EUROPEAN CENTRAL BANK
EUROSYSTEM

Working Paper Series

Adonis Antoniades

Commercial bank failures during the Great Recession:

the real (estate) story

Macroprudential Research Network

No 1779 / April 2015

Macroprudential Research Network
This paper presents research conducted within the Macroprudential Research Network (MaRs). The network is composed of economists from the European System of Central Banks (ESCB), i.e. the national central banks of the 27 European Union (EU) Member States and the European Central Bank. The objective of MaRs is to develop core conceptual frameworks, models and/or tools supporting macro-prudential supervision in the EU.
The research is carried out in three work streams: 1) Macro-financial models linking financial stability and the performance of the economy; 2) Early warning systems and systemic risk indicators; 3) Assessing contagion risks.
MaRs is chaired by Philipp Hartmann (ECB). Paolo Angelini (Banca d'Italia), Laurent Clerc (Banque de France), Carsten Detken (ECB), Simone Manganelli (ECB) and Katerina Šmídková (Czech National Bank) are workstream coordinators. Javier Suarez (Center for Monetary and Financial Studies) and Hans Degryse (Katholieke Universiteit Leuven and Tilburg University) act as external consultants. Fiorella De Fiore (ECB) and Kalin Nikolov (ECB) share responsibility for the MaRs Secretariat.
The refereeing process of this paper has been coordinated by a team composed of Gerhard Rünstler, Kalin Nikolov and Bernd Schwaab (all ECB).
The paper is released in order to make the research of MaRs generally available, in preliminary form, to encourage comments and suggestions prior to final publication. The views expressed in the paper are the ones of the author(s) and do not necessarily reflect those of the ECB or of the ESCB.

Acknowledgements
A signicant portion of the project was completed while the author was Economist at the Financial Research Division of the European Central Bank. I thank Charles Calomiris, Pierre-André Chiappori, Stijn Claessens, Giovanni Dell'Ariccia, Hans Degryse, Luc Laeven, Simone Manganelli, Maria Soledad Martinez Peria, Perry Mehrling, Alexander Popov, Ricardo Reis, Bernard Salanié, seminar participants at the European Central Bank and the International Monetary Fund, and an anonymous referee for helpful comments. The views expressed in this paper are those of the author and do not necessarily reflect the views of the BIS, the Eurosystem, or the ECB.

Adonis Antoniades
Bank for International Settlements; e-mail: adonis.antoniades@bis.org

Postal address	60640 Frankfurt am Main, Germany
Telephone	+49 69 1344 0
Internet	www.ecb.europa.eu

ISSN	1725-2806 (online)
ISBN	978-92-899-1592-2
DOI	10.2866/162423
EU catalogue number	QB-AR-15-019-EN-N

Abstract

The primary driver of commercial bank failures during the Great Recession was exposure to the real estate sector, not aggregate funding strains. The main "toxic" exposure was credit to non-household real estate borrowers, not traditional home mortgages or agency-issued MBS. Private-label MBS contributed to the failure of large banks only. Failed banks skewed their portfolios towards product categories that performed poorly on aggregate, and within each category invested in assets of lower quality than survivor banks did. They expanded more rapidly into real estate during the pre-crisis period, but rapid growth alone cannot explain differences in asset performance.

JEL classification: G21, G28
Keywords: bank failures, Great Recession, real estate, mortgage-backed securities, credit lines

Non-technical summary

This paper sets out to identify the major drivers of commercial bank failures in the United States during the Great Recession. Aggregate funding pressures in the banking sector during 2007-2008 have been widely discussed in the literature as a precipitating cause of the crisis and have been directly connected to the failure of some large broker-dealers. Although funding pressures may have indeed exacerbated strains on the profitability of financial institutions, the majority of commercial bank failures took place after 2008, that is during a period by which funding pressures in the banking sector had completely abated. The timing of these failures suggests that the primary cause of failure for commercial banks cannot have been illiquidity due to aggregate shocks in the markets for wholesale funds.

I argue that commercial bank failures can be explained by the deterioration of conditions in the real estate sector, a process which started as early as 2006 and lasted well after the funding crisis ended. I identify three sources of bank exposure to the real estate sector, which operate through its (a) illiquid assets, (b) marketable securities, and (c) off-balance sheet credit line portfolios, and ask whether pre-crisis choices which shifted the balance of each portfolio towards real estate products increased the probability of bank failure during the Great Recession.

I find that accumulation of real estate risk was a strong contributor to failure for all banks, but more so for large banks. In particular, accounting for pre-crisis exposures to real estate increases the fit of a baseline model of failure by approximately 50% for small banks (Assets<\$1 billion) and by 150% for large banks (Assets> \$1 billion).

I find no evidence that holdings of traditional home mortgage loans or of agency-issued MBS contributed more to bank failures than exposures to non-real estate loans and non-MBS securities did. The estimates indicate that the primary drivers of failure were exposure to loans and commitments issued to non-household real estate borrowers. Exposure to private-label MBS (the securitization vehicle for subprime loans) increased the probability of failure for large banks only.

I perform further tests to assess whether the composition of a bank's sources of income is a more relevant predictor of failure than its exposure to real estate products, and find that it is not. The results are robust to accounting for the co-determination of the product mix and locational mix by banks, to an alternative definition of bank failure which includes all banks that received government assistance in the form of capital injections through the Troubled Asset Relief Program (TARP), and to the exclusion of banks deemed too big to fail.

The question remains of how it is that the identified toxic pre-crisis exposures influenced the financial health of banks and led to subsequent failure during the crisis. To answer this, I track the performance of loans and securities moving through the crisis and find that (a) failed banks invested more heavily in real estate products that performed uniformly poorly across both failed and survivor banks during the crisis (systematic component), and (b) within each of the potentially toxic product categories failed banks invested in assets of lower quality than survivor banks did (idiosyncratic component).

The portfolio effects discussed above rely on a snapshot of the business model with which banks entered the crisis, and I perform further tests to examine how this model evolved during the buildup to the crisis. During this period, both failed and survivor banks moved towards a more real estate-focused business model, but there is no evidence of an increase in on-balance sheet exposure to either traditional home mortgages or agency-issued MBS. Failed banks built their exposure to real estate products at a more rapid pace than survivor banks did, but I find that rapid expansion alone cannot explain the within-category differences in asset performance observed during the crisis.

I. Introduction

The recent financial crisis was marked by a number of failures of large financial institutions.[1] The stresses that led to the failure of financial institutions during the peak of the crisis in 2007-2008 have been discussed extensively in the press and generated a number of scholarly articles,[2] with the commentary regarding bank risk and failure during this episode to a large extent being informed by the experience of brokers-dealers.

The wave of commercial bank failures that immediately followed the main events of the crisis received less attention. The FDIC reported 492 bank failures from January 1, 2005 to December 31, 2013. Although the rapid deterioration in funding conditions in the markets for wholesale funds has been identified as one of the precipitating causes of the crisis (Gorton and Metrick (2012)) and has been tied to the rapid deleveraging of brokers-dealers (Adrian and Shin (2009)), the majority of commercial bank failures during this episode (462 failures) took place after 2008, in a period during which aggregate funding pressures in the banking sector had abated. As Cole and White (2012) discuss, the risk-determinants for commercial banks during the Great Recession were much different than those for broker-dealers, and in this paper I build on Cole and White (2012) to provide further evidence in support of this thesis.

Bank failures result in the loss of non-transferable components of charter value, such as profitable lending opportunities, the presence of which can countervail the moral hazard problems created by the deposit insurance system (Demsetz, Saidenberg and Strahan (1996), Keeley (1990)). Failing banks may impose externalities on competitors within the relevant market for deposits, in the form of increased funding costs (Acharya and Mora (2012)), and can also have an adverse effect on real economic activity (Ashcraft (2005)).

Even in the absence of actual failure, the banks' response to distress can directly affect the real economy through the bank credit channel. Studying the Great Depression Calomiris and Mason (2003) show that variation in credit supply due to bank distress can explain income growth and activity in the construction sector in 1931-1932. Cornett et al. (2011) show that during the financial crisis of 2007-2008 liquidity risk led to a significant contraction of credit. And as Peek and Rosengren (2000) show, with the globalization of banking the bank channel is no longer local but can operate across borders and affect the real economy in

[1] New Century Financial Corporation filed for bankruptcy in April 2007, Countrywide Financial Corporation warned of financial difficulties in July 2007 and was acquired by Bank of America in June 2008, Bear Stearns liquidated two MBS hedge funds in July 2007 and was acquired by JPMorgan Chase & Co in March 2008, and September 2008 was the epicenter of the crisis with Fannie Mae and Freddie Mac placed in government conservatorship, Lehman Brothers and Washington Mutual filing for bankruptcy, and AIG bailed out by the Federal Reserve Bank of New York. The Federal Reserve Bank of St. Louis provides a detailed description of the timeline of the crisis at http://timeline.stlouisfed.org/index.cfm?p=timeline

[2] See for example, Ivashina and Scharfstein (2010), Gorton and Metrick (2012), Reinhart (2011), Johnson and Mamun (2012), Brunnermeier (2009)

countries other than the one in which bank risk originated.

Given the negative consequences of excessive risk-taking in the banking sector, it is important for policy-makers to understand which particular choices made by banks, as reflected in their business model, increase bank risk and raise the probability of failure. Recent studies have examined bank performance during the financial crisis of 2007-2008,[3] but with the exception of Cole and White (2012) these studies do not consider bank failure as the performance metric and do not attempt to attribute variation in bank performance to granular differences in the composition of the banks' various portfolios (the product mix).

Composition effects are important. We know, for example, that during the Great Recession the real estate sector experienced severe stresses. Empirical models that aim at examining the determinants of bank failure during this episode should therefore account for the specific channels through which stresses in the real estate sector may have transmitted onto the banks' balance sheets and contributed to bank distress and eventual failure; this paper makes progress on this front.

I examine a pre-crisis snapshot of the banks' business model, and identify three possible channels through which stresses in the real estate sector could have transmitted onto bank balance sheets. These channels operate through the composition of a bank's (1) illiquid assets portfolio, (2) marketable securities portfolio, and (3) off-balance sheet portfolio of credit lines. For each of these portfolios, I consider how pre-crisis choices which shifted the composition of the portfolio towards real-estate products impacted the probability of bank failure during the Great Recession.

I first ask whether portfolio composition holds relevance in predicting the probability of failure, and find that accumulation of real estate risk was a strong contributor to failure for all banks but more so for large banks. Pseudo-R2 measures of fit indicate that accounting for the compositions of banks' product mix into real estate products improves the fit of a baseline model by an approximate 50% for small banks (assets less that $1 billion) and 150% for large banks (assets greater than $1 billion).

Contrary to what the commentary surrounding the crisis would suggest, I find no evidence that commercial banks which held more of their illiquid assets in traditional home mortgage loans, rather than in non-real estate loans, experienced a higher probability of failure. This result should not be interpreted as stating that the mass of defaults on traditional home mortgage loans did not pose problems to financial intermediaries. Rather, the result suggests that *commercial banks* were successful at offloading part of home mortgage risk to other financial intermediaries and at adequately provisioning capital for the residual risk that was kept

[3]See for example, Berger and Bouwman (2013), Beltratti and Stulz (2012), Fahlenbrach, Prilmeier and Stulz (2012), Cole and White (2012).

on balance sheet.

In terms of loan exposures that did contribute to bank failure, I confirm the results of Cole and White (2012) and find that it was banks which placed a greater emphasis on other non-household real estate loans (such as commercial real estate and land development projects), and on loans for investment-type purchases of multifamily properties that were more likely to fail during the crisis. I also find that home equity loans were a precipitating factor in bank failures, but this result is more difficult to interpret due to the fact that home equity loans are substitutes for a range of credit products (small business, student, consumer loans, etc...) and their performance is subject to a wider array of influences than just the performance of the real estate sector.

I also examine whether a high concentration of MBS in a bank's portfolio of marketable securities contributed to bank risk. I find no evidence that holdings of agency-issued MBS impacted the probability of bank failure more severely than holdings of non-MBS securities. I do find, however, that holdings of private-label MBS –the securitization instrument for subprime mortgages– contributed to the probability of failure of large banks. The survival of small banks was not impacted by holdings of private-label MBS possibly due to their very low levels of exposure to this asset category.

The absence of a link between holdings of agency-issued MBS and bank failure can be subject to several interpretations. First, the Federal Reserve's support of the market for agency-issued MBS was successful in stemming the potential significant mark-to-market losses that banks would have had to take on these assets. The timing of the reduction in unrealized losses for agency-issued MBS that banks listed in their books provides support for this hypothesis. Second, it may also be the case that government sponsored enterprise (GSE) rules on conforming loans were successful in securing underlying assets of higher quality than those backing the corresponding issuances led by private parties. Testing this theory is unfortunately not possible with the balance sheet data employed in this paper due to the absence of information on default rates for the underlying assets.

Drawdown risk was significantly raised during the crisis of 2007-2008. Studies have shown that firms drew down their credit lines during the crisis in anticipation of shocks to their liquidity position (Ivashina and Scharfstein (2010), Campello et al. (2011)), and that riskier borrowers tend to utilize a larger portion of their credit lines, especially so during a crisis (Dwyer, Zhang and Zhao (2011)). I find that banks which substituted lines of credit to non-household real estate borrowers –such as for commercial real estate, land development projects, etc...– for lines of credit to non-real estate borrowers were more likely to fail during the crisis. Exposure to home equity lines of credit (henceforth, HELOCs) on the other hand, appears to have reduced the probability of bank failure. This could be due to the active cancellations of HELOCs by banks during the crisis, which limited the banks' exposure to the drawdown risk discussed in Dwyer, Zhang and Zhao (2011).

I perform further tests, in the spirit of DeYoung and Torna (2013), to assess the degree to which the composition of a bank's sources of income (the income mix) is a more relevant predictor of failure than the bank's product mix. I find that accounting for a bank's income mix does not affect the identified relations between a banks' product mix and the probability of bank failure. Importantly, I also find that the income mix carries significantly less explanatory power than the product mix in predicting failure on the horizon examined in this paper. I therefore conclude that the product mix was the dominant mechanism driving bank failures during the Great Recession. The results are robust to the inclusion of location fixed effects to account for the co-determination of the product mix and locational mix by banks,to an alternative definition of bank failure which includes all banks which received government assistance in the form of capital injections through the Troubled Asset Relief Program (TARP), and to the exclusion of banks deemed "too big to fail".

The question still remains of how it is that the identified "toxic" exposures contributed to bank failure. I track the performance of various assets moving through the crisis and find, as one would expect, that real estate loans exhibited higher non-performing loan rates and lower returns than non-real estate loans. Loans to non-household real estate borrowers had the highest non-performing rates. Also in line with expectations, I find that private-label MBS performed worse than the reference portfolio of non-MBS securities.[4] Agency-issued MBS on the other hand performed better than the reference non-MBS portfolio possibly due to the Federal Reserve's support of this market.

The aforementioned differences in performance across asset categories hold for both failed and surviving banks, indicating that stresses in the real estate sector were partly systemic in nature. This raises the possibility that variation in the probability of bank failure could have been driven solely by ex-ante portfolio choices which skewed the composition of each bank portfolio towards asset categories that during the crisis performed uniformly poorly across all banks.

A complementary mechanism would be that *within* each potentially "toxic" asset category there also existed idiosyncratic differences in asset performance between failed and surviving banks; I find support for this view too in the data. The real estate loan portfolios of failed banks exhibited consistently higher average non-performing loan rates than those of surviving banks, and the differences in performance are significant across years, bank size and loan categories. Returns from interest payments indicate that the

[4] I use unrealized mark-to-market gains to asses the performance of securities.

ex-post differences in non-performing loan rates were priced in the right direction by failed banks during the pre-crisis years.[5] Returns, however, were not high enough to compensate for the loss rates that the loan portfolios of failed banks experienced during the crisis.

I also find that for both small and large banks the agency-issued MBS held by failed banks performed worse than those held by survivor banks during the crisis. The direction of the difference runs in the same direction for holdings of private-label MBS but this result is much less robust. This could be driven by strategic misreporting of the fair value of private-label MBS but could also be a statistical artifact due to the small number of commercial banks that held private-label MBS on their balance sheets.

The portfolio effects discussed above rely on a snapshot of the business model with which banks entered the crisis, and I perform further tests to examine how this model evolved during the buildup to the crisis. Comparing the business model in 2005 to the one in 2001, I find that banks uniformly increased their exposure to all real estate products both in their loan and in their credit line portfolios; an important exception is the decrease in exposure to traditional home mortgages. In terms of the securities portfolio, I find that on-balance sheet exposure to MBS remained relatively flat during this period, with the exception of large banks which increased their exposure to private-label MBS.

