3. The results are shown in columns (1) and (3) of Table IV, for small and large banks respectively. The reported coefficients are average marginal effects (AMEs) and are interpreted as the percentage point increase in the average probability of failure for a 1 percentage point increase in the value of the corresponding covariate.

Pre-crisis profitability and non-preforming loan rates are not strongly related to bank default during the crisis. High pre-crisis profitability may have been the result of risk underpricing. And the very low pre-crisis NPL rates are not likely to be informative about the order of magnitude increase in NPL rates that banks experienced during the crisis.

The main result is that high pre-crisis reliance on stable sources of funding - core deposits and equity capital - is associated with a lower probability of failure. The following sections will show that failed banks' *main source* of distress during the crisis was underpriced cash flow risk stemming from their pre-crisis investment choices in real estate. Funding risk mattered less and served primarily as a vehicle for pricing bank-specific asset risk.

V. The Real Estate Story

To examine the extent to which a bank's pre-crisis exposure to the real estate sector impacted its probability of failure during the crisis, I introduce variables that capture the composition into real estate products of a bank's (1) illiquid assets, (2) marketable securities, and (3) off-balance sheet credit line portfolios. All variables are normalized by total assets. I posit that pre-crisis choices that increased the exposure of each of these three portfolios to real estate products increased the probability of bank failure during the crisis.

A. Introducing Real Estate Risk to the Baseline Model

I opt for a formulation that allows me to interpret the coefficients of the real estate variables as within-portfolio substitution effects. These effects reflect portfolio allocation decisions by banks more closely than effects corresponding to models where the substitution is between a real estate product and the omitted category of cash.

To obtain substitution effects, in introducing the real estate variables in each of the illiquid assets, marketable securities, and credit line portfolios, I retain the base variables that describe the bank's total exposure to each portfolio. I can therefore read the coefficients on real estate variables as the marginal effect on the probability of failure of substituting a unit of a real estate product for a representative bundle of residual non-real estate products in the relevant portfolio. For example, if we let the estimated coefficient on traditional home mortgage loans be denoted by β, then increasing the pre-crisis exposure to traditional home mortgages by the equivalent of 1% of total assets, while at the same time decreasing the exposure to non-real estate illiquid assets by the same amount, would increase the probability of failure during the crisis by β%.

In the illiquid assets portfolio I include three types of real estate loans: (1) traditional home mortgages, (2) home equity loans, and (3) real estate loans to non-household borrowers. The first category captures traditional mortgage loans to households. The second category involves household real estate loans collateralized by the equity that the borrower already holds on their property.

The third category is a broad category that includes all other real estate loans, such as investment-type loans secured by multifamily properties, loans for commercial real estate properties, construction, and land development projects, etc. These loans are distinctly different from traditional home mortgages. They are harder to diversify and their cash flow risk is assessed along a more complex set of dimensions, such as rental income potential and experience in managing multifamily properties. I therefore lump these loans together in one category that may yield a narrative that is distinct from that of home-mortgage risk.

To control for real estate risk in the bank's portfolio of marketable securities, I include the holdings of (1) agency MBS and (2) private-label MBS. Agency MBS are issued or guaranteed by government-sponsored enterprises (GSEs), such as Ginnie Mae, Fannie Mae and Freddie Mac, and must conform to a set of standards that are put in place to cup the risk-profile of the underlying home mortgages. Furthermore, GSEs enjoy an implicit government guarantee that is typically priced into agency MBS. Private-label MBS on the other hand, are issued by private parties, are subject to less stringent underwriting requirements, and are the primary securitization vehicle for subprime mortgages and CRE loans.[17]

The last potential source of real estate risk I consider resides within the off-balance sheet credit line portfolio. During the crisis, the drawdown risks identified in Dwyer, Zhang and Zhao (2011) may have been particularly pronounced for lines of credit extended to real-estate borrowers. To test this hypothesis, I include two variables capturing exposure (1) to household real estate borrowers through home equity lines of credit (HELOCs), and (2) to non-household real estate borrowers.

Even though this formulation separately accounts for home equity loans and HELOCs, their coefficients cannot be meaningfully interpreted econometrically. The cross-sectional correlation

[17] Prior to the crisis, securitizations of loans with multifamily property collateral were also predominantly private-label, but agency activity in this market has increased post crisis.

between these two exposures is very high, raising concerns about multicollinearity. From an economic standpoint, home equity credit serves as a substitute for a wide array of credit products – such as small business and student loans – and its performance can be subject to a set of influences that extend beyond exogenous stresses in real estate markets.

In unreported tests, I find that removing exposure to HELOCs from the list of explanatory variables, to mitigate the impact of collinearity on the estimates, has no significant effect on the coefficients of the main explanatory variables. And the net effect of home equity credit is economically marginal. Nonetheless, for the remainder of the analysis I retain these two control variables to ensure that the omitted category of each portfolio – in relation to which the main effects will be interpreted – is free from real estate risk.

B. Pre-crisis Trends and Cross-Sectional Differences

I first ask whether amid heightened levels of activity in real estate markets banks grew *their own exposure* to real estate. Table V shows difference-in-means tests for the banks' exposure to each real estate product in 2001 and 2005. For completeness, I also report results for the residual non-real estate part of each portfolio.

Commercial banks moved towards a more real estate-focused model primarily by using their on- and off- balance sheet capacity to fund non-household real estate credit. The increase was partly accommodated by shedding exposure to mortgage credit – traditional home mortgages and for small banks agency MBS – and to non-real estate loans. Increases in home equity loans and private-label MBS were comparatively smaller.

By 2005, failed and survivor banks' balance sheets differed substantially in their exposure to non-household real estate risk (Table VI). The average difference in exposure to non-household real estate loans between failed and survivor banks was 19.6% and 16.7% of total assets, respectively for small and large banks. For credit lines extended to non-household real estate borrowers the differences were smaller but economically significant at 6.4% and 4.8% for small and large banks, respectively. Remarkably, by 2005 the banks that ended up failing during the crisis had roughly half of their assets invested in non-household real estate credit.

The data do not reveal increased exposure to home mortgage credit by failed banks. Regardless of bank size, failed banks had lower exposure to traditional home mortgages and agency MBS than survivor banks did, although for large banks the differences are not statistically significant.

C. Probit Estimates

The difference-in-means tests suggest that exposure to non-household real estate credit may have precipitated bank failures during the Great Recession. To test this hypothesis more rigorously, I re-estimate the baseline probit model presented in Section IV, now augmented to include the real estate portfolio composition variables discussed above. Columns (2) and (4) of Table IV report the estimated coefficients for small and large banks, respectively. For the reasons outlined earlier, coefficients for home equity loans and lines of credit are reported with no further discussion.

The real estate risk that mattered most for bank failures was primarily non-household. Credit to non-household real estate borrowers (both loans and credit lines) increased the probability of failure over and above the base effect of non-real estate exposures in the corresponding portfolios. Neither exposure to traditional home mortgages nor to agency MBS increased the probability of failure, and the effect of holdings of private-label MBS was confined to larger banks.[18]. The pseudo-R2 values, reported at the bottom row of Table IV, suggest that accounting for real estate risk yields a substantial improvement in fit from the baseline model (columns (1) and (3)), particularly for large banks.

Stable sources of funding, such as core deposits and equity capital, maintain their positive effect on bank resilience. This raises the question of which aspect of banks' pre-crisis business model was more influential in determining the probability of failure during the crisis.

VI. Pecking Order of Risk Drivers

I perform a counterfactual exercise that asks how the aggregate probability of failure would have decreased had banks entered the crisis with lower exposure to each source of risk. The exercise

[18]This is likely a result of the limited exposure that small banks had to this asset category (Table VI)

uses (1) the pre-crisis distributional properties of each variable, to discipline the magnitude of the reduction in exposure, and (2) the estimated workhorse model to project the resulting effect of each exposure reduction on the aggregate probability of failure.

More concretely, for each variable that raised a bank's probability of failure (eg, exposure to non-household real estate credit) I decrease each bank's 2005 level down to the bottom quartile of the cross-sectional distribution for that year and bank size category. For variables that decreased the probability of failure (eg, core-deposit funding), I increase each bank's 2005 level up to the top quartile of the corresponding distribution. I do not change the total size of each portfolio or the total size of the liability structure of the bank, in order to estimate substitution effects.

I then use the estimated model parameters shown in columns (2) and (4) of Table IV to estimate the resulting change in the probability of failure predicted by the model, averaged across all banks in the sample. I perform this exercise separately for the subsamples of small and large banks. The results are shown in Table VII.

For both small and large banks, reductions in exposure to loans and credit lines to non-household real estate borrowers would have had the most significant impact on their probability of survival. Respectively for these two products, the average probability of failure would have declined by 5 and 3 percentage points for small banks, and by 7 and 4 percentage points for large banks. A reduction in exposure to private-label MBS would have affected large banks only, resulting in a decrease in the average probability of failure of 2 percentage points. Given the actual loss rates in the sample – 7 and 10 percentage points for small and large banks, respectively – the impact of real estate risk is economically significant. The results also show that even if the estimated effects of agency MBS and traditional home mortgages were statistically significant, their economic impact would have been minimal.

Although nontrivial, the effect of reliance on stable sources of funds is of secondary importance compared to the main effect of non-household real estate risk. Substituting core-deposit or equity capital for wholesale funding would have resulted in a decrease in the aggregate probability of failure equal to 2 and 1 percentage points respectively for small banks and 3 and 2 percentage points for large banks.

VII. Robustness

The results in the previous section provide empirical support for the central thesis of this paper: exposure to non-household real estate credit was the primary driver of U.S. commercial bank failures during the Great Recession. In this section, I subject this finding to a series of tests that demonstrate its robustness against a number of alternative hypotheses.

A. Local Economic Conditions

Local economic conditions impacted bank failures during the Great Recession (Aubuchon and Wheelock (2010)). A concern is that the results presented thus far may reflect a correlation between a bank's choice of product mix and its exposure to local economic shocks.

The paper's results are not driven by small, geographically non-diversified banks. The sample excludes small banks with asset size less than $50 million, which are the most likely to be geographically non-diversified, and the main results hold for the subsample of large banks with asset size greater than $1 billion, which are the most likely to be widely geographically diversified. Nonetheless, it may still be possible that cross-sectional differences in geographical diversification patterns, and therefore in exposure to local economic shocks, correlate with differences in loan product choices.

I address these concerns by employing a host of proxies designed to capture bank-specific levels of exposure to local economic shocks. Though imperfect, these proxies should perform well in absorbing the first-order effects of local economic conditions on the financial health of banks. To the extent that bank failures may also impact local economic conditions, the resulting estimates would be lower bounds to the true effect of real estate risk on bank failure.

I construct three county-level measures of local economic shocks that capture, respectively, the rate of decline in per capita income (source: Bureau of Economic analysis), the percentage point increase in unemployment rates (source: Bureau of Labor Statistics), and the rate of decline in house prices (source: Federal Housing Finance Agency). All proxies are measured at the county level and the rates are annualized over the 2006-2009 period. Ending the window in 2009 strikes a balance between relying on variation in economic conditions that is plausibly exogenous to the (lagged) effects of bank failure, and ensuring that the time window extends enough into the crisis to absorb some of the sharpest cross-sectional shocks.[19]

I then use data from FDIC's Summary of Deposits to create for each bank a weighted average of its exposure to each economic shock (three variables), using as weights the proportion of the bank's total deposits that are held in each county prior to the crisis. The construction is shown below, where θ_i is a proxy for bank i's exposure to economic shock ϵ, d_{ij} is the portion of total deposits of bank i that are held in county j and ϵ_j is the size of the economic shock in county j.

$$\theta_i = \sum_j d_{ij}\epsilon_j \tag{5}$$

I rely on the 2005 distribution of deposits to get a more complete picture of the counties in which the bank's loans originated. The geography of deposits ignores branch-driven financial integration (Gilje, Loutskina and Strahan (2016)), larger lenders' ability to extend credit in counties in which they do not have a large physical footprint, and the purchase of loans from other originators. Nonetheless, deposit-weighted shocks should be good overall proxies for a bank's exposure to local economic conditions.

The results are shown in columns (2)-(5) and (8)-(11) of Table VIII, for small and large banks respectively. Columns (1) and (7) show the coefficient on the workhorse real estate model for reference. In columns (2) and (8) I add to the workhorse model the change in local income, in columns (3) and (9) the change in unemployment rates, in columns (4) and (10) the change in HPI, and in columns (5) and (11) all three proxies at the same time. In all cases, the results are similar to the ones obtained from the workhorse model.

I employ an additional approach where I saturate the main specification with state fixed effects that for a given bank are set to 1 if the bank has one or more branches located in that state. The results are shown in columns (6) and (12), and are similar to those obtained for the main specification. One noticeable difference is that in the subsample of larger banks the coefficients experience large swings in magnitude, possibly a result of sample attrition that significantly reduces

[19]In unreported regressions, I find that the results hold if use the values of county-level controls annualised over the entire 2006-2013 period.

the sample size in relation to the number of fixed effects to be estimated, and makes the estimated coefficients unstable.[20]

B. Government Interventions and Non-Receivership Exits

Policy interventions during the crisis may have distorted the true picture of bank failures by providing lifelines to fundamentally insolvent banks that would have failed absent government support. There is evidence, for example, of both regulatory inconsistency in bank supervision (Agarwal et al. (2014)) and of factors unrelated to bank fundamentals influencing a state's or a regulator's decision to intervene during a banking crisis (Acharya and Yorulmazer (2007), Brown and Din (2009), Duchin and Sosyura (2012)).

The definition of bank failure I employ, which identifies as failed institutions only banks that were placed under FDIC receivership, may therefore introduce biases by construction. In the context of my empirical strategy, bias in the coefficients of interest would arise if both of the following two conditions hold: (1) a policy intervention correlates with a bank's exposure to real estate credit, and (2) the correlation is due to factors unrelated to fundamental insolvency. Political connections, for example, would not satisfy the first condition.

An important intervention during the 2007-08 crisis in the U.S. was the Capital Purchase Program (CPP) that was announced as part of the Troubled Asset Relief Program (TARP) and was "launched to stabilize the financial system by providing capital to viable financial institutions of all sizes throughout the nation".[21] The Treasury's stated policy was to make program participation contingent on the bank's classification ranking that employed formal supervisory ratings and favored institutions with strong fundamentals.

