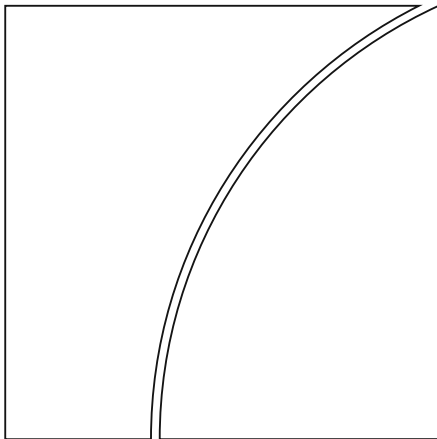BANK FOR INTERNATIONAL SETTLEMENTS

BIS Working Papers
No 530

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

by Adonis Antoniades

Monetary and Economic Department

November 2015

BIS Working Papers are written by members of the Monetary and Economic Department of the Bank for International Settlements, and from time to time by other economists, and are published by the Bank. The papers are on subjects of topical interest and are technical in character. The views expressed in them are those of their authors and not necessarily the views of the BIS.

This publication is available on the BIS website (www.bis.org).

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

Adonis Antoniades[*]

November 23, 2015

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 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. In addition, within each product category they held assets of lower quality than those held by survivor banks.

Keywords: bank failures, Great Recession, real estate, mortgage-backed securities, credit lines, credit growth

JEL Classification: G21, G28, R33

I. Introduction

A number of large financial institutions failed during the financial crisis of 2007-2008.[1] The main drivers of these failures have been discussed extensively in the press and have generated a number of scholarly articles, with analyses being informed to a large extent by the experience of brokers-dealers. The wave of commercial bank failures that immediately followed the main events of the financial crisis received considerably less attention.

The main determinants of balance sheet stress for commercial banks were much different than those for brokers-dealers. Though aggregate funding strains have been identified as one of the precipitating causes of the crisis, with a particularly pronounced impact on brokers-dealers,[2] funding conditions alone cannot explain commercial bank failures. The FDIC reported 492 bank failures from January 1, 2005 to December 31, 2013. However, the vast majority of these failures - 462 failures - took place after the last quarter of 2008. That is, during a period when aggregate funding pressures in the banking sector had completely abated. Furthermore, throughout the financial crisis commercial banks had access to lender of last resort facilities at the Federal Reserve's discount window.

In understanding bank failures during this episode, the role of real estate risk is important. The real estate sector experienced a severe and extended downturn during the Great Recession. Empirical models that aim to examine the determinants of bank failures during this episode should therefore account for the specific channels through which stresses in the real estate sector may have transmitted onto bank balance sheets, thereby contributing to bank distress and eventual failure; the paper makes progress on this front.

I identify three channels through which stresses in the real estate sector could impact a bank's financial health. These channels operate through the bank's exposure to real estate risk in each of its (1) illiquid assets, (2) marketable securities, and (3) off-balance sheet credit line portfolios. For each of these three portfolios, I consider how pre-crisis choices that yielded high portfolio exposure to real estate risk impacted the probability of bank failure during the crisis. Identification relies on cross-sectional variation in pre-crisis portfolio composition. For each portfolio, the estimator identifies the marginal effect of substitution of real estate for non-real estate products – i.e., within-portfolio composition effects – on the probability of failure

---

[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 Gorton and Metrick (2012)),Adrian and Shin (2009), Brunnermeier (2009), Brunnermeier and Pedersen (2009)

during the Great Recession.

Banks raised their exposure to real estate risk substantially in the run-up to the crisis, but did not do so uniformly across real estate products. Whereas they increased their exposure to non-household real estate borrowers – such as investors in multifamily properties, developers of commercial real estate and land development projects – and in the case of large banks also to private-label MBS, they shed their exposure to traditional household real estate products – such as home mortgages and agency MBS. The evidence points to a shift of retained exposure from traditional household real estate products to non-core real estate products.

I find that the resulting pre-crisis portfolio composition, as obtained from a 2005 snapshot of bank balance sheets, holds relevance in predicting the probability of failure during the Great Recession, and more so for large banks. Pseudo-R2 measures of fit indicate that accounting for portfolio exposure to real estate risk improves the fit of a baseline model by an approximate 50% for small banks (assets less that $1 billion) and by 150% for large banks (assets greater than $1 billion).

At a more granular level, I find no evidence that exposure to household real estate credit contributed to bank failures. This result should not be interpreted as suggesting that the documented mass of defaults on home mortgage loans did not pose problems to financial intermediaries. Rather, it points to the offloading of household mortgage risk, that the securitisation process facilitated, from commercial banks to other financial intermediaries. And, possibly, to adequate allocation of capital for the residual risk that was kept on-balance sheet. In addition, as discussed below, the trajectory of unrealized book gains on agency MBS suggests that agency and (implicit) government guarantees on underlying loans, as well as policy interventions during the crisis, were successful in stemming the development of severe price pressures in that market.[3]

The exposures that mattered most for bank failures were loans and credit lines extended to non-household real estate borrowers. In a counterfactual exercise I estimate that had the 2005 levels of exposure to loans and credit lines to non-household real estate borrowers been reduced independently down to the lowest quartile of their corresponding distribution, the aggregate probability of failure would have declined respectively by 5 and 3 percentage points for small banks, and by 7 and 4 percentage points for large banks. The effects are economically significant, and of the order of magnitude of the empirical loss rates observed in the data – 7 and 10 percentage points for small and large banks, respectively.

Exposure to private-label MBS – the securitization instrument for subprime mortgages and commercial real estate loans – mattered, but less so and only for large banks. Small banks were not impacted, possibly

---

[3] The agency guarantee effectively removes credit risk from the product, in the process introducing prepayment risk, which is, however, priced less aggressively by investors.

due to their very low levels of exposure to this product. Applying the same counterfactual reduction in exposure as described above, would have resulted in a 2 percentage point decline in the average probability of failure of large banks.

These effects are not driven by correlations between the banks' exposure to non-household real estate and their geographical market targeting. Using various proxies for county-level economic conditions, and relying on information about the geographical distribution and relative size of bank branches, I create and include as additional controls bank-level measures of exposure to local economic conditions during the crisis. I also test an alternative specification in which I saturate the model with state fixed effects, activated if the bank has a physical branch presence in the state. Though imperfect, these proxies should capture the first-order effects of potential biases in the coefficients arising from the banks' co-determination of their product and locational mix. That their inclusion does not affect the main results, strongly suggests that the paper's main findings primarily enter through the product-mix channel.

In a number of additional tests, I find the results to be robust to concerns about the confounding effects of the composition of the bank's sources of income, to the influence of government interventions in the form of capital injections through the Troubled Asset Relief Program (TARP), to accounting for off-balance sheet exposures to asset-backed commercial paper conduits, and to excluding too-big-to-fail banks from the sample.

The paper's main findings bring to the fore the detrimental impact of non-household real estate credit on commercial banks' resilience during the Great Recession. In the aftermath of the crisis, references to the non-household real estate sector did emerge in public reports, examining, often in isolation, the failure of specific financial institutions. A notable example is the Examiner's Report on the failure of Lehman Brothers, which documents the significant role that losses on the bank's commercial real estate portfolio played in its eventual demise.[4] At the same time, a broader discussion of the contribution of the non-household real estate sector to the cross-sectional distribution of commercial bank failures has been largely absent from analyses of the crisis, which tend instead to focus on the role of real estate credit to household borrowers. Duca and Ling (2015) show, however, that commercial real estate (CRE) markets experienced as deep a downturn as residential mortgage markets during the crisis. The authors attribute price movements in CRE markets to shifts in risk premia, which declined in the run-up to the crisis and increased sharply during the crisis. Levitin and Wachter (2013) argue that the boom in CRE markets was partly driven by innovations in commercial mortgage-backed security (CMBS) markets, which resulted in traditional investors in CRE markets being outbid by collateralized debt obligation (CDO) packagers with lower underwriting standards.

---

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

The question remains as to 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 that real estate loans exhibited higher non-performing rates than non-real estate loans, across both failed and survivor banks. Loans to non-household real estate borrowers were the worst performer. Also in line with expectations, I find that private-label MBS performed worse than the reference portfolio of non-MBS securities.[5] Agency MBS, on the other hand, performed better than the reference portfolio, likely because of agency and (implicit) government guarantees associated with these securities, and due to the Federal Reserve's support of this market.

The differences in performance between household and non-household real estate loans are broadly consistent with known differences in the general features of these products. For example, compared to residential real estate (RRE) loans, CRE loans are larger and harder to diversify, rely on more complex repayment sources, and are rarely fully amortized, with balloon payments of principal often required upon maturity (Levitin and Wachter (2013)). In addition CRE borrowers are subject to prepayment penalties that make refinancing costly, and they face arguably lower disincentives for strategic defaults.

That real estate products underperform non-real estate ones also in the portfolios of surviving banks, points to the presence of *aggregate* strains in the real estate sector during the Great Recession. Under such aggregate strains, certain types of real estate products performed consistently poorly – regardless of the identity of the bank holding them – and the probability of bank failure could have been raised solely by ex-ante portfolio choices that skewed the composition of each bank portfolio towards these products. The results discussed earlier, show that this is precisely what failed banks did during the run-up to the crisis.

Further analysis reveals a second margin along which failed banks' investment choices compromised their financial position during the crisis. Not only did failed banks skew their portfolios towards the worst performing product categories, but within each category they invested in assets of lower quality than those that survivor banks invested in. During the crisis, the real estate loan portfolios of failed banks exhibited on average higher non-performing loan rates than those of survivor banks, and the differences in performance are significant across years, bank size and real estate loan categories. Furthermore, the MBS held by failed banks performed worse than those held by survivor banks. This result is robust for agency MBS, but less so for private-label MBS. This could be driven by strategic misreporting of the fair value of private-label MBS but could also be a statistical artifact of the small number of commercial banks with exposure to private-label MBS.

Differences in asset performance cannot be solely explained by the comparatively more rapid pace at

---

[5]I use unrealized mark-to-market gains to assess the performance of securities.

which failed banks accumulated exposure to real estate products during the run-up to the crisis. Failed banks did indeed increase their exposure to both loans and credit commitments to non-household real estate borrowers substantially more than survivor banks during this period. However, I find that the subset of survivor banks 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.

I also examine interest returns on loans, to gauge the extent to which the ex-ante pricing behavior of banks was consistent with ex-post portfolio risk. I find that the pre-crisis interest returns of the banks' real estate loan portfolios were lower than those of their non-real estate portfolios, which is in sharp contrast to the higher non-performing rates of real estate loans during the crisis. However, I also find that the ex-post differences in non-performing loan rates between failed and surviving banks' real estate portfolios were partially priced in by failed banks during the pre-crisis years.[6]

Understanding the characteristics of business models that are most prone to introducing financial fragilities across banks is of paramount importance to bank supervisors and regulators. The only study known to the author that (a) considers bank failure as the performance metric, and (b) attributes variation in bank performance to granular differences in the composition of the banks' various portfolios – i.e., the banks' "product mix" – is Cole and White (2012).[7] My paper builds on Cole and White (2012) to provide a more comprehensive understanding of the impact of stresses in the real estate sector on commercial bank failures during the Great Recession. Compared to Cole and White (2012), I make two sets of incremental contributions. The first set pertains to completeness, the second to identification.