Failed and survivor banks moved towards this more real-estate-centric business model at different paces, as failed banks increased their exposure to loans for multifamily properties and to both loans and commitments to other non-household real estate borrowers more rapidly than survivor banks did during the buildup to the crisis. I do find, however, that the differences in asset performance within product categories discussed earlier cannot be solely attributed to the rapid expansion of failed banks into the real estate sector. Difference-in-means tests show that the subset of surviving institutions that also expanded rapidly into real estate during the pre-crisis period did not experience the same subpar levels of asset performance as failed banks did during the crisis.

This paper builds on Cole and White (2012) to provide a more refined understanding of the impact of stresses in the real estate sector on commercial bank failures during the Great Recession. I provide a more complete treatment which recasts the question as one about portfolio choice and, where the focus of Cole and White (2012) is on the banks' loan portfolio, I also examine the banks' marketable securities and off-balance sheet credit line portfolios in detail. In addition, I consider and reject a number of alternative hypotheses

[5]The dataset does not contain information on returns for each of the real estate categories separately, but rather contains aggregate returns for real estate assets. Therefore, the analysis cannot determine whether the risk component that was priced was the one due to portfolio allocation choices across product categories or the one due to idiosyncratic differences in risk levels within each product category.

such as the impact of the income mix, the co-determination of the locational and product mixes, and the effect of capital infusions through TARP. Importantly, I track the performance of various assets moving through the crisis and shed light on the specific manner in which portfolio risk materialized on commercial banks' balance sheets. Last, whereas Cole and White (2012) consider bank failures only in 2009, and have to rely on estimated proxies for "would be" failures for later years, I use more complete data which include all bank failures until the end of 2013.

The rest of the paper proceeds as follows: Section II discusses the relevant literature, Section III presents the data sources and outlines the timeline of bank failures and evolution of bank risk moving through the Great Recession. Section IV discusses the identification strategy. Section V presents estimates of the baseline model for bank failure. Section VI augments the model to account for exposures to the real estate sector and examines the potential presence of a size dichotomy in the results. Section VII tests the main results for robustness against a number of alternative specifications. Section VIII tracks the performance of various real estate assets moving through the crisis and identifies the presence of significant variation in performance across both asset categories and banks. Section IX describes changes in the banks' business models during the buildup to the crisis and tests whether differences in asset performance can be attributed to the rapid pace with which failed banks expanded into the real estate sector prior to the crisis; Section X concludes.

II. Literature Review

The paper builds on the extensive literature on the determinants of bank failures during crises, and contributes to the literature by examining the role of real estate in the wave of commercial bank failures during the Great Recession.

The depletion of a bank's capital buffers is the trigger of bank failure and a number of empirical studies have naturally focused on the effect of bank capital on the probability of failure. The New England experience of the early 1990s has shown that even seemingly well-capitalized banks can fail, as capital buffers deteriorate rapidly when banks approach failure (Peek and Rosengren (1997)). In a more recent paper, Berger and Bouwman (2013) exploit an exogenous source of variation in the stock of capital buffers to study the effect of capital on two dimensions of bank performance, probability of survival and market share, and find the effect to vary across banking crises, market crises, and normal times. In particular, capital increases the probability of survival and market share of smaller banks for all three types of crises, but improves the performance of medium and large banks primarily during banking crises. Though these studies advance our understanding of bank capital's primary function as the buffer that stands between bank survival and failure, they do not speak to the root causes of the losses that capital buffers are set to absorb.

Bank failure is normally attributed to excessive risk-taking by banks, and some studies have modeled bank risk as an outcome variable of managerial quality and/or corporate governance. Wheelock and Wilson (2000) show that during the 1984-1993 banking crisis banks with low managerial quality were more likely to fail and less likely to be acquired. Laeven and Levine (2009) use an international sample of banks to study the effect of conflicts of interest between managers and shareholders on risk-taking during the early 2000s. They find that banks with more powerful owners tend to take greater risks and also find the impact of banking regulations to vary with shareholder concentration. Beltratti and Stulz (2012) confirm the findings of Laeven and Levine (2009) for the pre-crisis period, but challenge the view that poor bank governance was a major cause of the crisis by showing that banks with more shareholder-friendly boards performed significantly worse during the crisis. In addition, Fahlenbrach and Stulz (2011) find no evidence that banks with incentive structures which better aligned the interests of shareholders to those of the CEO performed better during the crisis. These studies identify agency-type drivers of bank risk, but, with the exception of Beltratti and Stulz (2012), abstract away from the specific ways in which risk-taking by bank management manifests itself in the choice of business model.

Related research has addressed directly the question of whether certain business models were more prone to distress than others during the financial crisis of 2007-2008. Ratnovski and Huang (2009) examine bank performance on a sample of large OECD banks and show that higher levels of capital adequacy, deposit funding, and asset liquidity were associated with both a lower probability of government intervention and lower stock price declines. Altunbas, Manganelli and Marques-Ibanez (2012) use a sample of listed banks operating in the European Union and the United States, and explore several measures of realized bank risk to show that credit expansion, lower dependence on deposit-funding, larger size, and weaker capital buffers in the run up to the crisis accounted for higher ex-post levels of distress. Fahlenbrach, Prilmeier and Stulz (2012) identify the presence of persistence in bank risk, showing that stock return performance during the 1998 crisis can predict stock return performance and the probability of failure during the Great Recession. The authors also show that reliance on short-term funding, high leverage, and high growth rates are all associated with poor bank performance in both crises. Beltratti and Stulz (2012) examine the determinants of stock return performance across an international sample of banks during the period from July 2007 to December 2008, and find that banks which were more dependent on wholesale funding and held less capital performed poorly during the crisis.

DeYoung and Torna (2013) focus on composition effects, and examine the degree to which the composition of a bank's income sources affected bank distress during the recent financial crisis. They show that for distressed banks the probability of bank failure increased with asset-based nontraditional activities (venture capital, investment banking and asset securitization), but declined with pure fee-based nontraditional activities (securities brokerage and insurance sales). DeYoung and Torna (2013) also show that banks with a substantial amount of asset-based nontraditional activities tended to take more risk on their traditional banking activities.

The Great Recession is strongly associated with the US real estate crisis and recent work has explored the link between real estate stresses and bank distress. Aubuchon and Wheelock (2010) find that both during the 2007-2010 and the 1987-92 episodes, bank failures were concentrated in regions with the largest declines in economic activity (as evident in declines in personal income or gross state product, and in increases in unemployment) and with the most severe stresses in the real estate market (as evident in declines in house prices and increases in delinquency rates). Beltratti and Stulz (2012) find that banks whose returns were more exposed to US real estate exhibited better stock performance during the crisis, but this effect they find to only be present in a subsample of very large banks (assets greater than $50 billion).

Cole and White (2012) is the only study known to the author that identifies the composition of a bank's loan portfolio into real estate products as a relevant predictor of bank failure during the Great Recession.[6] Cole and White (2012) decompose the bank's loan portfolio into various categories of real estate loans and show that exposure to commercial real estate loans, loans for construction and development projects, and multifamily mortgages increased the probability of failure relative to exposure to non-real estate loans. The authors do not find similar effects stemming from holdings of traditional mortgages or MBS, though the absence of an effect for MBS holdings is likely a result of their model not explicitly accounting for holdings of MBS.[7]

III. Data Sources and Timeline of Failures

I obtain financial data for commercial banks from the Reports of Condition and Income (*Call Reports*) made available online in summary form by the Federal Reserve Bank of Chicago. The reports cover all commercial

[6] Cole and Fenn (2008) examine the effect of portfolio choices on bank failure during the 1985-92 crisis.

[7] The model in Cole and White (2012) accounts for aggregate holdings of marketable securities, but does not have any refinements beyond that level. The authors infer the non-effect of MBS holdings from the lack of a statistically significant coefficient on marketable securities in the subsample of large banks, which, the authors argue, are the banks more likely to have held MBS on their balance sheets.

banks and contain detailed financial information in a number of different schedules (balance sheet, income statement, securities holdings, etc...). I obtain the list of failed institutions from FDIC and merge the two datasets using the FDIC certificate number as the key identifier.

The FDIC reported 492 bank failures during the period January 1, 2005 to December 31, 2013. When I merge with the 2005 call reports, I have 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 drop small banks with average assets in 2004 less than $50 million, and have 5,802 banks (323 failed), and then drop banks that entered the sample after 2004, and have 5,634 banks remaining in the sample (301 failed). Last, I drop banks that exited the sample before Dec 31, 2013 without being reported as bank failures by the FDIC (possibly due to mergers, parent BHC failure, or changes in reporting requirements) and I am left with a final sample of 4,320 banks of which 301 failed between January 1, 2005 and December 31, 2013.

A. Timeline of Bank Failures

Figure I shows the number of bank failures per quarter for the period January 1, 2005 to December 31, 2013. A total of 301 commercial banks in the sample failed during this period. The first bank failure in the sample occurred in the last quarter of 2007.[8] The rate of bank failures per quarter picked up steam in 2009 and reached a high of 32 banks failing during the third quarter of that year (up from 16 during the second quarter). The number of failures gradually declined past that point, and by the fourth quarter of 2013 it had dropped down to two failures.

[Figure I about here]

B. Evolution of Default Risk

The deterioration of funding conditions in the markets for wholesale funds has been identified as one of the precipitating causes of the crisis,[9] but the timeline of commercial bank failures shown above exhibits a significant lag with respect to the time-series variation in aggregate funding conditions, as proxied for

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

[9]See for example Gorton and Metrick (2012)

example by the TED spread (shown in II). That the mass of bank failures takes place in a period during which funding pressures in the banking sector had completely abated, suggests that commercial bank failures during this episode cannot be solely explained by the inability of banks to meet short term debt obligations due to deteriorating funding conditions.

[Figure II about here]

To get a better sense for how default risk evolved across the banking sector during the crisis, I examine the time series variation in a measure of default risk, the z-score. The z-score is defined in Equation 1, where μ_{ROA} is the mean of the distribution of asset returns ($\tilde{ROA}$), CAR is total equity capital divided by total assets, and σ_{ROA} is the standard deviation of asset returns. A state of insolvency results when $\tilde{ROA} + CAR < 0$. If profits (and hence $\tilde{ROA}$) are normally distributed then the z-score is inversely related to the probability of insolvency (Roy (1952)). Banks with higher z-scores are therefore further removed from a state of insolvency.

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

In Figure III, I plot the yearly evolution of the z-score separately for the groups of failed and survivor banks through to the end of 2013. For each year, I plot the median z-score for all quarters for all banks in each group.[10] Failed banks enter the crisis with a lower median z-score than survivor banks. The median z-score of failed banks increases until 2007 but drops significantly in 2008. As expected, the downward trend in the median z-score of failed banks continues at an accelerating pace through to 2013.

Additional insights are obtained from observing the variation in the z-score for survivor banks. For these banks we first observe a small decline in the z-score in 2008, followed by a steeper drop in 2009. The declining trend continues through to 2011 – that is during a period where funding conditions had already returned to their pre-crisis levels– and starts reversing in 2012. The path of the z-score for survivor banks suggests that bank failures were not solely driven by mechanisms idiosyncratic to the failed institutions, but were at least partly due to systemic stresses that also affected institutions that survived the crisis.

[Figure III about here]

To further understand what the main determinants of the time-series variation in the z-score were during this period, I plot the evolution of CAR and ROA in Figures IV and V respectively. I plot ROA instead of

[10] I aggregate over the four quarters to avoid over-interpreting variation in the z-score due to seasonal variation in ROA. I plot the median instead of the mean because the z-score is highly skewed. The observed time trends remain unchanged if I plot the natural logarithm of the z-score instead.

μ_{ROA} as it tracks more closely the shocks in profitability that banks experienced moving through the crisis. For completeness, in Figure V I also show a plot of the evolution of σ_{ROA} but do not comment further on it because during this period volatility in ROA very closely tracks the time-series variation in ROA.

Failed banks enter the crisis with lower median capital buffers than survivor banks. The size of the capital buffers is increasing for both groups until 2007. The capital buffers of failed banks experience the first losses in 2008, whereas those of survivor banks continue to gradually increase in size through the crisis. The path of ROA on the other hand, shows that for both failed and survivor banks declines in profitability began as early as 2007, though the declines were more pronounced for failed banks. These early declines in profitability were likely due to a combination of rising funding costs[11] and increasing rates of non-performing loans. Failed banks experience another steep decline in profitability in 2009, with large and negative returns persisting through to 2013, suggesting that non-performing loans may be the more prevalent explanation for losses past 2008. Profitability started recovering in 2010 for surviving banks and in 2011 for failed banks, though the latter observation may be a result of sample attrition.

[Figures IV-VI about here]

IV. Identification Strategy

The z-score is a good proxy for bank risk, but has certain limitations. One is that at a certain distance from failure the z-score may be only weakly correlated with the probability of bank failure.[12]. Furthermore, variation in the z-score (or its constituent components) does not offer insights into what the underlying causes of shifts in bank risk may be; understanding what these mechanisms are is fundamental to microprudential regulation.

A commercial bank can broadly be viewed as consisting in three portfolios: (a) assets, (b) liabilities, and (c) an off-balance sheet portfolio of credit lines. The performance of these three portfolios determines variation in the bank's equity capital through its impact on profitability. Equity capital reflects the net book

[11] In its early stages, the crisis manifested as a liquidity crisis which raised the funding costs of banks, particularly those depending more heavily on wholesale funding. In addition, Acharya and Mora (2012) show that during the crisis failing banks scrambling for liquidity sought to attract deposits by raising their rates. This put funding pressures on healthy banks which reacted by raising their deposit rates too.

[12] In my sample the correlation between the failure dummy and the z-score in 2005 is very low at approximately -0.10

worth of the bank, and as a stock variable it can be thought to obey the law of motion shown in Equation 2:

$$\begin{aligned} Capital_{it+1} = Capital_{it} &+ \sum_{a} (Asset_{ait} \cdot R^{asset}_{ait}) + \sum_{l} (Liability_{lit} \cdot R^{liability}_{lit}) \\ &+ \sum_{f} (Off_{fit} \cdot R^{off}_{fit}) + \sum_{x} (Other_{xit} \cdot R^{other}_{xit}) + \epsilon_{it} \end{aligned} \tag{2}$$

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 to capital due to the performance of each asset, liability, and off-balance sheet product, indexed a, l, f, respectively, with levels (stock) denoted by $Asset_{ait}$, $Liability_{lit}$, and Off_{fit}, and corresponding net returns R^{asset}_{ait}, $R^{liability}_{lit}$, and R^{off}_{fit}. I also allow for the possibility that the stock of capital may be affected by other observable factors and unobservable idiosyncratic shocks, denoted by $Other_{xit}$ and ϵ_{it} respectively.

A bank becomes insolvent when its capital buffers are depleted, so we can determine the relative influence of each explanatory variable on the probability of bank failure by estimating 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, $I(.)$ 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, in which the pre-crisis financial condition of the bank determines its capital stock and thereby the probability of failure during the crisis.

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

$$\begin{aligned} W_i = \beta^C \cdot Capital_i &+ \sum_{a} \beta^A_a \cdot Asset_{ai} + \sum_{l} \beta^L_l \cdot Liability_{li} \\ &+ \sum_{f} \beta^F_f \cdot Off_{fi} + \sum_{x} \beta^X_x \cdot Other_{xi} + \kappa + \epsilon_i \end{aligned} \tag{4}$$

Banks actively manage their business model in response to changing economic and financial conditions, and one can reasonably assume that during the recent financial crisis, such active management was at least partly driven by each bank's internal assessment of its probability of default. Using contemporaneous financial variables to fit a model of bank failure during the crisis would thus introduce endogeneity bias to the estimates.[13] To address this source of endogeneity, I focus on a pre-crisis snapshot of the banks' business models and ask whether cross-sectional differences in business models can explain the probability of failure

[13]This source of endogeneity can be exacerbated by the inclusion of bank fixed effects.

during the crisis.

I choose 2005 as the pre-crisis year and make this choice based on two identifying assumptions. First, in 2005 banks did not anticipate the severe shocks that the banking sector would experience during the financial crisis,[14] and the business models observed in 2005 were not set in response to the banks' internal assessments of their probability of failure *due to the events of the impending crisis.* This is a reasonable assumption to make, as 2005 was followed by one more year of rapid credit expansion, the first aggregate shocks in the real estate and financial sectors were experienced in 2006 and 2007 respectively, and in my sample there were virtually no bank failures until 2008.[15] The second identifying assumption is that 2005 is close enough to the crisis, to ensure that the static 2005 picture is a good proxy for the financial condition and business model in which the banks entered the crisis.

V. Baseline Model

I focus on a key set of financial variables to capture the bank's financial condition and business model. I include standard 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. In addition, I augment the model to include additional indicators of risk identified in the literature on bank failures. Table I provides definitions for the variables used.