Empirical evidence suggests that, on average, CPP-participation did not indicate fundamental insolvency (Ng, Vasvari and Wittenberg-Moerman (forthcoming), Bayazitova and Shivdasani (2012)). Importantly, Bayazitova and Shivdasani (2012) do not find that exposure to real estate was related

[20]The estimator drops a number of banks whose survival can be predicted perfectly by the fixed effects.

[21]In February 2009, the Treasury also announced the Capital Assistance Program (CAP) that, based on the results of a stress test, would provide capital assistance to the bank if the required capital could not be raised privately. CAP closed in November 2009, without making any investments.

to the likelihood of approval of a CPP application.

I nonetheless test whether the main results hold if I drop from my sample (a) all banks that received assistance from the CPP directly, and (b) banks whose parent BHC received assistance from the CPP. I obtain CPP participation data from the U.S. Treasury's CPP transaction report.[22] The results are shown in columns (2) and (5) of Table IX and are qualitatively similar to the main results shown in columns (1) and (4). Some differences in the magnitude of coefficients in the subsample of large banks are owing to the significant reduction in sample size resulting from the exclusion of CPP-participants.

To address any residual concerns about the influence of regulatory discretion on bank failure outcomes, I estimate the workhorse model by relying on a definition of bank failure that employs a capital-based rule that has less scope for contamination by regulatory discretion. More specifically, for each bank I find the minimum Tier 1 leverage ratio reported during the period 2006–2013. I then define as failed any bank with a minimum Tier 1 leverage ratio below a predefined threshold. I use a range of thresholds, ranging from 1% to 4% in 1 percentage point increments. This measure may under-represent failures, in cases where the scope for underreporting losses is higher – eg, for banks with significant holdings of non-performing assets in opaque markets with no readily available price information.

The coefficients are shown in Table AI in the Appendix, and they confirm that the main results are not driven by potential biases arising from regulatory discretion. The results for private-label MBS now vanish, possibly a result of the reporting biases discussed above.

A related concern is that banks that exited the sample without having been reported as failed by FDIC, perhaps due to a merger, are instances of bank failure that are not included in my sample.[23] Though possible for some institutions, it is not clear that all merged entities were insolvent. For example, the strategy of acquiring an insolvent institution prior to receivership does

[22]The dataset contains 737 transactions that took place between October 28, 2008 and December 29, 2009, corresponding to 705 unique institutions. I drop from the list of TARP recipients the eight banks which were forced to participate in the CPP in October 2008 and match the remaining CPP participants with call report data. Some TARP participants are Thrift Holding Companies which file different call reports, and others are dropped from the sample as a result of the data selection process described in Section 3. In the resulting subsamples of small and large banks, I have 370 and 118 TARP participants respectively.

[23]For non-failed banks, sample construction requires the bank to submit a call report in 2013.

not unconditionally dominate a post-receivership strategy of acquiring deposits and selected assets under loss-sharing agreements with the FDIC.

To address this concern I reestimate the main effects on a sample that also includes banks that exited without having been reported as failed by FDIC. I first define failure as FDIC receivership, which treats non-receivership exits as non-failures. I then rely on the series of capital-based rules described earlier to create progressively stricter failure rules that do not depend on FDIC receivership. The results are shown in Table AII and are very similar to the ones shown in the main sample that excludes non-receivership exits.

C. Income Mix

I also test whether the effects of the product mix on bank failure are merely driven by correlations with the income mix of the banks, which DeYoung and Torna (2013) show to also have affected bank distress.[24] I include the ratios of stakeholder income, fee-for-service income, traditional fee income, and net interest income to total income as additional control variables, all variables defined as in DeYoung and Torna (2013).

The results are shown in columns (3) and (6) of Table IX. The main effects are virtually identical to those in the reference model, with only the coefficient of private-label MBS in the subsample of large banks dropping its statistical significance to the 17% level.

D. Other Robustness Tests

The results are not driven by correlations between on-balance sheet exposure to non-household real estate credit and off-balance sheet exposure to asset-backed commercial paper conduits (Acharya, Schnabl and Suarez (2013)). Accounting for large banks' liquidity and credit enhancements provided to asset-backed commercial paper (ABCP) conduits has no effect on the main coefficients (column (7) of Table IX). Neither are the coefficients affected by dropping the 10 largest banks to account for possible "too-big-too-fail" effects (column (8)).

[24] DeYoung and Torna (2013) identify the effect of income mix choices on bank distress for distressed banks close to failure. In this paper I examine the presence of an effect across all banks viewed at a certain horizon from failure.

The main effects are not a byproduct of possible non-linearities associated with the lack of common support among the control variables. Using propensity score matching, I create subsamples of survivor banks that match failed banks on all characteristics used in the main specification, except for the degree of exposure to real estate products in each portfolio (Table AIII). Estimates on the matched samples retain the direction and statistical significance of the main results, though the magnitude of the effects increases appreciably (Table AIV). The results are also robust to the choice of pre-crisis year (Table AV).

In further, unreported, tests I find that the estimates remain unchanged after controlling for the value of mortgage servicing assets that are part of a bank's intangible assets. Last, estimating the main model with a linear ordinary least squares (OLS) estimator, yields estimates that are strongly statistically significant and of similar order of magnitude as the AMEs obtained from the non-linear estimator.

VIII. The Operation of Risk Channels

This section examines the operation of risk channels during the crisis.

A. Drivers of Risk

Though identifying the drivers of banks' risk-taking behaviour in non-household real estate markets extends beyond the scope of this work I contain the search space by ruling out some plausible explanations.

I first examine whether non-household real estate risk was merely a manifestation of a bank's broader risk-taking culture. If it was, then failed banks' insolvency might have been driven by a general risk-taking channel, rather than by one specific to non-household real estate.

To test this hypothesis, I include a bank's pre-crisis distance to default – its z-score in log form – as a measure of its overall risk-taking level (Laeven and Levine (2009)). The results are shown in columns (2) and (6) in Table X. Banks with higher pre-crisis distance to default were less likely to fail during the crisis. However, this aggregate risk-channel does not explain away the effect of non-household real estate risk and contributes only marginally to fit.

I then test whether non-household real estate risk reflected a bank's overall risk-taking in *growth markets*. In this particular episode these would be credit markets for real estate borrowers, household or otherwise.

To test this hypothesis, I construct a bank-specific proxy for the average risk in all mortgage loans originated by the bank during the 2001-2005 period.[25] I obtain mortgage loan origination data from the *Home Mortgage Disclosure Act (HMDA)* and proxy for borrower risk with the loan-to-income (LTI) ratio, a standard measure of a borrower's debt servicing capacity.[26] I then estimate the benchmark real estate model including this new variable as a control (columns (3) and (7) of Table X). Although catering to riskier mortgage borrowers prior to the crisis increases the probability of failure during the crisis, the main effect of non-household real estate credit remains unchanged. Simultaneously controlling for both overall risk and mortgage-related risk yields similar results (columns 4 and 8).

The empirical analysis in the following subsections examines how the various risk drivers became operational during the crisis. The analysis considers both asset-side (investment) and liability-side (funding) risks, and examines the presence of both aggregate and idiosyncratic channels of risk propagation. An aggregate channel operates via variation in shocks across products that is unrelated to the identity of the bank investing in the products. For example, some products performed worse than others in the crisis regardless of whether a surviror or failed bank had invested in them; failed banks may have invested more in this product. An idiosyncratic channel may still be product-specific but operates via variation in shocks across banks. For example, for any given product failed banks may have invested in the wrong tail of the corresponding risk distribution.

[25]The results remain unchanged if I only use the loans that were originated by the lender but not sold to other intermediaries, or if I only use 2005 originations.

[26]Incomplete merging between the Call Reports and HMDA results in significant sample attrition, particularly for smaller banks.

B. Default Rates on Real Estate Loans

Cash flow risk on the asset side stems from banks' investment choices. I use the non-performing loan (NPL) rate as a measure of performance for the different loan portfolios, and plot quarterly averages for the period 2005-2013 for the three real estate loan categories. For reference, I also plot NPL rates for non-real estate loans.[27] The plots are shown in Figure V.

The trajectory of NPL rates for the surviving banks – panels (a) and (b) for small and large banks, respectively – reveals the aggregate component of the crisis. Across real estate loan categories, NPL rates peaked during the 2010-2011 period, and were significantly higher than those of non-real estate loans. NPL rates for home equity loans were possibly moderated by the fact that during the crisis a significant portion of home equity loans were still within their draw period.[28] Large banks experienced higher NPL rates than small banks.

This aggregate channel affected the solvency of failed banks, because they invested more heavily in the worst performing category: real estate loans to non-household borrowers. NPL rates for traditional home mortgages were also high, but on the margin this was not the main determinant of banks' solvency. As shown earlier, failed banks were less exposed to this product than survivor banks. It is also possible that banks may have adequately allocated capital ex-ante to absorb unexpected losses on traditional home mortgages.[29]

The graphs also point to the presence of a bank-specific loss channel. Panels (c) and (d) display average NPL rates for small and large failed banks, respectively. On average, the real estate loan portfolios of failed banks performed significantly worse than those of survivor banks; at their peak, the NPL rates of failed banks were roughly 3-5 times larger than those of survivor banks. In the subsample of large failed banks these trends become less clear as we move deeper into the crisis, because of sample attrition due to bank failures.

I test whether the real estate loan portfolios of failed banks consistently underperformed those

[27] The results remain unchanged if I exclude leases from the reference category of non-real estate loans.

[28] During the draw period, the borrower on a home equity loan is making only interest payments and the loan is not on a full amortization schedule, the sudden commencement of which could could result in a default.

[29] Unfortunately, the pre-crisis call reports do not contain the per-unit-of-exposure capital allocations that would have been needed to test this hypothesis.

of survivor banks during the crisis. To do so, I estimate the following OLS regression:

$$Performance_{ikt} = \gamma_{kT} \cdot Failed_i + \delta_{kT} \cdot Econ_i + u_{ikt} \tag{6}$$

$Performance_{ikt}$ is the NPL rate for bank i's portfolio of loan product k in year-quarter t. $Failed_i$ is a dummy variable indicating whether the bank failed during the crisis. $Econ_i$ is a vector of variables that capture the bank's exposure to local economic shocks to employment, income, and housing prices, derived from the 2005 county-level distribution of banks' branches and the aggregate 2006-2009 shifts in local economic conditions, to mitigate the impact of simultaneity bias (as discussed in Section VII). γ_{kT} allow for the sensitivity of banks to local economic conditions to vary across products and years. δ_{kT} estimate idiosyncratic differences in performance for product k in year T. I estimate the model separately for each loan product and each year, relying on four quarters of data and clustering standard errors at the bank level to account for serial correlation in the error terms over the reporting quarters.

The results are shown in Panels A and B of Table XI, respectively for small and large banks. Differences in loan performance are not consistently present in the years immediately prior to the crisis. After 2007, however, failed banks report significantly higher NPL rates on their real estate loans than survivor banks do, and the differences are consistent across time, bank size, and loan categories. The largest differences are for non-household real estate loans.

No similarly consistent patterns emerge for non-real estate loans. This further strengthens the hypothesis that differences in NPL rates between failed and survivor banks cannot be attributed to unobserved factors that would have influenced loan performance equally across loan categories, such as for example a "random draw" mechanism whereby failed banks just happened to draw loans from the wrong tail of the risk distribution.

C. Interest Returns on Real Estate Loans

I then examine whether banks' ex-ante pricing behavior was consistent with ex-post loan performance. I proxy for loan pricing with interest returns. For the period I examine, the call reports do not provide data on interest income that are disaggregated down to the three different real estate loan categories. I therefore plot returns for the banks' aggregate real estate and non-real estate portfolios (Figure VI).

Real estate risk was on average underpriced ex-ante. Real estate loans interest returns that are consistently lower than the corresponding returns on non-real estate loans. This is in contrast to their significantly higher NPL rates during the crisis. The spread is maintained during the crisis, likely a result of the significant increase in the NPL rates of real estate loans, which reduce the proportion of interest-generating loans in the portfolio.[30]

Idiosyncratic differences in NPL rates between failed and survivor banks' real estate portfolios were priced in the correct direction ex-ante but not fully. This is shown in Panels C and D of Table XI, where Equation 6 is estimated on interest returns. Because of the earlier-mentioned lack of disaggregated interest income data, it is not possible to ascertain whether the risk component that was priced was the aggregate one (higher portfolio exposure to non-household real estate) or the idiosyncratic one (lower loan quality in each category). Nonetheless, it is clear that the ex-ante pricing spread is significantly lower than the ex-post NPL spread shown earlier. Differences in interest returns naturally reverse during the crisis, because of the significant reduction in interest-generating loans in failed banks' loan portfolios.

D. Mark-to-market losses on MBS Securities

Book losses on the banks' security portfolios also differed across banks and security types. I use the difference between the fair and amortised cost value of securities, divided by their amortised cost value as a measure of portfolio performance. This metric gives a sense for potential capital gains/losses per unit of exposure, were a bank to liquidate its securities.

Regardless of bank size, private-label MBS significantly underperform the baseline group of non-MBS securities during the crisis (Figure VII). Agency MBS on the other hand, outperform the baseline non-MBS portfolio during the crisis. This is not a surprising result, given the agency and

[30] I compute returns over the aggregate stock of loans to maintain consistency in the denominator of NPL rates and interest returns.

(implicit) government guarantees associated with the underlying assets, and the series of Treasury and Federal Reserve interventions that aimed to support the market for agency MBS during the crisis.

Tests for level differences (Equation 6) point to the relative underperformance of securities held by failed banks (Panels E and F of Table XI). For the agency MBS and non-MBS portfolios, the differences are identified strongly. For private-label MBS on the other hand, differences are less robustly identified. This could be a result of the small number of banks with non-zero holdings of private-label MBS, but could also be driven by reporting biases.[31]

E. Pre-Crisis Growth and Asset Performance

Studies show that the rapid growth of the real estate sector prior to the crisis resulted in a relaxation of lending standards (see, for example, Mian and Sufi (2009)). In my sample, failed banks did indeed increase their exposure to both loans and commitments to non-household real estate borrowers at a more rapid pace than survivor banks did during the run-up to the crisis (Table AVI in the Appendix). This pattern does not extend to traditional home mortgages, agency MBS, and private-label MBS.[32]

Rapid growth into real estate, however, does not explain differences in on-balance sheet asset performance. I focus on a subsample of survivor banks that grew their exposure to real estate risk significantly during the run-up to the crisis and find that their assets outperform those of failed banks, with level differences similar to the ones presented earlier (Table AVII).[33]

[31] The reported fair value of securities could be affected by positive bias, generated by banks attempting to conceal the true extent of the decline in asset quality or responding to price pressures that they deemed unrelated to fundamentals. The scope for reporting bias should be larger for (a) private-label MBS, the pricing of which relies more heavily on private information, (b) banks more heavily exposed to private-label MBS (eg., large banks) and (c) failing banks which, in the presence of shrinking capital buffers, faced an increasingly higher marginal benefit of inflating the fair value of their securities holdings.