I provide a more granular examination of the real estate channel and produce additional evidence in support of the causal interpretation of the main results. First, I track the performance of bank assets moving through the crisis, and generate important insights into the specific manner in which portfolio risk materialized on commercial banks' balance sheets during this episode. Second, I examine interest returns to show that real estate risk was not priced adequately prior to the crisis, but that differentials in real estate risk – between failed and survivor banks' loan porfolios – were partly priced in the correct direction. Third, I exploit growth patterns during the pre-crisis period to show that the rapid accumulation of exposure to real estate risk alone cannot explain differences in asset performance between failed and survivor banks during the crisis. Fourth, whereas the focus of the analysis in Cole and White (2012) is on banks' loan portfolios, I also examine the

---

[6]As the dataset does not contain information on returns for each of the real estate loan categories separately, I have to rely on broad aggregate returns for real estate loans. Therefore, the analysis cannot determine whether the risk component that was priced was the one due to allocation choices across product categories or the one due to idiosyncratic differences in risk levels within each product category.

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

banks' marketable securities and off-balance sheet credit line portfolios, and find the latter to be a significant source of fragility.[8]

In addition, my empirical strategy differs from Cole and White (2012) on several fronts. First, I estimate the effect of each real estate exposure as the marginal effect of substitution within the most relevant bank portfolio – illiquid assets, marketable securities, credit lines – rather than within the broader asset structure of the bank. This rids the estimates of biases that may arise from unobserved characteristics that are common among real estate and non-real estate products within each portfolio. Second, 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. Third, I provide a more rigorous treatment for the potentially confounding effects of shifts in local economic conditions during the crisis.

The rest of the paper proceeds as follows: Section II discusses the relevant literature, Section III presents the data sources and discusses the timeline of bank failures and evolution of bank risk moving through the Great Recession. Section IV presents the empirical methodology. Section V estimates a baseline model of bank failure, and Section VI augments the baseline model to account for real estate risk and presents the paper's main findings. Section VII tests the main results against a number of alternative interpretations. 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 concludes.

II. Literature Review

Bank failures are not frictionless events. They may result in the loss of non-transferable components of charter value (Demsetz, Saidenberg and Strahan (1996), Keeley (1990)) and can directly impact real economic activity (Ashcraft (2005)). Furthermore, banks' response to distress can negatively impact the economy even in the absence of actual failures. For example, bank distress during the Great Recession can explain income growth and activity in the construction sector (Calomiris and Mason (2003)). Research focusing on the recent financial crisis shows that distressed and failing banks may raise the cost of funding for their non-failed competitors (Acharya and Mora (2012)), and banks most exposed to liquidity risk can significantly contract their supply of credit (Ivashina and Scharfstein (2010), Cornett et al. (2011), and Antoniades (forthcoming)).

---

[8]The empirical specification in Cole and White (2012) accounts for aggregate holdings of marketable securities, but does not have any refinements beyond that level. Although the authors report that they do not find MBS holdings to have an effect on bank failure, this result rests on rather generous assumptions about the share of MBS in the banks' marketable securities portfolio.

The depletion of a bank's capital buffers is normally the trigger of bank 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)). Berger and Bouwman (2013) show that capital raises the probability of survival and market share of smaller banks during banking crises, market crises, and normal times, but improves the performance of medium and large banks primarily during banking crises. These studies advance our understanding of bank capital's primary function as the buffer that stands between bank survival and failure, but do not directly speak to the root causes of the losses that capital buffers are set to absorb.

In thinking about bank performance, risk-taking becomes central. A number of studies have examined the root determinants of bank risk during the recent financial crisis – see for example, Laeven and Levine (2009), Fahlenbrach and Stulz (2011), Beltratti and Stulz (2012). The common thread in these studies is the presence of agency-type drivers of risk, stemming perhaps from firm culture, whose effects are either amplified or subdued via differences in corporate governance. Cheng, Hong and Scheinkman (2015) identify a causal relation that runs in the reverse direction, from firm risk to managerial pay, as risk-averse managers require more pay to compensate them for working in riskier firms. These studies generate important findings, which, with the exception of Beltratti and Stulz (2012), abstract from the specific channels via which agency problems generate the eventual risk.

Related research has taken on 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), Altunbas, Manganelli and Marques-Ibanez (2012), Beltratti and Stulz (2012), Fahlenbrach, Prilmeier and Stulz (2012)). The common finding in these studies is that banks with fragile funding structures performed worse during the crisis, with some evidence that aggregate stresses in the real estate sector may have impacted bank performance.

Other studies rely on a significantly more granular decomposition of the banks' business models to identify the major drivers of failure. Cole and White (2012) provide the first evidence that the composition of the banks' loan portfolio – particularly the choices pertaining to real estate products – was a major driver of US commercial bank failures during the recent crisis. DeYoung and Torna (2013) find that the composition of banks' sources of income also mattered for bank failures.

III. Data Sources and the 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 banks and contain detailed financial information in a number of different schedules. 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). The final sample contains 4,320 banks, 301 of which 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.[9] The rate of bank failures picked up in 2009-2010, but has been gradually declining since then, with only two failures recorded in my sample in the fourth quarter of 2013.

B. Evolution of Default Risk

Although the deterioration of funding conditions in the markets for wholesale funds has been identified as one of the precipitating causes of the crisis,[10] the pattern of commercial bank failures shown above exhibits a significant lag with respect to the time-series variation in aggregate funding conditions during the crisis, as

---

[9]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.

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

proxied for example by the TED spread (Figure II).[11] That the mass of failures takes place in a period during which aggregate funding pressures in the banking sector had completely abated, suggests that commercial bank failures during this episode cannot be attributed to banks' inability to meet their short-term debt obligations due to sudden aggregate funding reversals. Furthermore, unlike brokers-dealers, commercial banks had *continuous* access to lender of last resort facilities at the Federal Reserve Bank's discount window throughout the crisis. And the Term Auction Facility (TAF) program that was implemented in December 2007 provided funds to depository institutions against a wide range of collateral, in a manner that helped the borrowing banks to avoid the "stigma" effect often associated with discount window borrowing.

To get a better sense for how default risk evolved across the commercial banking sector during the crisis, in Figure III I plot separately for the groups of failed and survivor banks the time series variation in a measure of default risk, the z-score.[12] 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)).

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

Variation in the median z-score of survivor banks should track aggregate levels of bank distress, free of idiosyncratic shocks that may have particularly affected failed banks. The z-score of survivor banks grows until 2007, but then enters a period of rapid declines until 2012 when it resumes growth. This pattern suggests that bank failures were not solely driven by forces idiosyncratic to failed institutions, but were at least partly due to systemic stresses that also affected institutions that survived the crisis. The presence of stresses idiosyncractic to failed banks is evident even prior to the crisis, as failed banks enter the crisis with a lower median z-score than survivor banks. Their median z-score drops significantly in 2008 and, as expected, the downward trend continues at an accelerating pace through to 2013.

The z-score is a good proxy for aggregate bank risk, but abstracts from the underlying drivers of risk. In the remainder of this paper, I examine specific aspects of the banks' business models to identify important sources of risk during the Great Recession.

---

[11]Tracking the LIBOR-OIS spread instead, paints a very similar picture of the time series evolution of aggregate funding pressures.

[12]For each year, I plot the median z-score for all quarters for all banks in each group. I aggregate over the four quarters to avoid over-interpreting variation in the z-score 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.

IV. Empirical Methodology

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

Bank capital reflects the net book worth of the bank, and it can be modeled as obeying the law of motion shown in Equation 2. For each bank i in time period t, capital in the next period is equal to the stock of capital the bank enters the current period with, plus net adjustments to capital due to the performance of each asset, liability, and off-balance sheet exposure, indexed a, l, f, respectively, with levels (stocks) denoted by $Asset_{ait}$, $Liability_{lit}$, and Off_{fit}, and corresponding net nominal returns R_{ait}^{asset}, $R_{lit}^{liability}$, and R_{fit}^{off}. The stock of capital may also 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.

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

Banks actively manage their business model in response to changing economic and financial conditions, and one can reasonably assume that during the recent crisis such active management was informed by the banks' internal assessment of default risk. Using contemporaneous financial variables to fit a model of bank failure during the crisis, would thus introduce simultaneity bias in the estimates.[13] To address this concern, 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 during the crisis.

To determine the relative influence of each variable of interest on the probability of bank failure, I estimate the probit model shown in Equation 3, where $Fail_i$ is a binary indicator variable which takes the value of 1 if bank i was placed under FDIC receivership during 2006-2013, $I(.)$ 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, where a pre-crisis snapshot of a bank's business model determines its capital stock – and thereby its probability of failure –

---

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

during the crisis.

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

$$W_i = \beta^C \cdot Capital_i + \sum_a \beta^A_a \cdot Asset_{ai} + \sum_l \beta^L_l \cdot Liability_{li}$$
$$+ \sum_f \beta^F_f \cdot Off_{fi} + \sum_x \beta^X_x \cdot Other_{xi} + \kappa + \epsilon_i \tag{4}$$

This is a "initial conditions" setup, where the banks' pre-crisis business models are subjected to exogenous crisis-related stresses, and the observed outcome is whether the bank has transitioned to a state of failure during the Great Recession. I choose 2005 as the base, pre-crisis, year. Identification relies on the assumption that in 2005 banks did not anticipate the severe stresses that the banking sector would experience during the crisis, and the business models observed in 2005 were therefore not set in response to internal assessments of the probability of failure due to the subsequent events of the crisis. This is a reasonable assumption to make, since 2005 was followed by one more year of rapid credit expansion, the first aggregate stresses in the real estate and financial markets were experienced in 2006 and 2007 respectively, and in my sample there were no commercial bank failures until the end of 2007. For each bank, I average the values of control and explanatory variables over the four quarters of 2005. The results presented throughout carry through if I use either 2004 or 2006 as the base year instead.

V. Baseline Model

The baseline model includes a key set of variables that describe the bank's financial condition and business model. Table I provides definitions for the variables used.

I decompose the bank's asset structure into three categories: money market instruments, marketable securities, and other illiquid assets.[14] The regression coefficients should be interpreted in reference to the omitted asset category of cash. I choose cash holdings as the omitted category, because cash is the most liquid, and least risky asset on the balance sheet.

I account for off-balance sheet drawdown risk by including the ratio of unused lines of credit to total assets.[15] Studies have shown that firms drew down their credit lines during the crisis in anticipation of shocks

---

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

[15]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.

to their liquidity position (Ivashina and Scharfstein (2010), Campello et al. (2011)). 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.

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

The asset decomposition described above accounts for liquidity. 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 reduce the probability of failure during banking crises (Berger and Bouwman (2013)). On the other hand, as Calomiris and Mason (2004) show, 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.

The ratio of non-performing loans to total loans measures asset quality.[17] I proxy for managerial quality with the bank efficiency ratio, which measures the bank's ability to turn non-financial resources into income. The ratio decreases in the presence of unproductive overhead, but could also decrease due to higher expenditures associated with relationship lending activities. To control for earnings, I include the return on average assets. In principle, more profitable banks should be better placed to absorb losses, by rebuilding their equity buffers from retained earnings. However, 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.

