"Residential House Prices, Commercial Real Estate and Bank Failures"

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Abstract

This study investigates the explanatory factors of bank failure during and after the Great Recession banking crisis (2008 – 2015) that uses residential real estate house price index (HPI) changes in each of the 9 Census regions and traditional bank financial statement variables. We find that the residential HPI change in each region of the United States have different effects on the likelihoods of bank failures. Since the residential HPI movements differ from region to region, we use both the regional location and its HPI change to isolate its effect on banks. Other more traditional and associated factors, like construction and land development lending, similarly explain bank failures during the main period of this banking crisis (2008 – 2011) but the movements of the regional residential HPI are distinguishing factors over this period. The real estate focus of other studies of this period have typically been on "subprime lending" and "mortgage securitizations," but we examine the effects of the residential HPI changes on the financial health of insured financial institutions (banks). Because banks held significant amounts of residential and commercial real estate loans, the financial health of the loans and banks are sensitive to the house price movements before, during and after the financial collapse in 2008.

Keywords: Bank Failures, Construction and Land Development Lending, Residential HPI

I. Introduction

Failures of banking companies (banks) have been costly to the FDIC by deposit insurance resolutions and the American public by reducing liquidity in the financial system and access to credit through individuals and businesses. [1] Over the 2008 – 2010 period the credit from banks decreased dramatically and only marginally increased by 2012. In addition, these bank failures caused the FDIC's Deposit Insurance Fund (DIF) balance to plummet in 2008 and 2009, go negative in 2009 and 2010, and then did not recover to a positive value until 2011 as bank failures waned. [2] While the largest wave of bank failures since the Great Depression occurred during the Thrift Crisis in the late 1980's and early 1990's (1987-1992), the wave of bank failures during the Great Recession (2007-2009) was less than half as severe in terms of numbers, but the average failed bank had asset sizes 27 times larger. This study examines the Great Recession banking crisis and demonstrates unique covariates that explain bank failures over this period. The U.S. residential house prices decreased over this crisis period, and we find that regional residential house price changes are important additional explanatory factors that have not been used in previous studies. We find these add significant power to explaining bank failures over this crisis. The residential real estate value plunge varied by region of the United States at different times creating large losses in value to homeowners. These value declines affected bank real estate loans similarly and we show that they are significant explanatory factors in identifying bank failures.

This study uses financial data from the individual banks' Reports of Condition and we add additional explanatory variables reflecting house price rates of change by census regions. We include, along with financial characteristics of banks, regional house price index annual changes that capture the effects of the residential house price movements on banks' likelihoods of failure.

[1] The following two Federal Deposit Insurance Corporation publications provide excellent coverages of the Great Recession Crisis and the Thrift Crisis and their impacts, respectively – "Crisis and Response: An FDIC History, 2008–2013" and "History of the 80's," Federal Deposit Insurance Corporation.
[2] The FDIC deposit insurance fund balances can be seen in the FDIC Annual Reports at the following site: https://www.fdic.gov/about/strategic/report/ .

Identifying house price rates of change effects by census regions on bank failures helps to isolate the general effects of residential house price movements on bank financial condition and that of developers and commercial real estate operators, apart from the asset securitization impacts. Our model uses a more traditional bank failure approach that is similar to the one used by Cole and White (2012) that uses selected bank-reported variables, but with the addition of the regional house price changes to show that they are important explanatory factors. This study empirically shows that the regional residential house price changes are important indicators of the bank failures that occurred over the Great Recession crisis period. Given the unique movements in these house price changes over this period, our model was not able to yield precise out-of-sample predictions, but the in-sample predictions and log-likelihood tests of goodness of fit do show greater predictive accuracy by including house price changes in the model. Other studies also use a similar more traditional approach by using mostly bank-reported financial items to construct the variables to estimate bank failure/survival. Sun et al. (2018) also uses bank-reported data to find a general significance between bank failures and house price changes over crisis periods but do not identify locations for these effects, and Berger and Bouwman (2013) focus on the usefulness of bank capital during financial crises.

The relatively large effect of residential house price declines can be seen by the banks' balance sheet holdings of residential real estate loans in Figure 2.[3] It shows the average relative holdings of these loans scaled by total assets from March 1999 through December 2016 for five separate asset size groups of banks – greater than \$250 billion, \$10 to \$250 billion, \$1 to \$10 billion, \$100 million to \$1 billion, and less than \$100 million. The largest two groups of banks quickly increased their residential real estate holdings before the crisis and held at least 25% of their assets in these loans until the end of 2008. We also note that the \$100 million to \$1 billion group of banks held at least 20 percent of their assets in residential loans through mid-2011. For all banks, their nonperforming loans in this category peaked at 25 percent of these loans in 2009Q4.

The residential house price changes also had large effects on the repayments of construction

[3] Individual bank reported financial data comes from Reports of Income and Condition (Call Reports).

and land development (C&D) loans that were made by banks as shown in Figure 3 by the portion of these loans relative to banks' total assets. When the house price changes declined the loan repayments also declined as many house construction projects became less profitable and more of them had to be charged off. The nonperforming C&D loans peaked at 17 percent of these loans in 2010Q1. Although a smaller portion of the average bank's asset size, they still comprised a large enough portion to cause problems for the bank if charged off. We develop the banking groups' average construction and land development lending percentages to their assets over the 2007-2009 period when they reached their maximum values on bank balance sheets. The largest portion was the $1 to $10 billion group with over 12%, next was the $100 million to $1 billion group with over 10% while the $10 to $250 billion group had about 5.5% of their assets. The largest banking group (over $250 billion) had the smallest percentage of their assets in these loans at slightly over 2%. In general, we note that the largest banks were heavily involved with residential mortgage lending and smaller banks were more concentrated in construction and land development loans.