[32] One caveat is that because of data limitations I can only measure growth in exposures held on-balance sheet – or off-balance sheet in the case of credit lines – but cannot take account of originations that the banks distributed through the securitization channel.

[33] To obtain the subsample of "high growth" survivor banks, for each product category and bank size bucket, I retain only survivor banks whose increase in exposure from 2001 to 2005 was at least as large as the average increase in exposure of the corresponding group of failed banks.

F. Funding Risk

Had aggregate funding pressures been the main channel via which funding risk affected bank failures, the effect of funding composition should have been more pronounced in the early failures when aggregate funding pressures were at their highest (Figure II). On the other hand, had funding risk affected bank failures via the pricing of bank-specific asset risk, its effect should have been more pronounced in the later failures when aggregate NPL rates, and therefore asset risk, were at their peak (Figure V).

To test this hypothesis, I re-estimate the main model examining separately early and later failures. I first estimate the model by defining as failed banks those that were placed under FDIC receivership between January 1, 2006 and December 31, 2009 and excluding from the sample later failures. I then estimate the model by defining as failed banks those that were placed under FDIC receivership between January 1, 2010 and December 31, 2013 and excluding from the sample earlier failures.

The results are shown in Table XII. The effect of core-deposit funding is smaller for the early failures. This corroborates the aggregate time-series evidence presented earlier, which suggests that aggregate funding pressures did not drive bank failures.

I use micro-level data on banks' funding costs to perform a more granular decomposition of the funding channel. I define the cost of funds as the annualized quarterly interest expense attributed to a particular source of funds, divided by the quarterly stock of the corresponding source of funds on the bank's balance sheet.[34] One caveat is that as the crisis progressed banks endogenously adjusted their funding mix towards the cheaper sources of funds. Given these endogenous adjustments to banks' funding mix, inferring funding prices from funding costs may result in negative bias in the price of the more expensive source of liabilities, non-core funding.

[34] The FDIC limit for insured deposits was raised from \$100,000 to \$250,000 on October 3, 2008 and was kept at that level thereafter. Although call reports contain information about the stock of time deposits at both the \$100,000 and \$250,000 thresholds, the corresponding interest expense entries are only reported at the \$100,000 threshold. Therefore, after the third quarter of 2008 in computing the funding costs of insured time deposits (a component of core deposits) I necessarily only include insured deposits less than \$100,000. This results in insured time deposits between \$100,000 and \$250,000 being included in non-core liabilities, which likely introduces negative bias in the estimation of non-core liability costs.

Figure VIII shows the time-series variation in funding costs for the banks' two major sources of debt capital: core-deposits and non-core liabilities. Three observations stand out. First, as expected, core deposits enjoy a cost advantage over non-core sources of funds. Second, the overall intertemporal patterns for both sources of funds follow those of the TED-spread shown in Figure II, with funding costs surging in 2007-08 but decreasing sharply after 2008. In unreported tests I find that by the end of 2008 for both failed and survivor banks funding costs had declined to 2006 levels but the pace of decline was slower for failed banks. Third, after 2008 the spread in funding costs between failed and survivor banks does not widen as substantially as the spread in NPL rates shown in Figure V did.

Panels (a) and (b) of Table XIII, test for the presence of a statistically significant spread in funding costs between failed and survivor banks, after controlling for the impact of local economic conditions as in Equation 6. With the exception of non-core liabilities for large banks, a positive spread is present even prior to the crisis. During the funding phase of the crisis, the spread widens substantially, across both sources of funds and both size categories, and remains at elevated levels after 2008. Compared to its levels immediately prior to the crisis (2005-2006), the spread widens more substantially for non-core liabilities, suggesting more aggressive repricing of risk by providers of non-core funds.

That the spread remains elevated after 2008, at a time when aggregate funding pressures had abated, indicates that differences in funding costs between failed and survivor banks during this period are likely driven by idiosyncratic rather than by aggregate factors. Panels (c) and (d) show that after controlling for the bank's solvency and asset quality – as proxied by the ratio of total equity to assets and the ratio of non-performing loans to assets – the spread narrows and returns to pre-crisis levels by 2009.[35] This result is consistent with the disciplining role of bank liability holders (Flannery (1998), Acharya and Mora (2015), Egan, Hortasu and Matvos (2017), and with the limited impact of bouts of aggregate illiquidity on bank solvency in earlier crises (Calomiris and Mason (2003*b*)).

[35] A widening of the spread after 2010 for large banks is likely a result of sample attrition due to bank failures.

IX. Conclusion

This paper asks which aspects of commercial banks' business models made them the most vulnerable to the deteriorating financial and economic conditions experienced during the Great Recession. Drawing from existing work, I focus on fragile funding structures and exposure to the real estate sector as the primary sources of bank fragility during this episode.

I first show that during the run-up to the crisis both failed and survivor banks increased their exposure to non-household real estate credit, but not to traditional real estate products such as home mortgage loans and agency MBS. Banks that subsequently failed, entered the crisis significantly more exposed to non-household real estate products than survivor banks did. Funding structures, by contrast, changed marginally during the same period.

Consistent with these pre-crisis trends, regression estimates show that exposure to non-household real estate borrowers was the main driver of bank failures during the crisis. The impact of fragile funding structures was of second order importance, and that of traditional home mortgages and agency MBS was marginal.

Though the source of banks' risk-taking in non-household real estate credit cannot be inferred from this paper's findings, I limit the search space by showing that it is not a mere byproduct of banks' aggregate risk-taking behaviour or their risk-taking in household mortgage markets.

I then examine the operation of risk channels at the micro level. I find that failed banks invested more in product categories with a high aggregate risk component and their investment within each product category also carried higher idiosyncratic risk. Idiosyncratic differences in asset quality cannot be explained solely by the more rapid pace at which failed banks expanded into real estate during the pre-crisis period.

Ex-post differences in aggregate risk between real estate and non-real estate credit were not priced in the right direction by either survivor banks or failed banks. Failed banks, however, did price their real estate portfolios as higher risk than those of survivor banks.

Funding fragility's influence on failure rates did not enter through an aggregate funding pressure channel. Rather, providers of non-core funds repriced risk more aggressively during and after the funding crisis. Post-2008 funding cost spreads reflect differences in bank solvency risk rather than shifts in aggregate factors unrelated to fundamentals.

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Figure I: Timeline of Commercial Bank Failures. This chart displays the number of bank failures per quarter for the period 2005-2013. Failure is defined as the bank having been placed under FDIC receivership during the quarter, and I obtain receivership data from the FDIC's list of failed banks. Sample selection is discussed in Section II.

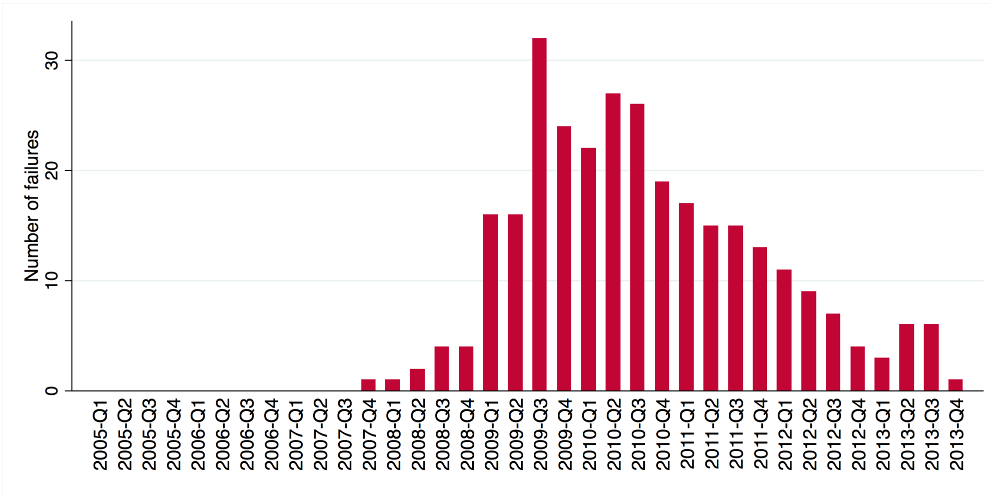

Figure II: The TED spread for the period 2005-2013. This figure shows daily and annual averages of the TED spread from 2005 to 2013. The TED spread measures funding strains in the banking sector and is defined as the difference between the 3-month LIBOR rate and the 3-month Treasury rate. Data on rates obtained from the Federal Reserve Economic Data (FRED), available online by the Federal Reserve Bank of St. Louis.

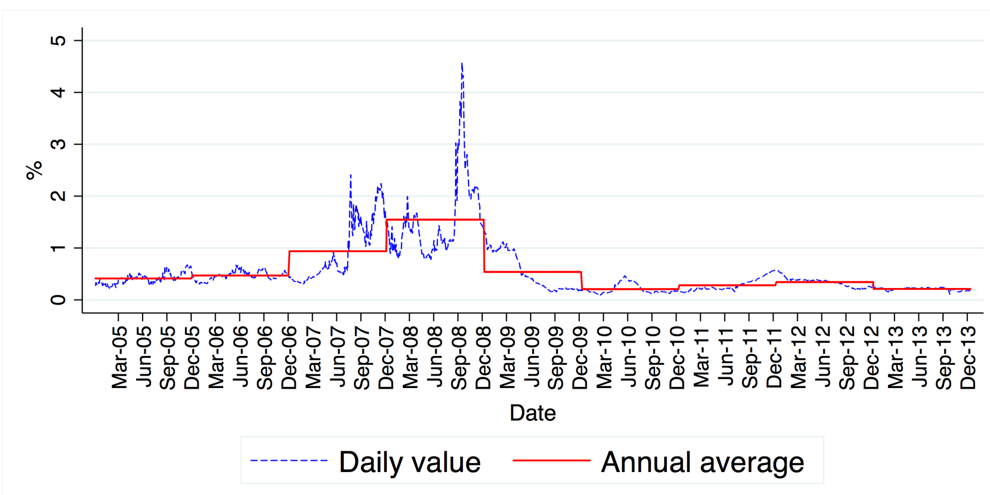

Figure III: Evolution of default risk. This chart displays the evolution of the median z-score in 2005-2013, shown separately for failed and survivor banks. The z-score is inversely related to the probability of default and is defined as the sum of equity capital plus the mean return on assets, divided by the standard deviation of the return of assets. Commercial bank data are from the Reports of Condition and Income (Call Reports) and bank failures are taken from the FDIC's list of failed banks. Sample selection is discussed in Section II.

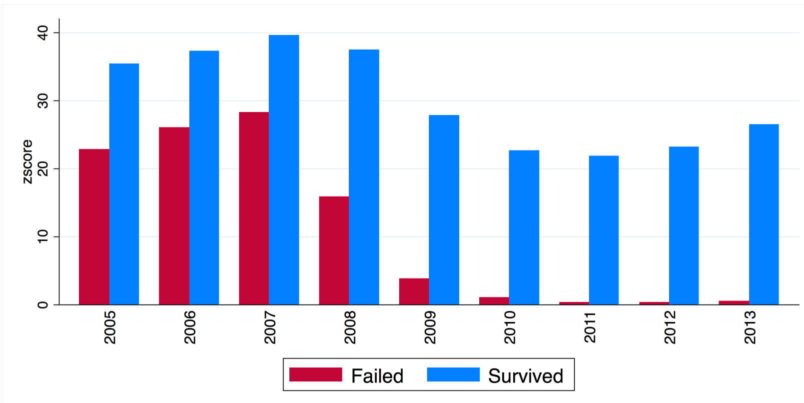

Figure IV: Evolution of housing prices. The dashed line displays monthly values for the S&P/Case-Shiller U.S. National Home Price Index (not seasonally adjusted). The index is a composite of single-family home price indexes for the nine U.S. Census divisions that measures shifts in the total value of all existing single-family housing stock. The solid line displays monthly values for the National Association of Real Estate Investment Trusts FTSE NAREIT Equity REITs Index. The index spans the commercial real estate space across the U.S. *Sources: S&P Dow Jones Indices LLC, National Association of Real Estate Investment Trusts (NAREIT)*

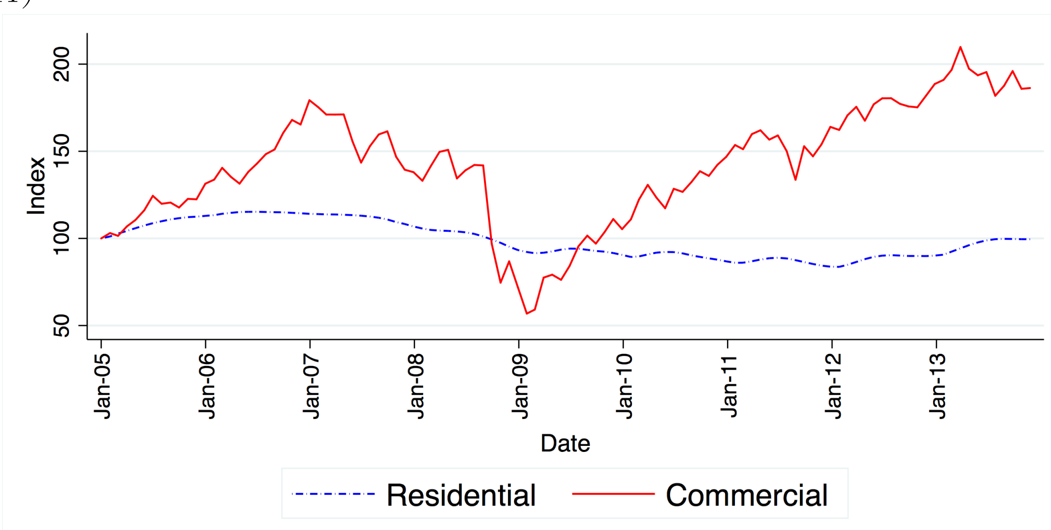

Figure V: Non-performing loan rates for real estate and non-real estate loans. This graph displays quarterly averages of NPL rates – defined as the ratio of NPLs to total loans – for three categories of real estate loans and for a reference portfolio of all other non-real estate loans for 2005-2013. Time labels correspond to beginning of year values. Panel (a) displays loan performance for survivor banks with mean asset size in 2004 less than $1 billion, panel (b) for survivor banks with mean asset size in 2004 greater than $1 billion, panel (c) for failed banks with mean asset size in 2004 less than $1 billion, and panel (d) for failed banks with mean asset size in 2004 greater than $1 billion. Loan performance data are from the Reports of Condition and Income (Call Reports) and bank failures are taken from the FDIC's list of failed banks. Sample selection is discussed in Section II.