I augment the model with three additional control variables. First, I include the ratio of core deposits to total assets. This is motivated by studies showing that, on metrics other than actual failure, banks with more stable funding structures performed better during the crisis (Ratnovski and Huang (2009), Beltratti and Stulz (2012), Fahlenbrach, Prilmeier and Stulz (2012)). I also include a dummy variable indicating whether the bank is member of a bank holding company (BHC), and thus able to rely on internal capital markets to weather the crisis (Campello (2002)). The last variable I include is the natural logarithm of total assets. Asset size can proxy for a number of unobservables, such as opacity and "too big to fail" effects. Although the direction of its net effect is not clear on a priori grounds, I nonetheless include asset size as a potentially important determinant of bank failure.

---

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

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

A.   Pre-crisis differences in baseline business models

Table II displays difference-in-means tests for the control variables used in the baseline model, for each averaged over the four quarters of 2005. All variables are winsorized at the 1% and 99% levels. I split banks into two size buckets using a $1 bil threshold applied to the average total assets of each bank for 2004. Bank size is the dimension most likely to sort out major differences in important unobservables across banks, and this split allows me to examine whether the paper's main findings are consistent across size categories.[18]

Differences between failed and survivor banks are more pronounced in the subsample of small banks. Consistently across size categories, failed banks rely less on core-deposit funding, hold less cash, and are less likely to be members of a BHC. Failed banks also hold less equity capital, smaller securities portfolios, and more illiquid assets, but the difference are statistically significant only in the subsample of small banks. Interestingly, – on metrics of performance such as the return on assets, efficiency, and non-performing loan rates – failed banks do not appear to perform worse than survivor banks prior to the crisis.

B.   Probit Estimates

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

This model serves as a benchmark for the paper's main specification described in the next section, so I will not discuss the results at length other than indicate that high reliance on stable sources of funding - core deposits and equity capital - prior to the crisis is associated with a lower probability of failure. What the variation in the TED-spread shown on Graph II demonstrates, however, is that commercial bank failures cannot be explained solely by the presence of sudden aggregate funding reversals that made otherwise solvent banks unable to meet their short-term obligations. The next sections will demonstrate that banks' main source of distress during the crisis was the accumulation of exposure to the non-core assets that the banks' non-core liabilities possibly funded during the run-up to the crisis.

---

[18]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.

VI. The Real Estate Story

The timeline of commercial bank failures and evolution of default risk presented earlier (Figures I, III), suggest the presence of a persistent shock that continued to adversely impact bank balance sheets even after aggregate funding pressures in the banking sector had abated. The collapse of real estate prices is such a shock and one that was arguably unanticipated by banks.

Figure IV shows the quarterly evolution of two real estate indices. The dashed line represents the S&P/Case-Shiller U.S. National Home Price Index, which measures shifts in the total value of all existing single-family housing stock in the US. The solid line represents the National Council of Real Estate Investment Fiduciaries (NCREIF) Property Index, which measures investment performance of commercial real estate properties acquired in the private market for investment purposes only. Both indices peaked prior to the financial crisis and their values declined rapidly during the crisis. The decline in residential real estate prices lasted longer, with sights of a recovery emerging late in 2012. Commercial real estate prices on the other hand recovered faster, but went through a significantly more volatile cycle. This is despite the fact that the NCREIF Property Index only includes investment-grade properties. In both cases, the decline in real estate prices was steep and prices did not recover as quickly as funding pressures abated.

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

A. Econometrics of Portfolio Decomposition

Portfolio decomposition can be performed in two ways. Both approaches utilize the same information set – subject to linear transformations of the decomposition variables – but they each identify distinctly different effects. To illustrate the differences, consider a stylized bank balance sheet, with the asset side comprising only in cash and two categories of illiquid assets: real estate loans and non-real estate loans.

One formulation would designate cash as the omitted category and include as explanatory variables (1) the ratio of real estate loans to assets and (2) the ratio of non-real estate loans to assets. This formulation effectively casts the question of portfolio allocation as one concerning the choice between the omitted asset category of cash and the two categories of illiquid assets. Estimating this model would identify relations

between asset composition and the probability of failure that are not representative of the portfolio choices typically made by banks.

Staying with the same example, a second formulation would keep cash as the omitted category, but include as explanatory variables the ratios of (1) total illiquid assets, and (2) real estate loans to total assets. This formulation casts the question of portfolio allocation as one that recognizes that there are two margins of adjustment at play. One operates *across* the aggregate balance sheet and determines the allocation between cash and illiquid assets. The second operates *within* the illiquid assets portfolio and determines the allocation between real estate and non-real estate loans. The latter margin of adjustment is the one we are interested in, as it speaks directly to whether real estate exposures contributed to bank failures over and above what otherwise similar types of exposures within the bank's relevant choice set did.

I therefore augment the baseline model with variables that capture the degree of exposure to various real estate products within the three portfolios of interest. At the same time, I retain as control variables the bank's aggregate exposure to each portfolio. All variables are normalized by total assets.

Each of the estimated coefficients will identify the impact on the marginal probability of failure of substituting one unit of the particular real estate exposure for one unit of a non-real estate exposure within each portfolio. For example, if we let the estimated coefficient on traditional home mortgages be β, then increasing the pre-crisis exposure to traditional home mortgages by the equivalent of 1% of total assets, while at the same time decreasing the exposure to non-real estate illiquid assets by the same amount, would increase the probability of failure during the crisis by $\beta\%$.

B. Real Estate Exposures

In the illiquid assets portfolio I include three types of real estate exposures: (1) traditional home mortgages, (2) home equity loans, and (3) real estate loans to non-household borrowers.

Part of the crisis-related commentary revolved around traditional home mortgages. The basic storyline involves mortgage borrowers who, perhaps carried away by rapidly rising home prices, overextended themselves and assumed loan obligations on which they would subsequently default during the downturn of the economy. I thus include exposure to traditional home mortgages as a possibly explanatory variable of bank failures. For completeness, I include as a separate category exposure to home-equity loans, which are loans collateralized by the equity that the borrower holds on their property.

I also include a loan category that represents exposure to *non-household borrowers* real estate borrowers. Loans secured by multifamily residential properties are investment-type loans targeting larger residential

properties, and their risk-level is assessed along dimensions such as rental income potential, experience in managing multifamily properties, etc... Similar considerations make loans for commercial real estate, construction, and land development projects distinctively different than household real estate credit, and I therefore aggregate these loan products to one category.

To control for the composition of the bank's portfolio of marketable securities, I include exposures to (1) agency and (2) private-label MBS. Agency MBS are issued or guaranteed by government-sponsored enterprises (GSEs), such as Ginnie Mae, Fannie Mae and Freddie Mac, and must conform to a set of standards that are put in place to cup the risk-profile of the underlying mortgages. Furthermore, GSEs enjoy an implicit government guarantee, which is typically priced into agency MBS. Private-label MBS on the other hand, are issued by private parties, are subject to less stringent underwriting requirements, and are the primary securitization vehicle for subprime mortgages and commercial real estate loans.[19]

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

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 be subject to a wide array of influences that extend beyond stresses in the real estate sector. In addition, 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 cross-sectional correlation between these two exposures is very high, and their independent effects are therefore hard to identify. For these reasons, in the remainder of the paper I will abstain from making inferences from the estimates for these two coefficients.[20]

C. Exposure accumulation

I first ask whether – amid heightened levels of activity in the real estate sector during the run-up to the crisis – banks grew *their own exposure* to real estate. To answer this question, for each real estate product

---

[19]Prior to the crisis, securitizations of loans with multifamily property collateral were also predominantly private-label, but in recent years agency activity in this market has been increasing.

[20]The results presented throughout remain unchanged if I remove exposure to HELOCs from the list of explanatory variables and only retain the on-balance sheet exposure to home equity loans, whose coefficient becomes undifferentiated from zero in most of the tests.

I compare the bank's average level of exposure in 2005 to its corresponding level in 2001. The results are shown in Table IV.

I find no evidence that banks increased their exposure to either agency MBS or traditional home mortgages during the run-up to the crisis. If anything, the difference-in-means tests point to a decrease in banks' exposure to these products. This is consistent with active securitisation channels facilitating commercial banks' off-loading of such risks to other financial intermediaries.

Banks, however, increased their exposure to all other real estate product categories. And they did so in magnitudes that more than offset the decrease in exposure to traditional home mortgage credit. These initial results demonstrate that, in terms of direct on- and off-balance sheet exposure, banks moved towards a more real estate-focused product mix during this period. However, with the exception of private-label MBS for large banks, they did not do so for the traditional home mortgage products one normally associates with the financial crisis of 2007-2008.

D.   Pre-crisis differences in exposure to real estate

With banks significantly increasing their exposure to real estate products in their portfolios during the run-up to the crisis, I test for differences in the resulting pre-crisis exposures of failed and survivor banks. Difference-in-means tests are shown in Table V, where, for completeness, I also report results for the residual non-real estate part of each portfolio.

Regardless of bank size, failed banks have lower exposure to traditional home mortgages and agency MBS than survivor banks, although for large banks the differences are not statistically significant. At the same time, failed banks have significantly higher exposure to non-household real estate loans, with the average difference in exposure between failed and survivor banks at 19.6% and 16.7% of total assets, respectively for small and large banks. Smaller, but economically significant differences exist for credit lines extended to non-household real estate borrowers (6.4% and 4.8% for small and large banks respectively).

E.   Probit estimates

The difference-in-means tests discussed above, suggest that exposure to non-household real estate credit may have precipitated bank failures during the Great Recession. To test this hypothesis more rigorously, I re-estimate the baseline probit model presented in Section V, now augmented to include the real estate portfolio composition variables described above. Columns (2) and (4) of Table III report the estimated

coefficients for small and large banks, respectively. For the reasons outlined earlier, coefficients for home equity loans and lines of credit are reported for completeness with no further discussion.

Real estate risk carries significant explanatory power in the context of bank failures. The pseudo-R2 values reported at the bottom row of Table III, indicate that the model that accounts for real estate risk (columns (2) and (4)) has a substantially better fit than the baseline model (columns (1) and (3)). Comparing the relative improvement in fit for the two subsamples, we see that real estate risk was a stronger driver of failure for large banks – with a roughly 150% increase in fit – than for small banks – for which, however, it remains substantial at roughly 50%.

The real estate risk that mattered most for bank failures was indeed primarily non-household. Neither exposure to traditional home mortgages nor to agency MBS increased the probability of failure over and above the base effect of non-real estate exposures in the illiquid assets and marketable securities portfolios, respectively. The probability of bank failure also increased with holdings of private-label MBS, but only for larger banks.[21]. Non-household real estate products – both loans and credit lines – on the other hand, enter with positive, economically and statistically significant coefficients.

The estimated coefficient for the effect of holdings o traditional home mortgages, should not be read as suggesting that there were no significant losses during the crisis stemming from exposure to this asset category. Rather, together with the earlier observations on the accumulation of real estate risk during the run-up to the crisis, these results suggest that commercial banks off-loaded part of that particular risk to other types of financial intermediaries through the securitisation channel. And, possibly, that they adequately provisioned capital for the residual risk associated with home mortgage loans retained on-balance sheet. The absence of an effect for holdings of agency MBS is likely driven by agency and (implicit) government guarantees associated with these securities, but also by the significant support that this market received through a number of Federal Reserve interventions.

F.   Economic Impact

The estimated coefficients of the probit model are average marginal effects (AMEs), which identify the increase in the probability of failure corresponding to infinitesimally small changes in the explanatory variables. This is a useful sensitivity measure, which does not, however, incorporate information about the range within which changes in each variable could reasonably be expected to vary.