The Great Recession may have ended in the mid-year of 2009 (according to the NBER), but the effects of the bank failures and retarded lending of the banking system severely plagued the recovery.[4] The financial crisis began in mid-2007 with the failure of Bear Stearns' hedge funds and it strengthened in the second half of 2008 when other large financial firms (including insured banks) failed or needed financial assistance. Many of these firms had large, global financial institutions at their center so that this crisis period contained the largest failed bank asset size in any period for the FDIC. The average failed bank asset size during the 2007-2016 period is $7.3 billion and contributed to the severity of the crisis and recession. Moreover, the regression analysis identifies that banks with larger asset sizes had higher likelihoods of failure relative to smaller banks over the early years of this crisis period. This period also gained public notice when some larger financially distressed banks received Open Bank Assistance (OBA) in 2008 and 2009.[5] This financial distress among larger banks led to a stream of papers that discuss their

[4] The following NBER site contains the timing of these economic cycles in the U.S., https://www.nber.org/cycles/.

[5] See Open Bank Assistance, Chapter 5 of Federal Deposit Insurance Corporation, *Managing the Crisis: the FDIC and RTC Experience 1980- 1994*, (1998).

practices involving nontraditional banking activities such as insurance underwriting, subprime lending and subprime mortgage securitizations. These papers include DeYoung, and Torna (2013), Sanders (2008), Gorton (2008), and Gorton and Metrick (2012).

This paper does not examine the more nontraditional banking activities as described above. Rather, it makes an important contribution to the literature by clearly identifying the impacts that regional residential house price changes and bank financial condition factors jointly had over the Great Recession crisis period on the likelihoods of bank failures. We know that separate regions had different house prices changes and bank failure outcomes and we see that in our estimated marginal effects. We also link these residential house price changes to the health of construction and land development loans for banks. The previous literature that focuses on explaining the causes of bank failures over this crisis period do not capture the important element of regional residential house price changes. This paper is able to identify the disparate real estate value change effects of separate regions on bank failures.

The remainder of this paper is organized as follows. Section II discusses the data that is used in this study. Section III presents the methodology and statistical approach that provides the econometric model and the empirical results. Section IV presents the summary and conclusion.

II. Data

This paper uses all FDIC-insured depository institutions for analysis that existed prior to a failure year. Table 1 defines the twenty-four predictor variables and identifies the *a priori* relationship we expect from the regressions to the likelihood of bank failure. Total book equity to assets (the tenth variable) begins the Call Report financial variables. One of the most interesting independent financial variables is the natural logarithm of total assets (lnsize) which is intended to control for bank size. The variable is included to account for large-scale diversification, economies of scale and scope, access to the capital markets, and an overall source of support for the entire organization – all factors that should reduce the likelihood of failure (β < 0). Note that to determine the marginal effect of the estimated coefficient in our nonlinear modeling (described below) on the likelihood of bank failures, the bank size effect must incorporate the value of bank size and we use the mean value for this. However, we find that the coefficient has a positive sign (β > 0) for the failure years of 2008 and 2009, being positive and significant only in 2009, showing that larger banks had a higher likelihood of failure during the depths of the crisis, and it turns negative (β < 0) in later failure years. This may be partially explained by the fact that many more failures were of larger banks in 2008 and 2009 than in later years that were in the sample as failed or OBA.

Previous studies have shown that bank examination ratings can become outdated quickly (Cole and Gunther, 1995). This can also be said as well for past financial variables. We expect that the greater the age of the prior financial data in terms of lagged variables, the more likely there will be a less significance in these variables. However, analysis of these earlier data on current bank failures indicates how long in advance banks may be considered to be a possible failure or survivor 1,2,3,4 or 5 years in the future. The bank-reported financial variables are accounting information that is included in the regressions to measure their financial condition. These variables are scaled by dividing by total assets.

The residential HPI changes are year-end Federal Housing Finance Agency (FHFA) residential housing price index relative changes of purchase only housing transactions for each census region.[6] These HPI variables are calculated as annual relative changes as in (1):

$$Regional\ HPI_{ijt} = \delta_{ijt} \times \left(\frac{Residential\ HPI_{ijt} - Residential\ HPI_{ijt-1}}{Residential\ HPI_{ij\ t-1}}\right) \qquad (1)$$

for each bank i where δ is a regional dummy variable that is 1 if a bank's home is in that region

[6] The Federal Housing Finance Association residential housing price index (HPI) is the quarterly Purchase Only (from Sales Price data) that is seasonally adjusted. The base for these regional HPI values is 1991Q1. The HPI is a broad measure of the annual movement of single-family house price changes. The HPI is a weighted, repeat-sales index, meaning that it measures average price changes in repeat sales on the same properties. This information is obtained by reviewing repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac since January 1975.

and 0 otherwise, j is each of the 9 U.S. Census region (New England, Middle Atlantic, South Atlantic, East North Central, East South Central, West North Central, West South Central, Mountain, and Pacific), and t = 2003q4, 2004q4, ..., 2015q4 where the time periods are listed as year-end quarters. These Regional HPI change variables are put into a series of cross-section regressions shown in equation (2) of the following Econometric Model subsection. Note that this Regional HPI variable combines both the regional locations effects and the effects of HPI rates of change on bank failures.[7]

Given the dramatic declines in residential house prices across U.S. housing markets from 2006 to 2011 (Figure 5) after which rates of change began to increase, these factors are significant explanations of bank failures by census region. Separate effects are generated for each census region because these house price movements are very different across regions. The model estimates the probability of bank failure in the year in question. Previous studies that use HPI changes do so by collapsing them into a single variable. We specify nine regional HPI change variables to capture market effects on the on financial conditions in different regions of the U.S. to separately identify the effects of these changes. Indeed, we can see that the large declines in home prices from 2008q4 - 2011q4 occurred particularly in the South Atlantic and Pacific regions and large increases took place subsequently.[8]

III. Methodology and Statistical Approach

In modeling bank failures, the dependent variable FAIL is binary (fail or survive). Our model is a logistic regression that produces odds-ratio estimates of failure and survival, as well as the mean marginal effects of these estimates. These bank failures are taken for each year over the 2008 – 2015 period, and the independent variables are used to estimate one through five year-end lags from the bank failure year. We limit the modeling to these years since there were few

[7] This approach is used rather than one that would create a variable of the HPI change for each banks' region as one variable.
[8] The website for the FHFA HPI Purchase only data is: https://www.fhfa.gov/

failures from 2003 to 2007 with the largest number of failures being 4 in 2004 (Figure 1). In this way, the bank failure regressions are a series of cross-sectional logistic regressions for each failure year. Our approach is similar to the one used by Cole and White (2012) with the exception of the inclusion of regional annual house price changes.