To control for capital adequacy I include the bank's equity capital ratio.[16] Thick capital buffers increase a bank's loss-absorbing capacity and are positively correlated with survival during banking crises (Berger and Bouwman (2013)). As Calomiris and Mason (2004) show, however, the presence of large capital buffers may also indicate the accumulation of significant on- and off- balance sheet risk, where the binding capital constraint would be a market rather than a regulatory one; capital could therefore also correlate positively with the probability of failure.

Commercial banks hold the majority of their assets in loans, and losses on a bank's loan portfolio normally constitute the prime cause of bank insolvency. To control for asset quality, I include the ratio of

[14]For each bank, I use the values of control variables averaged over the four quarters of 2005.

[15]At any point in time, banks estimate their own internal models of bank risk and the estimates of these models are fed directly into the decision-making processes of the bank. Though one cannot reasonably argue that the 2005 levels of financial variables were not partly determined in response to the banks' own internal assessments of their probability of failure, it would nonetheless not be controversial to assume that these models did not incorporate information about the impending crisis.

[16]The results reported throughout the paper remain unchanged if I include the equity capital to risk-weighted assets ratio or the Tier 1 leverage ratio instead.

non-performing loans to total loans.[17]

I proxy for managerial quality by including the bank efficiency ratio, which measures the bank's ability to turn resources into income. The ratio decreases in the presence of unproductive overhead, but could also decrease due to higher expenditures reflecting the more customer-centric business model employed in relationship lending. The direction of the effect of this variable is thus difficult to predict on a priori grounds.

To control for earnings, I include the return on average assets. More profitable banks are better placed to absorb losses on equity, by rebuilding their equity buffers from retained earnings, and are thus expected to have a lower probability of failure. On the other hand, during the upswing of the cycle high asset returns may also reflect excess risk, and may thus be associated with a higher probability of failure during the downturn.

The last CAMEL indicator is asset liquidity. Banks with high asset liquidity are better positioned to absorb negative liquidity shocks, such as the ones experienced during the recent financial crisis, and high asset liquidity should thus be associated with a lower probability of default. Though it is common practice in the literature to include a single ratio of total liquid assets over assets as the sole measure of asset liquidity, I choose cash holdings as the omitted category and decompose the asset structure of the bank into three remaining categories: holdings of money market instruments, holdings of marketable securities, and other illiquid assets.[18] These three asset categories have different levels of both asset liquidity and asset risk, and their coefficients should be interpreted relative to the base effect of the omitted category of holdings of cash, which is the most liquid and least risky asset.

I augment the model with four additional control variables that could affect bank risk. First, I include a dummy variable indicating whether the bank is member of a bank holding company (BHC). Members of a BHC can draw on internal capital markets to dumpen the impact of financial shocks (as in Campello (2002) for example) and ceteris paribus should be more likely to survive a crisis. The second variable is the natural logarithm of total assets. Size can proxy for a number of unobservables, such as opacity and "too big to fail" effects, and though it is not clear on a priori grounds in which direction the net effect of asset size should be, I nonetheless include size as a possibly significant determinant of bank failure.

The third variable is the ratio of core deposits to total assets, which captures the extent to which a bank is funded with stable sources of funds. As argued earlier, the timing of bank failures suggests that aggregate funding shocks cannot have been the primary cause of commercial bank failures. On metrics other than

[17] Following Campello (2002), I define non-performing loans as loans past due 90 days or more and still accruing plus loans not accruing. This definition reduces the effect of managerial discretion in reporting losses.

[18] The results presented throughout remain virtually unchanged if I include an additional category for trading assets or if I include trading assets in the marketable securities category.

actual failure, however, a number of studies have shown that banks with more stable funding structures performed better during the crisis (Ratnovski and Huang (2009), Beltratti and Stulz (2012), Fahlenbrach, Prilmeier and Stulz (2012)) so I include the funding structure of the bank as a contributing factor to bank performance during the crisis.

Last, I include the ratio of unused lines of credit to total assets to capture the effect of drawdown risk on the probability of failure.[19] Ivashina and Scharfstein (2010) show that rapid take-down demand after the collapse of Lehman Brothers had an adverse effect on the liquidity position of banks that participated in loan syndicates with Lehman. In addition, 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. Drawdown risk can thus be directly related to default risk.

A. Summary Statistics and Difference-in-Means Tests

Panel (a) of Table II displays summary statistics for the 2005 levels of the explanatory variables used in the baseline model, averaged over four quarters. All variables are winsorized at the 1% and 99% levels.

The distribution of asset size is skewed to the right, with the median asset size at $155 mil but the mean asset size much higher at $1.6 bil. 19% of the banks are members of a BHC. The average ROAA is 1.2%. The average bank efficiency ratio is 1.66, indicating that for each $1 in non-interest expense the average bank generates $1.66 of total non interest and net interest income. On average, during the pre-crisis period only a very low percentage (0.6%) of the banks' loans were non-performing.

The average bank is funded by a combination of 10% equity capital, 67% core deposits; the remaining 23% represents less stable sources of funds. These figures indicate that on average the funding structure of a commercial bank is far more stable than that of a broker-dealer. Regarding asset composition, the average commercial bank holds 4% of its assets in cash, 3.0% in money market instruments (reverse repo and federal funds sold), 23% in marketable securities, and 70% in other illiquid assets. Last, for every $1 of assets held on the balance sheet, banks on average hold $0.12 of off-balance sheet exposure to unused lines of credit.[20]

To test for differences in means between the groups of failed and survivor banks, I perform a series of univariate comparisons and the results are shown in Panel (b) of Table II. The average survivor bank is an order of magnitude larger than the average failed bank and 5% more likely to be a member of a BHC. Failed

[19] I exclude commitments associated with credit cards from the aggregate measure of credit lines, to avoid skewing the distribution of the variable towards the few large credit card issuers in the sample.

[20] Excluding credit card commitments.

banks have a higher efficiency ratio but are not significantly different in profitability from survivor banks. Survivor banks enter the crisis with a slightly higher rate of non-performing loans, but are better-capitalized by 0.7% and obtain 7% more of their funds from stable, core-deposit funding. Survivor banks are also more liquid. They hold 0.7% more of their assets in cash, 10% in marketable securities, 0.4% less in money market instruments, and 10% less in illiquid assets. These ratios suggest that one important difference in the asset structure of survivor and failed banks is the extent to which they substitute marketable securities for illiquid assets. Last, survivor banks are 7% less exposed to credit lines and, interestingly.

[Table II about here]

B. Probit Estimates

To identify the independent effect of each variable on the probability of failure, I estimate the binary probit model described earlier and shown in Equation 3. The results are shown in column (1) of Table III, where the reported coefficients are average marginal effects (AMEs) and are interpreted as the increase in the average probability of failure for a unit increase in the corresponding covariate.[21]

Larger banks are less likely to fail and, as expected, so are banks with BHC membership. More profitable banks have a lower probability of failure, but more efficient banks are more likely to default. These two variables may be reflecting choices regarding the bank's product mix, a possibility which I will explore in the next section, and interpretation of their coefficients should thus be treated with caution.

Banks that were funded more by equity capital and core deposits had a lower probability of failure. On asset composition, substituting holdings of money market instruments, marketable securities and illiquid assets for cash all result in a higher probability of failure, though this effect is not statistically significant for holdings of marketable securities. Last, off-balance sheet exposure to credit lines results in a higher probability of failure during the crisis.

High levels of non-performing loans in 2005 are not positively related to the probability of failure. There can be two explanations for this result. The first, and more likely explanation, is that the levels of non-performing loans in 2005 do not reflect the *unanticipated* surge in losses that banks experienced during the crisis. A second explanation could involve strategic (under)reporting of loan losses by banks, though this mechanism is more likely to have gained in significance during the recession, when the true extent of the

[21] Average marginal effects (AMEs) are different from the often-used marginal effects at the means (MEMs). The MEM estimator imposes a linear approximation of the probit model around a single point representing an arbitrary "average" bank, and thus ignores the distribution of risk along the probit curve; the AME estimator, however, fully incorporates this information.

losses started becoming more clear to the banks.

[Table III about here]

VI. The Real Estate Story

One of the characteristics of the financial crisis of 2007-2008 is the severe stresses experienced in the markets for wholesale funds. As discussed in Section III, however, funding pressures in the banking sector had almost completely abated by the time commercial banks started experiencing the bulk of their losses and we witnessed the mass of bank failures.

A longer-lasting shock came in the collapse of real estate prices. For example, Figure VII shows the S&P/Case-Shiller U.S. National Home Price Index, which measures shifts in the total value of all existing single-family housing stock in the US. The index clearly demonstrates that unlike the recovery in funding conditions, the steep declines in housing prices during 2007 and 2008 did not reverse until much later in 2012-2013, and even then housing prices remained significantly below pre-crisis levels.

[Figure VII about here]

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 three groups of variables that capture the composition of a bank's three portfolios of (1) illiquid assets, (2) marketable securities, and (3) off-balance sheet credit lines into real estate products. I posit that pre-crisis choices that increased the exposure of each of these portfolios to real estate increased the probability of bank failure.

One approach to incorporating information about portfolio choice into the baseline model, would be to decompose, in the simplest case for example, the ratio of illiquid assets into two ratios (a) the ratio of illiquid assets *not invested in real estate loans* and (b) the ratio of illiquid assets *invested in various categories of real estate loans*. This particular formulation would effectively cast the question of portfolio allocation as one concerning the choice between the omitted asset category of cash and real estate loans (or non-real estate loans). Estimating this model would thus identify some rather trivial relations between asset risk and the probability of failure –i.e. entering the crisis having invested more of a bank's assets in real estate loans rather than in cash increases the probability of failure.

In reference to the example above, a more relevant formulation is one that casts the question of portfolio choice as one between holdings of real estate loans and holdings of other non-real estate loans. Banks do of course choose the composition of their assets into liquid and illiquid ones based on a number of considerations, such as for example liquidity risk, but one can think of the next margin of adjustment as taking place internally within each portfolio.

To identify such substitution effects, I augment the baseline model with ratios that capture the degree of exposure to various real estate products within the three portfolios of interest, while at the same time retaining the ratios of total illiquid assets, total marketable securities, and total unused lines of credit to total assets in the list of control variables. From an interpretation standpoint, under this specification the coefficients of the variables that capture real estate exposures identify the incremental effect of such exposures on the probability of bank failure relative to the baseline effect of non-real estate exposures within each of the corresponding portfolios. The coefficient for traditional home mortgage loans, for example, would answer the question of "how would the marginal probability of failure change if a bank substituted traditional home mortgage loans for non-real estate loans in its illiquid assets portfolio?".

A. Portfolio Decomposition into Real Estate Products

Banks hold a significant portion of their illiquid assets in loans, and a high portion of loans is normally invested in real estate. To identify the effect of real estate exposures on the probability of failure, I augment the baseline model with the ratios to total assets of loans in four real estate categories: (1) traditional home mortgages, (2) home equity loans, (3) loans secured by multifamily residential properties, and (4) other real estate loans to non-household borrowers. Each of the estimated coefficients will identify the impact on the marginal probability of failure of substituting one unit of the particular category of real estate loan for one unit of a non-real estate illiquid asset.[22]

Part of the commentary surrounding the crisis has revolved around traditional home mortgages. The basic storyline involves mortgage borrowers who, carried away by rapidly rising home prices, overextended themselves and assumed loan obligations on which they would consequently default during the downturn of the economy. The first ratio thus tests whether exposure to traditional home mortgages contributed to bank failures during the crisis.

A home-equity loan is collateralized by the equity that the borrower holds on his property, and its default risk is also tied to price fluctuations in the housing market. These loans, however, are used as substitutes for a wide array of credit products, such as consumer loans and small business loans, and the mechanisms

[22]For example, if the estimated coefficient on traditional home mortgages is β then this should be read as "shifting 1% of assets from non-real estate illiquid assets into traditional home mortgages will increase the probability of failure by β%".

governing their performance are rather more involved than those for traditional home mortgages.

The last two categories represent real estate loans to *non-household borrowers*. Loans secured by multifamily residential properties are not traditional mortgage loans, but rather commercial loans representing investments in larger residential properties, and their risk-level is assessed along dimensions such as rental income potential, experience in managing multifamily properties, etc... The ratio of non-household real estate loans to total assets examines whether loans in other non-household real estate loan categories –such as loans for commercial real estate, construction or land development projects– impacted the probability of bank failure. Both of these categories of real estate represent higher-risk loans, which have been shown to have a detrimental effect on bank health during crises (Cole and Fenn (2008), Cole and White (2012)).

Choices regarding a bank's portfolio of marketable securities may have also impacted bank health during the crisis. Entering the recent financial crisis *brokers-dealers* held a significant portion of their assets in mortgage-backed securities (MBS), and subsequently experienced severe liquidity spirals of market and funding illiquidity (as in Brunnermeier and Pedersen (2009)), which in some instances led to insolvency.[23] It is thus reasonable to ask whether holdings of MBS was a contributing factor to the failure of commercial banks too.

To control for the composition of the bank's portfolio of marketable securities, I include the ratios of agency-issued and private-label MBS to total assets. Agency-issued MBS are issued or guaranteed by government-sponsored enterprises, such as Ginnie Mae, Fannie Mae or Freddie Mac, and must conform to a set of criteria that are put in place to cup the risk-profile of the underlying mortgages. Private-label MBS on the other hand, are issued by private parties, are subject to less stringent underwriting requirements, and are therefore more likely to serve as the securitization vehicle for higher-risk assets (e.g. subprime mortgage loans).

The last source of exposure I consider is off-balance sheet exposure from unused lines of credit. During the period of the crisis, the drawdown risks identified in Dwyer, Zhang and Zhao (2011) should have been particularly pronounced for lines of credit extended to real-estate borrowers. To test this hypothesis, I include the ratios to total assets for two categories of credit lines: credit lines extended to household real estate borrowers (HELOCs) and credit lines extended to other non-household real estate borrowers (commercial real estate, land development projects, etc...). The coefficients for these variables should be interpreted in relation to the base effect of credit lines issued to non-real estate borrowers.

[23] The collapse of Bear Stearns for example.

B. Summary Statistics and Difference-in-Means Tests

Panel (a) of Table IV displays summary statistics for the composition ratios. In 2005, banks held 17% of their assets in non-MBS securities, 6% in agency-issued MBS, and a very small portion of the order of 0.2% in private-label MBS. As the median indicates, in 2005 most commercial banks did not hold any private-label MBS on their balance sheets. Banks also held on average 24% of their assets in non-real estate illiquid assets, 15% in traditional home mortgages, 2% in home equity loans, 1% in loans secured by multifamily residential properties, and 27% in other non-household real estate loans. Regarding off-balance sheet exposures, banks held unused lines of credit to non-real estate borrowers at 6% of total assets, to non-household real estate borrowers at 4% of total assets, and HELOCs at 2%.

Panel (b) of Table IV displays difference-in-means tests for survivor vs failed banks for the real-estate related predictors. Significant differences exist in the means of the distributions of these variables between the two groups. Failed banks hold on average 8% less of their assets in non-MBS securities, 2% less in agency MBS and 0.1% more in private-label MBS, though the latter difference is not statistically significant.[24] Failed banks hold a significantly lower portion of their assets in non-real estate illiquid assets and traditional home mortgages(6% and 4% respectively), they do however invest 0.7% more in home equity loans, 1.3% more in multifamily loans and 18% more in non-household real estate loans. These differences suggest that it is potentially the exposure to real estate loan categories other than traditional home mortgages that might have been one of the driving factors of bank failures during the crisis. Last, failed banks hold less exposure to credit lines to non-real estate borrowers (0.4%), higher exposure to HELOCs (0.3%), and significantly higher exposure to credit lines for non-household real estate projects (6%).

[Table IV about here]

C. Probit Estimates

The difference-in-means tests discussed above suggest that exposure to certain categories of real estate assets 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 5, now augmented to include the portfolio composition variables described above. The results are shown in column (2) of Table III.

There is no substitution effect for holdings of agency-issued MBS but the probability of bank failure

[24]The difference in holdings of private-label MBS should be viewed in the context of most banks having had no exposure to private-label MBS in 2005.

increases significantly with holdings of private-label MBS. From the four real estate loan categories, traditional home mortgages is the only category with a coefficient that is both economically and statistically undifferentiated from 0. All other real estate loan products enter with positive coefficients that are statistically significant at the 1% level. Exposure to lines of credit issued to non-household real estate borrowers increased the probability of bank failure relative to non-real estate lines of credit but, surprisingly, HELOCs decreased the probability of bank failure.

The estimated coefficient for the effect of holdings o traditional home mortgage, should not be read as suggesting that there were no significant losses during the crisis stemming from rising non-performing loan rates in this category. Rather, the results suggest that commercial banks were successful in off-loading part of that particular risk to other types of financial intermediaries, possibly through the securitisation channel, and in provisioning an adequate amount of capital for the residual risk associated with home mortgage loans retained on-balance sheet. Furthermore, the absence of an effect for holdings of agency-issued MBS could be a result of the significant support that this market received through a number of interventions carried out by the Federal Reserve.