To assess the economic impact of each real estate product on bank failure, I perform a counterfactual

---

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

exercise in which I decrease the banks' 2005 exposure to that product down to the lowest quartile of the cross-sectional distribution of exposure levels in that year. I measure economic impact as the resulting change in the probability of failure predicted by the model, averaged across all banks in the sample. This approach naturally accounts for the distributional properties of each explanatory variable. I perform this exercise for one product at a time and do so separately for the subsamples of small and large banks, using the model estimates shown in columns (2) and (4) of Table III. The resulting probability estimates should be interpreted as the effect of reducing the exposure to each product, while at the same time increasing by an equal amount the exposure to a representative bundle of non-real estate products within the corresponding portfolio – i.e., conditioning on the size of the portfolio remaining constant.

The results are shown in Table VI. For both subsamples, the most significant reductions in the probability of failure would have been effected by reductions in the exposure to loans and credit lines to non-household real estate borrowers. Specifically, the average probability of failure would have declined by 5, and 3 percentage points for small banks, and by 7 and 4 percentage points, for large banks, respectively for these two products. A reduction in exposure to private-label MBS would have affected large banks only, resulting in a decrease in the average probability of failure of 2 percentage points. Given the loss rates observed in the sample – 7 and 10 percentage points for small and large banks, respectively – the ipact of real estate risk is economically significant. Furthermore, the table shows that even if the coefficients of agency MBS and traditional home mortgages had been statistically significant, their economic impact would have been minimal.

VII. Robustness Tests

I subject the main findings of the paper to a series of robustness tests, with the results shown in Tables VII-VIII. For reference, columns (1) and (7) in Table VII and columns (1) and (5) in Table VIII report the coefficients for the paper's core rel estate model for small and large banks, respectively.

A. Product Mix vs Locational Mix

One concern is that the paper's main findings may reflect a correlation between the banks' choice of product mix and their choice of locational mix. For example, banks that prior to the crisis accumulated exposures to non-household real estate borrowers, may have also entered geographical markets that during the crisis were hit by economic shocks unrelated to the banks' credit activities, yet somehow correlated with the banks' ex-ante portfolio choices. In this instance, the increase in the probability of failure resulting from exposure to

non-household real estate borrowers may potentially be driven by omitted variable bias.

In the context of a banking crisis, it is not easy to completely disentangle the two effects. For example, regional shifts in real estate prices may raise the probability of bank failure, but may also be a result of banks' adjusting their credit supply in response to increases in the probability of failure. Similarly, regional declines in average economic activity may both cause and be a result of bank failures in the region.

To address concerns about the confounding effects of banks' locational choices, I employ the use of several proxies designed to capture bank-specific levels of exposure to local economic shocks. Though imperfect, these proxies should perform well in absorbing the first order effects of local economic conditions on the financial health of banks. To the extent that their values may simultaneously be influenced by bank failures, the resulting estimates would be lower bounds to the true effect of real estate risk on bank failures.

I construct three county-level measures of local economic shocks that capture, respectively, declines in income, rises in unemployment rates, and declines in house prices. I obtain income data from the Bureau of Economic analysis, unemployment rates from the Bureau of Labor Statistics, and House Price Index (HPI) data from the Federal Housing Finance Agency. I compute annualised rates of decline for per capita income and the HPI, and annualised level increases for unemployment rates, for the period 2006-2009. Ending the window in 2009 strikes a balance between using variation in the data that is plausibly exogenous to the (lagged) effects of bank failures, and ensuring that the time window extends far enough into the crisis to absorb some of the sharpest cross-sectional shocks in local economic conditions. In unreported regressions, I find that the results hold if use the values of county-level controls annualised over the entire 2006-2013 period instead.

I then create bank-specific measures of exposure to each of these economic shocks. To do so, I rely on data from FDIC's Summary of Deposits to create for each bank a weighted average of its exposure to each economic shock, using as weights the proportion of the bank's total deposits in 2005 that were held in branches in each county. I rely on the 2005 distribution of deposits, to get a more complete picture of the counties in which the bank's loans were originated. Relying on information on the distribution of branch deposits, these measures ignore financial integration between counties, as well as larger lenders' ability to extend credit in counties in which they do not have a large physical footprint. Nonetheless, they should be good overall proxies for bank-specific exposure to economic shocks.

The results are shown in columns (2)-(5) and (8)-(11) of Table VII. In columns (2) and (8) I add to the core real estate model the proxy for shocks to local income, in columns (3) and (9) the proxy for shocks to unemployment rates, in columns (4) and (10) the proxy for HPI declines, and in columns (5) and (11) all

three proxies at the same time. In all cases, the results are similar to the ones obtained for the model that does not control for local economic shocks (columns (1) and (7)).

I also employ an alternative approach and saturate the main specification with state fixed effects, which for a given bank are set to 1 if the bank has one or more branches located in that state. The results are shown in columns (6) and (12), and are similar to those obtained for the main specification. One noticeable difference is that in the subsample of larger banks the coefficients experience large swings in magnitude. This is due to sample attrition,[22] which significantly reduces the sample size in relation to the number of fixed effects to be estimated, and makes the estimated coefficients rather unstable.

Taken together, these results 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.

B. Product Mix vs Income Mix

I also test whether the effects of the product mix on bank failure are merely driven by correlations with the income mix of the banks, which DeYoung and Torna (2013) have shown to affect bank distress.[23] I include the ratios of stakeholder income, fee-for-service income, traditional fee income, and net interest income to total income as additional control variables, all variables defined as in DeYoung and Torna (2013). The results are shown in Table VIII.

Columns (2) and (6) show the estimates for the baseline model augmented only with the income-mix ratios. The fit of the income mix model is significantly lower than for the model that accounts for real estate risk in the product mix (columns (1) and (5)). Re-introducing real estate risk in columns (3) and (7), yields significant gains in explanatory power. Importantly, the coefficients capturing real estate risk are virtually identical to those in the reference model, with only the coefficient of private-label MBS dropping statistical significance at the 10% level. These results show that once one accounts for the product mix that banks entered the crisis with, the incremental explanatory power of the income mix is relatively lower.

C. The Impact of TARP

The definition of bank failure I employ, identifies as failed institutions only banks that were placed under FDIC receivership. One could hypothesize, however, that policy interventions during the crisis distorted

---

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

[23]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 true picture of bank failures by providing lifelines to insolvent banks that 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".[24]

Although it is certainly possible that some banks might 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 (forthcoming) show that banks that participated in CPP had stronger fundamentals compared to non-CPP participants, and this holds true both for the periods prior to and during the program's initiation. The authors connect CPP participation with price pressures on banks' equity, unrelated to fundamentals, stemming from negative media coverage.

I nonetheless test whether the main results hold if I drop from my sample (a) all banks that received assistance from the CPP directly, and (b) banks whose parent BHC received assistance from the CPP. I obtain CPP participation data from the U.S. Treasury's CPP transaction report.[25] The results are shown in columns (4) and (8) of Table VIII and are qualitatively similar to the main results shown in columns (1) and (5). Some differences in the magnitude of coefficients in the sample of large banks are likely due to the significant reduction in sample size resulting from dropping CPP-participants.

D.   Other Robustness Tests

The results are robust to accounting for large banks' off-balance sheet risk stemming from liquidity and credit enhancements provided to asset-backed commercial paper (ABCP) conduits (column (9)). The results

---

[24]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 required capital could not be raised privately. CAP closed in November 2009, without making any investments.

[25]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.

also remain unchanged if I drop the 10 largest banks to account for the possibility of biases arising from "too-big-too-fail" effects (column (10)).

Furthermore, in unreported regressions I find that including the bank's pre-crisis z-score as an additional control variable does not impact the magnitude and statistical significance of the coefficients, and contributes only marginally to fit. Last, estimating the main model with a linear ordinary least squares (OLS) estimator, yields coefficients that are strongly statistically significant and of similar order of magnitude as the AMEs obtained from the non-linear estimator.

VIII. Asset Performance

The previous section identified a set of pre-crisis portfolio exposures that raised the probability of bank failure during the crisis. The empirical analysis in this section aims at understanding how it is that these exposures affected bank health during the crisis, and provides further evidence in support of a causal interpretation of the relations identified earlier. The results indicate that, compared to those of survivor banks, the investment choices of failed banks fell short in two ways. First, they involved a focus on product categories that performed poorly across all banks during the crisis. Second, within each product category failed banks invested in worse-performing assets than survivor banks did.

A. Non-Performing Real Estate Loans

I use the ratio of non-performing loans to total loans as a measure of performance for the different loan portfolios, and plot quarterly averages for the period 2004-2013 for the three real estate loan categories. For reference, I also plot non-performing loan rates for non-real estate loans.[26] The plots are shown in Figure V.

The trajectory of non-performing loan rates for surviving banks – panels (a) and (b) for small and large banks, respectively – reveals a systemic component of the crisis. Non-performing loan rates peaked during the 2010-2011 period, and for two of the three real estate loan categories were significantly higher than for the aggregate non-real estate reference portfolio. Non-performing rates for home equity loans were also higher, but possibly moderated by the fact that during the crisis a significant portion of home equity loans were still within their draw period.[27] The fact that these patterns are present in the subsample of surviving institutions points to the presence of aggregate pressures in the real estate sector.

---

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

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

The worst-performing category was real estate loans to non-household borrowers. Although non-performing loan rates for traditional home mortgages were also significantly elevated, they did not drive bank failures, because failed banks entered the crisis with lower exposure to this asset category than survivor banks did. Another explanation could be that banks allocated adequate capital ex-ante to absorb unexpected losses on traditional home mortgages.[28] Large survivor banks appear to have experienced larger losses on real estate loans than small survivor banks.

The graphs also point to quality differences between failed and survivor banks' investment choices within each real estate loan category. Panels (c) and (d) display average non-performing loan rates for small and large *failed* banks, respectively. On average, the real estate loan portfolios of failed banks performed significantly worse than those of survivor banks. These differences started appearing as early as 2007, and, at their peak, the non-performing loan rates of failed banks were approximately 3-5 times larger than those of survivor banks. In the subsample of large failed banks these trends become less clear as we move deeper into the crisis, because bank exits rapidly decrease the size of what is already a very small subsample.

I perform difference-in-means tests to test the hypothesis that the real estate loan portfolios of failed banks consistently underperformed those of survivor banks during the crisis. The results are shown in Panels A and B of Table IX, respectively for small and large banks. Note that all of the difference-in-means tests presented in this section remain unchanged if I control for bank-specific exposure to local economic shocks. Differences in loan performance are not consistently present in the years immediately prior to the crisis. After 2007, however, failed banks report higher non-performing loan rates, and the differences are consistent across time, bank size, and real estate loan categories.

No similar patterns exist consistently for non-real estate loans. This suggests that the differences in non-performing loan rates between failed and survivor banks cannot be attributed solely to aggregate economic shocks in the specific geographical markets that the banks operate in. Neither can they be attributed to a "random draw", whereby failed banks just happened to pull loans from the wrong tail of the risk distribution consistently across loan categories.

---

[28]Loan performance in any category can be influenced by an idiosyncratic component that drives losses over and above those provided for by the regulatory or the banks' internal credit risk model. Bank failure will be driven by the magnitude of this component, which during the crisis might have been higher for non-household real estate products than for traditional home mortgages. Unfortunately, the pre-crisis Call Reports do not contain the kind of refined data that would be required to test this theory.