The census regional residential HPI change variables that we utilize are components that have not been used in previous bank failure estimations as separate regional effects. We use census regional HPI change variables that highlight their locational effects; having a unique estimation variable for each census region identifies the effects of HPI changes on bank failures for that region. Figure 4 shows the Census regions. Including these variables makes sense given the dramatic changes in residential house prices over this Great Recession period. The movement of these regional HPI changes can indicate the movement of real estate prices generally and can be predictors of commercial and residential real estate values regionally.

These effects on financially distressed banks are directly and indirectly linked. That is, a direct link is the decline in these house prices can lead to events like mortgage delinquencies and foreclosures on their balance sheet that ultimately leads to bank losses and potential failure. Even in post-2011 period when most regional residential HPI values are increasing (see Figure 5), the volume of mortgage lending relative to a property value can still have a negative effect on a bank's financial health when a mortgagor has payment delinquencies and defaults. The indirect linkage is that the changes in residential house prices can be highly correlated with many more local economic indicators like GDP or unemployment. The decline in these indicators will have negative impacts of banks' financial well-being.

For our empirical study, we consider the bank sample to be commercial banks, savings banks and savings & loan institutions that are insured by the FDIC. Bank failures include banks that are closed by their federal supervisory agency and resolved by the FDIC for disposition or allowed to remain operating with federal government assistance (OBA).[9] In addition to these failed and

[9] Banks that participated in TARP or any special FDIC or Federal Reserve program during the Great Recession period does not qualify them as receiving OBA.

OBA banks, we also include in this sample banks that have negative net book equity after including reserves and assuming 50 percent of their nonperforming assets go to default.[10] We label these banks as technical failures. These technical failure banks are used for every sample period when they are active and contain negative net book equity values. We are studying financially distressed banks on a continuum from failed, technically failed and survivors.

The approach to bank failure modeling is that once a bank is declared to be disposed of by the FDIC it will remain in that failure state whereas ongoing banks including those that receive OBA and technical failures can continue operating and may change states within the next year. Many assisted and technical failure banks survive and will show up in the sample of surviving banks in later years, and surviving banks in one year may change state in later years also. This process has two supervisory outcomes and is consistent with a logistic estimation procedure (Maddala, 1988). Once a bank is determined to be failed it drops out of the sample (with the exception of many assisted banks that survived and technical failures) and will not appear in the following banking samples.

A. Econometric Model

We estimate a logistic model and use it to forecast bank failures and survival conditioned on institution size, bank financial failure components, and regional HPI factors. These variables are from one to five year-ends preceding each bank's year of failure and survivor banks from that same period. The financial components are bank-reported variables that indicate its financial health. As a group, they are proxies for components used by federal bank regulators to evaluate and rate bank financial health– Capital adequacy, Asset Quality, Management, Earning, Liquidity, and Sensitivity to Market Risk (CAMELS). For example, a bank that has a greater amount of capital, lower nonperforming assets, good management, higher earnings and greater access to funding has a lower probability of failure. This model includes regional residential HPI

[10] The net book equity formula is the following: $\text{Capital}_t + \text{Reserves}_t - 0.5(\text{Non-Performing Assets}_t + \text{Non-Accrual Assets}_t)$. See Cole & White (2011).

changes to account for movements in housing prices for each census region. Given the dramatic declines in residential house prices across U.S. housing markets during the Great Recession period, these factors are considered to be significant explanations of bank failures from different census regions. The model estimates the probability of bank failure in the year in question by using series of cross-section regressions with 1 to 5 year differences between failures and the explanatory variables. Estimated marginal effects are derived from the regression estimated coefficients and measured at the means of the included variables for each of the respective sample periods. We assume the unobserved underlying response variable, Yit, is a linear function as in (2):

$$Y_{it} = \alpha_1 + \sum_{j=1}^{9} ME_{1j}(\textit{Regional HPI}_{ij(t-v)q4}) + \sum_{j=10}^{24} ME_{2j}(\textit{Financial Failure Variables}_{ij(t-v)q4}) + \varepsilon_{it} \quad (2)$$

for each bank (i) where the ME_{1j} = 1, . . . 9 are the marginal effects for the FHFA residential changes in each census region; ME_{2j} = 10, . . . 24, are marginal effects for bank financial variables that are proxies of the component CAMELS ratings of bank condition; t are failure years for the dependent variable where t = 2008, 2009, …, 2015; (t-v)q4 are the covariate dates that are the year-end quarter of the preceding years where v = 1, …, 5 to represent the one- to five-year lags in the regressions. The theoretic background to this binary logistic model is as follows. The ε_{it} are assumed to have a cumulative logistic function that is similar for each group – failure or survivor -- (Maddala, 1988). We estimate the single constant terms (α1) under the assumption that the proportional odds among the groups are independent of the explanatory variables such that the slope parameters are the same for each group. In general, to separate the failed from the survivor group requires a single plane and more for more than two dimensions. We designate group 1 institutions as failures and group 0 as surviving institutions in the year of observation. In practical terms, this means that the probability of an observation i belonging to failed banks (group 1), conditional on the regressors, is $F(\alpha_1+\beta' X_i)$; the conditional probability of its belonging to non-failed banks (group 0) is $1 - F(\alpha_1+\beta' X_i)$ where α_1 is the estimated intercept term, β is a vector of estimated coefficients for the logistic regression and F( ) is the cumulative logistic function.