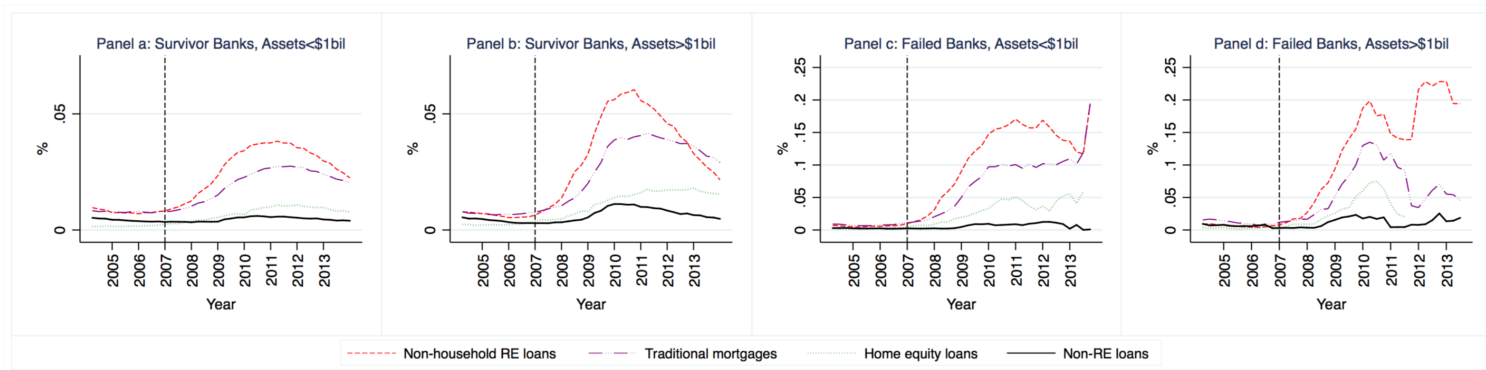

Figure VI: Interest returns on aggregate real estate and non-real estate loan portfolios. This graph displays quarterly averages of loan returns – defined as the ratio of interest income to the book value of the stock of loans in each loan category – for real estate loans and for a reference portfolio of all other non-real estate loans for 2005-2013. Time labels correspond to beginning of year values. Panel (a) displays loan performance for survivor banks with mean asset size in 2004 less than $1 billion, panel (b) for survivor banks with mean asset size in 2004 greater than $1 billion, panel (c) for failed banks with mean asset size in 2004 less than $1 billion, and panel (d) for failed banks with mean asset size in 2004 greater than $1 billion. Data on loan returns are from the Reports of Condition and Income (Call Reports) and bank failures are taken from the FDIC's list of failed banks. Sample selection is discussed in Section II.

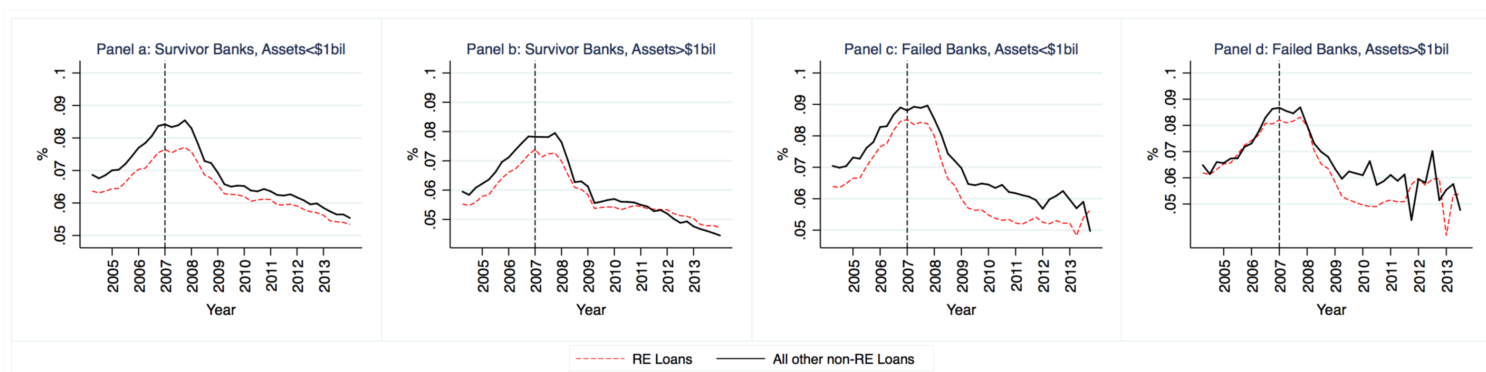

Figure VII: Normalized unrealized gains on MBS and non-MBS security portofolios. This graph displays quarterly averages of unrealized capital gains – defined as the difference between fair and amortized cost value divided by amortized cost value – for agency and private-label MBS, as well as for a reference portfolio of all other non-MBS securities for 2005-2013. Time labels correspond to beginning of year values. Panel (a) displays MBS performance for survivor banks with mean asset size in 2004 less than $1 billion, panel (b) for survivor banks with mean asset size in 2004 greater than $1 billion, panel (c) for failed banks with mean asset size in 2004 less than $1 billion, and panel (d) for failed banks with mean asset size in 2004 greater than $1 billion. MBS data are taken from the Reports of Condition and Income (Call Reports) and bank failures from the FDIC's list of failed banks. Sample selection is discussed in Section II.

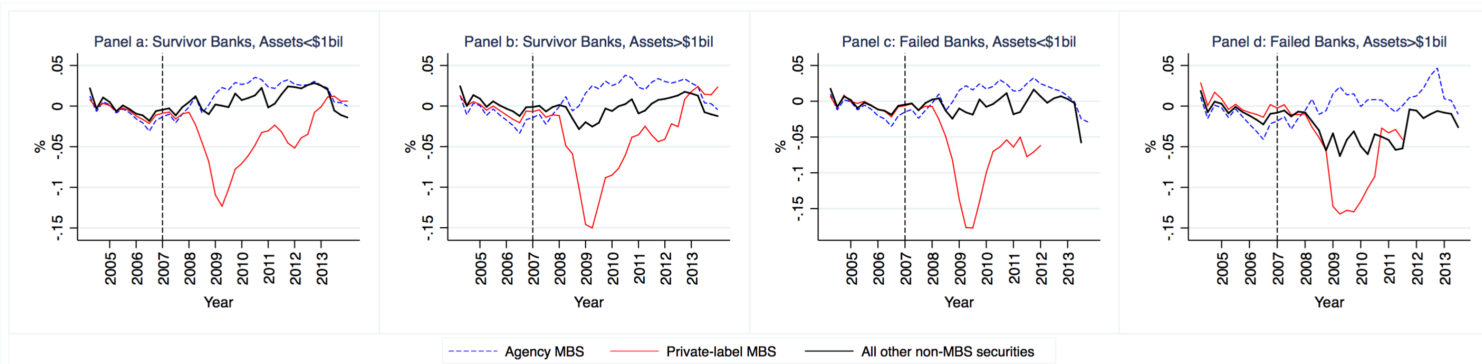

Figure VIII: Normalized funding costs for core and non-core sources of funds. This graph displays quarterly averages of the cost of funding for core deposits and for other non-core liabilities. I define the cost of funds as the annualized quarterly interest expense attributed to a particular source of funds, divided by the quarterly stock of the corresponding source of funds on the bank's balance sheet. Time labels correspond to beginning of year values. Panel (a) displays funding costs for survivor banks with mean asset size in 2004 less than $1 billion, panel (b) for survivor banks with mean asset size in 2004 greater than $1 billion, panel (c) for failed banks with mean asset size in 2004 less than $1 billion, and panel (d) for failed banks with mean asset size in 2004 greater than $1 billion. Data on funding costs are taken from the Reports of Condition and Income (Call Reports) and bank failures from the FDIC's list of failed banks. Sample selection is discussed in Section II.

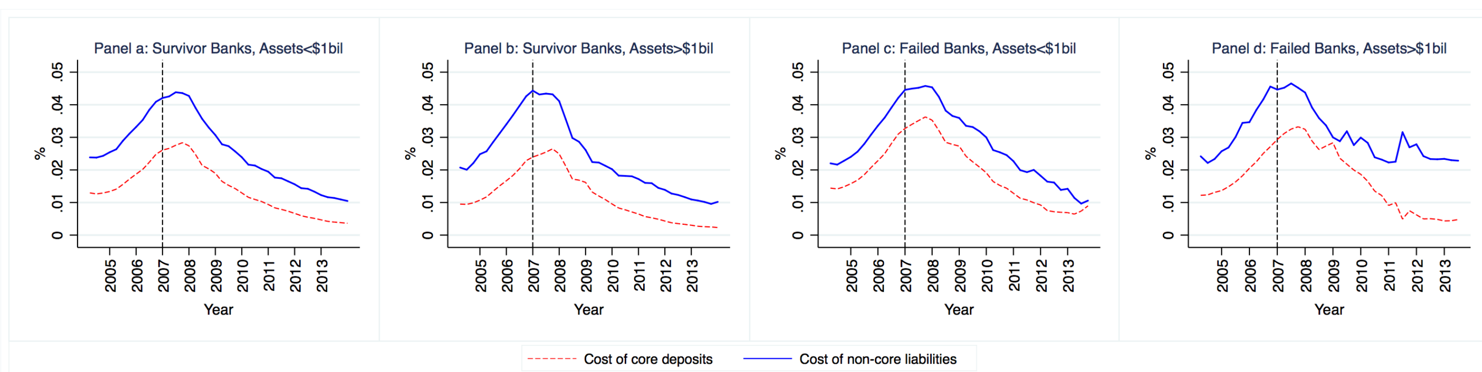

Table I: Definitions

VARIABLE	DEFINITION
logAssets	The natural logarithm of assets
BHC membership	The bank is a member of a Bank Holding Company
ROAA	Net income divided by average assets
Efficiency	(Total non interest income + Net interest income)/ (Total non interest expense)
Non-performing loans	Loans past due more than 90 days plus loans not accruing divided by total loans
Equity capital	Total equity capital divided by assets
Core Deposits	The sum of demand deposits, MMDA and other savings deposits, NOW, ATS and other interest-bearing transaction accounts, and insured time deposits, divided by total assets
Money market	The sum of federal funds sold and securities purchased under agreement to resell divided by total assets
Securities	The sum of held-to-maturity, available-for-sale, and trading securities divided by total assets
Illiquid assets	Total assets minus the sum of cash, federal funds sold, securities purchased under agreement to resell, securities held-to-maturity, available-for-sale securities, and trading securities, divided by total assets
Credit lines	Total unused loan commitments (excluding credit card lines) divided by total assets
Securities excluding MBS	Total securities less the sum of Agency and Private-label MBS, divided by total assets
Agency MBS	MBS issued or guaranteed by a government sponsored enterprise (GSE), divided by total assets
Private-label MBS	MBS issued by non-GSE issuers, divided by total assets
Illiquid assets excluding RE loans	Total illiquid assets minus total real estate loans, divided by total assets
Traditional home mortgages	Closed-end loans secured by 1-4 family residential properties divided by total assets
Home equity loans	Open-end loans secured by 1-4 family residential properties divided by total assets
Non-household RE loans	All other real estate loans divided by total assets
Credit lines excluding RE lines	Total unused loan commitments (excluding credit card lines) minus total unused real estate commitments, divided by total assets
Non-household RE lines	Commitments to fund commercial real estate, construction, and land development loans, divided by total assets
Home equity lines of credit	Revolving, open-end lines secured by 1-4 family residential properties divided by total assets

Table II: Difference-in-means tests for changes in the banks' baseline business model between 2001 and 2005. This table displays tests for the equality of means for the 2001 and 2005 levels of a set of variables describing the banks' baseline business model. The left panel displays tests for banks with average assets in 2004 less than \$1 billion and the right panel for banks with average assets in 2004 greater than \$1 billion. Commercial bank data are taken from the Reports of Condition and Income (Call Reports) and bank failures from the FDIC's list of failed banks. Sample selection is discussed in Section II. The values of the variables are averages obtained over the four quarters of 2001 and 2005. Heteroscedasticity-robust standard errors are reported. The levels of statistical significance are *** p<0.01, ** p<0.05, and * p<0.10

SIZE	SMALL (ASSETS < \$1 bil)			LARGE (ASSETS > \$1 bil)		
Variables	2001	2005	Diff	2001	2005	Diff
Assets (\$ bil)	0.15	0.22	0.069***	12.18	20.98	8.803***
BHC membership	0.18	0.17	-0.006*	0.49	0.41	-0.072***
ROAA	0.01	0.01	0.002***	0.01	0.01	0.001***
Efficiency	1.59	1.65	0.062***	1.74	1.82	0.087***
Non-performing loans	0.01	0.01	-0.001***	0.01	0.01	-0.002***
Equity capital	0.11	0.10	-0.004***	0.09	0.10	0.006***
Core deposits	0.69	0.68	-0.015***	0.58	0.57	-0.009*
Cash	0.05	0.04	-0.005***	0.04	0.04	-0.007***
Money market	0.05	0.03	-0.023***	0.03	0.02	-0.011***
Securities	0.23	0.23	-0.002*	0.22	0.23	0.004
Illiquid Assets	0.67	0.70	0.031***	0.70	0.71	0.014***
Credit lines	0.09	0.11	0.025***	0.17	0.20	0.032***

Table III: Difference-in-means tests for the banks' pre-crisis baseline business model. This table displays tests for the equality of means for a set of variables describing the banks' baseline business model in 2005. The left panel displays tests for banks with average assets in 2004 less than \$1 billion and the right panel for banks with average assets in 2004 greater than \$1 billion. Commercial bank data are taken from the Reports of Condition and Income (Call Reports) and bank failures from the FDIC's list of failed banks. Sample selection is discussed in Section II. The values of the variables are averaged over the four quarters of 2005. Heteroscedasticity-robust standard errors are reported. The levels of statistical significance are *** p<0.01, ** p<0.05, and * p<0.10