B.   Interest Returns on Real Estate Loans

To examine whether interest returns for real estate loans compensated for their comparatively higher non-performing rates, I plot the average interest return of real estate loans and compare it to that of non-real estate loans. For the period I examine, the Call Reports do not provide data on interest income that are disaggregated down to the three different real estate loan categories I examine in this paper, and I therefore plot returns for the bank's aggregate real estate loan portfolio.

As can be seen in Figure VI, in contrast to the relatively higher non-performing rates during the crisis, the returns on the real estate loan portfolio are consistently lower than the corresponding returns on non-real estate loans. During the crisis, these differences are likely driven by the higher non-performing loan rates of real estate exposures, which lead to a smaller portion of loans actually generating interest income.[29] Importantly, however, this same pattern is already present in 2004-2005, when non-performing loan rates were low. This suggests that prior to the crisis banks did not fully anticipate the higher non-performing rates of real estate loans that would occur during the crisis.

For the category of real estate loans, however, differences in non-performing loan rates between failed and survivor banks during the crisis were priced in the correct direction ex-ante (Panels C and D of Table IX). Due to the lack of disaggregated interest income data in the call reports, it is not possible to 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 higher risk product categories – or the one due to idiosyncratic investment choices within each real estate product category – i.e., failed banks supplied credit to higher risk borrowers within each product category. Differences in interest returns between failed and survivor banks naturally reverse during the crisis, because the returns are computed over the complete stock of loans, which includes non-performing loans.

C.   Gains on MBS Securities

Notable differences in performance also exist between banks' holdings of agency MBS, private-label MBS, and securities in the residual non-MBS portfolio. I measure performance as the difference between the fair and amortised cost value of securities, divided by their amortised cost value. This metric gives a sense for potential capital gains (losses) per unit of exposure, were the bank to liquidate part of its securities portfolio.

---

[29]I compute returns over the aggregate stock of loans to maintain consistency in the definition of non-performing rates and interest returns.

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 market gains of MBS carry a positive bias. This bias should be stronger for (a) private-label MBS, the pricing of which relies more heavily on private information, (b) large banks for which, due to their higher exposure to private-label MBS, positive reporting biases would have a greater balance sheet impact, and (c) failing banks which, in the presence of shrinking capital buffers, faced an increasingly higher marginal benefit of inflating the fair value of their securities holdings.

As can be seen in Figure VII, for both small and large survivor banks (panels (a) and (b), respectively) private-label MBS significantly underperform the baseline group of non-MBS securities during the crisis. Agency MBS on the other hand, outperform the baseline non-MBS portfolio during the crisis. Though this result may seem counterintuitive, it needs to be viewed against the backdrop of agency and (implicit) government guarantees associated with the underlying assets, and of a series of Treasury and Federal Reserve interventions that aimed at supporting the market for agency MBS during the crisis. The same general patterns are observed in panels (c)-(d) of Figure VII, where the plots are reproduced for failed banks.

Difference-in-means tests for failed and survivor banks point to the relative underperformance of securities held by failed banks (Panels E and F of Table IX). For the agency MBS and non-MBS portfolios, the differences are identified strongly. For private-label MBS on the other hand, differences are less robustly identified. This could be due to the small number of banks with non-zero holdings of private-label MBS, but could also be driven by the reporting biases discussed above.

D.   Investment Choices and Pre-Crisis Growth

Studies have shown that the rapid growth of the real estate sector prior to the crisis was accompanied by a relaxation of lending standards (see, for example, Mian and Sufi (2009)). In my sample, failed banks did indeed increase their exposure to both loans and commitments to non-household real estate borrowers at a more rapid pace than survivor banks did. This pattern does not extend to traditional home mortgages, agency MBS, and private-label MBS.[30]

Rapid growth into real estate exposures alone, however, does not explain ex-post differences in asset

---

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

performance. Comparing asset performance across categories between failed banks and a subsample of survivor banks that also grew their exposure to real estate risk rapidly during the run-up to the crisis,[31] yields differences in asset performance similar to the ones presented earlier. The results are shown in the Appendix.

IX. 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 skewed the balance of the portfolio towards real estate products impacted the probability of bank failure during the crisis.

I first show that, during the run-up to the crisis, both failed and survivor banks increased their exposure to non-household real estate credit, but not to traditional real estate products such as home mortgage and agency MBS. Banks that failed during the crisis, entered the crisis more exposed to non-household real estate products than survivor banks did, and regression estimates indicate that these non-core exposures were the main drivers of bank failures during the crisis – neither traditional home mortgages nor agency MBS mattered for failures.

To provide further evidence of the impact of real estate exposures on bank failures, I track the performance of various real estate product categories and find, as one would expect, that real estate products performed worse than non-real estate ones during the crisis. Non-household real estate products were the worst performers. Furthermore, within each of the identified "toxic" real estate product categories, I find that failed banks invested in assets that performed worse than the ones held by survivor banks. Ex-post differences in asset quality, however, cannot be solely attributed to the faster pace at which failed banks expanded into real estate during the pre-crisis period.

---

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

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.

Antoniades, Adonis. forthcoming. "Liquidity Risk and the Credit Crunch of 2007-2008: Evidence from Micro-Level Data on Mortgage Loan Applications." *Journal of Financial and Quantitative Analysis*.

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.

Cheng, Ing-Haw, Harrison Hong, and Jose Scheinkman. 2015. "Yesterday's Heroes: Compensation and Risk at Financial Firms." *Journal of Finance*, 70(2): 839–879.

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.

Duca, John V., and David.C Ling. 2015. "The Other (Commercial) Real Estate Boom and Bust: The Effects of Risk Premia and Regulatory Capital Arbitrage." *working paper*.

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.

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.

Levitin, Adam J., and Susan M. Wachter. 2013. "The Commercial Real Estate Bubble." *Harvard Business Law Review*, 3(1): 83–118.

Mian, Atif Rehman, and Amir Sufi. 2009. "The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis." *The Quarterly Journal of Economics*, 124(4): 1449–1496.

Ng, Jeffrey, Florin P. Vasvari, and Regina Wittenberg-Moerman. forthcoming. "Media Coverage and the Stock Market Valuation of TARP Participating Banks." *European Accounting Review*.

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.