We report the marginal effects of each variable rather than the actual estimated coefficients. The marginal effects provide the degree to which a change in the respective variable contributes to the likelihood of bank failure (a positive sign) or survival (a negative sign). These effects are then evaluated by taking the variable change times its coefficient and adding to that the product of each variable evaluated at its sample mean and its estimated coefficient. This is equivalent to specifying all other variables are held constant at their overall sample mean values. The significance level of the estimated parameter is also reported and can be interpreted as the significance of the marginal effect of the variable that is changed.[11]

Figure 5 shows the regional HPI relative changes that are consistently significant to explain bank failures for most of the logistic regressions in two or more sample years. These census regions include the South Atlantic and Pacific that have higher likelihoods of failure and shows large decreases in HPI changes over the 2005 - 2008 period, and the West North Central region also has higher failure likelihoods for 2013 and 2014 failures where its HPI changes are moderate. The East and West South Central regions have lower failure likelihood effects over the 2008 – 2012 period where their HPI changes also remain moderate. Their effects on bank failures can be seen by the regression results that are discussed in the next section.

Table 2 shows the difference in the regression variable values between the five years of 2008q4 and 2013q4. Most of the regional HPI annual changes reached their troughs at year-end 2008 and were recovering by 2013. The regional HPI annual changes do not have statistical tests on their mean differences because standard deviations are not available but the sheer magnitudes of these changes indicate the importance of the changes in these variables. Just based on the relative change differences, the Pacific (rre_pac_chg) and South Atlantic (rre_sa_chg) regions are over 30 and 20 percent, respectively, between those two time periods. The West North Central (rre_wnc_chg) region is lower at nine percent, while the East (rre_esc_chg) and West South Central (rre_wsc_chg) regions have eight percent differences. For the bank-reported

[11] This is only an approximation at large samples sizes. In our case the sample size for each regression between 8983 and 6134 which can normally considered large sample sizes particularly since they include the universe of banks for each year.

variable differences, it is interesting that both the equity-asset ratio (tepr) is significantly smaller in 2013q4 relative to 2008q4. Also, except for multifamily house lending, all other lending categories are smaller in 2013q4 than in 2008q4.

B. Empirical Results

Tables 3-6 present the results for the marginal effects for failure years 2008, 2009, 2012, and 2014. They show the explanatory effects of the variables on bank failures over the sample range. We assume that all marginal effects are estimated for positive changes in the variable in question. For the 2008 failures (Table 3), the South Atlantic (rre_sa_chg) and Pacific (rre_pac_chg) regions have consistently (statistical significance occurs in a majority of the posted regressions) positive and significant ME-Mean values that have their HPI change variables explain higher likelihoods of failure for banks in those regions when the HPI variable is increased. The East South Central (rre_esc_chg) region shows a consistent negative ME-Mean effect that shows lower likelihoods of failure. Among the Call Report variables, the capital–asset ratio, the non-performing assets (loans and securities) variable (npap_lnlsdebtr), brokered deposits (bdpr) and construction and land development loans secured by real estate (reconpr) have positive and consistently significant effects that explain higher failure likelihoods. The positive sign for the tepr variable is contrary to the hypothesis that increases in capital reduce the likelihood of failure. The loans to finance commercial real estate, construction and land development not secured by real estate (recompr) variable exhibits consistently negative and significant marginal effects that explain lower failure likelihoods for banks in 2008. This is contrary to hypotheses.

Bank failures in 2009 (Table 4), the peak year of actual failed bank assets at approximately \$2 trillion, show the continued relevance of regional house price changes and selected Call Report variables to explain bank failures. The South Atlantic (rre_sa_chg) and Pacific (rre_pac_chg) HPI changes have positive and consistent significant effects for the 2009 bank failure regressions. The West South Central (rre_wsc_chg) and East South Central (rre_esc_chg) regions have HPI changes that are negative and consistently significant. There are multiple Call Report variables that that have positive and negative effects on the likelihood of bank failures. The equity-asset (tepr) variable, non-performing assets (npap_lnlsdebtr), brokered deposits (bdpr), secured real estate loans for construction and land development (reconpr), loans for multi-family real estate (remulpr), and the asset size (lnsize) variable have consistently significant and positive effects to explain bank failures. Again the tepr variable sign is contrary to hypotheses. This is the only set of regressions that have banks' asset sizes as positive and mostly significant in the sample period of 2008 – 2015 bank failures. The loan-loss reserve (llrpr), return-on-assets (roapr), securities (secpr) and consumer loans (conspr) have consistent negative and significant effects that lower the failure likelihoods with an increase in the value of these variables.

The economic transformation from the Great Recession period can be seen in Table 5 that shows the bank failure regressions in 2012. There are no consistent significant regional HPI changes for this failure year. Call Report variables show that the bank equity-asset ratio (tepr) and loan-loss reserves (llrpr) have consistent significant and negative effects on bank failures, consistent with hypotheses and contrary to prior years' results. Non-performing assets (npap_lnlsdebtr), multifamily loans (remulpr) and non-secured loans for commercial real estate (recompr) are consistently positive and significant explanations for bank failures. Note that the loans for construction and land development that are secured by real estate (reconpr) are not consistently significant. This is the first failure period since the Great Recession period of 2008 where these commercial real estate loans secured by real estate are not consistently significant for the majority of the posted regressions.