SIZE	SMALL (ASSETS < \$1bil)			LARGE (ASSETS > \$ 1bil)		
VARIABLE	Survived	Failed	Diff	Survived	Failed	Diff
Assets (\$ bil)	0.21	0.28	0.068***	22.77	4.16	-18.610***
BHC membership	0.17	0.12	-0.050**	0.43	0.26	-0.169*
ROAA	0.01	0.01	0.000	0.01	0.01	-0.000
Efficiency	1.64	1.73	0.088***	1.79	2.09	0.297***
Non-performing loans	0.01	0.00	-0.002***	0.01	0.01	0.000
Equity capital	0.10	0.09	-0.007***	0.10	0.09	-0.007
Core deposits	0.68	0.62	-0.064***	0.58	0.50	-0.077***
Cash	0.04	0.04	-0.006***	0.04	0.03	-0.011***
Money market	0.03	0.03	0.005**	0.02	0.03	0.005
Securities	0.23	0.13	-0.104***	0.23	0.21	-0.014
Illiquid Assets	0.69	0.80	0.107***	0.71	0.73	0.022
Credit lines	0.11	0.18	0.072***	0.20	0.19	-0.015

Table IV: The effects of real estate risk on bank failure. This table shows the results of estimating a probit model of the probability of a commercial bank failing during 2006-2013, estimated separately for small and large banks. Failure is defined as the bank having been placed under FDIC receivership between January 1, 2006 and December 31, 2013. Columns (1)-(2) report estimates over the subsample of banks with average assets in 2004 less than $1 billion, and columns (3)-(4) report estimates over the subsample of banks with average assets in 2004 greater than $1 billion. Columns (1) and (3) report estimates for the baseline model that only uses a standard set of predictors of failure. Columns (2) and (4) augment the baseline model to include variables that capture the bank's product mix, accounting for the exposure of the bank's loan, securities, and credit line portfolios to various categories of real estate products. Commercial bank data are taken from the Reports of Condition and Income (Call Reports) and bank failures from the FDIC's list of failed banks. Sample selection is discussed in Section II. The models are estimated using the financial variables averaged over the four quarters of 2005. The reported coefficients are average marginal effects. Heteroscedasticity-robust standard errors are reported. The levels of statistical significance are *** p<0.01, ** p<0.05, and * p<0.10

SIZE	SMALL (ASSETS < $1bil)		LARGE (ASSETS > $1bil)	
MODEL	BASELINE	PRODUCT	BASELINE	PRODUCT
VARIABLE	(1)	(2)	(3)	(4)
logAssets	-0.00	-0.01	-0.02	0.03
	(0.01)	(0.01)	(0.02)	(0.02)
BHC membership	-0.03**	-0.02*	-0.05	-0.00
	(0.01)	(0.01)	(0.04)	(0.03)
ROAA	-1.34	-1.37	-4.53	-1.73
	(0.91)	(0.88)	(4.01)	(3.19)
Efficiency	0.02	-0.00	0.12**	-0.01
	(0.01)	(0.02)	(0.05)	(0.04)
Non-performing loans	0.21	0.50	1.45	0.03
	(0.55)	(0.52)	(2.49)	(2.44)
Equity capital	-0.44**	-0.45**	-0.86*	-1.02*
	(0.18)	(0.19)	(0.49)	(0.56)
Core deposits	-0.23***	-0.16***	-0.24*	-0.23**
	(0.04)	(0.04)	(0.12)	(0.11)
Money market	0.60**	0.24	1.22	1.00
	(0.24)	(0.21)	(1.23)	(0.92)
Securities	0.19	0.16	1.04	0.54
	(0.17)	(0.15)	(1.00)	(0.74)
Illiquid Assets	0.43**	0.18	1.17	0.54
	(0.17)	(0.15)	(0.95)	(0.71)
Credit lines	0.47***	0.12	0.06	-0.43
	(0.05)	(0.11)	(0.19)	(0.30)
Agency MBS		-0.02		0.16
		(0.08)		(0.25)
Private-label MBS		0.58		1.97**
		(0.57)		(0.99)
Traditional home mortgages		-0.02		0.14
		(0.07)		(0.19)
Home equity loans		1.10***		2.63*
		(0.29)		(1.51)
Non-household RE loans		0.26***		0.56***
		(0.05)		(0.18)
Non-household RE lines		0.47***		0.81**
		(0.13)		(0.39)
Home equity lines of credit		-1.30***		-3.88**
		(0.43)		(1.92)
Number of banks	4,041	4,041	279	279
Failed	274	274	27	27
Pseudo-R2	0.179	0.268	0.147	0.378

Table V: Difference-in-means tests for changes in the banks' real estate models between 2001 and 2005. This table displays tests for the equality of means for the banks' average level of exposure to the real estate sector in 2001 and 2005, through the composition of the loan, marketable securities, and credit line portfolios. The left panel displays tests for banks with average assets in 2004 less than \$1 billion and the right panel for banks with average assets in 2004 greater than \$1 billion. Commercial bank data are taken from the Reports of Condition and Income (Call Reports) and bank failures from the FDIC's list of failed banks. Sample selection is discussed in Section II. The values of the variables are averages obtained over the four quarters of 2001 and 2005. Heteroscedasticity-robust standard errors are reported. The levels of statistical significance are *** $p<0.01$, ** $p<0.05$, and * $p<0.10$

SIZE	SMALL (ASSETS < \$1bil)			LARGE (ASSETS > \$ 1bil)		
VARIABLE	2001	2005	Diff	2001	2005	Diff
Securities excluding MBS	0.17	0.17	-0.001	0.12	0.12	-0.003
Agency MBS	0.06	0.06	-0.002*	0.09	0.10	0.004
Private-label MBS	0.00	0.00	0.000	0.01	0.01	0.002***
Illiquid assets excluding RE loans	0.28	0.24	-0.034***	0.29	0.27	-0.027***
Traditional home mortgages	0.17	0.15	-0.016***	0.14	0.12	-0.018***
Home equity loans	0.01	0.02	0.007***	0.02	0.03	0.014***
Non-household RE loans	0.21	0.28	0.074***	0.24	0.28	0.048***
Credit lines excluding RE lines	0.05	0.06	0.007***	0.10	0.10	0.004*
Non-household RE lines	0.02	0.04	0.012***	0.04	0.06	0.015***
Home equity lines of credit	0.01	0.01	0.005***	0.02	0.03	0.011***

Table VI: Difference-in-means tests for pre-crisis real estate exposures. This table displays tests for the equality of means for variables capturing the banks' level of exposure to the real estate sector through the composition of the loan, marketable securities, and credit line portfolios, for the groups of survivor and failed banks. The left panel displays tests for banks with average assets in 2004 less than \$1 billion and the right panel for banks with average assets in 2004 greater than \$1 billion. Commercial bank data are taken from the Reports of Condition and Income (Call Reports) and bank failures from the FDIC's list of failed banks. Sample selection is discussed in Section II. The values of the variables are averaged over the four quarters of 2005. Heteroscedasticity-robust standard errors are reported. The levels of statistical significance are *** $p<0.01$, ** $p<0.05$, and * $p<0.10$

SIZE	SMALL (ASSETS < \$1bil)			LARGE (ASSETS > \$ 1bil)		
VARIABLE	Survived	Failed	Diff	Survived	Failed	Diff
Securities excluding MBS	0.17	0.09	-0.085***	0.12	0.11	-0.012
Agency MBS	0.06	0.04	-0.018***	0.10	0.09	-0.005
Private-label MBS	0.00	0.00	0.000	0.01	0.01	0.005
Illiquid assets excluding RE loans	0.25	0.19	-0.057***	0.28	0.18	-0.098***
Traditional home mortgages	0.15	0.11	-0.043***	0.12	0.10	-0.025
Home equity loans	0.02	0.03	0.009***	0.04	0.02	-0.019***
Non-household RE loans	0.27	0.47	0.196***	0.27	0.43	0.167***
Credit lines excluding RE lines	0.06	0.06	-0.002	0.11	0.06	-0.046***
Non-household RE lines	0.03	0.10	0.064***	0.05	0.10	0.048***
Home equity lines of credit	0.01	0.02	0.004***	0.03	0.01	-0.020***

Table VII: Economic impact. The table shows the reduction in the average loss rate for a counterfactual exercise in which the average levels of exposure to real estate products in 2005 are reduced down to the lowest quartile of the distribution for that year. For the two categories of stable funding sources, the exposure is raised up to the top quartile of their corresponding distributions. The average loss rate is the probability of failure as predicted by the model in columns (2) and (4) of Table IV, averaged across all banks in each subsample. Each row corresponds to a reduction in a single exposure, with all other exposures remaining at their empirically observed levels. Commercial bank data are taken from the Reports of Condition and Income (Call Reports) and bank failures from the FDIC's list of failed banks. Sample selection is discussed in Section II.

VARIABLE	SMALL (ASSETS $<$ \$1bil)	LARGE (ASSETS $>$ \$1bil)
Private-label MBS	0.00[!]	0.02
Non-household RE loans	0.05	0.07
Non-household RE lines	0.03	0.04
Agency MBS	0.00[!]	0.01[!]
Traditional home mortgages	0.00[!]	0.01[!]
Core-deposits	0.02	0.03
Equity capital	0.01	0.02
Number of banks	4,041	279
Failed	274	27
Loss rate in data	0.07	0.10
Loss rate from model	0.07	0.10

[!] The estimated average marginal effects for these variables are not statistically significant

Table VIII: Controlling for the effects of local economic shocks. This table shows the results of estimating a probit model of the probability of a commercial bank failing during 2006-2013, estimated separately for small and large banks. Failure is defined as the bank having been placed under FDIC receivership between January 1, 2006 and December 31, 2013. Columns (1)-(6) report estimates over the subsample of banks with average assets in 2004 less than $1 billion, and columns (7)-(12) report estimates over the subsample of banks with average assets in 2004 greater than $1 billion. Columns (1) and (7) report the estimates for the paper's core real estate model for reference. Columns (2) and (8) include a bank-specific measure of local income shocks, derived from county-level data on per capita income declines during the 2006-2009 period, aggregated up to the bank level using bank branch-level data on deposit account balances in 2005. Columns (3) and (9) include a similarly-constructed proxy for local unemployment rates, derived from county-level data on the increase in unempolyment rates during the 2006-2009 period. Columns (4) and (10) include a similarly-constructed proxy for local declines in housing prices, derived from zip code-level data on annualised house price index (HPI) declines during the 2006-2009 period. Columns (5) and (11) include simultaneously all three proxies in columns (2)-(4) and (8)-(10). Columns (6) and (12) do not include proxies for local economic conditions but saturate the core model in columns (1) and (2) with state fixed effects, for each state and bank set to 1 if a bank had a branch in the state in 2005. Commercial bank data are taken from the Reports of Condition and Income (Call Reports), bank failures from the FDIC's list of failed banks, branching information from the FDIC's Summary of Deposits, income statistics from the Bureau of Economic Analysis, unemployment rates from the Bureau of Labor Statistics, and housing price index data from the Federal Housing Finance Agency. Sample selection is discussed in Section II. The models are estimated using the financial variables averaged over the four quarters of 2005. The reported coefficients are average marginal effects. Estimates for the coefficients of baseline variables are suppressed for brevity. Heteroscedasticity-robust standard errors are reported. The levels of statistical significance are *** p<0.01, ** p<0.05, and * p<0.10

SIZE	SMALL (ASSETS < $1bil)						LARGE (ASSETS > $1bil)					
MODEL	PROD	INC	UNMPL	HPI	ALL	FE	PROD	INC	UNMPL	HPI	ALL	FE
VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Securities	0.16	0.20	0.19	0.28*	0.27*	0.17	0.54	0.92	0.53	0.60	0.75	3.65***
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.17)	(0.74)	(0.74)	(0.71)	(0.73)	(0.72)	(1.17)
Illiquid Assets	0.18	0.23	0.24*	0.33**	0.33**	0.22	0.54	0.93	0.59	0.68	0.81	3.45***
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.17)	(0.71)	(0.72)	(0.70)	(0.72)	(0.71)	(1.09)
Credit lines	0.12	0.13	0.15	0.09	0.12	0.16	-0.43	-0.42	-0.42	-0.46	-0.42	-2.19***
	(0.11)	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)	(0.30)	(0.31)	(0.30)	(0.30)	(0.31)	(0.61)
Agency MBS	-0.02	-0.04	-0.05	-0.04	-0.05	-0.05	0.16	0.21	0.12	0.17	0.15	0.21
	(0.08)	(0.08)	(0.09)	(0.08)	(0.08)	(0.09)	(0.25)	(0.26)	(0.25)	(0.25)	(0.26)	(0.44)
Private-label MBS	0.58	0.51	0.61	0.04	0.24	0.58	1.97**	1.70*	1.77*	1.72*	1.56*	3.87***
	(0.57)	(0.58)	(0.57)	(0.60)	(0.59)	(0.64)	(0.99)	(0.95)	(0.98)	(0.97)	(0.94)	(1.34)
Traditional home mortgages	-0.02	-0.03	-0.07	-0.02	-0.06	0.05	0.14	0.13	0.08	0.10	0.08	-0.16
	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.19)	(0.17)	(0.18)	(0.18)	(0.18)	(0.40)
Home equity loans	1.10***	1.04***	0.91***	0.88***	0.83***	1.09***	2.63*	2.60*	2.32	3.05**	2.38	2.26
	(0.29)	(0.28)	(0.29)	(0.28)	(0.28)	(0.33)	(1.51)	(1.54)	(1.55)	(1.50)	(1.54)	(2.11)
Non-household RE loans	0.26***	0.23***	0.21***	0.20***	0.18***	0.20***	0.56***	0.59***	0.41**	0.50***	0.44**	0.78**
	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.18)	(0.17)	(0.18)	(0.18)	(0.18)	(0.33)
Non-household RE lines	0.47***	0.43***	0.42***	0.45***	0.42***	0.44***	0.81**	0.72*	0.82**	0.83**	0.75*	4.09***
	(0.13)	(0.12)	(0.12)	(0.12)	(0.12)	(0.13)	(0.39)	(0.39)	(0.40)	(0.40)	(0.40)	(0.66)
Home equity lines of credit	-1.30***	-1.37***	-1.32***	-1.26***	-1.30***	-1.42***	-3.88**	-3.85**	-3.89*	-4.34**	-3.86*	-5.76*
	(0.43)	(0.42)	(0.43)	(0.41)	(0.41)	(0.46)	(1.92)	(1.96)	(2.05)	(1.99)	(2.09)	(3.01)
Number of banks	4,041	4,041	4,041	4,041	4,041	3,573	279	279	279	279	279	137
Failed	274	274	274	274	274	274	27	27	27	27	27	27
Pseudo-R2	0.268	0.274	0.291	0.29	0.299	0.34	0.378	0.402	0.419	0.405	0.429	0.615