The coefficients for both home equity loans and HELOCs should be interpreted with caution. Home equity loans are substitutes for a wide array of loan products (such as small business and student loans) and their performance can also be affected by reasons unrelated to stresses in the real estate sector. Also, during the course of the crisis banks canceled a significant number of HELOCs, thus effectively severing the link between HELOCs and the type of drawdown risk discussed in Dwyer, Zhang and Zhao (2011). Last, the correlation between these two exposures is close to unity and the coefficients cannot be interpreted in isolation from each other. For these reasons, in the remainder of the paper I will abstain from making further inferences based on the estimates for these two coefficients.[25]

D. Size Dichotomy

The literature has traditionally studied differences in bank behavior by dividing banks into different size groups, as size is the dimension most likely to sort out major differences in important unobservables across banks.[26] To test whether the effects of the various real estate exposures on the probability of bank failure apply uniformly across small and large banks, I split the sample by size using a $1 bil threshold applied to

[25]The results presented throughout remain unchanged if I remove exposure to HELOCs from the list of controls and only retain the on-balance sheet exposure to home equity loans (the coefficient of which is undifferentiated from zero for most of the tests).

[26]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.

the average total assets of each bank for 2004.

Table V shows difference-in-means tests for survivor and failed banks for the portfolio decomposition variables, estimated separately for the subsamples of small and large banks. The patterns observed for small banks are very similar to the ones for the complete sample. The patterns are also similar for the subsample of large banks, with a few minor differences. No statistically significant differences exist in holdings of agency MBS or traditional mortgages between failed and survivor banks, though the differences run in the same direction as for small banks. Also, and in contrast to the direction of differences in the subsample of small banks, large failed banks hold a smaller portion of their assets in home equity loans and have smaller off-balance sheet exposures to HELOCs and other non-real estate lines of credit than large survivor banks.

[Table V about here]

Table VI reports the estimated coefficients for the binary probit model, estimated separately over the two subsamples. Columns (1) and (3) show the estimates for the baseline model, respectively for small and large banks, and columns (2) and (4) the estimates for the model which accounts for the banks' portfolio composition into real estate products (the product mix). For both subsamples, the effects are consistent with those obtained over the complete sample, with the exception of the coefficient for private-label MBS holdings which is now statistically not significant for the subsample of small banks. As can be seen in the difference-in-means tests in Table V, this is likely a result of the limited exposure that small banks had to this asset category.[27]

The values of the pseudo-R2 measure of fit for the baseline model, shown at the bottom of columns (1) and (3), indicate that the baseline model holds approximately the same predictive power for both small and large banks. Comparing these baseline values to those for the models that account for the real-estate product mix in columns (3) and (4), we see that controlling for exposures to the real estate sector significantly improves the explanatory power of the model for both groups. Comparing the relative improvements in fit for the two subsamples, however, we see that real estate exposures carry more explanatory power in the model estimated over the sample of large banks (roughly 150% increase in fit) compared to the model estimated over the sample of small banks (roughly 50% increase in fit). Standard caveats regarding the interpretation of pseudo-R2 measures of fit not withstanding, these observations indicate that exposure to the real estate sector had a detrimental role in the bank's ability to survive the crisis.

[27] In unreported regressions, I find that the results over the subsample of large banks remain unchanged if I drop the 10 largest banks to account for the possibility of biases arising from too-big-too-fail considerations.

[Table VI about here]

VII. Robustness

A. Product Mix vs Income Mix

Motivated by DeYoung and Torna (2013) I test whether the income mix of the bank carries explanatory power with regards to the probability of failure.[28] To do so, 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. The variables are defined as in DeYoung and Torna (2013).

Columns (1) and (6) of Table VII show the model with the product mix variables for reference, and Columns (2) and (7) show the estimates for the baseline augmented only with the income-mix ratios. The fit is significantly lower than for the model with real estate exposures. Re-introducing the product-mix variables to this model (columns (3) and (8)) yields significant gains in explanatory power for both subsamples, without affecting the coefficients on the key explanatory variables. These patterns suggest that once one accounts for the product mix that banks entered the crisis with, the income mix does not carry much additional explanatory power in determining the probability of bank failure.

[Table VII about here]

B. Product Mix vs Locational Mix

The results presented thus far document a positive relation between real estate exposures and the probability of bank failure. I test whether this relation holds even after one controls for local economic conditions. The question this test aims at answering is whether a portfolio skewed towards real estate products affected bank failure irrespective of choices regarding the geographical markets banks chose to serve.

I follow the approach of Cornett et al. (2011) and saturate the model with state-level indicator variables, which for a given bank are set to 1 if the bank has one or more branches located in that particular state. I obtain branching information from the FDIC's Summary of Deposits. As Cornett et al. (2011) argue, these indicator variables will work well in sweeping out the effect of local economic conditions for small banks, but would likely fare worse for larger banks, which by relying more on credit-scoring and less on personal relationships with borrowers tend to serve borrowers further removed from the location of their branches.

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

The results are shown in columns (4) and (9) of Table VI. The estimates for the subsample of small banks remain relatively unchanged, except for the coefficient for multifamily properties that now narrowly misses significance at the 10% level while, however, retaining its order of magnitude. For the subsample of large banks, the results remain qualitatively unchanged, but the magnitude of several coefficients increases appreciably and the effect of non-household real estate loans moves closer to zero and loses statistical significance. Given the high demands placed on the estimator due to the high number of fixed effects, the estimates over the two subsamples strongly suggest that the effect of the bank's product mix on the probability of failure cannot be explained solely by the co-determination of product and locational mix.[29]

C. The Impact of TARP

The definition of bank failure used thus far only includes banks which were placed under FDIC receivership. One could hypothesize that government interventions which took place during the crisis distorted the true picture of bank failures, by rescuing banks which would have failed absent government support. Prominent among these interventions was the Troubled Asset Relief Program (TARP) and in particular the Capital Purchase Program (CPP), which was announced as part of TARP and was "launched to stabilize the financial system by providing capital to viable financial institutions of all sizes throughout the nation".[30]

Although it is certainly possible that a number of banks would have failed were it not for capital infusions through CPP, the empirical evidence suggests that on average CPP-participation did not indicate fundamental insolvency. The Treasury's stated policy was to make program participation contingent on the bank's classification ranking, which employed CAMELS ratings and favored institutions with strong fundamentals. Bayazitova and Shivdasani (2012) show that although banks with stronger asset quality did not apply for CPP funds, among the banks that did apply for funds the ones with stronger asset quality were more likely to be approved. In addition, they find no evidence that banks with weaker capital ratios were more likely to be approved. In a similar study, Ng, Vasvari and Wittenberg-Moerman (2011) show that banks which participated in CPP had stronger fundamentals compared to non-CPP participants, and that holds true both for the periods prior to and during the program's initiation.

[29] A limitation of the probit estimator is that it becomes unstable when an indicator variable can perfectly predict success or failure, and in these instances datapoints are dropped to increase stability. For example, if all banks with branches in a particular state survived, then all banks with branches in that state are dropped from the estimation. This attrition mechanism reduces the size of the subsample of large banks appreciably and makes the estimates for this subsample rather unstable, particularly so due to the large number of fixed effects that would still need to be estimated over a small sample size.

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

I nonetheless test whether the bank's product mix remains a relevant predictor of failure if one adopts a broader definition of bank failure that includes CPP-participating institutions as potentially failing banks. I obtain CPP participation data from the U.S. Treasury's CPP transaction report.[31] I define as potentially failing (a) banks which received assistance from the CPP directly, and (b) banks whose parent BHC received assistance from the CPP, and re-estimate the probit models presented in this section using this more broad definition of failure.

The results are shown in columns (5) and (10) and are qualitatively similar to the ones presented in the previous subsections, albeit with some changes in statistical significance and magnitude, likely a result of the extreme redefinition of bank failure in this test. Interestingly, the coefficients suggest a positive link between the probability of failure and exposure to agency-issued MBS and a negative link for holdings of traditional home mortgages. The first finding possibly points to price pressures due to agency-MBS holdings as a driver behind CPP-participation, which was not, however, related to fundamental insolvency.[32]

VIII. Asset Performance

The previous section identified a set of pre-crisis portfolio exposures which increased the probability of bank failure during the crisis. This section aims at understanding how it is that these exposures affected bank health during the crisis. In particular, I propose two mechanisms through which exposure to an asset category may have increased the probability of bank failure.

One mechanism is that failed banks had invested disproportionately more in asset categories whose performance during the crisis was unexpectedly poor *across all banks*. For example, under this hypothesis, loans for the purchase of multifamily properties exhibited unanticipated high default rates during the crisis, and any bank whose ex-ante loan portfolio choices placed a heavier emphasis on this product faced a higher probability of bank failure.

A complementary mechanism is that idiosyncratic factors driving bank lending policies may have generated variation in asset performance between failed and survivor banks, *within* each asset category. According to this mechanism, for example, loans for the purchase of multifamily properties held by failed banks per-

[31] The dataset contains 737 transactions, which 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 due to 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.

[32] Ng, Vasvari and Wittenberg-Moerman (2011) also find that the significantly lower returns for the CPP banks relative to the non-CPP banks can be attributed to negative media coverage which exerted downward pressure on banks' stock returns.

formed significantly worse than those held by survivor banks. In the following subsections I provide empirical evidence for the existence of both of these mechanisms.

A. Non-Performing Real Estate Loans

I first consider the bank's loan portfolio. For each loan category, as a measure of loan performance I use the ratio of non-performing loans to total loans in the particular category. The non-performing loan ratio is a good measure of the extent to which the loan portfolio can contribute to capital losses and thereby to an increase in the probability of failure. I plot quarterly averages of the non-performing loan ratios for the period 2004-2013 for traditional home mortgages, home equity loans, loans for the purchase of multi-family properties, and non-household real estate loans. I also plot the non-performing loan ratio for all other non-real estate loans and leases to serve as the reference category.[33]

The plots are shown in Figure VIII. The top two panels (a-b) display the non-performing loan rates for survivor banks (small-large respectively). The non-performing loan rates are at very low levels before the crisis, across all loan categories, start rising as early as 2007 for some loan categories, and peak during 2010-2011. Large banks have higher non-performing loan rates than smaller banks. Traditional home mortgages, loans for the purchase of multifamily properties and non-household real estate loans, all perform significantly worse than the reference category of non-real estate loans; non-household real estate loans are the worst performer of the group. Home equity loans on the other hand, appear to perform only marginally worse than non-real estate loans. A possible explanation for this observation is that home equity loans have a time-lag in the revelation of strains on the borrower's repayment schedule, because during the crisis a significant portion of home equity loans were still within their draw period.[34]

These observations suggest that investments in at least three of the four real estate loan categories proved ex-post to be significantly more risky than investments in non-real estate loans. The fact that these patterns are present in the subsample of surviving institutions points to the presence of systemic stresses in these product categories.

The plots appear to contradict the earlier finding that on-balance sheet exposure to traditional home mortgages did not affect the probability of bank failure. One possible explanation is that banks with high levels of exposure to traditional home mortgage loans had lower exposure to other more risky real estate

[33]The results remain unchanged if I exclude leases and focus exclusively on non-real estate loans.

[34]During the draw period, the borrowers on home equity loans were making only interest payments and the loans had not moved to a full amortization schedule, the sudden commencement of which would have resulted in a steep increase in non-performing loans. Exposure to home equity loans is an ongoing concern for banks and were repeatedly discussed, for example, in Citigroups's annual reports during and after the crisis.

debt. After all, survivor banks held a higher portion of their illiquid assets in traditional home mortgages than failed banks did, but held lower portions in other risky loan categories. Another explanation could be that adequate capital has been allocated ex-ante to absorb future losses from home mortgage loans.[35]

To examine whether there exists support in the data for the presence of differences in loan performance between survivor and failed banks *within each loan category*, in the bottom two panels I plot non-performing loan rates for failed banks (panels (c) and (d) for small and large banks respectively). On average the real estate loan portfolios of failed banks performed significantly worse than those of survivor banks. These differences started manifesting themselves as early as 2007, and at the peak of the losses non-performing loan rates of failed banks were approximately 3-5 times larger than the corresponding rates of survivor banks. In the subsample of large failed banks these trends become less clear as we move deeper into the crisis, due to a combination of the small sample size and sample attrition by failed banks.

[Figure VIII about here]

The patterns observed in the graphs lend support to the hypothesis that within each real estate loan category, failed banks invested in loans of lower quality than survivor banks did. To test this hypothesis more rigorously, I perform difference-in-means tests for the non-performing loan rates of the four real estate loan categories, as well as for the aggregate reference portfolio of non-real estate loans, for the population of survivor and failed banks for each of the years 2004-2013. The results, shown in Table VIII, support the hypothesis that the real estate loan portfolios of failed banks consistently underperformed those of survivor banks. Interestingly, differences in loan performance are not evident during the pre-crisis period and peak after the epicenter of the financial crisis in 2007-2008. No similar patterns exist for the non-performing loan rates of non-real estate loans that are consistent across time and size categories. This indicates that the differences in loan performance rates between failed and survivor banks cannot be attributed solely to a "random draw" mechanism according to which failed banks just happened to pull loans from the wrong tail of the risk distribution uniformly across all loan categories.

[Table VIII about here]

[35] In this instance one should think of the relevant binding constraint for capital as an internal constraint and not the regulatory one. Losses in any loan category can be thought of as having an anticipated component, for which adequate capital was provided, and an unanticipated one for which capital provisions fell short. Bank failure will be driven by the magnitude of the unanticipated component, which during the crisis could have been lower for traditional home mortgages compared to other loan categories. Unfortunately, the Call Reports do not contain the kind of refined data that would be required to test this theory.

B. Returns on Real Estate Loans

Non-performing loan rates proxy for one aspect of loan performance, that is the rate at which a bank's capital buffers are depleted due to borrowers not servicing their loans. Being investments, however, loans also have a capital-generating function in the form of interest payments on the outstanding principal. To examine whether the returns for real estate loans compensated for their comparatively higher non-performing rates, I plot the rate of return of real estate loans and compare it to the rate of return of non-real estate loans.[36] As can be seen in Figure IX, the returns of real estate loans are consistently lower than the corresponding returns of non-real estate loans. The same differences are also present in 2004-2005, suggesting that during the build-up to the crisis banks did not fully anticipate the comparatively higher rates of non-performance exhibited by real estate loans during the crisis.

[Figure IX about here]

I perform a differences-in-means test for the returns of the real estate loan portfolio of failed and survivor banks, and the results are shown in Table IX. Up until and including 2007, the returns on real estate for failed banks are slightly higher than the returns for survivor banks, indicating that during the pre-crisis period the differences in asset performance observed during the crisis were on average partially priced into loan interest rates. Due to the lack of disaggregated income data on the call reports, one cannot ascertain whether the risk component that was priced was the one due to portfolio allocation choices (i.e. failed banks invested more of their real estate portfolio into high-risk categories such as commercial real estate loans) or the one due to idiosyncratic differences in risk levels within each loan category.

The differences between failed and survivor banks naturally reverse during the crisis, because the returns are taken over the complete stock of loans including non-performing loans.[37] The magnitude of the returns indicates that during the period when non-performing loan rates reached their peak (2010-2011) the returns on the real estate portfolio could support approximately a 6% rate of loan losses; as was shown earlier, the non-performing loan rates of failed banks were much higher during this period.

[Table IX about here]

[36] Unfortunately, the Call Reports do not provide income data that are disaggregated down to the four different real estate loan categories for the period I examine, so the plots show the time series variation for the aggregate return of the real estate loan portfolio.

[37] This was done to achieve consistency in comparing non-performing rates to interest returns for the various assets.

C. MBS Portfolio Performance

I also compare the performance of the two categories of MBS against that of the aggregate non-MBS security portfolio of the banks. For each asset category in the securities portfolio, I measure performance as the ratio of unrealized gains on securities to the amortised cost value of the securities.[38] Unrealized gains (losses) provide a market-based performance metric that can realize in the form of positive (negative) earnings upon selling the securities and thereby impact the capital position of the bank.

One caveat is that during the crisis banks may have been strategically overstating the fair value of their MBS portfolios, either in an attempt to conceal the true extent of potential capital losses, or in response to what they may have perceived as price pressures driven by "irrational" investor sentiment rather than by fundamentals. It is thus likely that the reported unrealized gains of MBS carry a positive bias. This bias should be stronger (a) for private-label MBS the pricing of which, unlike for agency-issued MBS, relied more on private information, (b) for large banks because they had higher exposure to private-label MBS, and (c) for failed banks which, due to the higher rate of depletion of their capital buffers during the crisis, faced a higher marginal cost of truthfully reporting unrealized losses on securities.