Table 6 contains the bank failure marginal effect estimates for 2014 failures. Recall there were only 18 bank failures in 2014 (Figure 1). The South Atlantic (rre_sa_chg) region has consistent ME-Mean HPI change effects that positively and significantly explain higher likelihoods of bank failures. There are three Call Report variables that significantly explain bank failures in all regressions. Non-performing assets (npap_lnlsdebtr) ME values are consistently significant and positive explanations for bank failures. The bank equity ratio (tepr) and asset size (lnsize) are consistently significant and negative explanations for bank failures (conforming with hypotheses). As was mentioned in the 2009 bank failure regressions, the negative estimated ME for bank asset size is the typical relationship to bank failures, unlike the estimated value for 2009 bank failures.

These regression tables show that the bank failures during and after the Great Recession period differ over the course of the recession and recovery. We see that financial distress occurred to larger banks that are shown by the consistently significant estimated values during the 2009 failures. The ME-Mean results also show that different regions of residential real estate HPI changes had consistently significant effects that explain bank failures over the 2008 through 2015 periods. These significant marginal effects that explain these bank failures demonstrate the residential house price changes and impacts of correlated regional economic variables are meaningful in determining effects on bank failures. We see these regional effects over the entire sample period (2003 – 2015). Some Call Report variables contain marginal effects that significantly explain bank failures, such as non-performing loans and securities (npap_lnlsdebtr), total equity capital-asset ratio (tepr), loan-loss reserves (llrpr), brokered deposits (bdpr) only for the 2008 – 2010 bank failures and commercial real estate loans for construction and land development that that are secured by real estate (reconpr) is consistently significant for the 2008 – 2011 period.

The estimated marginal effects, especially for the regional residential HPI variables, vary greatly for the different estimation periods. Depending on the period in which the residential house price relative changes are measured, they show very different effects for their relationship to bank failures. As we observe, the sample period is unstable for the regional residential real estate markets, and their changing condition does have an effect on the accuracy of the out-of-sample tests that we show below.

C. **Regression Fit and Forecast Tests**

In this sub-section, we compare the fits and forecasts of the regression models that use the regional annual residential HPI changes and the traditional bank-reported variables (HPI-CR) and the bank-reported variables (CR). As Table 13 shows, the HPI-CR model significantly improves the bank failure estimation fits using the likelihood ratio tests. More specifically, the improvements in fit are statistically significant for most of the 1- to 5-year lagged regressions for the Failure Years from 2008 through 2015.

The In-Sample and Out-of-Sample receiver operating characteristic (ROC) curve comparisons between these two models are shown in Figures 6 and 7, respectively, where the area under the curve (AUC) comparisons utilize an algorithm suggested by DeLong, DeLong, and Clarke-Pearson (1988). These ROC comparisons test the models' relative abilities to accurately forecast bank failures. We compare each AUC and plot their differences in the vertical bar graphs. These In-Sample ROC comparisons match the Likelihood Ratio test results. They demonstrate that the HPI-CR model has better regression fits overall and they have significantly superior fits, especially for the three-, four- and five-year lagged regressions. The Out-of-Sample ROC comparisons show that the CR model has significantly better prediction forecasts for most regression settings. The difference in these In-Sample and Out-of-Sample results is due to the sample period is a very unstable period for the residential housing market that is the only difference between the two models. The Purchase Only, FHFA regional Residential HPI values during the 2003-2010 period has a volatility (standard deviation) that is over four times as large as that over the prior 1992-2002 period. Also, this volatility over the 2011-2016 period is approximately twice as large as this 1992-2002 period. This demonstrates the volatile movement of these HPI values over the sample period explains the dramatically different out-of-sample results.

Tables 7, 8 and 9 are the tables for the out-of-sample tests of the Actual failures and Tables 10, 11 and 12 are for the combination of Actual and Technical (Actual-Technical) failures tabulations. These out-of-sample tabulations are forecasts of the estimated regressions that are one year ahead of the estimation period. So if there is a regression of 2009 failures on 2006q4 independent variables, then the out-of-sample tabulation would be the 2010 failure projections using 2007q4 independent variables. These tables validate the logistic regression's forecast abilities but identify the hazards of using the regional residential HPI changes during a periods of instability in real estate markets. These out-of-sample tabulations show that these regressions produce very accurate forecasts for the one- and two-year forecasts out-of-sample tests for 2009 bank failures, given that the uninformed level is 50 percent. The three-year forecast has a much lower accuracy because the regional real estate market changes are relatively unstable. The dramatic impact in the regional residential housing price changes from 2006q4 to 2007q4 can be observed by the movements of the estimated coefficients of HPI changes in Table 4.

The one- and two-year look ahead forecast results of the estimated models are robust considering that misclassifications are operationally small. For the one-year forecasts for Actual and Actual-Technical failures (Tables 7 and 10), we find accurate failure predictions in 98 and 95 percent of the failure cases, respectively, For misclassifications, only 8 and 6 percent of surviving banks are misclassified as failures while 2 and 5 percent of banks that failed are misclassified as surviving. For the 2-year look-ahead of these two failure groups (Tables 8 and 11), the correct failure predictions are 92 and 91 percent, respectively, while the number of misclassified banks are small. As expected, these results show that the 2009 failure predictions for the 2-year look ahead forecast is less compared to the 1-year look ahead. The three-year look-ahead forecast results (Tables 9 and 12) show that the correct predictions of failing banks are 62 and 67 percent for the Actual and Actual-Technical failure groups. As discussed above, the instability of the regional residential real estate markets to predict well due to high volatility over these time periods is a primary cause of these declines in accurate bank failure predictions.

IV. Summary and Conclusions

The recent financial crisis and Great recession of 2007-2009 had several root causes, one of which was commercial real estate lending. Much of the existing literature focuses on subprime mortgages as a root cause. We show that construction and land development loans are significant in explaining bank failures through 2011 and regional residential house price movements have been significant explanatory factors through 2015. It is important to know that the residential house price changes have important effects on the financial health of residential real estate and construction and development loans, and therefore to bank failures. We find that residential house price changes in different regions explain whether a bank has a higher or lower likelihood of failure throughout the sample period. Our results are supported by additional testing beyond our regression analysis.