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.
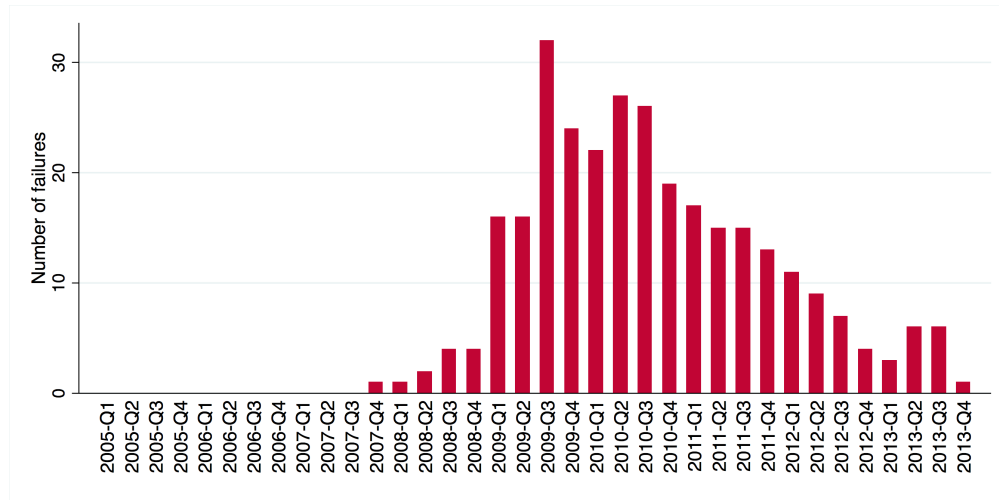
Figure II: The TED spread for the period 2005-2013. This figure shows daily and annual averages of the TED spread from 2005 to 2013. The TED spread measures funding strains in the banking sector and is defined as the difference between the 3-month LIBOR rate and the 3-month Treasury rate. Data on rates obtained from the Federal Reserve Economic Data (FRED), available online by the Federal Reserve Bank of St. Louis.
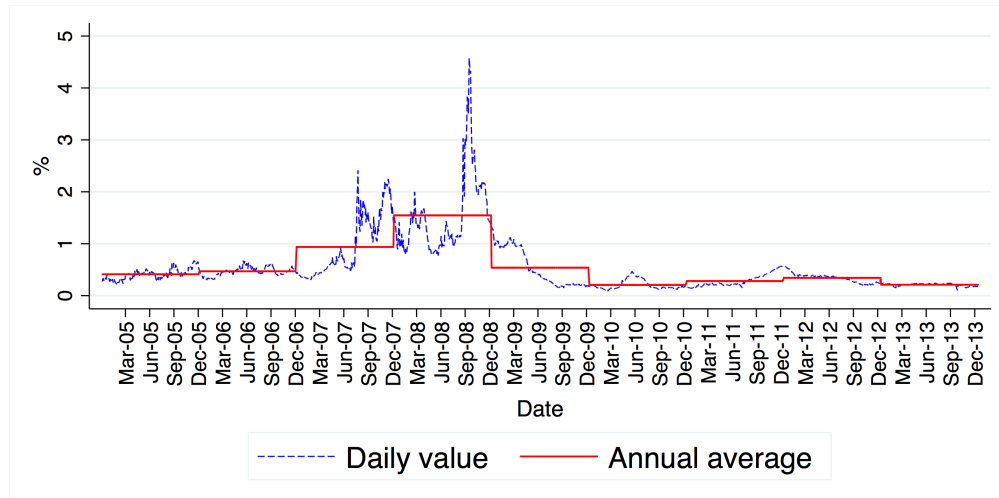
Figure III: Evolution of default risk. This chart displays the evolution of the median z-score in 2005-2013, shown separately for failed and survivor banks. The z-score is inversely related to the probability of default and is defined as the sum of equity capital plus the mean return on assets, divided by the standard deviation of the return of assets. Commercial bank data are from the Reports of Condition and Income (Call Reports) and bank failures are taken from the FDIC's list of failed banks. Sample selection is discussed in Section III.
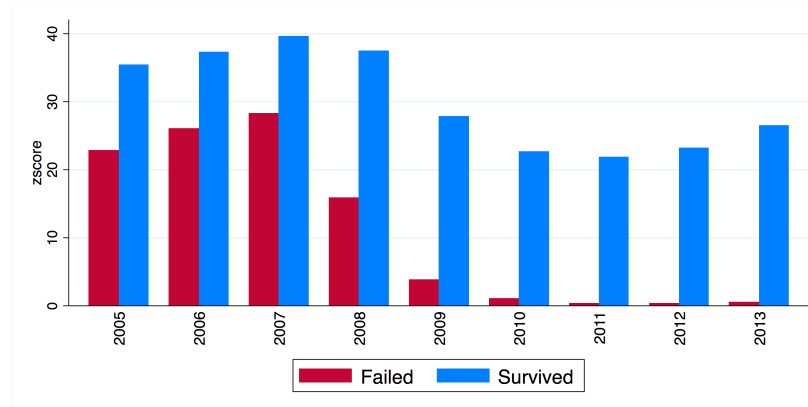
Figure IV: Evolution of housing prices. The dashed line displays quarterly values for the S&P/Case-Shiller U.S. National Home Price Index (not seasonally adjusted). The index is a composite of single-family home price indexes for the nine U.S. Census divisions, which measures shifts in the total value of all existing single-family housing stock. The solid line displays quarterly values for the NCREIF Property Index. The index is a composite total rate of return measure of investment performance of a very large pool of individual commercial real estate properties acquired in the private market for investment purposes only. *Sources: S&P Dow Jones Indices LLC, National Council of Real Estate Investment Fiduciaries (NCREIF)*
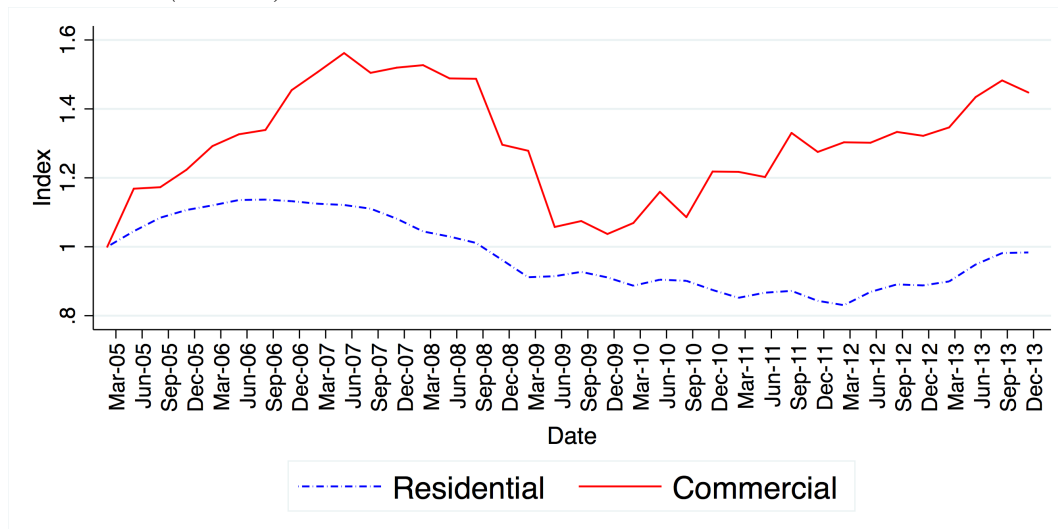
Figure V: Non-performing loan rates for real estate and non-real estate loans. This graph displays quarterly averages of asset performance for three categories of real estate loans and for a reference portfolio of all other non-real estate loans for 2004-2013. I use the ratio of non-performing loans 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.
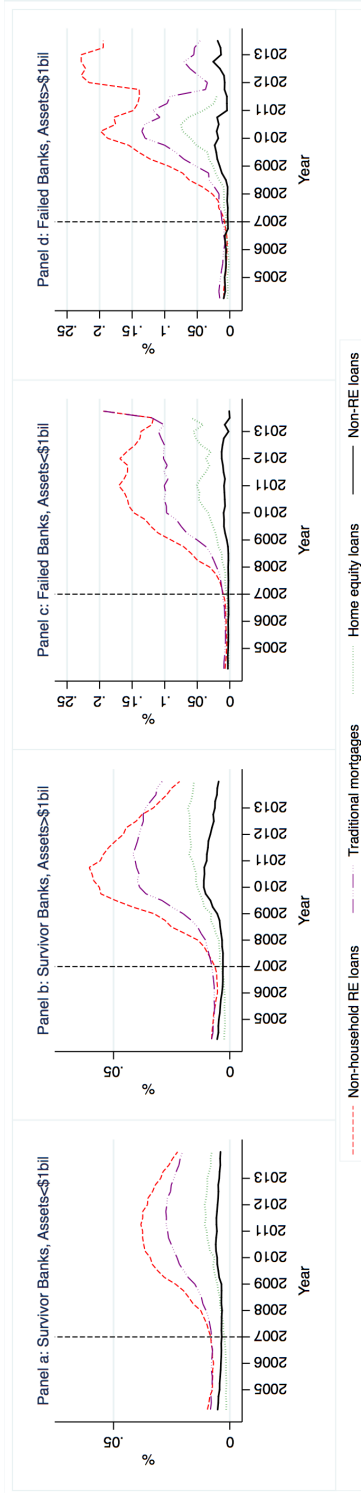
Figure VI: Interest returns on aggregate real estate and non-real estate loan portfolios. This graph displays quarterly averages of asset returns for real estate loans and for a reference portfolio of all other non-real estate loans for 2004-2013. I use the ratio of interest income received to total 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.
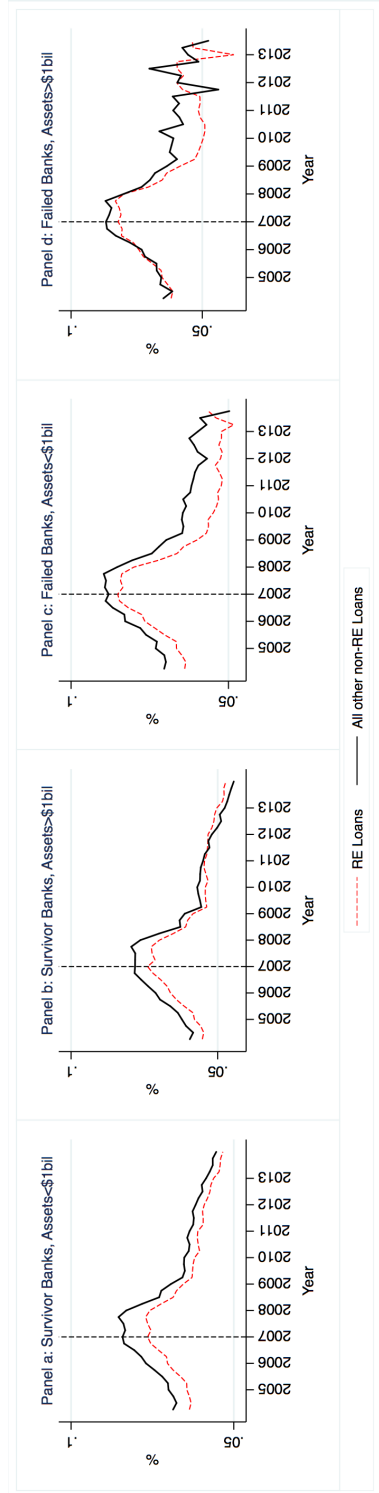
Figure VII: Rate of unrealized gains on MBS and non-MBS security portofolios. This graph displays quarterly averages of asset performance for agency and private-label MBS, as well as for a reference portfolio of all other non-MBS securities for 2004-2013. I use unrealized capital gains, defined as the 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.
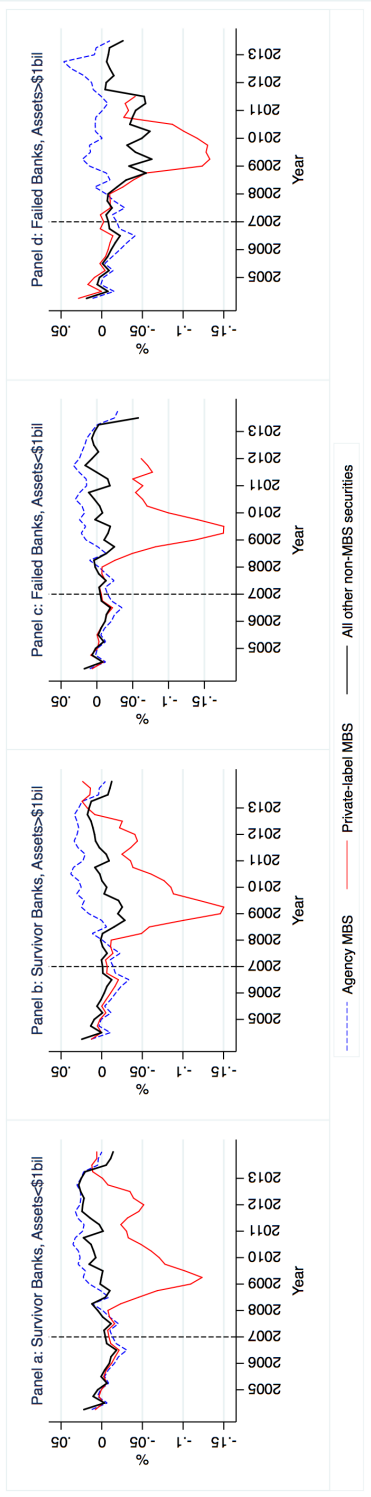
Table I: Definitions

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
Non-household RE loans	All other real estate loans divided by total assets
Credit lines excluding RE lines	Total unused loan commitments (excluding credit card lines) minus total unused real estate commitments, divided by total assets
Non-household RE lines	Commitments to fund commercial real estate, construction, and land development loans, divided by total assets
Home equity lines of credit	Revolving, open-end lines secured by 1-4 family residential properties divided by total assets

Table II: Difference-in-means tests for standard predictors of failure. This table displays tests for the equality of means for a standard set of predictors of failure included in the baseline model. The left panel displays tests for banks with average assets in 2004 less than \$1 billion and the right panel for banks with average assets in 2004 greater than \$1 billion. Commercial bank data are 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
Assets (\$ bil)	0.21	0.28	0.068***	22.77	4.16	-18.610***
BHC membership	0.17	0.12	-0.050**	0.43	0.26	-0.169*
ROAA	0.01	0.01	0.000	0.01	0.01	-0.000
Efficiency	1.64	1.73	0.088***	1.79	2.09	0.297***
Non-performing loans	0.01	0.00	-0.002***	0.01	0.01	0.000
Equity capital	0.10	0.09	-0.007***	0.10	0.09	-0.007
Core deposits	0.68	0.62	-0.064***	0.58	0.50	-0.077***
Cash	0.04	0.04	-0.006***	0.04	0.03	-0.011***
Money market	0.03	0.03	0.005**	0.02	0.03	0.005
Securities	0.23	0.13	-0.104***	0.22	0.21	-0.009
Illiquid Assets	0.69	0.80	0.107***	0.72	0.73	0.017
Credit lines	0.11	0.18	0.072***	0.20	0.19	-0.015