The corresponding plots are shown in Figure X. For both small and large survivor banks (panels a and b respectively), private-label MBS clearly underperform the baseline group of non-MBS securities, exhibiting significantly higher unrealized losses during the crisis. Agency-issued MBS on the other hand, outperform the baseline group during the crisis. Though this result may seem counterintuitive, it needs to be viewed against the backdrop of a series of Treasury and Federal Reserve interventions, which aimed at supporting the market for agency-issued MBS during the crisis. The same general patterns are observed in panels (c)-(d) where the plots are reproduced for failed banks. For small failed banks, the performance of private-label MBS declines more sharply than for small survivor banks, but that does not appear to be the case for large banks, possibly due to the reporting biases discussed earlier.

[Figure X about here]

Difference-in-means tests are shown in Table X. There is some evidence for differences in performance for the portfolios of agency-issued MBS and non-MBS securities between failed and survivor banks. Differences in performance for private-label MBS, on the other hand, are less robustly identified. This could be due to the small number of banks with actual holdings of private-label MBS, but could also be due to the reporting biases discussed above.

[38] Unrealized gains is the difference between the fair value and the amortized cost value of the securities.

[Table X about here]

IX. Changes in the Business Model

The probit estimates discussed earlier, indicate that a business model that was skewed towards certain categories of real estate products contributed significantly to the probability of failure during the crisis. A policy-relevant question is whether banks grew into this model during the rapid-growth phase of the real estate sector which preceded the crisis. To answer this question, for each real estate product, I compare the bank's average level of exposure in 2005 to its corresponding levels in 2001, and perform a series of difference-in-means tests to assess how the business model evolved during this period. The results are shown in Table XI, separately for small and large banks.

There is no evidence that banks increased their exposure to agency-issued MBS, but large banks did increase their holdings of private-label MBS during this period. In terms of the illiquid assets portfolio, there was a reduction in the holdings of traditional home mortgages, possibly a result of a highly active securitization channel, and a simultaneous increase in the holdings of all other categories of real estate loans. The banks also increased their off-balance sheet exposure to both HELOCs and to lines of credit to other non-household real estate borrowers. These tests show that banks uniformly moved towards a more real-estate focused product mix, but, with the exception of private-label MBS for large banks, did not do so for the home mortgage products one normally associates with the financial crisis of 2007-2008.

[Table XI about here]

The differences in asset performance between failed and survivor banks discussed in the previous section may not be completely disjoint from differences in the pace at which failed and survivor banks moved into the more real-estate focused business model during the buildup to the crisis. One could posit, for example, that banks which rapidly expanded their holdings of non-household real estate loans were able to do so by relaxing credit standards in this sector. Under this hypothesis, surviving banks which expanded rapidly into non-household real estate loans during the pre-crisis phase should also have experienced high rates of non-performing loans during the crisis.

In Table XII I first test whether failed banks moved towards the real estate business model at a more rapid pace than survivor banks did. Failed banks increased their exposure to loans for multifamily properties, and to both loans and commitments to non-household real estate borrowers at a more rapid pace than survivor banks did, but a similar pattern does not extend to other real estate products. This evidence is supportive of the hypothesis that differences in asset performance might have been driven by differences in the pace at which banks moved into real estate during the pre-crisis period.

To test the "growth" hypothesis more rigorously I re-estimate the difference-in-means tests, but for each asset category and for each size group, I only keep the subsample of 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.[39] The estimated differences for real estate loans and MBS securities are shown respectively in Tables XIII-XIV. Even after this extreme re-sampling exercise, the differences in loan performance remain largely unchanged from the ones using the complete sample, thus rejecting the growth hypothesis for the loan portfolio. For the marketable securities portfolio the hypothesis is rejected for agency-issued MBS but the results are inconclusive for private-label MBS holdings, possibly due to the reporting biases discussed in the previous subsection.[40]

[Tables XII-XIV about here]

X. Conclusion

This paper asks whether exposure to real estate was one of the precipitating factors in the wave of commercial bank failures that took place during the Great Recession. I identify three channels through which stresses in the real estate sector may have transmitted onto bank balance sheets. These are a bank's portfolios of (1) illiquid assets, (2) marketable securities, and (3) off-balance sheet credit line commitments. Relying on a snapshot of the banks' pre-crisis business models, for each of these portfolios I consider how pre-crisis choices which shifted the balance of the portfolio towards real estate products impacted the probability of bank failure during the crisis.

I show that accounting for these three sources of exposure to real estate significantly improves the fit of a baseline model of bank failure. A pseudo-R2 measure of fit indicates an approximate 50% improvement in fit for the model estimated over a sample of small banks and a 150% improvement for the model estimated over a sample of large banks. Pre-crisis choices regarding a bank's product mix into real estate products,

[39]In unreported regressions, I find the results to hold if I instead consider the subsample of survivor banks with *total* exposure in 2005 higher than the average total exposure in 2005 of the group of failed banks.

[40]One caveat is that due to data limitations the results can only speak to growth in exposures held on-balance sheet (or off-balance sheet in the case of credit lines) but do not take into account originations that the banks distributed through the securitization channel. This is more of a concern for residential mortgages, the securitization channel of which was very active during the buildup to the crisis.

are far more important in predicting the probability of failure than choices regarding its income mix.

The results indicate that exposures to real estate in all three portfolios contributed to the probability of bank failure, but I find no evidence that holdings of traditional home mortgages or of agency-issued MBS were the main culprits. Instead, it was loans for the purchase of multifamily properties and loans and credit lines extended to non-household real estate borrowers that were the main drivers of bank failures. These results are consistent across bank size categories. I also find that substituting private-label MBS for non-MBS securities in the banks' portfolio of marketable securities raised the probability of failure for large banks only.

I find that during the buildup to the crisis both failed and survivor banks increased their exposure to real estate products, and, as one would expect, real estate products performed worse then non-real estate ones during the crisis. In addition, within each of the identified "toxic" product categories failed banks invested in assets that performed worse than the corresponding ones held by survivor banks. I do find, however, that ex-post differences in asset quality cannot be solely attributed to the faster pace at which failed banks expanded into real estate during the pre-crisis period.

References

Acharya, Viral V., and Nada Mora. 2012. "Are Banks Passive Liquidity Backstops? Deposit Rates and Flows during the 2007-2009 Crisis." National Bureau of Economic Research, Inc NBER Working Papers 17838.

Adrian, Tobias, and Hyun Song Shin. 2009. "Money, Liquidity, and Monetary Policy." *American Economic Review*, 99(2): 600–605.

Allen, Linda, and Anthony Saunders. 1986. "The large-small bank dichotomy in the federal funds market." *Journal of Banking & Finance*, 10(2): 219–230.

Altunbas, Yener, Simone Manganelli, and David Marques-Ibanez. 2012. "Bank Risk during the Financial Crisis: Do business models matter?" Bangor Business School, Prifysgol Bangor University (Cymru / Wales) Working Papers 12003.

Ashcraft, Adam B. 2005. "Are Banks Really Special? New Evidence from the FDIC-Induced Failure of Healthy Banks." *American Economic Review*, 95(5): 1712–1730.

Aubuchon, Craig P., and David C Wheelock. 2010. "The geographic distribution and characteristics of U.S. bank failures, 2007-2010: do bank failures still reflect local economic conditions?" *Federal Reserve Bank of St. Louis Review*, , (Sep): 395–415.

Bayazitova, Dinara, and Anil Shivdasani. 2012. "Assessing TARP." *Review of Financial Studies*, 25(2): 377–407.

Beltratti, Andrea, and Ren M. Stulz. 2012. "The credit crisis around the globe: Why did some banks perform better?" *Journal of Financial Economics*, 105(1): 1–17.

Berger, Allen N., and Christa H.S. Bouwman. 2013. "How does capital affect bank performance during financial crises?" *Journal of Financial Economics*, 109(1): 146–176.

Brunnermeier, Markus K. 2009. "Deciphering the Liquidity and Credit Crunch 2007-2008." *Journal of Economic Perspectives*, 23(1): 77–100.

Brunnermeier, Markus K., and Lasse Heje Pedersen. 2009. "Market Liquidity and Funding Liquidity." *Review of Financial Studies*, 22(6): 2201–2238.

Calomiris, Charles W., and Joseph Mason. 2004. "Credit Card Securitization and Regulatory Arbitrage." *Journal of Financial Services Research*, 26(1): 5–27.

Calomiris, Charles W., and Joseph R. Mason. 2003. "Consequences of Bank Distress During the Great Depression." *American Economic Review*, 93(3): 937–947.

Campello, Murillo. 2002. "Internal capital markets in financial conglomerates: Evidence from small bank responses to monetary policy." *Journal of Finance*, 57(6): 2773–2805.

Campello, Murillo, Erasmo Giambona, John R. Graham, and Campbell R. Harvey. 2011. "Liquidity Management and Corporate Investment During a Financial Crisis." *Review of Financial Studies*, 24(6): 1944–1979.

Cole, Rebel Allen, and George W. Fenn. 2008. "The role of commercial real estate investments in the banking crisis of 1985-92." University Library of Munich, Germany MPRA Paper.

Cole, Rebel Allen, and Lawrence White. 2012. "Déjà Vu All Over Again: The Causes of U.S. Commercial Bank Failures This Time Around." *Journal of Financial Services Research*, 42(1): 5–29.

Cornett, Marcia Millon, Jamie John McNutt, Philip E. Strahan, and Hassan Tehranian. 2011. "Liquidity risk management and credit supply in the financial crisis." *Journal of Financial Economics*, 101(2): 297–312.

Demsetz, Rebecca S., Marc R. Saidenberg, and Philip E. Strahan. 1996. "Banks with something to lose: the disciplinary role of franchise value." *Economic Policy Review*, , (Oct): 1–14.

DeYoung, Robert, and Gkhan Torna. 2013. "Nontraditional banking activities and bank failures during the financial crisis." *Journal of Financial Intermediation*, 22(3): 397–421.

Dwyer, Douglas W., Jing Zhang, and Janet Yinqing Zhao. 2011. "Usage and Exposures at Default of Corporate Credit Lines: An Empirical Study." Moody's Analytics.

Fahlenbrach, Rdiger, and Ren M. Stulz. 2011. "Bank CEO incentives and the credit crisis." *Journal of Financial Economics*, 99(1): 11–26.

Fahlenbrach, Rdiger, Robert Prilmeier, and Ren M. Stulz. 2012. "This Time Is the Same: Using Bank Performance in 1998 to Explain Bank Performance during the Recent Financial Crisis." *Journal of Finance*, 67(6): 2139–2185.

Gorton, Gary, and Andrew Metrick. 2012. "Securitized banking and the run on repo." *Journal of Financial Economics*, 104(3): 425–451.

Ivashina, Victoria, and David S. Scharfstein. 2010. "Bank Lending During the Financial Crisis of 2008." *Journal of Financial Economics*, 97(3): 319–338.

Johnson, Mark Anthony, and Abdullah Mamun. 2012. "The failure of Lehman Brothers and its impact on other financial institutions." *Applied Financial Economics*, 22(5): 375–385.

Kashyap, Anil K, and Jeremy C. Stein. 2000. "What Do a Million Observations on Banks Say about the Transmission of Monetary Policy?" *American Economic Review*, 90(3): 407–428.

Keeley, Michael C. 1990. "Deposit Insurance, Risk, and Market Power in Banking." *American Economic Review*, 80(5): 1183–1200.

Laeven, Luc, and Ross Levine. 2009. "Bank governance, regulation and risk taking." *Journal of Financial Economics*, 93(2): 259–275.

Ng, Jeffrey, Florin P. Vasvari, and Regina Wittenberg-Moerman. 2011. "The Impact of TARP's Capital Purchase Program on the Stock Market Valuation of Participating Banks." Chicago Booth Research Paper No. 10-10.

Peek, Joe, and Eric Rosengren. 1997. "How well capitalized are well-capitalized banks?" *New England Economic Review*, , (Sep): 41–50.

Peek, Joe, and Eric Rosengren. 2000. "Collateral damage: Effects of the Japanese bank crisis on real activity in the United States." *The American Economic Review*, 90(1): 30–45.

Ratnovski, Lev, and Rocco Huang. 2009. "Why are Canadian Banks More Resilient?" *IMF Working Paper*, 1–19.

Reinhart, Vincent Raymond. 2011. "A Year of Living Dangerously: The Management of the Financial Crisis in 2008." *Journal of Economic Perspectives*, 25(1): 71–90.

Roy, Arthur D. 1952. "Safety first and the holding of assets." *Econometrica*, 20: 431–449.

Wheelock, David C, and Paul W. Wilson. 2000. "Why do Banks Disappear? The Determinants of U.S. Bank Failures and Acquisitions." *The Review of Economics and Statistics*, 82(1): 127–138.

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 III.

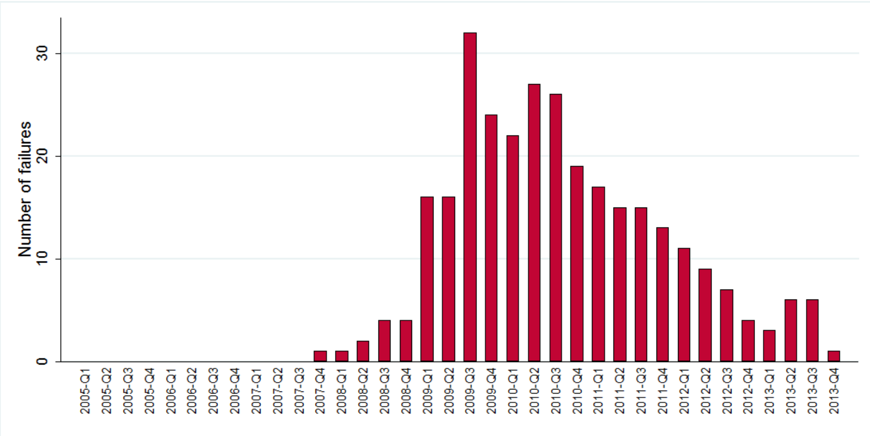

Figure II: The TED spread for the period 2004-2012. This figure shows daily and annual averages of the TED spread from 2000 to 2011. The TED spread measures funding strains in the banking sector and is defined as the difference between the 3-month LIBOR rate and the 3-month Treasury rate. Data on rates obtained from the Federal Reserve Economic Data (FRED), available online by the Federal Reserve Bank of St. Louis.

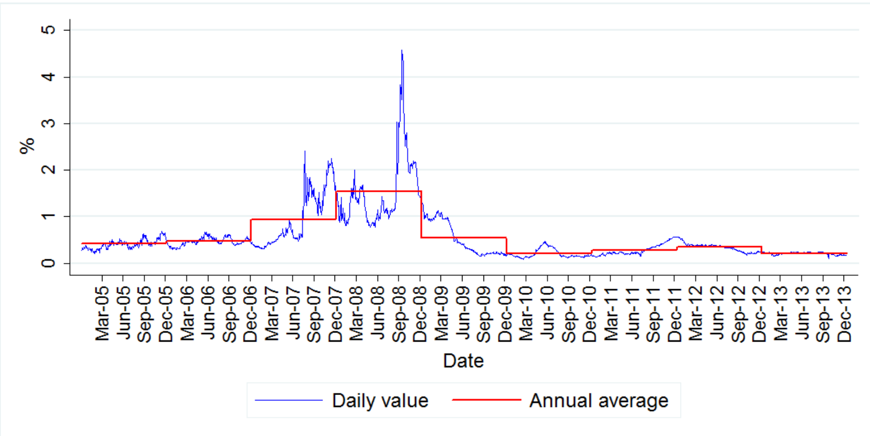

Figure III: Evolution of default risk. This chart displays the evolution of the median z-score in 2005-2013, shown separately for failed and survivor banks. The z-score is inversely related to the probability of default and is defined as the sum of equity capital plus the mean return on assets, divided 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 III.

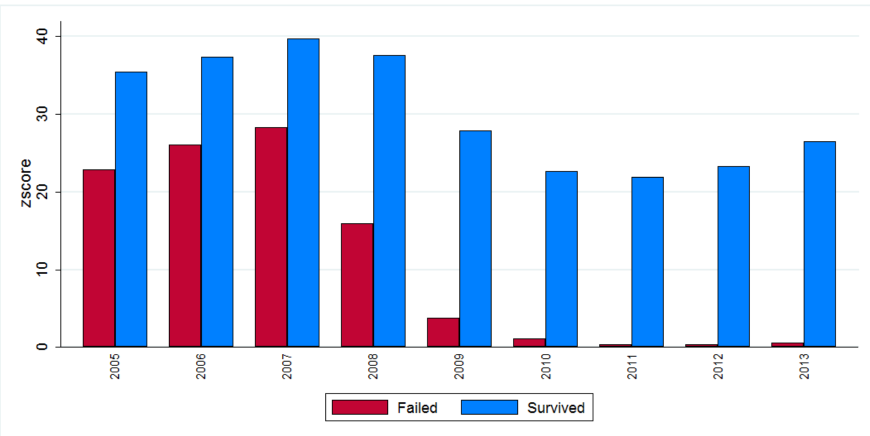

Figure IV: Evolution of the median equity capital ratio. This chart displays the evolution of the median equity capital over assets ratio during 2005-2013, shown separately for failed and survivor banks. Commercial bank data are from the Reports of Condition and Income (Call Reports) and bank failures are taken from the FDIC's list of failed banks. Sample selection is discussed in Section III.