Table IX: Robustness tests. This table shows the results of estimating a probit model of the probability of a commercial bank failing during 2006-2013, estimated separately for small and large banks. Failure is defined as the bank having been placed under FDIC receivership between January 1, 2006 and December 31, 2013. Columns (1)-(3) report estimates over the subsample of banks with average assets in 2004 less than $1 billion, and columns (4)-(8) report estimates over the subsample of banks with average assets in 2004 greater than $1 billion. Columns (1) and (4) report the estimates for the paper's core real estate model for reference. Columns (2) and (5) exclude all banks that participated in the Capital Purchase Program (CPP), either directly or through their Bank Holding Company. Columns (3) and (6) add variables that capture the bank's income mix, accounting for stakeholder, fee-for-service, traditional fee, and net interest income (as in DeYoung and Torna (2013)). Column (7) includes controls for large banks' off-balance sheet risk through liquidity and credit enhancements provided to ABCP conduits. Column (8) excludes the 10 largest banks from the sample, to mitigate the impact of too-big-too-fail banks. Commercial bank data are taken from the Reports of Condition and Income (Call Reports), bank failures from the FDIC's list of failed banks, CPP participation data from the U.S. Treasury's CPP transaction report, and mortgage borrower data from the Home Mortgage Disclosure Act (HMDA) loan application register. Sample selection is discussed in Section II. The models are estimated using the financial variables averaged over the four quarters of 2005. The reported coefficients are average marginal effects. Estimates for the coefficients of baseline variables are suppressed for brevity. Heteroscedasticity-robust standard errors are reported. The levels of statistical significance are *** $p<0.01$, ** $p<0.05$, and * $p<0.10$

SIZE	SMALL (ASSETS < $1bil)			LARGE (ASSETS > $1bil)				
MODEL	PROD	TARP	INC	PROD	TARP	INC	SPV	TBTF
VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Securities	0.16	0.12	0.23	0.54	0.74	0.81	0.54	0.54
	(0.15)	(0.16)	(0.16)	(0.74)	(0.87)	(0.70)	(0.74)	(0.76)
Illiquid Assets	0.18	0.15	0.21	0.54	1.04	0.59	0.55	0.54
	(0.15)	(0.16)	(0.16)	(0.71)	(0.88)	(0.68)	(0.71)	(0.74)
Credit lines	0.12	0.12	0.13	-0.43	-1.02**	-0.52*	-0.44	-0.44
	(0.11)	(0.12)	(0.11)	(0.30)	(0.44)	(0.29)	(0.30)	(0.32)
Agency MBS	-0.02	-0.01	-0.03	0.16	0.06	0.17	0.16	0.16
	(0.08)	(0.09)	(0.08)	(0.25)	(0.32)	(0.25)	(0.26)	(0.27)
Private-label MBS	0.58	0.47	0.55	1.97**	2.33*	1.30	1.95*	2.04**
	(0.57)	(0.61)	(0.57)	(0.99)	(1.30)	(0.95)	(1.00)	(1.02)
Traditional home mortgages	-0.02	-0.02	0.00	0.14	-0.11	0.25	0.14	0.14
	(0.07)	(0.07)	(0.07)	(0.19)	(0.24)	(0.23)	(0.19)	(0.20)
Home equity loans	1.10***	1.17***	1.13***	2.63*	3.81*	2.33*	2.63*	2.73*
	(0.29)	(0.32)	(0.29)	(1.51)	(2.13)	(1.20)	(1.51)	(1.56)
Non-household RE loans	0.26***	0.27***	0.27***	0.56***	0.84***	0.55***	0.56***	0.58***
	(0.05)	(0.05)	(0.05)	(0.18)	(0.21)	(0.16)	(0.18)	(0.19)
Non-household RE lines	0.47***	0.54***	0.43***	0.81**	1.06**	0.83**	0.82**	0.83**
	(0.13)	(0.13)	(0.13)	(0.39)	(0.53)	(0.37)	(0.40)	(0.42)
Home equity lines of credit	-1.30***	-1.21**	-1.31***	-3.88**	-5.57**	-3.36**	-3.87**	-4.03**
	(0.43)	(0.47)	(0.43)	(1.92)	(2.60)	(1.43)	(1.91)	(2.00)
Number of banks	4,041	3,671	4,041	279	161	279	279	269
Failed	274	264	274	27	24	27	27	27
Pseudo-R2	0.268	0.306	0.271	0.378	0.553	0.425	0.378	0.371

Table X: The sources of risk. This table shows the results of estimating a probit model of the probability of a commercial bank failing during 2006-2013, estimated separately for small and large banks. Failure is defined as the bank having been placed under FDIC receivership between January 1, 2006 and December 31, 2013. Columns (1)-(4) report estimates over the subsample of banks with average assets in 2004 less than \$1 billion, and columns (5)-(8) report estimates over the subsample of banks with average assets in 2004 greater than \$1 billion. Columns (1) and (5) report the estimates for the paper's core real estate model for reference. Columns (2) and (6) include the bank's pre-crisis z-score (logged) as a control variable, to account for bank risk-taking. Columns (3) and (7) account for the risk profile of banks' mortgage borrowers by including the average loan-to-income ratio for all mortgage loans originated by the bank during 2001-2005. Columns (4) and (8) account for both overall risk-taking and mortgage borrower risk. Commercial bank data are taken from the Reports of Condition and Income (Call Reports), bank failures from the FDIC's list of failed banks, CPP participation data from the U.S. Treasury's CPP transaction report, and mortgage borrower data from the Home Mortgage Disclosure Act (HMDA) loan application register. Sample selection is discussed in Section II. The models are estimated using the financial variables averaged over the four quarters of 2005. The reported coefficients are average marginal effects. Estimates for the coefficients of baseline variables are suppressed for brevity. Heteroscedasticity-robust standard errors are reported. The levels of statistical significance are *** p<0.01, ** p<0.05, and * p<0.10

SIZE	SMALL (ASSETS < \$1bil)				LARGE (ASSETS > \$1bil)			
MODEL	PROD	ZSCORE	LTI	BOTH	PROD	ZSCORE	LTI	BOTH
VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Securities	0.16	0.13	0.35	0.35	0.54	0.81	0.49	0.49
	(0.15)	(0.15)	(0.26)	(0.26)	(0.74)	(0.73)	(0.76)	(0.76)
Illiquid Assets	0.18	0.13	0.42	0.42	0.54	0.83	0.57	0.57
	(0.15)	(0.15)	(0.26)	(0.26)	(0.71)	(0.70)	(0.73)	(0.73)
Credit lines	0.12	0.11	0.08	0.08	-0.43	-0.41	-0.41	-0.41
	(0.11)	(0.10)	(0.13)	(0.13)	(0.30)	(0.27)	(0.33)	(0.33)
Agency MBS	-0.02	-0.04	-0.07	-0.07	0.16	0.09	0.19	0.19
	(0.08)	(0.08)	(0.12)	(0.12)	(0.25)	(0.23)	(0.26)	(0.26)
Private-label MBS	0.58	0.33	0.76	0.76	1.97**	1.79**	1.61*	1.61*
	(0.57)	(0.59)	(0.79)	(0.79)	(0.99)	(0.90)	(0.96)	(0.96)
Traditional home mortgages	-0.02	0.00	-0.08	-0.08	0.14	0.06	0.17	0.17
	(0.07)	(0.06)	(0.09)	(0.09)	(0.19)	(0.17)	(0.19)	(0.19)
Home equity loans	1.10***	0.97***	1.49***	1.49***	2.63*	2.18	2.79*	2.79*
	(0.29)	(0.28)	(0.40)	(0.40)	(1.51)	(1.50)	(1.61)	(1.61)
Non-household RE loans	0.26***	0.26***	0.28***	0.28***	0.56***	0.54***	0.46***	0.46***
	(0.05)	(0.05)	(0.07)	(0.07)	(0.18)	(0.16)	(0.18)	(0.18)
Non-household RE lines	0.47***	0.44***	0.75***	0.75***	0.81**	0.76**	0.85**	0.85**
	(0.13)	(0.12)	(0.17)	(0.17)	(0.39)	(0.37)	(0.43)	(0.43)
Home equity lines of credit	-1.30***	-1.14***	-1.80***	-1.60***	-3.88**	-3.38*	-4.66**	-4.09*
	(0.43)	(0.41)	(0.59)	(0.56)	(1.92)	(1.91)	(2.09)	(2.09)
logzscore		-0.02***		-0.03***		-0.05**		-0.05**
		(0.00)		(0.01)		(0.02)		(0.02)
avgLTI			0.01**	0.01**			0.06**	0.05**
			-0.01	(0.01)			(0.03)	(0.03)
Number of banks	4,041	4,040	2,500	2,499	279	279	263	263
Failed	274	273	235	234	27	27	27	27
Pseudo-R2	0.268	0.279	0.256	0.267	0.378	0.415	0.400	0.435

Table XI: Asset performance through the crisis. This table displays tests for level differences in asset performance between the groups of survivor and failed banks after controlling for the influence of local economic conditions. Panel A displays level differences in the NPL rates of various categories of real estate loans, as well as for the aggregate portfolio of all other non-real estate loans, for the group of small banks (Assets < \$1 bil). I define the NPL rate as loans past due 90 days and not accruing divided by total loans in each loan category. Panel B repeats for large banks. Panel C displays level differences in the loan returns of the banks' aggregate real estate and aggregate non-real estate loan portfolios, for the group of small banks. I define loan returns as total interest income from the loan portfolio divided by the total volume of loans in the portfolio. Panel D repeats for large banks. Panel E displays level differences in the rate of unrealized gains for the banks' agency MBS, private-label MBS, and aggregate non-MBS portfolios, for small banks. I define the rate of unrealized gains as the difference between fair and amortized cost value divided by amortized cost value. Panel F repeats for large banks. Bank financial data are taken from the Reports of Condition and Income (Call Reports) and bank failures from the FDIC's list of failed banks. Sample selection is discussed in Section II. The values of the variables are obtained over the four quarters of each year. Standard errors are clustered at the bank level. The levels of statistical significance are *** p<0.01, ** p<0.05, and * p<0.10

	2005	2006	2007	2008	2009	2010	2011	2012	2013
Panel A: Non-performing loan rates (small banks)									
Non-real estate loans	-0.0013***	-0.0010***	-0.0008**	-0.0003	0.0038***	0.0023*	0.0040*	0.0049	0.0009
Traditional home mortgages	-0.0007	0.0016**	0.0061***	0.0199***	0.0531***	0.0677***	0.0648***	0.0710***	0.0848***
Home equity loans	0.0013***	0.0017***	0.0037***	0.0095***	0.0189***	0.0348***	0.0259***	0.0295***	0.0347*
Non-household RE loans	-0.0014**	0.0003	0.0095***	0.0458***	0.0892***	0.1167***	0.1164***	0.1080***	0.0930***
Panel B: Non-performing loan rates (large banks)									
Non-real estate loans	0.0012	0.0017	-0.0007	0.0034*	0.009	0.0049	-0.0021	0.0101***	0.0117***
Traditional home mortgages	0.0031	-0.0001	0.0023	0.0127***	0.0479***	0.0792***	0.0405	0.0282***	0.0233***
Home equity loans	-0.001	-0.0004	-0.0002	0.0065	0.0220**	0.0413**	0.0089***	.	.
Non-household RE loans	-0.0025*	-0.0017	0.0036	0.0299***	0.0772***	0.1127***	0.1111***	0.1960***	0.1739***
Panel C: Loan returns (small banks)									
Non-RE loan returns	0.0037***	0.0046***	0.0040***	0.0011	-0.0007	-0.0009	-0.0028*	0.0003	0
RE loan returns	0.0042***	0.0079***	0.0066***	-0.0024***	-0.0058***	-0.0072***	-0.0062***	-0.0046***	-0.0036**
Panel D: Loan returns (large banks)									
Non-RE loan returns	0.0006	0.0057	0.0053	0.003	0.0036	0.0054	0.0045***	0.0104***	0.0075***
RE loan returns	0.0085***	0.0099***	0.0108***	0.0044***	-0.0017	-0.0045	0.0004	0.0025***	0.0060***
Panel E: Unrealized gains (small banks)									
Non-MBS securities	-0.0023***	-0.0007	-0.0011**	-0.0089***	-0.0136***	-0.0111***	-0.0153***	-0.0227***	-0.011
Agency MBS	-0.0030***	-0.0027**	-0.0021**	-0.0019**	-0.0046***	-0.0071***	-0.0042	-0.0110***	-0.0156***
Private-label MBS	0.0025	0.0025	0.0029	-0.0107	-0.0599***	-0.0214	-0.0259	.	.
Panel F: Unrealized gains (large banks)									
Non-MBS securities	-0.0069**	-0.0073***	-0.0055***	-0.0198***	-0.0322**	-0.0467***	-0.0423***	-0.0253***	-0.0163***
Agency MBS	-0.0015	-0.0048*	-0.0036	-0.0017	-0.0090***	-0.0233***	-0.0282***	-0.0023	-0.0093***
Private-label MBS	0.0016	0.0071	0.0053	0.0376**	-0.0071	-0.0101	0.0007	.	.