Table III: The effects of real estate risk on bank failure. This table shows the results of estimating a probit model of the probability of a commercial bank failing during 2006-2013, estimated separately for small and large banks. Failure is defined as the bank having been placed under FDIC receivership between January 1, 2006 and 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 (2) and (4) augment the baseline model to include variables that capture the bank's product mix, accounting for the exposure of the bank's loan, securities, and credit line portfolios to various categories of real estate products. Commercial bank data are 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	-0.00	-0.01	-0.02	0.03
	(0.01)	(0.01)	(0.02)	(0.02)
BHC membership	-0.03**	-0.02*	-0.05	-0.00
	(0.01)	(0.01)	(0.04)	(0.03)
ROAA	-1.34	-1.37	-4.54	-1.71
	(0.91)	(0.88)	(4.02)	(3.21)
Efficiency	0.02	-0.00	0.12**	-0.01
	(0.01)	(0.02)	(0.05)	(0.04)
Non-performing loans	0.21	0.50	1.44	0.01
	(0.55)	(0.52)	(2.49)	(2.44)
Equity capital	-0.44**	-0.45**	-0.84*	-1.02*
	(0.18)	(0.19)	(0.48)	(0.56)
Core deposits	-0.23***	-0.16***	-0.24*	-0.23**
	(0.04)	(0.04)	(0.12)	(0.11)
Money market	0.60**	0.24	1.21	0.98
	(0.24)	(0.21)	(1.22)	(0.92)
Securities	0.19	0.16	1.05	0.53
	(0.17)	(0.15)	(0.98)	(0.73)
Illiquid Assets	0.43**	0.18	1.16	0.52
	(0.17)	(0.15)	(0.93)	(0.70)
Credit lines	0.47***	0.12	0.06	-0.42
	(0.05)	(0.11)	(0.19)	(0.30)
Agency MBS		-0.03		0.15
		(0.08)		(0.25)
Private-label MBS		0.58		1.96**
		(0.57)		(0.98)
Traditional home mortgages		-0.02		0.15
		(0.07)		(0.19)
Home equity loans		1.10***		2.65*
		(0.29)		(1.51)
Non-household RE loans		0.26***		0.57***
		(0.05)		(0.18)
Non-household RE lines		0.47***		0.80**
		(0.13)		(0.40)
Home equity lines of credit		-1.30***		-3.90**
		(0.43)		(1.93)
Number of banks	4,041	4,041	279	279
Failed	274	274	27	27
Pseudo-R2	0.179	0.268	0.147	0.378

Table IV: 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 2001 and 2005. Heteroscedasticity-robust standard errors are reported. The levels of statistical significance are *** p<0.01, ** p<0.05, and * p<0.10

SIZE	SMALL (ASSETS < $1bil)			LARGE (ASSETS > $ 1bil)		
VARIABLE	2001	2005	Diff	2001	2005	Diff
Securities excluding MBS	0.17	0.17	-0.001	0.12	0.12	-0.003
Agency MBS	0.06	0.06	-0.002*	0.09	0.10	0.004
Private-label MBS	0.00	0.00	0.000	0.01	0.01	0.002***
Illiquid assets excluding RE loans	0.28	0.24	-0.034***	0.30	0.27	-0.027***
Traditional home mortgages	0.17	0.15	-0.016***	0.14	0.12	-0.018***
Home equity loans	0.01	0.02	0.007***	0.02	0.03	0.014***
Non-household RE loans	0.21	0.28	0.074***	0.24	0.28	0.048***
Credit lines excluding RE lines	0.05	0.06	0.007***	0.10	0.10	0.004*
Non-household RE lines	0.02	0.04	0.012***	0.04	0.06	0.015***
Home equity lines of credit	0.01	0.01	0.005***	0.02	0.03	0.011***

Table V: Difference-in-means tests for pre-crisis real estate exposures. This table displays tests for the equality of means for variables capturing the banks' level of exposure to the real estate sector through the composition of the loan, marketable securities, and credit line portfolios, for the groups of survivor and failed banks. The left panel displays tests for banks with average assets in 2004 less than $1 billion and the right panel for banks with average assets in 2004 greater than $1 billion. Commercial bank data are 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	0.17	0.09	-0.085***	0.12	0.11	-0.007
Agency MBS	0.06	0.04	-0.018***	0.10	0.09	-0.005
Private-label MBS	0.00	0.00	0.000	0.01	0.01	0.005
Illiquid assets excluding RE loans	0.25	0.19	-0.057***	0.28	0.18	-0.102***
Traditional home mortgages	0.15	0.11	-0.043***	0.12	0.10	-0.025
Home equity loans	0.02	0.03	0.009***	0.04	0.02	-0.019***
Non-household RE loans	0.27	0.47	0.196***	0.27	0.43	0.167***
Credit lines excluding RE lines	0.06	0.06	-0.002	0.11	0.06	-0.046***
Non-household RE lines	0.03	0.10	0.064***	0.05	0.10	0.048***
Home equity lines of credit	0.01	0.02	0.004***	0.03	0.01	-0.020***

Table VI: Economic impact. The table shows the reduction in the average loss rate for a counterfactual exercise in which the average levels of exposure to real estate products in 2005 are reduced down to the lowest quartile of the distribution for that year. The average loss rate is defined as the probability of failure as predicted by the model in columns (2)and (4) of Table III, and averaged across all banks in each subsample. Each row corresponds to a reduction in a single exposure, with all other exposures remaining at their empirically observed levels. Commercial bank data are 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.

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

Table VII: Controlling for the effect of local economic shocks. This table shows the results of estimating a probit model of the probability of a commercial bank failing during 2006-2013, estimated separately for small and large banks. Failure is defined as the bank having been placed under FDIC receivership between January 1, 2006 and September 30, 2013. Columns (1)-(6) report estimates over the subsample of banks with average assets in 2004 less than $1 billion, and columns (7)-(12) report estimates over the subsample of banks with average assets in 2004 greater than $1 billion. Columns (1) and (7) report the estimates for the paper's core real estate model for reference. Columns (2) and (8) include a bank-specific measure of local income shocks, derived from county-level data on per capita income declines during the 2006-2009 period, aggregated up to the bank level using bank branch-level data on deposit account balances in 2005. Columns (3) and (9) include a similarly-constructed proxy for local unemployment rates, derived from county-level data on the increase in unemployment rates during the 2006-2009 period. Columns (4) and (10) include a similarly-constructed proxy for local declines in housing prices, derived from zip code-level data on annualised house price index (HPI) declines during the 2006-2009 period. Columns (5) and (11) include simultaneously all three proxies in columns (2)-(4) and (8)-(10). Columns (6) and (12) do not include proxies for local economic conditions but saturate the core model in columns (1) and (2) with state fixed effects, for each state and bank set to 1 if a bank had a branch in the state in 2005. Commercial bank data are 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, income statistics from the Bureau of Economic Analysis, unemployment rates from the Bureau of Labor Statistics, and housing price index data from the Federal Housing Finance Agency. Sample selection is discussed in Section III. The models are estimated using the financial variables averaged over the four quarters of 2005. The reported coefficients are average marginal effects. Estimates for the coefficients of baseline variables are suppressed for brevity. Heteroscedasticity-robust standard errors are reported. The levels of statistical significance are *** $p<0.01$, ** $p<0.05$, and * $p<0.10$

SIZE	SMALL (ASSETS < $1bil)						LARGE (ASSETS > $1bil)					
MODEL	PROD	INC	UNMPL	HPI	ALL	FE	PROD	INC	UNMPL	HPI	ALL	FE
VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Securities	0.16	0.20	0.19	0.28*	0.27*	0.17	0.53	0.91	0.52	0.60	0.74	3.65***
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.17)	(0.73)	(0.74)	(0.71)	(0.73)	(0.72)	(1.16)
Illiquid Assets	0.18	0.23	0.24*	0.33**	0.33**	0.22	0.52	0.91	0.57	0.66	0.79	3.43***
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.17)	(0.70)	(0.72)	(0.69)	(0.71)	(0.71)	(1.08)
Credit lines	0.12	0.13	0.15	0.09	0.12	0.16	-0.42	-0.42	-0.42	-0.45	-0.41	-2.18***
	(0.11)	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)	(0.30)	(0.32)	(0.31)	(0.31)	(0.32)	(0.61)
Agency MBS	-0.03	-0.04	-0.05	-0.04	-0.05	-0.05	0.15	0.20	0.11	0.16	0.15	0.19
	(0.08)	(0.08)	(0.09)	(0.08)	(0.08)	(0.09)	(0.25)	(0.25)	(0.25)	(0.25)	(0.26)	(0.44)
Private-label MBS	0.58	0.51	0.61	0.04	0.23	0.58	1.96**	1.69*	1.76*	1.71*	1.55*	3.86***
	(0.57)	(0.58)	(0.57)	(0.60)	(0.59)	(0.64)	(0.98)	(0.95)	(0.98)	(0.97)	(0.94)	(1.34)
Traditional home mortgages	-0.02	-0.03	-0.07	-0.02	-0.06	0.05	0.15	0.14	0.09	0.10	0.09	-0.15
	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.19)	(0.18)	(0.19)	(0.18)	(0.18)	(0.40)
Home equity loans	1.10***	1.04***	0.91***	0.88***	0.83***	1.10***	2.65*	2.62*	2.34	3.06**	2.40	2.35
	(0.29)	(0.28)	(0.29)	(0.28)	(0.28)	(0.33)	(1.51)	(1.54)	(1.55)	(1.50)	(1.54)	(2.11)
Non-household RE loans	0.26***	0.23***	0.21***	0.20***	0.18***	0.20***	0.57***	0.59***	0.41**	0.50***	0.45**	0.79**
	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.18)	(0.17)	(0.18)	(0.18)	(0.19)	(0.33)
Non-household RE lines	0.47***	0.43***	0.42***	0.45***	0.42***	0.44***	0.80**	0.72*	0.81**	0.83**	0.74*	4.08***
	(0.13)	(0.12)	(0.12)	(0.12)	(0.12)	(0.13)	(0.40)	(0.39)	(0.40)	(0.40)	(0.40)	(0.65)
Home equity lines of credit	-1.30***	-1.37***	-1.32***	-1.26***	-1.30***	-1.42***	-3.90**	-3.87**	-3.90*	-4.35**	-3.88*	-5.82*
	(0.43)	(0.42)	(0.43)	(0.41)	(0.41)	(0.46)	(1.93)	(1.97)	(2.06)	(2.00)	(2.10)	(3.01)
Number of banks	4,041	4,041	4,041	4,041	4,041	3,573	279	279	279	279	279	137
Failed	274	274	274	274	274	274	27	27	27	27	27	27
Pseudo-R2	0.268	0.274	0.291	0.29	0.299	0.34	0.378	0.402	0.419	0.405	0.428	0.615