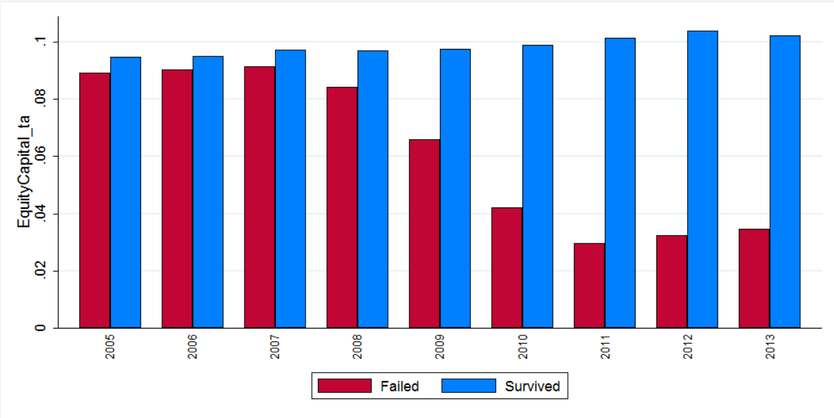

Figure V: Evolution of the median return on assets. This chart displays the evolution of the median return on assets during 2005-2013, shown separately for failed and survivor banks. Commercial bank data are from the Reports of Condition and Income (Call Reports) and bank failures are taken from the FDIC's list of failed banks. Sample selection is discussed in Section III.

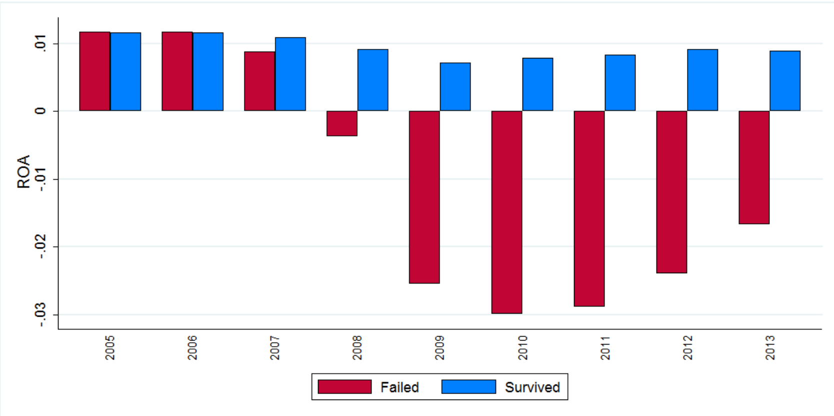

Figure VI: Evolution of the median standard deviation of asset returns. This chart displays the evolution of the median standard deviation of asset returns during 2005-2013, shown separately for failed and survivor banks. The standard deviation is taken over the 16 quarters prior to the measurement quarter. 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 III.

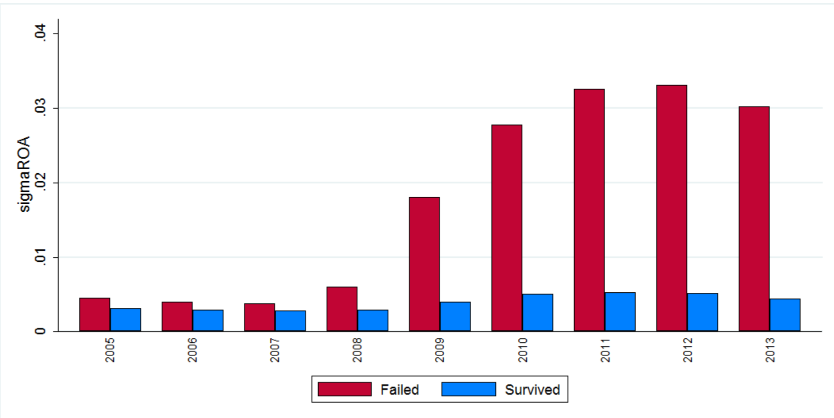

Figure VII: Evolution of housing prices. This graph displays quarterly values for the S&P/Case-Shiller U.S. National Home Price Index (not seasonally adjusted). The index is a composite of single-family home price indices for the nine U.S. Census divisions, which measures shifts in the total value of all existing single-family housing stock. *Source: S&P Dow Jones Indices LLC.*

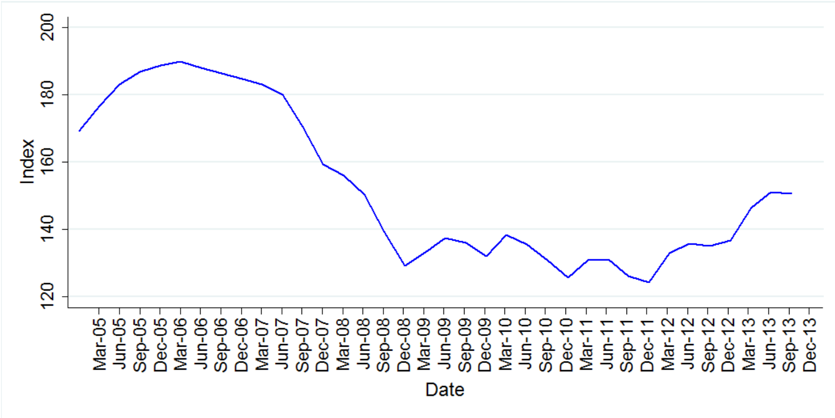

Figure VIII: Performance of real estate loans. This graph displays quarterly averages of asset performance for four categories of real estate loans and for a reference portfolio of all other non-real estate loans for 2005-2013. I use the ratio of non-performing loans to total loans in each loan category as an inverse measure of loan performance; the higher the value of this measure the higher the losses a bank expects to experience on its loan portfolio. 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 III.

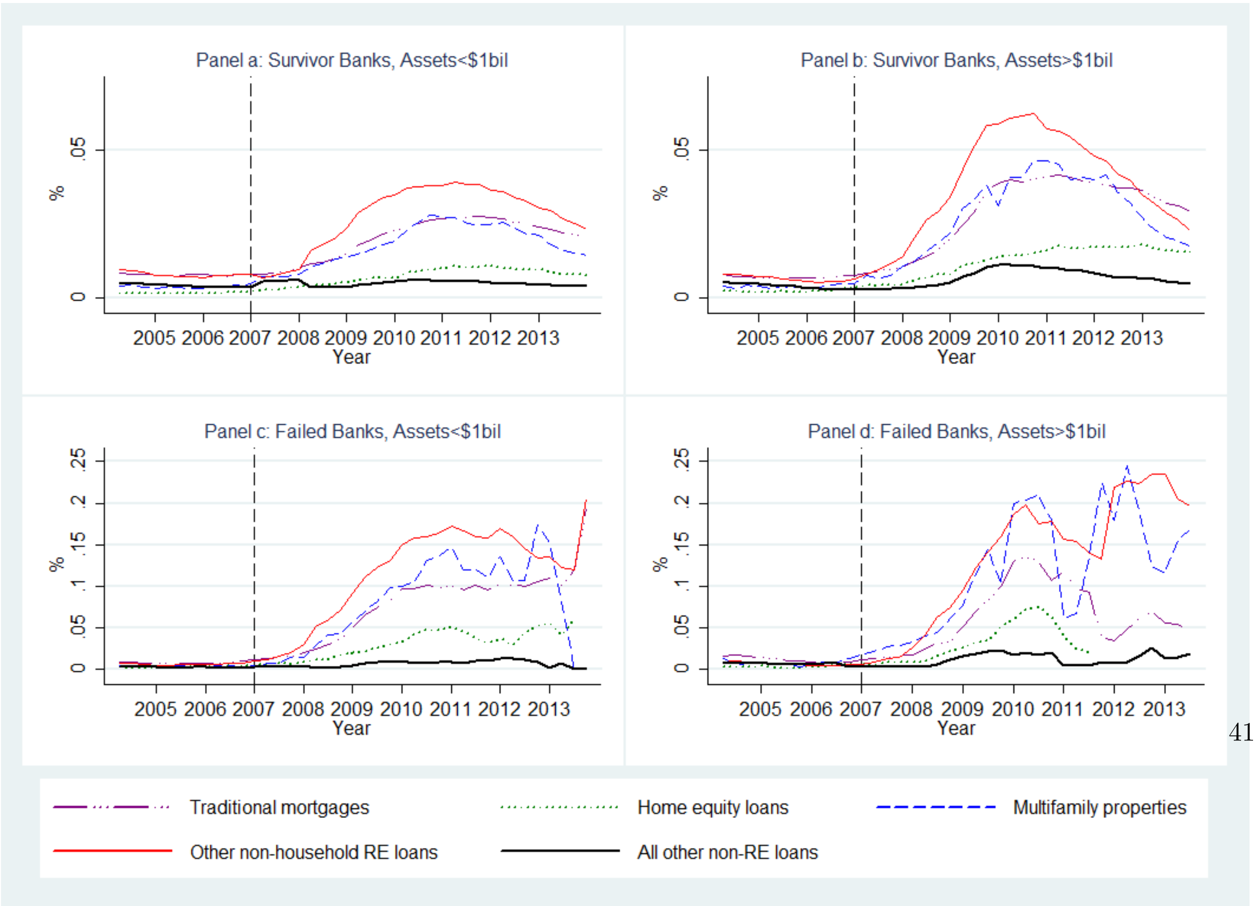

Figure IX: Returns on real estate loans. This graph displays quarterly averages of asset returns for real estate loans and for a reference portfolio of all other non-real estate loans for 2005-2013. I use the ratio of interest income received to total loans in each loan category as the measure of loan returns; the higher the value of this measure the higher the returns the bank receives on its portfolio. 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 III.

Figure X: Performance of MBS. This graph displays quarterly averages of asset performance for agency-issued and private-label MBS, as well as for a reference portfolio of all other non-MBS securities for 2005-2013. I use unrealized capital gains, defined as the difference between fair and amortized cost value divided by amortized cost value, as a measure of MBS performance; the higher the value of this variable is, the higher the capital gains the bank can expect to book by trading the securities. 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 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 III.

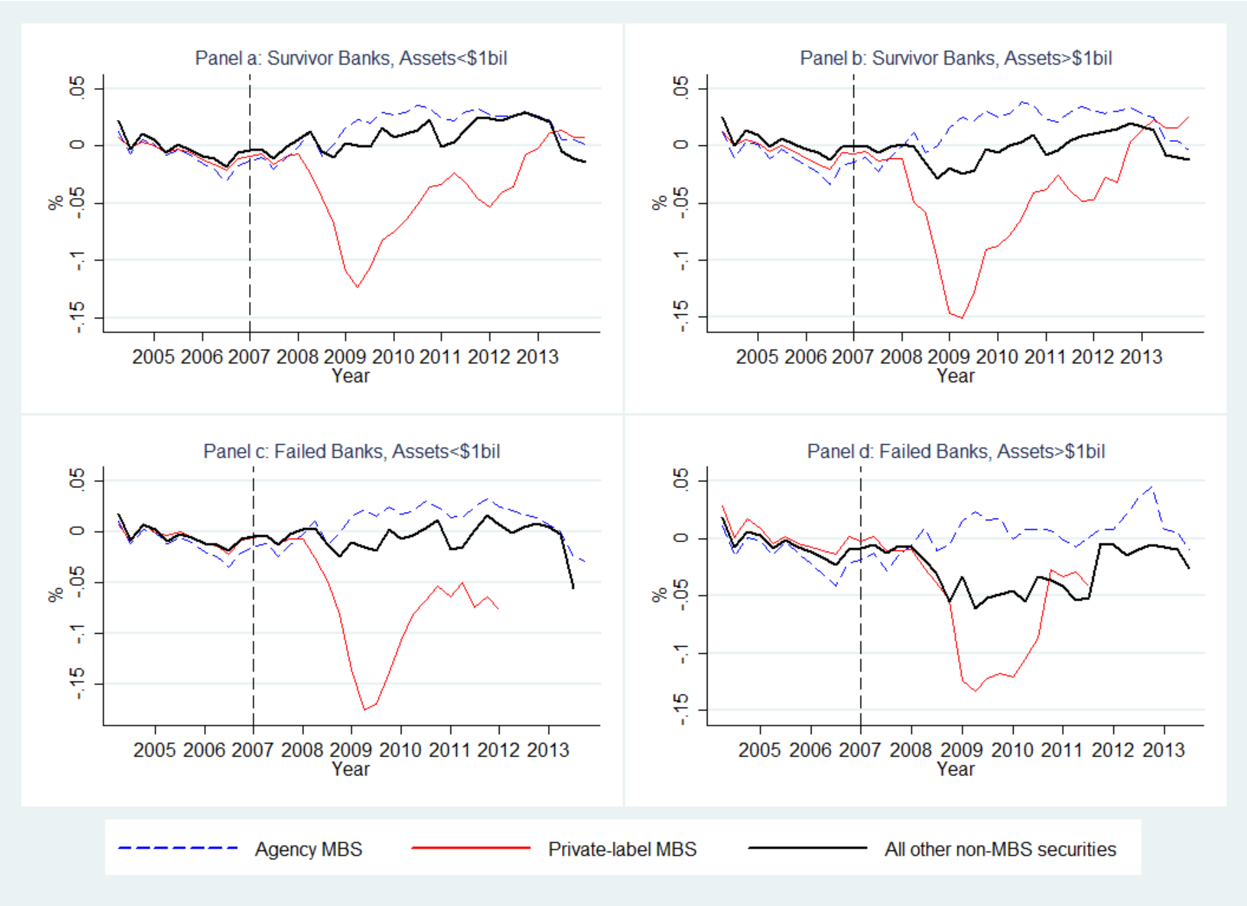

Table I: Definitions

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 and available-for-sale 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 and available-for-sale 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
Multifamily properties	Loans secured by multifamily properties divided by total assets
Other 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
Other 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: Summary statistics and difference-in-means tests for standard predictors of failure. Panel (a) displays summary statistics for a standard set of predictors of failure included in the baseline model. Panel (b) displays tests for the equality of means for the groups of survivor and failed banks. 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 III. 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

	Panel (a)				Panel (b)		
Variables	Mean	Median	SD	N	Survived	Failed	Diff
Assets ($ bil)	1.557	0.155	26.10	4,320	1.6263	0.6278	-0.9985**
BHC membership	0.186	0	0.389	4,320	0.1898	0.1362	-0.0536***
ROAA	0.0124	0.0117	0.00575	4,320	0.0124	0.0127	0.0003
Efficiency	1.657	1.600	0.351	4,320	1.6492	1.7603	0.1110***
Non-performing loans	0.00624	0.00387	0.00731	4,320	0.0063	0.0049	-0.0014***
Equity capital	0.102	0.0943	0.0279	4,320	0.1021	0.0947	-0.0074***
Core deposits	0.668	0.685	0.113	4,320	0.6731	0.6048	-0.0683***
Cash	0.0408	0.0339	0.0266	4,320	0.0413	0.0344	-0.0069***
Money market	0.0281	0.0174	0.0335	4,320	0.0278	0.0323	0.0045**
Securities	0.227	0.202	0.140	4,320	0.2334	0.1375	-0.0959***
Illiquid Assets	0.702	0.729	0.146	4,320	0.6949	0.7944	0.0995***
Credit lines	0.119	0.105	0.0775	4,320	0.1144	0.1814	0.0670***

Table III: Real estate predictors of failure. This table shows the results of estimating a probit model of the probability of a commercial bank failing during 2006-2013. Column (1) reports estimates for the baseline model which only uses a standard set of predictors of failure. Column (2) augments the model to include variables that capture the product mix of the banks, accounting for the exposure of the bank's loan, securities, and credit line portfolios to various categories of real estate 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 III. 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

MODEL VARIABLE	BASELINE (1)	PRODUCT (2)
logAssets	-0.0070*	-0.0032
	(0.0040)	(0.0044)
BHC membership	-0.0321***	-0.0171*
	(0.0108)	(0.0096)
ROAA	-1.7765**	-1.6122*
	(0.8941)	(0.8625)
Efficiency	0.0348**	0.0047
	(0.0137)	(0.0144)
Non-performing loans	0.0852	0.5588
	(0.5449)	(0.5145)
Equity capital	-0.5343***	-0.5184***
	(0.1724)	(0.1802)
Core deposits	-0.2368***	-0.1653***
	(0.0351)	(0.0342)
Money market	0.6315***	0.2772
	(0.2379)	(0.2069)
Securities	0.2267	0.1663
	(0.1781)	(0.1549)
Illiquid Assets	0.4609***	0.1989
	(0.1731)	(0.1512)
Credit lines	0.4361***	0.0533
	(0.0523)	(0.1028)
Agency MBS		-0.0094
		(0.0786)
Private-label MBS		0.9800**
		(0.4468)
Traditional home mortgages		-0.0296
		(0.0627)
Home equity loans		1.1863***
		(0.2956)
Multifamily properties		0.3756***
		(0.1379)
Other non-household RE loans		0.2461***
		(0.0471)
Other non-household RE lines		0.5449***
		(0.1196)
Home equity lines of credit		-1.4701***
		(0.4335)
Number of banks	4,320	4,320
Failed	301	301
Pseudo-R2	0.166	0.267