An aspect that is unique for bank failures during the period of the Great Recession is that many larger banks failed compared to previous downturns. We see that for the 2009 failures the estimated logistic model coefficient for bank's asset sizes (lnasset) is positive and significant while this coefficient is positive and insignificant in 2008. The positive sign indicates that larger banks in these periods have a greater likelihood of failure. We note that the typical bank failure models show that smaller banks have a higher likelihood of failure. All of these factors demonstrate that the recent financial crisis had some unique financial causes and effects.

For the critical peak failure year of 2009 we interestingly find that, for Actual and Actual-Technical failures, the one-year look-ahead forecast has a 98 percent and 95 percent (Tables 7 and 10) accuracy respectively, with an operationally small number of misclassifications. Although not shown, the predictive accuracies for the other one- through three-year look-ahead forecasts vary greatly for all failure years due to the regional residential HPI instability. This phenomena is highlighted by the diverse ROC results where the In-Sample shows the estimation advantages of using the regional HPI changes while the Out-of-Sample demonstrate the opposite effects. These results show that for the period of the most failures during the Great Recession (2009-2010) prior bank lending and investing activities had prescience for predicting bank failures and financial distress. Even the two-year look ahead is successful in forecasting failures, but with greater misclassifications of survivors as failures. These results indicate that there existed strong evidence in 2007 and 2008 that banks, even large banks, were approaching a period of severe weakening and distressed financial conditions.

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Table 1: FHFA HPI and Call Report Variable Definitions

Variable	Description	Expected Sign on Likelihood of Faiilure
rre_ma_chg	FHFA residential price index for the Middle Atlantic Census Region annual relative change.	Ambiguous
rre_sa_chg	FHFA residential price index for the South Atlantic Census Region annual relative change.	Ambiguous
rre_mt_chg	FHFA residential price index for the Mountain Census Region annual relative change.	Ambiguous
rre_pac_chg	FHFA residential price index for the Pacific Census Region annual relative change.	Ambiguous
rre_ne_chg	FHFA residential price index for the New England Census Region annual relative change.	Ambiguous
rre_enc_chg	FHFA residential price index for the East North Central Census Region annual relative change.	Ambiguous
rre_esc_chg	FHFA residential price index for the East South Central Census Region annual relative change.	Ambiguous
rre_wsc_chg	FHFA residential price index for the West South Central Census Region annual relative change.	Ambiguous
rre_wnc_chg	FHFA residential price index for the West North Central Census Region annual relative change.	Ambiguous
tepr	Total book equity volume.	−
llrpr	Loan loss reserves for loans, leases & bank's securities.	−
roapr	Return on assets (ROA) is the annualized net bank income.	−
npap_lnlsdebtr	Non-performing assets are the loans, leases & bank's securities that have repayments that have past-due and nonaccrual statuses, and other real estate owned balances.	+
secpr	Securities held to maturity plus securities held for sale.	−
bdpr	Brokered deposits are deposit liabilities that are typically raised through national brokers rather from local customers.	− or +
lnsize	Natural logarithm of bank's asset size.	Ambiguous
cashduepr	Total cash & balances due from depository institutions.	−
goodwillpr	Goodwill intangible assets.	+
rer14pr	Loans secured by 1-4 family residential properties.	−
remulpr	Loans secured by multi-family (more than 5) residential properties.	+
reconpr	Loans for construction or land development secured by these properties secured by real estate.	+
recompr	Loans to finance commercial real estate, construction and land developent not secured by real estate.	+
cipr	Loans for commercial and industrial purposes.	−
conspr	Loans to individuals for houshold, family and other personal expenditures.	−

Note: All bank reported variables are ratios divided by the bank's asset volume.

Table 2: Statistical Comparison of 2008q4 and 2013q4

	Statistics Data 2008q4			Statistics Data 2013q4			2013q4 - 2008q4	
	N	Mean	SD	N	Mean	SD	Difference	t-test
FHFA HPI Variables								
rre_ma_chg	535	-0.05053		457	0.03069		0.08122	N/A
rre_sa_chg	1,107	-0.14223		819	0.07834		0.22057	N/A
rre_mt_chg	453	-0.14275		329	0.11165		0.25439	N/A
rre_pac_chg	420	-0.21760		305	0.15306		0.37067	N/A
rre_ne_chg	252	-0.07015		219	0.03134		0.10149	N/A
rre_enc_chg	1,496	-0.07688		1,279	0.05849		0.13538	N/A
rre_esc_chg	642	-0.04006		584	0.03826		0.07832	N/A
rre_wsc_chg	1,192	-0.02077		1,024	0.05880		0.07957	N/A
rre_wnc_chg	1,921	-0.04411		1,652	0.04436		0.08846	N/A
Call Report Variables								
tepr	8,150	0.11484	0.06952	6,695	0.11115	0.05371	-0.00369	***
llrpr	8,150	0.00965	0.00668	6,695	0.00986	0.00592	0.00021	**
roapr	8,150	0.00184	0.03132	6,695	0.00236	0.42872	0.00052	
npap_lnlsdebtr	8,150	0.03085	0.03587	6,695	0.02417	0.02955	-0.00669	***
secpr	8,150	0.19562	0.14959	6,695	0.23504	0.16243	0.03943	***
bdpr	8,150	0.04513	0.09086	6,695	0.02039	0.05419	-0.02473	***
lnsize	8,150	11.99589	1.36076	6,695	12.20022	1.33713	0.20433	***
cashduepr	8,150	0.05792	0.06897	6,695	0.09847	0.09413	0.04055	***
goodwillpr	8,150	0.00460	0.01805	6,695	0.00328	0.01345	-0.00132	***
rer14pr	8,150	0.20210	0.15648	6,695	0.18996	0.14339	-0.01214	***
remulpr	8,150	0.01676	0.03481	6,695	0.02051	0.03870	0.00375	***
reconpr	8,150	0.07442	0.08294	6,695	0.03243	0.03411	-0.04199	***
recompr	8,150	0.16080	0.11639	6,695	0.15883	0.11915	-0.00197	
cipr	8,150	0.09235	0.07403	6,695	0.07871	0.06641	-0.01364	***
conspr	8,150	0.04139	0.05494	6,695	0.03106	0.04651	-0.01033	***

Notes:

Values for each variable are measured at each time period.