Table XII: Different Failure Periods. This table shows the results of estimating a probit model of the probability of a commercial bank failing during different subperiods of the Great Recession, estimated separately for small and large banks. Columns (1)-(3) report estimates over the subsample of banks with average assets in 2004 less than \$1 billion, and columns (4)-(6) report estimates over the subsample of banks with average assets in 2004 greater than \$1 billion. Columns (1) and (4) provide for reference the base estimates with failure defined as the bank having been placed under FDIC receivership between January 1, 2006 and December 31, 2013. In columns (2) and (5) failure is defined as the bank having been placed under FDIC receivership between January 1, 2006 and December 31, 2009, with all later failures dropped from the sample. In columns (3) and (6) failure is defined as the bank having been placed under FDIC receivership between January 1, 2010 and December 31, 2013, with all earlier failures dropped from the sample. Commercial bank data are taken from the Reports of Condition and Income (Call Reports) and bank failures from the FDIC's list of failed banks. Sample selection is discussed in Section II. The models are estimated using the financial variables averaged over the four quarters of 2005. The reported coefficients are average marginal effects. Estimates for the coefficients of baseline variables are suppressed for brevity. Heteroscedasticity-robust standard errors are reported. The levels of statistical significance are *** p<0.01, ** p<0.05, and * p<0.10

SIZE	SMALL (ASSETS < \$1bil)			LARGE (ASSETS > \$1bil)		
MODEL	2006-2013	2006-2009	2010-2013	2006-2013	2006-2009	2010-2013
VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)
Equity capital	-0.45**	-0.27**	-0.29*	-1.02*	-0.30	-1.28**
	(0.19)	(0.12)	(0.17)	(0.56)	(0.30)	(0.51)
Core deposits	-0.16***	-0.05**	-0.11***	-0.23**	-0.05	-0.16**
	(0.04)	(0.02)	(0.03)	(0.11)	(0.08)	(0.08)
Securities	0.16	0.33***	-0.04	0.54	-0.43**	1.49*
	(0.15)	(0.12)	(0.12)	(0.74)	(0.17)	(0.78)
Illiquid Assets	0.18	0.24**	0.09	0.54	-0.32***	1.54**
	(0.15)	(0.12)	(0.12)	(0.71)	(0.12)	(0.78)
Credit lines	0.12	0.13*	0.00	-0.43	-0.04	-0.37
	(0.11)	(0.07)	(0.08)	(0.30)	(0.15)	(0.25)
Agency MBS	-0.02	-0.07	0.07	0.16	0.20	0.10
	(0.08)	(0.05)	(0.08)	(0.25)	(0.14)	(0.20)
Private-label MBS	0.58	0.38	0.36	1.97**	1.31***	0.74
	(0.57)	(0.32)	(0.54)	(0.99)	(0.49)	(0.85)
Traditional home mortgages	-0.02	-0.01	-0.02	0.14	0.03	-0.03
	(0.07)	(0.05)	(0.05)	(0.19)	(0.13)	(0.14)
Home equity loans	1.10***	0.65***	0.64***	2.63*	2.13**	0.80
	(0.29)	(0.16)	(0.25)	(1.51)	(0.96)	(0.88)
Non-household RE loans	0.26***	0.13***	0.17***	0.56***	0.27***	0.35**
	(0.05)	(0.03)	(0.04)	(0.18)	(0.10)	(0.14)
Non-household RE lines	0.47***	0.14*	0.40***	0.81**	0.56***	0.00
	(0.13)	(0.08)	(0.11)	(0.39)	(0.20)	(0.34)
Home equity lines of credit	-1.30***	-0.99***	-0.60*	-3.88**	-3.12**	-1.42
	(0.43)	(0.25)	(0.36)	(1.92)	(1.28)	(1.17)
Number of banks	4,041	3,855	3,953	279	264	267
Failed	274	88	186	27	12	15
Pseudo-R2	0.268	0.274	0.255	0.378	0.551	0.347

Table XIII: Funding costs through the crisis. This table displays tests for level differences in funding costs between the groups of survivor and failed banks, for core-deposits and for non-core liabilities. I define the cost of funds as the annualized quarterly interest expense attributed to a particular source of funds, divided by the quarterly stock of the corresponding source of funds on the bank's balance sheet. Panel A displays level differences for the group of small banks (Assets < \$1 bil), after controlling for the influence of local economic conditions. Panel B repeats for large banks. Panels C and D repeat the regressions shown in Panels A and B, now also controlling for the bank's equity buffers and asset quality – as proxied by the ratio of total equity to assets and the ratio of non-performing loans to total assets, respectively. Data on banks' funding costs are taken from the Reports of Condition and Income (Call Reports) and bank failures from the FDIC's list of failed banks. Sample selection is discussed in Section II. The values of the variables are obtained over the four quarters of each year. Standard errors are clustered at the bank level. The levels of statistical significance are *** p<0.01, ** p<0.05, and * p<0.10

Differences: Failed - Survivor	2005	2006	2007	2008	2009	2010	2011	2012	2013
Panel A: Funding spread (small banks)									
Core deposits	0.0035***	0.0059***	0.0076***	0.0074***	0.0068***	0.0043***	0.0028***	0.0018***	0.0029***
Non-core liabilities	-0.0002	0.0013***	0.0021***	0.0034***	0.0057***	0.0041***	0.0025***	0.0018*	-0.0002
Panel B: Funding spread (large banks)									
Core deposits	0.0036***	0.0056***	0.0078***	0.0094***	0.0086***	0.0062***	0.0024***	0.0016***	0.0022***
Non-core liabilities	0.0017	0.001	0.0017	0.0037*	0.0071***	0.0072***	0.0125***	0.0122***	0.0132***
Panel C: Spread net of bank risk (small banks)									
Core deposits	0.0034***	0.0056***	0.0065***	0.0055***	0.0038***	0.0020***	0.0010**	0.0005	0.0015*
Non-core liabilities	-0.0004	0.0011***	0.0012***	0.0020***	0.0019***	0.0001	-0.0009	-0.0014	-0.0038***
Panel D: Spread net of bank risk (large banks)									
Core deposits	0.0037***	0.0055***	0.0065***	0.0070***	0.0049***	0.0014	0.0001	-0.0013	-0.0005
Non-core liabilities	0.0014	0.0004	0.0006	0.001	0.0018	0.0004	0.0067***	0.0062*	0.0084***

Appendix

Table AI: Alternative definitions of failure. This table shows the results of estimating the paper's core real estate model of the probability of a commercial bank failing during 2006-2013, by relying on a simple capital-based rule to redefine failure. Columns (1)-(5) report estimates over the subsample of banks with average assets in 2004 less than \$1 billion, and columns (6)-(10) report estimates over the subsample of banks with average assets in 2004 greater than \$1 billion. Columns (1) and (6) repeat, for reference, estimates for the paper's core model, with failure defined as the bank having been placed under FDIC receivership between January 1, 2006 and December 31, 2013. Columns (2) and (7) use a cutoff rule that defines as failed any bank with a minimum Tier 1 leverage ratio during the period 2006-2013 of less that 1%. Columns (3) and (8) raise the threshold to 2%, columns (3) and (8) to 2%, columns (4) and (9) to 3% and columns (5) and (10) to 4%. Commercial bank data are taken from the Reports of Condition and Income (Call Reports), and bank failures from the FDIC's list of failed banks. Sample selection is discussed in Section II. The reported coefficients are average marginal effects. Estimates for the coefficients of baseline variables are suppressed for brevity. Heteroscedasticity-robust standard errors are reported. The levels of statistical significance are *** p<0.01, ** p<0.05, and * p<0.10

SIZE	SMALL (ASSETS < \$1bil)					LARGE (ASSETS > \$1bil)				
MODEL	receivership	T1<0.01	T1<0.02	T1<0.03	T1<0.04	receivership	T1<0.01	T1<0.02	T1<0.03	T1<0.04
VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Securities	0.16	0.07	0.08	0.14	0.01	0.54	0.61	0.98	1.03	1.50**
	(0.15)	(0.11)	(0.14)	(0.17)	(0.15)	(0.74)	(0.47)	(0.67)	(0.69)	(0.74)
Illiquid Assets	0.18	0.08	0.15	0.22	0.10	0.54	0.40	0.62	0.90	1.24*
	(0.15)	(0.11)	(0.14)	(0.16)	(0.15)	(0.71)	(0.53)	(0.67)	(0.69)	(0.72)
Credit lines	0.12	0.04	-0.00	-0.04	-0.03	-0.43	0.01	-0.07	-0.38	-0.35
	(0.11)	(0.08)	(0.10)	(0.12)	(0.13)	(0.30)	(0.15)	(0.19)	(0.27)	(0.30)
Agency MBS	-0.02	-0.04	0.01	0.03	-0.02	0.16	0.02	0.14	0.19	0.13
	(0.08)	(0.06)	(0.08)	(0.09)	(0.09)	(0.25)	(0.12)	(0.18)	(0.22)	(0.22)
Private-label MBS	0.58	-0.03	0.60	0.58	0.97	1.97**	0.21	-0.51	-0.10	0.33
	(0.57)	(0.47)	(0.50)	(0.58)	(0.65)	(0.99)	(0.40)	(0.79)	(0.82)	(0.86)
Traditional home mortgages	-0.02	-0.03	-0.01	-0.07	-0.11	0.14	0.15	0.13	-0.00	0.06
	(0.07)	(0.05)	(0.06)	(0.06)	(0.07)	(0.19)	(0.13)	(0.16)	(0.16)	(0.19)
Home equity loans	1.10***	0.63***	1.10***	1.44***	1.74***	2.63*	-0.49	-0.07	-0.56	-0.44
	(0.29)	(0.24)	(0.29)	(0.33)	(0.35)	(1.51)	(0.72)	(1.05)	(1.12)	(1.23)
Non-household RE loans	0.26***	0.10***	0.19***	0.28***	0.32***	0.56***	0.31**	0.55***	0.51***	0.61***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.18)	(0.12)	(0.19)	(0.17)	(0.19)
Non-household RE lines	0.47***	0.25***	0.40***	0.49***	0.54***	0.81**	0.23	0.43*	0.72**	0.70*
	(0.13)	(0.10)	(0.12)	(0.14)	(0.15)	(0.39)	(0.21)	(0.24)	(0.35)	(0.37)
Home equity lines of credit	-1.30***	-0.65*	-1.09**	-1.34***	-1.72***	-3.88**	0.62	0.04	0.50	0.17
	(0.43)	(0.36)	(0.43)	(0.48)	(0.52)	(1.92)	(0.75)	(1.20)	(1.28)	(1.33)
Number of banks	4,041	4,041	4,041	4,041	4,041	279	279	279	279	279
Failed	274	131	231	306	371	27	9	14	18	22
Pseudo-R2	0.268	0.193	0.215	0.229	0.242	0.378	0.458	0.442	0.355	0.370

Table AII: Including non-receivership exits. This table shows the results of estimating the paper's core real estate model of the probability of a commercial bank failing during 2006-2013 on a sample that includes banks that exited prior to 2013 without having been reported by FDIC as failed. Columns (1)-(5) report estimates over the subsample of banks with average assets in 2004 less than $1 billion, and columns (6)-(10) report estimates over the subsample of banks with average assets in 2004 greater than $1 billion. Columns (1) and (6) show estimates for the paper's core model with failure defined as the bank having been placed under FDIC receivership between January 1, 2006 and December 31, 2013. Columns (2) and (7) use a cutoff rule that defines as failed any bank with a minimum Tier 1 leverage ratio during the period 2006-2013 of less that 1%. Columns (3) and (8) raise the threshold to 2%, columns (3) and (8) to 2%, columns (4) and (9) to 3% and columns (5) and (10) to 4%. Commercial bank data are taken from the Reports of Condition and Income (Call Reports), and bank failures from the FDIC's list of failed banks. Sample selection is discussed in Section II. The reported coefficients are average marginal effects. Estimates for the coefficients of baseline variables are suppressed for brevity. Heteroscedasticity-robust standard errors are reported. The levels of statistical significance are *** p<0.01, ** p<0.05, and * p<0.10

SIZE	SMALL (ASSETS < $1bil)					LARGE (ASSETS > $1bil)				
MODEL	receivership	T1<0.01	T1<0.02	T1<0.03	T1<0.04	receivership	T1<0.01	T1<0.02	T1<0.03	T1<0.04
VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Securities	0.17	-0.04	-0.06	-0.05	-0.12	0.37	0.55	0.75	0.65	1.01*
	(0.13)	(0.08)	(0.12)	(0.15)	(0.14)	(0.58)	(0.33)	(0.46)	(0.49)	(0.55)
Illiquid Assets	0.17	-0.02	-0.01	0.03	-0.02	0.35	0.37	0.45	0.52	0.78
	(0.13)	(0.08)	(0.11)	(0.14)	(0.13)	(0.56)	(0.35)	(0.44)	(0.46)	(0.53)
Credit lines	0.09	0.02	-0.01	-0.05	-0.03	-0.33	0.02	-0.03	-0.24	-0.21
	(0.08)	(0.06)	(0.08)	(0.09)	(0.10)	(0.23)	(0.11)	(0.14)	(0.20)	(0.23)
Agency MBS	-0.04	-0.03	0.00	0.05	0.01	0.11	0.03	0.13	0.14	0.09
	(0.07)	(0.05)	(0.06)	(0.07)	(0.08)	(0.20)	(0.09)	(0.13)	(0.17)	(0.17)
Private-label MBS	0.35	-0.03	0.32	0.24	0.56	1.24**	0.16	-0.28	-0.03	0.22
	(0.40)	(0.34)	(0.35)	(0.42)	(0.50)	(0.55)	(0.23)	(0.48)	(0.45)	(0.47)
Traditional home mortgages	-0.00	-0.02	0.00	-0.04	-0.07	0.06	0.09	0.07	-0.02	0.06
	(0.05)	(0.04)	(0.05)	(0.05)	(0.06)	(0.14)	(0.09)	(0.12)	(0.13)	(0.15)
Home equity loans	0.86***	0.50***	0.87***	1.12***	1.43***	1.58	-0.46	-0.10	-0.47	-0.47
	(0.23)	(0.19)	(0.23)	(0.26)	(0.29)	(1.01)	(0.49)	(0.71)	(0.73)	(0.83)
Non-household RE loans	0.20***	0.07**	0.14***	0.21***	0.24***	0.40***	0.24**	0.43***	0.37***	0.43***
	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.15)	(0.10)	(0.16)	(0.14)	(0.15)
Non-household RE lines	0.33***	0.20***	0.30***	0.37***	0.43***	0.65**	0.16	0.30	0.52*	0.52*
	(0.10)	(0.07)	(0.10)	(0.11)	(0.12)	(0.31)	(0.16)	(0.19)	(0.27)	(0.29)
Home equity lines of credit	-1.06***	-0.53*	-0.90***	-1.08***	-1.54***	-2.47*	0.58	0.23	0.48	0.26
	(0.34)	(0.29)	(0.34)	(0.38)	(0.42)	(1.36)	(0.50)	(0.82)	(0.82)	(0.89)
Number of banks	5,115	5,115	5,115	5,115	5,115	391	391	391	391	391
Failed	274	133	235	316	392	27	9	14	18	22
Pseudo-R2	0.232	0.163	0.179	0.186	0.204	0.351	0.458	0.430	0.339	0.354