Table IV: Summary statistics and difference-in-means tests for real estate variables. Panel (a) displays summary statistics 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. Panel (b) displays tests for the equality of means for the groups of survivor and failed banks. 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 III. 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

	Panel (a)				Panel (b)		
Variables	Mean	Median	SD	N	Survived	Failed	Diff
Securities excluding MBS	0.165	0.140	0.120	4,320	0.1709	0.0913	-0.0796***
Agency MBS	0.0582	0.0307	0.0730	4,320	0.0593	0.0433	-0.0160***
Private-label MBS	0.00156	0	0.00654	4,320	0.0015	0.0022	0.0007
Illiquid assets excluding RE loans	0.244	0.227	0.113	4,320	0.2479	0.1878	-0.0601***
Traditional home mortgages	0.150	0.135	0.0958	4,320	0.1528	0.1107	-0.0421***
Home equity loans	0.0199	0.00920	0.0266	4,320	0.0194	0.0262	0.0067***
Multifamily properties	0.0131	0.00586	0.0209	4,320	0.0122	0.0252	0.0130***
Other non-household RE loans	0.271	0.255	0.141	4,320	0.2586	0.4351	0.1765***
Credit lines excluding RE lines	0.0631	0.0513	0.0505	4,320	0.0634	0.0591	-0.0043
Other non-household RE lines	0.0385	0.0247	0.0447	4,320	0.0340	0.0976	0.0636***
Home equity lines of credit	0.0162	0.00719	0.0220	4,320	0.0160	0.0185	0.0026**

Table V: Difference-in-means tests for real estate variables for small and large banks. 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 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 III. 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	0.1746	0.0896	-0.0850***	0.1155	0.1084	-0.0071
Agency MBS	0.0569	0.0386	-0.0183***	0.0958	0.0907	-0.0051
Private-label MBS	0.0012	0.0013	0.0001	0.0067	0.0116	0.0049
Illiquid assets excluding RE loans	0.2457	0.1887	-0.0570***	0.2803	0.1782	-0.1020***
Traditional home mortgages	0.1547	0.1118	-0.0429***	0.1244	0.0997	-0.0247
Home equity loans	0.0183	0.0270	0.0087***	0.0361	0.0171	-0.0191***
Multifamily properties	0.0118	0.0227	0.0109***	0.0177	0.0506	0.0329***
Other non-household RE loans	0.2593	0.4420	0.1827***	0.2478	0.3653	0.1175***
Credit lines excluding RE lines	0.0605	0.0589	-0.0016	0.1069	0.0611	-0.0458***
Other non-household RE lines	0.0328	0.0972	0.0645***	0.0532	0.1015	0.0482***
Home equity lines of credit	0.0147	0.0190	0.0042***	0.0344	0.0141	-0.0202***

Table VI: Real estate predictors of failure for small and large banks. 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 September 30, 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, which only uses a standard set of predictors of failure. Columns (3) 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 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 III. 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	-0.0001	-0.0062	-0.0210	0.0245
	(0.0056)	(0.0057)	(0.0228)	(0.0211)
BHC membership	-0.0252**	-0.0173*	-0.0489	-0.0104
	(0.0110)	(0.0101)	(0.0379)	(0.0337)
ROAA	-1.3400	-1.3884	-4.5371	-1.5885
	(0.9132)	(0.8849)	(4.0221)	(3.2943)
Efficiency	0.0194	-0.0010	0.1194**	0.0018
	(0.0147)	(0.0155)	(0.0488)	(0.0415)
Non-performing loans	0.2058	0.4994	1.4400	-0.2520
	(0.5456)	(0.5185)	(2.4864)	(2.4279)
Equity capital	-0.4393**	-0.4503**	-0.8369*	-1.0911*
	(0.1845)	(0.1900)	(0.4791)	(0.5630)
Core deposits	-0.2255***	-0.1573***	-0.2413*	-0.2006**
	(0.0373)	(0.0370)	(0.1244)	(0.1009)
Money market	0.6033**	0.2421	1.2063	0.6984
	(0.2367)	(0.2101)	(1.2247)	(0.8151)
Securities	0.1897	0.1620	1.0517	0.2955
	(0.1730)	(0.1558)	(0.9844)	(0.6578)
Illiquid Assets	0.4288**	0.1866	1.1605	0.4060
	(0.1684)	(0.1526)	(0.9338)	(0.6135)
Credit lines	0.4740***	0.1158	0.0631	-0.3814
	(0.0542)	(0.1080)	(0.1889)	(0.2972)
Agency MBS		-0.0244		0.2054
		(0.0839)		(0.2661)
Private-label MBS		0.5746		2.1150**
		(0.5719)		(0.9768)
Traditional home mortgages		-0.0258		0.0929
		(0.0657)		(0.1851)
Home equity loans		1.0982***		2.5365*
		(0.2911)		(1.4293)
Multifamily properties		0.2667*		1.1666***
		(0.1470)		(0.4082)
Other non-household RE loans		0.2562***		0.3451*
		(0.0505)		(0.1984)
Other non-household RE lines		0.4774***		0.8857**
		(0.1253)		(0.4163)
Home equity lines of credit		-1.2947***		-3.9024**
		(0.4319)		(1.8683)
Number of banks	4,041	4,041	279	279
Failed	274	274	27	27
Pseudo-R2	0.179	0.267	0.147	0.377

Table VII: 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 September 30, 2013. 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) report estimates for the baseline model augmented 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. Columns (2) and (7) augment the baseline model to include 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)). Columns (3) and (8) augment the baseline model with variables that capture both the product and income mix of the bank. Columns (4) and (9) augment the baseline model to include variables that capture the bank's product mix, and state-level indicator variables that are set to 1 if the bank had a branch in the particular state in 2005, and 0 otherwise. Columns (5) and (10) use the model in columns (1) and (6) but redefine failure to also include banks that participated in the Capital Purchase Program (CPP), either directly or at the BHC level. Commercial bank data are from the Reports of Condition and Income (Call Reports), bank failures are taken from the FDIC's list of failed banks, branching information from the FDIC's Summary of Deposits, and CPP participation data from the U.S. Treasury's CPP transaction report. Sample selection is discussed in Section III. 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	PRODUCT	INCOME	PR. & INC.	STATE FE	TARP	PRODUCT	INCOME	PR. & INC.	STATE FE	TARP
VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Securities	0.1620	0.2357	0.2331	0.1740	0.2069	0.2955	1.1683	0.5572	3.4063***	0.3313
	(0.1558)	(0.1915)	(0.1621)	(0.1739)	(0.1931)	(0.6578)	(0.9274)	(0.7173)	(1.1210)	(1.1132)
Illiquid Assets	0.1866	0.4098**	0.2164	0.2273	0.3972**	0.4060	1.0482	0.4234	3.4033***	1.5073
	(0.1526)	(0.1826)	(0.1563)	(0.1685)	(0.1908)	(0.6135)	(0.9004)	(0.6812)	(1.1036)	(1.0982)
Credit lines	0.1158	0.4403***	0.1289	0.1523	0.2050	-0.3814	-0.0982	-0.4438	-2.0158***	-0.9394**
	(0.1080)	(0.0540)	(0.1068)	(0.1153)	(0.1336)	(0.2972)	(0.2013)	(0.2803)	(0.5774)	(0.4085)
Agency MBS	-0.0244		-0.0280	-0.0485	0.1676*	0.2054		0.1884	0.4235	0.7207*
	(0.0839)		(0.0827)	(0.0894)	(0.1003)	(0.2661)		(0.2662)	(0.4341)	(0.4327)
Private-label MBS	0.5746		0.5393	0.5754	0.2299	2.1150**		1.4556	4.2155***	3.1302
	(0.5719)		(0.5696)	(0.6435)	(0.8651)	(0.9768)		(0.9558)	(1.2366)	(2.1793)
Traditional home mortgages	-0.0258		-0.0045	0.0466	-0.0558	0.0929		0.2202	-0.0676	-0.3085
	(0.0657)		(0.0670)	(0.0679)	(0.0792)	(0.1851)		(0.2209)	(0.3557)	(0.4008)
Home equity loans	1.0982***		1.1314***	1.0925***	0.8406**	2.5365*		2.2322*	3.7835**	2.2957
	(0.2911)		(0.2901)	(0.3268)	(0.4086)	(1.4293)		(1.1686)	(1.9295)	(2.3597)
Multifamily properties	0.2667*		0.2937**	0.2196	0.3019	1.1666***		1.0085***	2.2527***	2.4451**
	(0.1470)		(0.1473)	(0.1690)	(0.2311)	(0.4082)		(0.3806)	(0.5711)	(1.1754)
Other non-household RE loans	0.2562***		0.2603***	0.1956***	0.2949***	0.3451*		0.3882**	0.2667	0.4712
	(0.0505)		(0.0505)	(0.0511)	(0.0658)	(0.1984)		(0.1794)	(0.2775)	(0.3074)
Other non-household RE lines	0.4774***		0.4413***	0.4527***	0.7290***	0.8857**		0.8572**	4.0342***	1.4174*
	(0.1253)		(0.1260)	(0.1318)	(0.1760)	(0.4163)		(0.3816)	(0.6660)	(0.7853)
Home equity lines of credit	-1.2947***		-1.3163***	-1.4241***	0.2038	-3.9024**		-3.3655**	-7.2595***	-1.1688
	(0.4319)		(0.4324)	(0.4561)	(0.5513)	(1.8683)		(1.4290)	(2.7454)	(2.5782)
Number of banks	4,041	4,041	4,041	3,573	4,041	279	279	279	137	279
Failed	274	274	274	274	634	27	27	27	27	142
Pseudo-R2	0.267	0.193	0.270	0.340	0.223	0.377	0.246	0.418	0.640	0.200

Table VIII: Difference-in-means tests for loan performance moving through the crisis. This table displays tests for each year in 2004-2012 for the equality of means for the performance of various categories of real estate loans, as well as for the aggregate performance of the reference portfolio of all other non-real estate loans, for the groups of survivor and failed banks. I use the ratio of non-performing loans to total loans in each loan category as an inverse measure of loan performance. 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 III. 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

Group	Small (Assets<$1 bil)			Large (Assets>$1 bil)		
Variables	Survived	Failed	Diff	Survived	Failed	Diff
2004						
Non-real estate loans	0.0049	0.0029	-0.0020***	0.005	0.0079	0.0029
Traditional home mortgages	0.0081	0.0083	0.0002	0.0073	0.0155	0.0082**
Home equity loans	0.0016	0.0022	0.0007*	0.0022	0.0034	0.0012
Multifamily properties	0.0038	0.0041	0.0002	0.0039	0.008	0.0041
Other non-household RE loans	0.0088	0.0061	-0.0027***	0.0078	0.0088	0.001
2005						
Non-real estate loans	0.0041	0.0023	-0.0017***	0.0039	0.006	0.0021
Traditional home mortgages	0.0077	0.0069	-0.0008	0.0067	0.0107	0.0041
Home equity loans	0.0016	0.0028	0.0013***	0.0022	0.0022	0
Multifamily properties	0.0035	0.0047	0.0012	0.0036	0.0053	0.0018
Other non-household RE loans	0.0073	0.0053	-0.0020***	0.0063	0.0055	-0.0008
2006						
Non-real estate loans	0.0036	0.0021	-0.0015***	0.003	0.0051	0.0021
Traditional home mortgages	0.0077	0.0093	0.0015*	0.0072	0.0092	0.002
Home equity loans	0.002	0.0039	0.0018***	0.0029	0.0049	0.0019
Multifamily properties	0.0043	0.0038	-0.0005	0.0045	0.0121	0.0077
Other non-household RE loans	0.0078	0.0077	-0.0001	0.0058	0.0055	-0.0004
2007						
Non-real estate loans	0.0058	0.0033	-0.0026***	0.0031	0.0035	0.0003
Traditional home mortgages	0.0091	0.0156	0.0065***	0.0094	0.0151	0.0057
Home equity loans	0.0032	0.0074	0.0042***	0.0045	0.0082	0.0037
Multifamily properties	0.0075	0.0109	0.0033	0.0081	0.0273	0.0191*
Other non-household RE loans	0.0082	0.0193	0.0111***	0.0109	0.0156	0.0048
2008						
Non-real estate loans	0.0036	0.0029	-0.0006*	0.0044	0.0092	0.0048***
Traditional home mortgages	0.0131	0.0351	0.0220***	0.0157	0.0349	0.0192***
Home equity loans	0.0047	0.0153	0.0105***	0.0073	0.0182	0.0109***
Multifamily properties	0.0123	0.0425	0.0302***	0.0172	0.0551	0.0379**
Other non-household RE loans	0.0194	0.0684	0.0490***	0.0275	0.0682	0.0407***
2009						
Non-real estate loans	0.0051	0.0086	0.0035***	0.0093	0.0204	0.0111**
Traditional home mortgages	0.0205	0.0787	0.0582***	0.0322	0.0916	0.0593***
Home equity loans	0.0066	0.0271	0.0205***	0.0123	0.042	0.0296***
Multifamily properties	0.0171	0.086	0.0690***	0.0332	0.135	0.1018***
Other non-household RE loans	0.0323	0.127	0.0947***	0.0529	0.148	0.0950***
2010						
Non-real estate loans	0.0058	0.0079	0.0021	0.0107	0.0176	0.0068
Traditional home mortgages	0.0256	0.0992	0.0736***	0.0399	0.1271	0.0872***
Home equity loans	0.0093	0.0461	0.0368***	0.0151	0.0686	0.0535***
Multifamily properties	0.026	0.1268	0.1008***	0.0435	0.1844	0.1408***
Other non-household RE loans	0.0378	0.1624	0.1247***	0.0605	0.1846	0.1241***
2011						
Non-real estate loans	0.0056	0.0096	0.0040*	0.0092	0.0056	-0.0036**
Traditional home mortgages	0.0273	0.0982	0.0709***	0.0402	0.0747	0.0345
Home equity loans	0.0106	0.0384	0.0278***	0.0171	0.0223	0.0052**
Multifamily properties	0.0255	0.1204	0.0949***	0.0414	0.1344	0.0930***
Other non-household RE loans	0.0379	0.1634	0.1255***	0.0522	0.1565	0.1042***
2012						
Non-real estate loans	0.0048	0.0098	0.005	0.007	0.0157	0.0087***
Traditional home mortgages	0.0254	0.1033	0.0779***	0.0372	0.0587	0.0215***
Home equity loans	0.0098	0.042	0.0322***	.	.	.
Multifamily properties	0.023	0.1268	0.1038***	0.034	0.1676	0.1336***
Other non-household RE loans	0.0332	0.1465	0.1133***	0.0406	0.2304	0.1897***
2013						
Non-real estate loans	0.0041	0.0051	0.001	0.0055	0.0165	0.0110***
Traditional home mortgages	0.0217	0.1119	0.0903***	0.0316	0.0499	0.0183***
Home equity loans	0.0082	0.0461	0.0379*	.	.	.
Multifamily properties	0.0159	0.0548	0.0389	0.0202	0.1617	0.1415***
Other non-household RE loans	0.0262	0.1268	0.1006***	0.0275	0.2012	0.1737***

Table IX: Difference-in-means tests for real estate loan returns moving through the crisis. This table displays tests for each year in 2004-2012 for the equality of means for the aggregate returns of the banks' real estate and non-real estate loan portfolios for the groups of survivor and failed banks. I define returns as total interest income from real estate loans divided by total holdings of real estate loans. 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 III. 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