Standard Deviation estimates (SD) are not available for regional HPI values.

Table 3: Logistic Regression 2008 Failures Marginal Effects Estimation

Estimated Marginal Effects with Regression p Values

DV= failure, OBA's & technical failures in **2008**

Sample: Commercial Banks, Savings Banks and Savings & Loans

	Independent Variable Estimation Date									
	2007q4		2006q4		2005q4		2004q4		2003q4	
Variables	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]
rre_ma_chg	0.002158	-0.00021	-0.026305	0.00162	-0.024242	0.00639	-0.015445	0.00803	-0.066991	0.00741
	0.018**		0.543		0.012**		0.079*		0.148	
rre_sa_chg	-0.003025	-0.00488	0.034783	0.00653	0.006380	0.01978	0.022561	0.01661	0.031966	0.01110
	0.1		0.023**		0.511		0.049**		0.052*	
rre_mt_chg	-0.009824	-0.00181	0.005337	0.00364	-0.008074	0.00976	0.010528	0.00692	0.010171	0.00364
	0.392		0.759		0.488		0.537		0.733	
rre_pac_chg	-0.001541	-0.00495	1.090974	0.00014	-0.003026	0.00807	0.019018	0.00973	0.022634	0.00715
	0.596		0.001***		0.847		0.043**		0.069*	
rre_ne_chg	-0.008080	-0.00071	0.044705	-0.00058	-0.077697	0.00199	-0.045927	0.00337	-0.037770	0.00357
	0.796		0.708		0.293		0.340		0.437	
rre_enc_chg	0.005429	-0.00642	-0.020728	-0.00030	-0.038877	0.00637	-0.004395	0.00816	-0.012173	0.00905
	0.514		0.000***		0.071*		0.520		0.238	
rre_esc_chg	-0.001581	0.00110	-0.049645	0.00477	-0.010820	0.00560	-0.161312	0.00416	-0.222019	0.00316
	0.137		0.173		0.013**		0.086*		0.081*	
rre_wsc_chg	-0.003320	0.00470	-0.031771	0.00891	-0.059586	0.00980	-0.030529	0.00639	-0.100352	0.00463
	0.023**		0.143		0.058*		0.588		0.191	
rre_wnc_chg	-0.004329	-0.00155	0.028227	0.00463	0.003764	0.01166	0.023199	0.01279	-0.006593	0.01267
	0.913		0.488		0.906		0.446		0.255	
tepr	-0.030946		-0.035341		-0.018568		0.009632		-0.007004	
	0.000***		0.008***		0.146		0.157		0.628	
llrpr	-0.013991		-0.184848		-0.474034		-0.182948		-0.039603	
	0.474		0.035**		0.006***		0.232		0.741	
roapr	-0.008187		-0.007940		-0.091767		-0.054200		-0.010896	
	0.264		0.069*		0.123		0.067*		0.166	
npap_lnlsdebtr	0.030130		0.093024		0.133656		0.076386		0.050757	
	0.000***		0.000***		0.000***		0.001***		0.011**	
secpr	-0.000894		-0.001624		-0.008980		-0.012712		-0.018819	
	0.58		0.683		0.236		0.028**		0.000***	
bdpr	0.001583		0.005481		0.000353		0.011532		0.016062	
	0.049**		0.005***		0.000***		0.034**		0.011**	

lnsize	0.000147	0.000224	0.000845	0.000573	0.000472
	0.069*	0.343	0.077*	0.334	0.406
cashduepr	0.001104	-0.011576	-0.005529	-0.032477	-0.010589
	0.578	0.318	0.75	0.080*	0.438
goodwillpr	0.020814	0.021811	0.001570	-0.027674	0.002958
	0.105	0.219	0.958	0.370	0.911
rer14pr	0.000867	0.003722	0.003356	0.006167	-0.012995
	0.472	0.234	0.577	0.264	0.029**
remulpr	0.004122	0.006903	0.013581	0.009705	-0.001903
	0.011**	0.181	0.176	0.296	0.853
reconpr	0.005306	0.019014	0.040388	0.037713	0.032167
	0.000***	0.000***	0.000***	0.000***	0.000***
recompr	-0.003744	-0.005746	-0.006035	-0.007159	-0.011314
	0.005***	0.072*	0.334	0.262	0.040**
cipr	0.001923	0.002285	-0.000402	-0.003619	-0.010230
	0.271	0.63	0.966	0.687	0.183
conspr	-0.002137	-0.011270	-0.028526	-0.019177	-0.019443
	0.553	0.291	0.107	0.300000	0.182
Constant	-5.237	-5.522	-6.058	-6.004	-4.200
	0.024**	0.006***	0.001***	0.000***	0.003***
Pseudo R2	0.521	0.371	0.252	0.221	0.190
AIC by N	0.074	0.094	0.108	0.109	0.106
AIC	623	800	938	957	954
Likelihood Ratio Test	624	442	300	258	213
Likelihood Ratio p	0	0	0	0	0
Chi Squared	303	378	305	288	252
Model Significance p	0	0	0	0	0
Failed & Technically "Failed" Banks	113	112	111	108	102
OBA Banks	3	3	3	3	3
Observations	8,369	8,501	8,647	8,787	8,983

Notes:

[1]Relative HPI Annual Change; p values on 2nd row; ***=1% **=5% *=10% Significance;

OBA is Open Bank Assistance & is included as Failed banks; Number of parameters is 25 & Model df is 24.

Constant is an Odds-Ratio estimate.