Table AIII: Matched sample characteristics. This table displays means for the core model's variables for failed banks and for matched subsamples of survivor banks. Columns (1)-(3) report means for banks with average assets in 2004 less than \$1 billion, and columns (4)-(6) report means for banks with average assets in 2004 greater than \$1 billion. Columns (1) and (4) show means for failed banks. Columns (2) and (5) show means for a subsample of survivor banks constructed by using a 1-nearest neighbor algorithm to match survivor banks to failed banks. Columns (3) and (6) use 2-nearest neighbor matching. Panel A shows means for the variables used for matching. Panel B shows the resulting means for the variables characterising banks' exposure to real estate in each portfolio. Commercial bank data are taken from the Reports of Condition and Income (Call Reports), and bank failures from the FDIC's list of failed banks. Sample selection is discussed in Section II. The levels of statistical significance for difference in means tests between failed and matched survivor banks are *** p<0.01, ** p<0.05, and * p<0.10

SIZE	SMALL (ASSETS < \$1bil)			LARGE (ASSETS > \$ 1bil)		
SUBSAMPLE	Failed	k-1	k-2	Failed	k-1	k-2
VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Matched variables						
logAssets	12.26	12.29	12.26	14.82	14.71	14.66
BHC membership	0.12	0.14	0.15	0.26	0.26	0.22
ROAA	0.01	0.01	0.01	0.01	0.01	0.01
Efficiency	1.73	1.72	1.70	2.09	2.06	2.03
Non-performing loans	0.00	0.00	0.00	0.01	0.01	0.01
Equity capital	0.09	0.10	0.10	0.09	0.09	0.10
Core deposits	0.62	0.61	0.61	0.50	0.52	0.52
Money market	0.03	0.04	0.04	0.03	0.02	0.02
Securities	0.13	0.13	0.13	0.21	0.18	0.17
Illiquid Assets	0.80	0.79	0.79	0.73	0.77	0.78
Credit lines	0.18	0.18	0.18	0.19	0.18	0.18
Securities	0.13	0.13	0.13	0.21	0.18	0.17
Panel B: Unmatched variables						
Agency MBS	0.04	0.04	0.04	0.09	0.07	0.06
Private-label MBS	0.00	0.00	0.00	0.01	0.00**	0.00**
Traditional home mortgages	0.11	0.13***	0.14***	0.10	0.14	0.14
Home equity loans	0.03	0.03	0.03	0.02	0.02	0.02
Non-household RE loans	0.47	0.37***	0.37***	0.43	0.37	0.36*
Non-household RE lines	0.10	0.07***	0.07***	0.10	0.06**	0.06**
Home equity lines of credit	0.02	0.03***	0.02***	0.01	0.02	0.02

Table AIV: Matched sample estimates. This table shows the results of estimating the paper's core real estate model of the probability of a commercial bank failing during 2006-2013 on a matched subsample of survivor banks. Failure is defined as the bank having been placed under FDIC receivership between January 1, 2006 and December 31, 2013. Columns (1)-(3) report estimates over the subsample of banks with average assets in 2004 less than \$1 billion, and columns (4)-(6) report estimates over the subsample of banks with average assets in 2004 greater than \$1 billion. Columns (1) and (4) show estimates for the paper's core model on the unmatched sample, for reference. Columns (2) and (5) use a 1-nearest neighbor matching algorithm to match survivor banks to failed banks, and columns (3) and (6) use 2-nearest neighbor matching. Banks are matched on all the variables used in the main specification, except for the variables capturing exposure to real estate in each portfolio (see Table AIII). Commercial bank data are taken from the Reports of Condition and Income (Call Reports), and bank failures from the FDIC's list of failed banks. Sample selection is discussed in Section II. The reported coefficients are average marginal effects. Estimates for the coefficients of baseline variables are suppressed for brevity. Heteroscedasticity-robust standard errors are reported. The levels of statistical significance are *** p<0.01, ** p<0.05, and * p<0.10

SIZE	SMALL (ASSETS < \$1bil)			LARGE (ASSETS > \$1bil)		
MODEL	unmatched	k-1	k-2	unmatched	k-1	k-2
VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)
Securities	0.16	0.45	0.38	0.54	-0.68	-1.86
	(0.15)	(0.72)	(0.66)	(0.74)	(6.26)	(3.81)
Illiquid Assets	0.18	-0.60	-0.43	0.54	-1.74	-2.53
	(0.15)	(0.72)	(0.65)	(0.71)	(6.48)	(3.94)
Credit lines	0.12	-0.72	-1.04**	-0.43	-1.16	-2.19**
	(0.11)	(0.47)	(0.45)	(0.30)	(0.87)	(0.91)
Agency MBS	-0.02	-0.37	-0.15	0.16	0.14	1.38
	(0.08)	(0.51)	(0.47)	(0.25)	(0.90)	(0.85)
Private-label MBS	0.58	0.27	2.19	1.97**	16.74***	6.95*
	(0.57)	(3.17)	(2.91)	(0.99)	(5.42)	(3.76)
Traditional home mortgages	-0.02	0.20	0.03	0.14	0.51	0.56
	(0.07)	(0.36)	(0.34)	(0.19)	(0.79)	(0.72)
Home equity loans	1.10***	6.23***	5.68***	2.63*	19.81***	12.44**
	(0.29)	(1.75)	(1.49)	(1.51)	(6.73)	(4.88)
Non-household RE loans	0.26***	1.24***	1.15***	0.56***	2.01***	2.08***
	(0.05)	(0.27)	(0.24)	(0.18)	(0.56)	(0.43)
Non-household RE lines	0.47***	1.20**	1.43***	0.81**	2.45**	2.35**
	(0.13)	(0.61)	(0.55)	(0.39)	(1.09)	(1.11)
Home equity lines of credit	-1.30***	-8.52***	-7.28***	-3.88**	-25.01***	-12.67**
	(0.43)	(2.45)	(2.10)	(1.92)	(8.91)	(6.15)
Number of banks	4,041	513	705	279	52	67
Failed	274	274	274	27	27	27
Pseudo-R2	0.268	0.147	0.145	0.378	0.441	0.407

Table AV: Using alternative pre-crisis snapshots. This table shows the results of estimating the paper's core real estate model of the probability of a commercial bank failing during 2006-2013, using alternative pre-crisis snapshots. Failure is defined as the bank having been placed under FDIC receivership between January 1, 2006 and December 31, 2013. Columns (1)-(3) report estimates over the subsample of banks with average assets in 2004 less than \$1 billion, and columns (4)-(6) report estimates over the subsample of banks with average assets in 2004 greater than \$1 billion. Columns (1) and (4) show estimates for the pre-crisis snapshot taken using 2004 averages, columns (2) and (5) using 2005 averages (the default year used throughout the paper), and columns (3) and (6) using 2006 averages. Commercial bank data are taken from the Reports of Condition and Income (Call Reports), and bank failures from the FDIC's list of failed banks. Sample selection is discussed in Section II. The reported coefficients are average marginal effects. Estimates for the coefficients of baseline variables are suppressed for brevity. Heteroscedasticity-robust standard errors are reported. The levels of statistical significance are *** p<0.01, ** p<0.05, and * p<0.10

SIZE	SMALL (ASSETS < \$1bil)			LARGE (ASSETS > \$1bil)		
MODEL	2004	2005	2006	2004	2005	2006
VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)
Securities	0.16	0.16	0.23	0.23	0.54	1.39
	(0.17)	(0.15)	(0.20)	(0.58)	(0.74)	(0.98)
Illiquid Assets	0.25	0.18	0.26	0.35	0.54	1.40
	(0.17)	(0.15)	(0.20)	(0.59)	(0.71)	(0.97)
Credit lines	-0.00	0.12	0.06	-0.56	-0.43	-0.48*
	(0.11)	(0.11)	(0.11)	(0.36)	(0.30)	(0.29)
Agency MBS	0.07	-0.02	-0.15	0.18	0.16	0.37
	(0.07)	(0.08)	(0.10)	(0.24)	(0.25)	(0.26)
Private-label MBS	0.45	0.58	0.67	2.64**	1.97**	1.29
	(0.82)	(0.57)	(0.52)	(1.25)	(0.99)	(0.92)
Traditional home mortgages	-0.10	-0.02	-0.05	0.11	0.14	0.12
	(0.07)	(0.07)	(0.07)	(0.20)	(0.19)	(0.19)
Home equity loans	0.85***	1.10***	0.91***	2.69***	2.63*	2.02
	(0.28)	(0.29)	(0.34)	(1.04)	(1.51)	(1.51)
Non-household RE loans	0.21***	0.26***	0.27***	0.46***	0.56***	0.52***
	(0.05)	(0.05)	(0.05)	(0.17)	(0.18)	(0.17)
Non-household RE lines	0.63***	0.47***	0.47***	0.97**	0.81**	1.11***
	(0.14)	(0.13)	(0.13)	(0.46)	(0.39)	(0.34)
Home equity lines of credit	-0.92**	-1.30***	-0.79*	-4.38**	-3.88**	-1.65
	(0.42)	(0.43)	(0.44)	(1.71)	(1.92)	(1.40)
Number of banks	4,040	4,041	4,041	279	279	278
Failed	273	274	274	27	27	26
Pseudo-R2	0.249	0.268	0.298	0.380	0.378	0.421

Table AVI: Difference-in-means tests for the pace of change in the banks' business model between failed and surviving banks. This table displays tests for the equality of means for the rate of change of the banks' average level of exposure to the real estate sector between 2001 and 2005 through changes in the composition of the loan, marketable securities, and credit line portfolios, for the groups of survivor and failed banks. For each variable, the rate of change is defined as the difference between the variable's average value in 2005 and its average value in 2001. The left panel displays tests for banks with average assets in 2004 less than \$1 billion and the right panel for banks with average assets in 2004 greater than \$1 billion. Commercial bank data are taken from the Reports of Condition and Income (Call Reports) and bank failures from the FDIC's list of failed banks. Sample selection is discussed in Section II. The values of the variables are averages obtained over the four quarters of the corresponding year. Heteroscedasticity-robust standard errors are reported. The levels of statistical significance are *** $p<0.01$, ** $p<0.05$, and * $p<0.10$

SIZE	SMALL (ASSETS < \$1bil)			LARGE (ASSETS > \$ 1bil)		
VARIABLE	Survived	Failed	Diff	Survived	Failed	Diff
Securities excluding MBS	0.000	-0.014	-0.0141***	-0.005	0.017	0.0219
Agency MBS	-0.001	-0.008	-0.0068**	0.004	0.003	-0.0012
Private-label MBS	0.000	-0.000	-0.0002	0.002	0.004	0.0023
Illiquid assets excluding RE loans	-0.032	-0.060	-0.0281***	-0.024	-0.061	-0.0368**
Traditional home mortgages	-0.016	-0.016	0.0006	-0.017	-0.028	-0.0110
Home equity loans	0.007	0.009	0.0020	0.015	0.005	-0.0099***
Non-household RE loans	0.069	0.141	0.0721***	0.044	0.090	0.0463***
Credit lines excluding RE lines	0.007	0.005	-0.0023	0.005	-0.006	-0.0107
Non-household RE lines	0.011	0.036	0.0254***	0.013	0.031	0.0181*
Home equity lines of credit	0.005	0.006	0.0004	0.012	0.004	-0.0079***

Table AVII: Asset performance through the crisis for a high-growth subsample of survivor banks. This table repeats the tests shown in Table XI, but for each product category I now only consider the subsample of survivor banks with increases in exposure levels between 2001 and 2005 at least as high as the mean of the distribution of the corresponding increase for the group of failed banks. Panel A displays level differences in the NPL rates of various categories of real estate loans, as well as for the aggregate portfolio of all other non-real estate loans, for the group of small banks (Assets < \$1 bil). I define the NPL rate as loans past due 90 days and not accruing divided by total loans in each loan category. Panel B repeats for large banks. Panel C displays level differences in the rate of unrealized gains for the banks' agency MBS, private-label MBS, and aggregate non-MBS portfolios, for small banks. I define the rate of unrealized gains as the difference between fair and amortized cost value divided by amortized cost value. Panel D repeats for large banks. Bank financial data are taken from the Reports of Condition and Income (Call Reports) and bank failures from the FDIC's list of failed banks. Sample selection is discussed in Section II. The values of the variables are obtained over the four quarters of each year. Standard errors are clustered at the bank level. The levels of statistical significance are *** $p<0.01$, ** $p<0.05$, and * $p<0.10$

	2005	2006	2007	2008	2009	2010	2011	2012	2013
Panel A: Non-performing loan rates (small banks)									
Non-real estate loans	-0.0012***	-0.0012***	-0.0010***	-0.0007*	0.0037***	0.0021	0.0040*	0.0048	0.0008
Traditional home mortgages	-0.0002	0.0017**	0.0063***	0.0196***	0.0525***	0.0682***	0.0649***	0.0713***	0.0850***
Home equity loans	0.0013***	0.0014**	0.0027**	0.0076***	0.0161***	0.0314***	0.0231***	0.0256***	0.0298*
Non-household RE loans	0.001	0.0016*	0.0091***	0.0401***	0.0781***	0.1012***	0.0992***	0.0953***	0.0827***
Panel B: Non-performing loan rates (large banks)									
Non-real estate loans	0.0021	0.0025	-0.0005	0.0039**	0.0098*	0.0059	-0.0018	0.0106***	0.0122***
Traditional home mortgages	0.0036*	0.0004	0.0037	0.0137***	0.0470***	0.0784***	0.0373	0.0253***	0.0195***
Home equity loans	-0.0003	0.0002	0.0009	0.0081**	0.0204**	0.0448**	0.0108***	.	.
Non-household RE loans	-0.0012	-0.001	0.0034	0.0270***	0.0826***	0.1244***	0.1160***	0.1896***	0.1651***
Panel C: Unrealized gains (small banks)									
Non-MBS securities	-0.0016**	0.0004	-0.0007	-0.0100***	-0.0143***	-0.0113***	-0.0157***	-0.0233***	-0.0109
Agency MBS	-0.0005	-0.0002	-0.0004	-0.0011	-0.0039***	-0.0057***	-0.0028	-0.0097***	-0.0148***
Private-label MBS	0.0038	0.0046	0.0041	-0.008	-0.0582***	-0.0215	-0.0257	.	.
Panel D: Unrealized gains (large banks)									
Non-MBS securities	-0.0028	-0.0050*	-0.0029	-0.0112	-0.0221	-0.0445***	-0.0444***	-0.0265***	-0.0176***
Agency MBS	0.0009	-0.0015	-0.0011	-0.0012	-0.0085***	-0.0217***	-0.0274***	-0.0030*	-0.0088***
Private-label MBS	0.0095	0.0167*	0.0095	0.0402**	-0.0008	0.0263	0.0357	.	.