Group	Small (Assets<$1 bil)			Large (Assets>$1 bil)		
Variables	Survived	Failed	Diff	Survived	Failed	Diff
2004						
Non-RE loan returns	0.0687	0.071	0.0022**	0.0602	0.0645	0.0043
RE loan returns	0.0637	0.0647	0.0010*	0.0559	0.0629	0.0070***
2005						
Non-RE loan returns	0.0734	0.0774	0.0040***	0.0676	0.0699	0.0023
RE loan returns	0.0675	0.0717	0.0042***	0.0625	0.0703	0.0078***
2006						
Non-RE loan returns	0.0817	0.0867	0.0050***	0.0766	0.0834	0.0068**
RE loan returns	0.0739	0.0823	0.0083***	0.0707	0.0799	0.0092***
2007						
Non-RE loan returns	0.0839	0.0883	0.0043***	0.078	0.0842	0.0062*
RE loan returns	0.0762	0.0829	0.0067***	0.0716	0.0814	0.0098***
2008						
Non-RE loan returns	0.0732	0.0742	0.0011	0.0642	0.0687	0.0045*
RE loan returns	0.0685	0.0658	-0.0027***	0.0612	0.0645	0.0033**
2009						
Non-RE loan returns	0.0653	0.0646	-0.0008	0.0563	0.0611	0.0048*
RE loan returns	0.0625	0.0562	-0.0063***	0.0541	0.0514	-0.0027*
2010						
Non-RE loan returns	0.0638	0.0631	-0.0007	0.0557	0.0623	0.0066*
RE loan returns	0.0609	0.0532	-0.0077***	0.0541	0.0496	-0.0045
2011						
Non-RE loan returns	0.0623	0.0599	-0.0024	0.0531	0.0573	0.0041***
RE loan returns	0.0594	0.0528	-0.0066***	0.0535	0.0535	0
2012						
Non-RE loan returns	0.0597	0.0606	0.0009	0.049	0.0588	0.0098***
RE loan returns	0.0572	0.0524	-0.0048***	0.0512	0.0536	0.0024***
2013						
Non-RE loan returns	0.0564	0.0571	0.0007	0.0457	0.0526	0.0070***
RE loan returns	0.054	0.0504	-0.0036**	0.0478	0.0537	0.0058***

Table X: Difference-in-means tests for MBS performance moving through the crisis. This table displays tests for each year in 2004-2012 for the equality of means for the performance of the banks' MBS portfolio and non-MBS portfolios, for the groups of survivor and failed banks. I use the rate of unrealized capital gains, defined as the difference between fair and amortized cost value divided by amortized cost value, as a measure of MBS performance. MBS 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 III. 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 * $p<0.10$

Group	Small (Assets<$1 bil)			Large (Assets>$1 bil)		
Variables	Survived	Failed	Diff	Survived	Failed	Diff
2004						
Non-MBS securities	0.0085	0.0045	-0.0040***	0.0118	0.0049	-0.0069*
Agency MBS	0.0031	-0.0003	-0.0034***	0.0016	-0.0011	-0.0027
Private-label MBS	0.0024	0.0013	-0.0011	0.005	0.0136	0.0086
2005						
Non-MBS securities	-0.0047	-0.0072	-0.0025***	0.0006	-0.0071	-0.0078***
Agency MBS	-0.0089	-0.0122	-0.0033***	-0.0109	-0.0131	-0.0022
Private-label MBS	-0.0068	-0.0052	0.0016	-0.0055	-0.0035	0.0019
2006						
Non-MBS securities	-0.01	-0.0108	-0.0008	-0.0053	-0.0142	-0.0089***
Agency MBS	-0.0206	-0.0238	-0.0032***	-0.0222	-0.0279	-0.0058**
Private-label MBS	-0.0143	-0.0124	0.0019	-0.0124	-0.0059	0.0065
2007						
Non-MBS securities	-0.0027	-0.004	-0.0013**	-0.0016	-0.0082	-0.0066***
Agency MBS	-0.0103	-0.0128	-0.0025***	-0.011	-0.0156	-0.0045
Private-label MBS	-0.01	-0.0075	0.0025	-0.0103	-0.0074	0.0029
2008						
Non-MBS securities	-0.0001	-0.0109	-0.0108***	-0.0162	-0.0341	-0.0179**
Agency MBS	0.0048	0.0028	-0.0020**	0.0054	0.002	-0.0034
Private-label MBS	-0.0625	-0.0746	-0.0121	-0.0892	-0.0614	0.0278*
2009						
Non-MBS securities	0.0056	-0.0106	-0.0162***	-0.0138	-0.0528	-0.0390***
Agency MBS	0.0246	0.0197	-0.0049***	0.0256	0.0157	-0.0099***
Private-label MBS	-0.097	-0.1534	-0.0564***	-0.1139	-0.1247	-0.0108
2010						
Non-MBS securities	0.0112	-0.0009	-0.0121***	0.0012	-0.0451	-0.0462***
Agency MBS	0.03	0.0227	-0.0073***	0.031	0.0068	-0.0242***
Private-label MBS	-0.0469	-0.0688	-0.0219	-0.056	-0.08	-0.0241
2011						
Non-MBS securities	0.0164	0	-0.0164***	0.0045	-0.0369	-0.0413***
Agency MBS	0.0276	0.023	-0.0045	0.0283	0.0004	-0.0279***
Private-label MBS	-0.0387	-0.0637	-0.025	-0.0399	-0.0349	0.005
2012						
Non-MBS securities	0.0254	0.0026	-0.0228***	0.0156	-0.0093	-0.0249***
Agency MBS	0.0269	0.0161	-0.0108***	0.0299	0.0275	-0.0025**
Private-label MBS	.	.	.	.	.	.
2013						
Non-MBS securities	-0.0025	-0.0139	-0.0114	-0.0042	-0.0177	-0.0135***
Agency MBS	0.0083	-0.0091	-0.0174***	0.0075	-0.0022	-0.0097***
Private-label MBS	.	.	.	.	.	.

Table XI: Difference-in-means tests for changes in the banks' business model 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 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 III. The values of the variables are averages obtained over the four quarters of 2005 and 2001. 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	0.1718	0.1707	-0.0011	0.1182	0.1152	-0.0031
Agency MBS	0.0576	0.0560	-0.0017*	0.0911	0.0953	0.0043
Private-label MBS	0.0011	0.0012	0.0001	0.0052	0.0070	0.0019***
Illiquid assets excluding RE loans	0.2768	0.2430	-0.0337***	0.2973	0.2705	-0.0268***
Traditional home mortgages	0.1683	0.1523	-0.0160***	0.1397	0.1212	-0.0185***
Home equity loans	0.0112	0.0185	0.0073***	0.0203	0.0341	0.0138***
Multifamily properties	0.0091	0.0123	0.0032***	0.0162	0.0209	0.0048***
Other non-household RE loans	0.1986	0.2693	0.0707***	0.2176	0.2597	0.0421***
Credit lines excluding RE lines	0.0536	0.0603	0.0067***	0.0984	0.1023	0.0039*
Other non-household RE lines	0.0234	0.0358	0.0125***	0.0430	0.0580	0.0150***
Home equity lines of credit	0.0092	0.0147	0.0055***	0.0208	0.0323	0.0114***

Table XII: 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 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 III. The values of the variables are averages obtained 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	0.0004	-0.0136	-0.0140***	-0.0055	0.0191	0.0245
Agency MBS	-0.0011	-0.0079	-0.0068**	0.0043	0.0042	-0.0001
Private-label MBS	0.0001	-0.0001	-0.0002	0.0016	0.0039	0.0023
Illiquid assets excluding RE loans	-0.0319	-0.0601	-0.0282***	-0.0228	-0.0637	-0.0409**
Traditional home mortgages	-0.0162	-0.0156	0.0006	-0.0174	-0.0284	-0.0110
Home equity loans	0.0071	0.0090	0.0020	0.0148	0.0049	-0.0099***
Multifamily properties	0.0030	0.0067	0.0037***	0.0034	0.0172	0.0138**
Other non-household RE loans	0.0659	0.1343	0.0684***	0.0404	0.0585	0.0182
Credit lines excluding RE lines	0.0069	0.0045	-0.0023	0.0049	-0.0058	-0.0107
Other non-household RE lines	0.0107	0.0361	0.0254***	0.0132	0.0313	0.0181*
Home equity lines of credit	0.0054	0.0059	0.0004	0.0122	0.0043	-0.0079***

Table XIII: Difference-in-means tests for loan performance moving through the crisis for a high-growth subsample of survivor banks. This table displays tests for each year in 2004-2012 for the equality of means for the performance of various categories of real estate loans, as well as for the aggregate performance of non-real estate loans, for the groups of survivor and failed banks. For each loan category I only keep 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 increases for the group of failed banks. I use the ratio of non-performing loans to total loans in each loan category as an inverse measure of loan performance. 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 III. 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

Group	Small (Assets<$1 bil)			Large (Assets>$1 bil)		
Variables	Survived	Failed	Diff	Survived	Failed	Diff
2004						
Non-real estate loans	0.0045	0.0029	-0.0016***	0.0043	0.0079	0.0036
Traditional home mortgages	0.0075	0.0083	0.0008	0.006	0.0155	0.0094***
Home equity loans	0.0016	0.0022	0.0006	0.0015	0.0034	0.0018
Multifamily properties	0.0031	0.0041	0.001	0.0016	0.008	0.0063
Other non-household RE loans	0.0055	0.0061	0.0006	0.0067	0.0088	0.002
2005						
Non-real estate loans	0.004	0.0023	-0.0016***	0.0036	0.006	0.0024
Traditional home mortgages	0.0072	0.0069	-0.0003	0.0059	0.0107	0.0048*
Home equity loans	0.0017	0.0028	0.0012***	0.0017	0.0022	0.0005
Multifamily properties	0.0029	0.0047	0.0018	0.0019	0.0053	0.0034
Other non-household RE loans	0.0053	0.0053	0	0.0052	0.0055	0.0003
2006						
Non-real estate loans	0.0037	0.0021	-0.0016***	0.0026	0.0051	0.0025
Traditional home mortgages	0.0076	0.0093	0.0016**	0.0065	0.0092	0.0026
Home equity loans	0.0023	0.0039	0.0015***	0.0023	0.0049	0.0026
Multifamily properties	0.0051	0.0038	-0.0013	0.0027	0.0121	0.0094
Other non-household RE loans	0.0068	0.0077	0.001	0.0058	0.0055	-0.0003
2007						
Non-real estate loans	0.0063	0.0033	-0.0030***	0.0029	0.0035	0.0006
Traditional home mortgages	0.0089	0.0156	0.0067***	0.0085	0.0151	0.0067
Home equity loans	0.0039	0.0074	0.0035***	0.0035	0.0082	0.0047*
Multifamily properties	0.0093	0.0109	0.0016	0.0082	0.0273	0.0191*
Other non-household RE loans	0.0111	0.0193	0.0082***	0.0109	0.0156	0.0047
2008						
Non-real estate loans	0.0039	0.0029	-0.0009***	0.0039	0.0092	0.0053***
Traditional home mortgages	0.0131	0.0351	0.0220***	0.0149	0.0349	0.0200***
Home equity loans	0.0058	0.0153	0.0095***	0.0065	0.0182	0.0117***
Multifamily properties	0.0141	0.0425	0.0284***	0.0337	0.0551	0.0214
Other non-household RE loans	0.0252	0.0684	0.0432***	0.0303	0.0682	0.0379***
2009						
Non-real estate loans	0.0052	0.0086	0.0034***	0.0088	0.0204	0.0116**
Traditional home mortgages	0.0204	0.0787	0.0583***	0.0331	0.0916	0.0585***
Home equity loans	0.0081	0.0271	0.0190***	0.0102	0.042	0.0318***
Multifamily properties	0.0224	0.086	0.0637***	0.0545	0.135	0.0805***
Other non-household RE loans	0.044	0.127	0.0830***	0.0537	0.148	0.0942***
2010						
Non-real estate loans	0.0059	0.0079	0.002	0.0104	0.0176	0.0071
Traditional home mortgages	0.0243	0.0992	0.0749***	0.041	0.1271	0.0861***
Home equity loans	0.0108	0.0461	0.0353***	0.0115	0.0686	0.0572***
Multifamily properties	0.0283	0.1268	0.0985***	0.05	0.1844	0.1344***
Other non-household RE loans	0.055	0.1624	0.1074***	0.0598	0.1846	0.1248***
2011						
Non-real estate loans	0.0055	0.0096	0.0041*	0.0086	0.0056	-0.0030*
Traditional home mortgages	0.0263	0.0982	0.0718***	0.0435	0.0747	0.0313
Home equity loans	0.0116	0.0384	0.0268***	0.0127	0.0223	0.0096***
Multifamily properties	0.0287	0.1204	0.0917***	0.0444	0.1344	0.0899***
Other non-household RE loans	0.0568	0.1634	0.1066***	0.0541	0.1565	0.1024***
2012						
Non-real estate loans	0.0049	0.0098	0.0049	0.0062	0.0157	0.0095***
Traditional home mortgages	0.0247	0.1033	0.0786***	0.0408	0.0587	0.0178***
Home equity loans	0.0123	0.042	0.0297***	.	.	.
Multifamily properties	0.0232	0.1268	0.1036***	0.0378	0.1676	0.1298***
Other non-household RE loans	0.0474	0.1465	0.0991***	0.0451	0.2304	0.1853***
2013						
Non-real estate loans	0.0043	0.0051	0.0008	0.005	0.0165	0.0115***
Traditional home mortgages	0.0214	0.1119	0.0906***	0.035	0.0499	0.0149***
Home equity loans	0.0112	0.0461	0.0349*	.	.	.
Multifamily properties	0.0151	0.0548	0.0398	0.0256	0.1617	0.1360***
Other non-household RE loans	0.0367	0.1268	0.0901***	0.0299	0.2012	0.1713***

Table XIV: Difference-in-means tests for MBS performance moving through the crisis for a high-growth subsample of survivor banks. This table displays tests for each year in 2004-2012 for the equality of means for the performance of the banks' MBS portfolio and non-MBS portfolios, for the groups of survivor and failed banks. For each security category I only keep 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 increases for the group of failed banks. I use unrealized capital gains, defined as the difference between fair and amortized cost value divided by amortized cost value, as a measure of MBS performance. MBS 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 III. 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

Group	Small (Assets<$1 bil)			Large (Assets>$1 bil)		
Variables	Survived	Failed	Diff	Survived	Failed	Diff
2004						
Non-MBS securities	0.0073	0.0045	-0.0028***	0.0064	0.0049	-0.0015
Agency MBS	0.0005	-0.0003	-0.0008	-0.0017	-0.0011	0.0006
Private-label MBS	0.0017	0.0013	-0.0003	0.0012	0.0136	0.0124*
2005						
Non-MBS securities	-0.0056	-0.0072	-0.0016**	-0.0039	-0.0071	-0.0032
Agency MBS	-0.0109	-0.0122	-0.0013	-0.0132	-0.0131	0.0002
Private-label MBS	-0.0087	-0.0052	0.0035	-0.0106	-0.0035	0.0071
2006						
Non-MBS securities	-0.0112	-0.0108	0.0004	-0.0076	-0.0142	-0.0066**
Agency MBS	-0.0227	-0.0238	-0.0011	-0.0251	-0.0279	-0.0029
Private-label MBS	-0.0168	-0.0124	0.0044	-0.0206	-0.0059	0.0147*
2007						
Non-MBS securities	-0.0031	-0.004	-0.0009*	-0.0036	-0.0082	-0.0046***
Agency MBS	-0.0119	-0.0128	-0.0009	-0.0135	-0.0156	-0.002
Private-label MBS	-0.0114	-0.0075	0.0039	-0.0147	-0.0074	0.0073
2008						
Non-MBS securities	0.0003	-0.0109	-0.0112***	-0.0249	-0.0341	-0.0092
Agency MBS	0.0041	0.0028	-0.0014*	0.0041	0.002	-0.0021
Private-label MBS	-0.0652	-0.0746	-0.0094	-0.0958	-0.0614	0.0343**
2009						
Non-MBS securities	0.0056	-0.0106	-0.0162***	-0.0215	-0.0528	-0.0314**
Agency MBS	0.0239	0.0197	-0.0041***	0.0245	0.0157	-0.0087***
Private-label MBS	-0.0979	-0.1534	-0.0555***	-0.129	-0.1247	0.0043
2010						
Non-MBS securities	0.0111	-0.0009	-0.0120***	-0.0013	-0.0451	-0.0438***
Agency MBS	0.0287	0.0227	-0.0060***	0.0291	0.0068	-0.0223***
Private-label MBS	-0.0469	-0.0688	-0.0219	-0.0704	-0.08	-0.0096
2011						
Non-MBS securities	0.0165	0	-0.0165***	0.0027	-0.0369	-0.0396***
Agency MBS	0.0265	0.023	-0.0035	0.0269	0.0004	-0.0264***
Private-label MBS	-0.0387	-0.0637	-0.0249	-0.0562	-0.0349	0.0213
2012						
Non-MBS securities	0.0258	0.0026	-0.0232***	0.0127	-0.0093	-0.0220***
Agency MBS	0.0258	0.0161	-0.0098***	0.0296	0.0275	-0.0021
Private-label MBS	.	.	.	.	.	.
2013						
Non-MBS securities	-0.0025	-0.0139	-0.0113	-0.0073	-0.0177	-0.0104***
Agency MBS	0.0072	-0.0091	-0.0163***	0.0073	-0.0022	-0.0095***
Private-label MBS	.	.	.	.	.	.