Table VIII: Other 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)-(4) report estimates over the subsample of banks with average assets in 2004 less than $1 billion, and columns (5)-(10) report estimates over the subsample of banks with average assets in 2004 greater than $1 billion. Columns (1) and (5) report the estimates for the paper's core real estate model for reference. Columns (2) and (6) omit controls for real estate risk, and 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 (7) augment the baseline model with variables that capture both real estate risk and the income mix of the bank. Columns (4) and (8) use the model in columns (1) and (6) but exclude all banks that participated in the Capital Purchase Program (CPP), either directly or through their Bank Holding Company. Column (9) augments the model in column (6) to include controls for large banks' off-balance sheet risk through liquidity and credit enhancements provided to ABCP conduits. Column (10) excludes the 10 largest banks from the sample, to mitigate the impact of too-big-too-fail banks. 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, 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. Estimates for the coefficients of baseline variables are suppressed for brevity. Heteroscedasticity-robust standard errors are reported. The levels of statistical significance are *** $p<0.01$, ** $p<0.05$, and * $p<0.10$

| SIZE | SMALL (ASSETS < $1bil) | | | | LARGE (ASSETS > $1bil) | | | | | |
| MODEL | PRODUCT | INCOME | PR. & INC. | TARP | PRODUCT | INCOME | PR. & INC. | TARP | SPV | TBTF |
VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Securities	0.16	0.24	0.23	0.12	0.53	1.17	0.81	0.71	0.55	0.54
	(0.15)	(0.19)	(0.16)	(0.16)	(0.73)	(0.93)	(0.70)	(0.86)	(0.73)	(0.76)
Illiquid Assets	0.18	0.41**	0.21	0.15	0.52	1.05	0.57	0.97	0.53	0.53
	(0.15)	(0.18)	(0.16)	(0.16)	(0.70)	(0.90)	(0.68)	(0.87)	(0.70)	(0.73)
Credit lines	0.12	0.44***	0.13	0.12	-0.42	-0.10	-0.50*	-1.01**	-0.43	-0.43
	(0.11)	(0.05)	(0.11)	(0.12)	(0.30)	(0.20)	(0.29)	(0.45)	(0.30)	(0.32)
Agency MBS	-0.03		-0.03	-0.01	0.15		0.16	0.04	0.16	0.16
	(0.08)		(0.08)	(0.09)	(0.25)		(0.25)	(0.32)	(0.25)	(0.27)
Private-label MBS	0.58		0.55	0.47	1.96**		1.30	2.28*	1.94*	2.03**
	(0.57)		(0.57)	(0.61)	(0.98)		(0.96)	(1.31)	(1.00)	(1.02)
Traditional home mortgages	-0.02		0.00	-0.02	0.15		0.26	-0.07	0.15	0.15
	(0.07)		(0.07)	(0.07)	(0.19)		(0.22)	(0.24)	(0.19)	(0.20)
Home equity loans	1.10***		1.13***	1.17***	2.65*		2.35**	3.84*	2.66*	2.75*
	(0.29)		(0.29)	(0.32)	(1.51)		(1.19)	(2.13)	(1.51)	(1.57)
Non-household RE loans	0.26***		0.27***	0.27***	0.57***		0.56***	0.86***	0.57***	0.59***
	(0.05)		(0.05)	(0.05)	(0.18)		(0.16)	(0.21)	(0.18)	(0.19)
Non-household RE lines	0.47***		0.43***	0.54***	0.80**		0.81**	1.04*	0.81**	0.82**
	(0.13)		(0.13)	(0.13)	(0.40)		(0.37)	(0.53)	(0.40)	(0.42)
Home equity lines of credit	-1.30***		-1.31***	-1.21**	-3.90**		-3.36**	-5.57**	-3.90**	-4.05**
	(0.43)		(0.43)	(0.47)	(1.93)		(1.42)	(2.60)	(1.91)	(2.01)
Number of banks	4,041	4,041	4,041	3,671	279	279	279	161	279	269
Failed	274	274	274	264	27	27	27	24	27	27
Pseudo-R2	0.268	0.193	0.271	0.306	0.378	0.246	0.425	0.551	0.378	0.371

Table IX: Asset performance through the crisis. Panel A displays difference-in-means tests between the groups of survivor and failed small banks (Assets < 1 \$bil) for the non-performing loan rates of various categories of real estate loans, as well as for the aggregate portfolio of all other non-real estate loans. I define non-performing loan rates as loans past due 90 days and not accruing divided by total loans in each loan category. Panel B repeats for large banks. Panel C displays difference-in-means tests between the groups of survivor and failed small banks for the loan returns of the banks' aggregate real estate and aggregate non-real estate loan portfolios. I define loan returns as total interest income from the loan portfolio divided by the total volume of loans in the portfolio. Panel D repeats for large banks. Panel E displays difference-in-means tests between the groups of survivor and failed small banks for the rate of unrealized gains for the banks' agency MBS, private-label MBS, and aggregate non-MBS portfolios. I define the rate of unrealized gains as the difference between fair and amortized cost value divided by amortized cost value. Panel F repeats for large banks. Bank financial data are 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

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Panel A: Non-performing loan rates (small banks)										
Non-real estate loans	-0.0020***	-0.0017***	-0.0015***	-0.0012***	-0.0006*	0.0035***	0.0021	0.0040*	0.005	0.001
Traditional home mortgages	0.0002	-0.0008	0.0015*	0.0065***	0.0220***	0.0582***	0.0736***	0.0709***	0.0779***	0.0903***
Home equity loans	0.0007*	0.0013***	0.0018***	0.0042***	0.0105***	0.0205***	0.0368***	0.0278***	0.0322***	0.0379*
Non-household RE loans	-0.0027***	-0.0019***	-0.0002	0.0095***	0.0481***	0.0938***	0.1230***	0.1238***	0.1150***	0.0980***
Panel B: Non-performing loan rates (largel banks)										
Non-real estate loans	0.0029	0.0021	0.0021	0.0004	0.0048***	0.0111**	0.0068	-0.0036**	0.0087***	0.0110***
Traditional home mortgages	0.0082**	0.0041	0.002	0.0057	0.0192***	0.0593***	0.0872***	0.0345	0.0215***	0.0183***
Home equity loans	0.0012	0	0.0019	0.0037	0.0109***	0.0296***	0.0535***	0.0052**	.	.
Non-household RE loans	0.0009	-0.001	0.0001	0.0077**	0.0411***	0.0960***	0.1254***	0.1022***	0.1877***	0.1684***
Panel C: Loan returns (small banks)										
Non-RE loan returns	0.0022**	0.0040***	0.0050***	0.0043***	0.0011	-0.0008	-0.0007	-0.0024	0.0009	0.0007
RE loan returns	0.0010*	0.0042***	0.0083***	0.0067***	-0.0027***	-0.0063***	-0.0077***	-0.0066***	-0.0048***	-0.0036**
Panel D: Loan returns (large banks)										
Non-RE loan returns	0.0043	0.0023	0.0068**	0.0062*	0.0045*	0.0048*	0.0066*	0.0041***	0.0098***	0.0070***
RE loan returns	0.0070***	0.0078***	0.0092***	0.0098***	0.0033**	-0.0027*	-0.0045	0	0.0024***	0.0058***
Panel E: Unrealized gains (small banks)										
Non-MBS securities	-0.0040***	-0.0025***	-0.0008	-0.0013**	-0.0108***	-0.0160***	-0.0122***	-0.0163***	-0.0233***	-0.0124
Agency MBS	-0.0034***	-0.0033***	-0.0032***	-0.0025***	-0.0020**	-0.0049***	-0.0073***	-0.0046	-0.0109***	-0.0171***
Private-label MBS	-0.0011	0.0016	0.0019	0.0025	-0.0121	-0.0600***	-0.0206	-0.0253	.	.
Panel F: Unrealized gains (large banks)										
Non-MBS securities	-0.0069*	-0.0078***	-0.0089***	-0.0066***	-0.0179**	-0.0326**	-0.0482***	-0.0404***	-0.0240***	-0.0136***
Agency MBS	-0.0027	-0.0022	-0.0058**	-0.0045	-0.0034	-0.0110***	-0.0242***	-0.0269***	-0.0013	-0.0083***
Private-label MBS	0.0086	0.0019	0.0065	0.0029	0.0278*	-0.0181	-0.0246	0.0014	.	.

Appendix: Asset Performance and Growth

Table AI: 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 the corresponding year. Heteroscedasticity-robust standard errors are reported. The levels of statistical significance are *** $p<0.01$, ** $p<0.05$, and * $p<0.10$

SIZE	SMALL (ASSETS < \$1bil)			LARGE (ASSETS > \$ 1bil)		
VARIABLE	Survived	Failed	Diff	Survived	Failed	Diff
Securities excluding MBS	0.000	-0.014	-0.0140***	-0.005	0.019	0.0245
Agency MBS	-0.001	-0.008	-0.0068**	0.004	0.004	-0.0001
Private-label MBS	0.000	-0.000	-0.0002	0.002	0.004	0.0023
Illiquid assets excluding RE loans	-0.032	-0.060	-0.0282***	-0.023	-0.064	-0.0409**
Traditional home mortgages	-0.016	-0.016	0.0006	-0.017	-0.028	-0.0110
Home equity loans	0.007	0.009	0.0020	0.015	0.005	-0.0099***
Non-household RE loans	0.069	0.141	0.0721***	0.044	0.090	0.0463***
Credit lines excluding RE lines	0.007	0.005	-0.0023	0.005	-0.006	-0.0107
Non-household RE lines	0.011	0.036	0.0254***	0.013	0.031	0.0181*
Home equity lines of credit	0.005	0.006	0.0004	0.012	0.004	-0.0079***

Table AII: Asset performance through the crisis for a high-growth subsample of survivor 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. Panel A displays difference-in-means tests between the groups of survivor and failed small banks (Assets < 1 $bil) for the non-performing loan rates of various categories of real estate loans, as well as for the aggregate portfolio of all other non-real estate loans. I define non-performing loan rates as loans past due 90 days and not accruing divided by total loans in each loan category. Panel B repeats for large banks. Panel C displays difference-in-means tests between the groups of survivor and failed small banks for the rate of unrealized gains for the banks' agency MBS, private-label MBS, and aggregate non-MBS portfolios. I define the rate of unrealized gains as the difference between fair and amortized cost value divided by amortized cost value. Panel D repeats for large banks. Bank financial data are 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

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Panel A: Non-perfoming loan rates (small banks)										
Non-real estate loans	-0.0016***	-0.0016***	-0.0016***	-0.0014***	-0.0009***	0.0034***	0.002	0.0041*	0.0049	0.0008
Traditional home mortgages	0.0008	-0.0003	0.0016**	0.0067***	0.0220***	0.0583***	0.0749***	0.0718***	0.0786***	0.0906***
Home equity loans	0.0006	0.0012***	0.0015***	0.0035***	0.0095***	0.0190***	0.0353***	0.0268***	0.0297***	0.0349*
Non-household RE loans	0.0008	0.0004	0.0009	0.0088***	0.0424***	0.0818***	0.1057***	0.1049***	0.1003***	0.0877***
Panel B: Non-performing loan rates (largel banks)										
Non-real estate loans	0.0036	0.0024	0.0025	0.0006	0.0053***	0.0116**	0.0071	-0.0030*	0.0095***	0.0115***
Traditional home mortgages	0.0094***	0.0048*	0.0026	0.0067	0.0200***	0.0585***	0.0861***	0.0313	0.0178***	0.0149***
Home equity loans	0.0018	0.0005	0.0026	0.0047*	0.0117***	0.0318***	0.0572***	0.0096***	.	.
Non-household RE loans	0.0025	0.0003	0.0005	0.0077**	0.0403***	0.1009***	0.1325***	0.1071***	0.1885***	0.1684***
Panel C: Unrealized gains (small banks)										
Non-MBS securities	-0.0028***	-0.0016**	0.0004	-0.0009*	-0.0112***	-0.0161***	-0.0121***	-0.0165***	-0.0237***	-0.0123
Agency MBS	-0.0008	-0.0013	-0.0011	-0.0009	-0.0014*	-0.0042***	-0.0061***	-0.0035	-0.0099***	-0.0160***
Private-label MBS	-0.0003	0.0035	0.0044	0.0039	-0.0094	-0.0591***	-0.0208	-0.0251	.	.
Panel D: Unrealized gains (large banks)										
Non-MBS securities	-0.0015	-0.0032	-0.0066**	-0.0046***	-0.0092	-0.0245*	-0.0458***	-0.0391***	-0.0216***	-0.0118***
Agency MBS	0.0006	0.0002	-0.0029	-0.002	-0.0021	-0.0099***	-0.0223***	-0.0255***	-0.001	-0.0078***
Private-label MBS	0.0124*	0.0071	0.0147*	0.0073	0.0343**	-0.0013	-0.0086	0.0207	.	.

Previous volumes in this series

All volumes are available on our website www.bis.org.