Table 4: Logistic Regression 2009 Failures Marginal Effects Estimation

Estimated Marginal Effects with Regression p Values
DV= failure, OBA's & technical failures in **2009**
Sample: Commercial Banks, Savings Banks and Savings & Loans

	Independent Variable Estimation Date									
	2008q4		2007q4		2006q4		2005q4		2004q4	
Variables	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]
rre_ma_chg	0.002126	-0.003317	0.030006	-0.000206	-0.005527	0.001616	-0.038290	0.006387	-0.046557	0.00803
	0.851		0.006***		0.787		0.120		0.057*	
rre_sa_chg	-0.003397	-0.019319	-0.041720	-0.00488	0.224960	0.006527	0.114065	0.019777	0.114123	0.016614
	0.307		0.113		0.000***		0.000***		0.000***	
rre_mt_chg	-0.002109	-0.007934	0.018293	-0.001809	0.005471	0.003642	0.047560	0.009761	0.045957	0.006916
	0.539		0.838		0.928		0.060*		0.177	
rre_pac_chg	-0.002507	-0.011214	-0.038860	-0.004946	3.792147	0.000138	0.084623	0.008067	0.054240	0.009727
	0.27		0.296		0.001***		0.000***		0.003***	
rre_ne_chg	0.000386	-0.002169	0.484798	-0.000706	0.878779	-0.000583	-0.357395	0.001993	-0.286383	0.003366
	0.935		0.129		0.135		0.121		0.065*	
rre_enc_chg	-0.002971	-0.014112	-0.003295	-0.006416	-3.392922	-0.000302	0.264137	0.006374	0.086056	0.008155
	0.638		0.840		0.248		0.014**		0.273	
rre_esc_chg	0.001337	-0.003156	0.006520	0.001098	-0.222500	0.004769	-0.053895	0.005595	-0.253627	0.004161
	0.918		0.625		0.031**		0.001***		0.045**	
rre_wsc_chg	0.006085	-0.003037	-0.051819	0.004696	-0.293627	0.008907	-0.127366	0.009801	-0.311626	0.00639
	0.814		0.032**		0.004***		0.117		0.013**	
rre_wnc_chg	-0.003008	-0.010396	0.400678	-0.00155	-0.031735	0.004625	0.062497	0.011664	-0.015460	0.012791
	0.785		0.241		0.085*		0.461		0.431	
tepr	-0.038555		-0.140407		-0.002147		-0.004638		0.027861	
	0.000***		0.000***		0.907		0.770		0.095*	
llrpr	-0.011496		-0.315466		-0.986620		-1.274991		-0.960389	
	0.127		0.183		0.002***		0.000***		0.003***	
roapr	-0.004632		-0.117615		-0.088066		-0.401346		-0.210064	
	0.045**		0.001***		0.013**		0.000***		0.004***	
npap_lnlsdebtr	0.016446		0.224892		0.359700		0.314115		0.248716	
	0.000***		0.000***		0.000***		0.000***		0.000***	
secpr	-0.003149		-0.005756		-0.038586		-0.033560		-0.034383	
	0.000***		0.592		0.003***		0.005***		0.003***	
bdpr	0.001010		0.032834		0.037482		0.000942		0.044445	
	0.003***		0.000***		0.000***		0.002***		0.000***	

lnsize	0.000028	0.001224	0.003193	0.003160	0.002742
	0.442	0.084*	0.000***	0.000***	0.002***
cashduepr	-0.001816	-0.018240	-0.023975	-0.085047	-0.072170
	0.102	0.53	0.417	0.027**	0.038**
goodwillpr	0.035070	0.112241	-0.093360	-0.233789	-0.242276
	0.000***	0.058*	0.124	0.002***	0.004***
rer14pr	-0.001212	0.012710	-0.016225	-0.013749	-0.007216
	0.028**	0.168	0.125	0.187	0.477
remulpr	0.001060	0.052370	0.049637	0.045890	0.060270
	0.171	0.000***	0.002***	0.003***	0.001***
reconpr	0.002878	0.090566	0.099658	0.101826	0.105120
	0.000***	0.000***	0.000***	0.000***	0.000***
recompr	-0.000513	0.019491	-0.001917	0.013235	0.018050
	0.365	0.048**	0.866	0.244	0.115
cipr	-0.001851	-0.003325	-0.016529	-0.002718	0.001231
	0.037**	0.805	0.339	0.870	0.942
conspr	-0.003008	-0.074378	-0.084205	-0.073685	-0.034303
	0.106	0.040**	0.049**	0.066*	0.343
Constant	1.761	-5.169	-5.861	-5.639	-5.469
	0.417	0.000***	0.000***	0.000***	0.000***
Pseudo R2	0.646	0.339	0.283	0.245	0.213
AIC by N	0.133	0.238	0.252	0.253	0.252
AIC	1,080	1,991	2,143	2,187	2,217
Likelihood Ratio Test	1,883	997	825	692	588
Likelihood Ratio p	0	0	0	0	0
Chi Squared	378	542	628	561	528
Model Significance p	0	0	0	0	0
Failed & Technically "Failed" Banks	354	355	350	334	321
OBA Banks	6	6	6	5	4
Observations	8,150	8,369	8,501	8,647	8,787

Notes:

[1]Relative HPI Annual Change; p values on 2nd row; ***=1% **=5% *=10% Significance;

OBA is Open Bank Assistance & is included as Failed banks; Number of parameters is 25 & Model df is 24.

Constant is an Odds-Ratio estimate.

Table 5: Logistic Regression 2012 Failures Marginal Effects Estimation

Estimated Marginal Effects with Regression p Values

DV= failure, OBA's & technical failures in **2012**

Sample: Commercial Banks, Savings Banks and Savings & Loans

	Independent Variable Estimation Date									
	2011q4		**2010q4**		**2009q4**		**2008q4**		**2007q4**	
Variables	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]
rre_ma_chg	-0.000068	-0.00280	-2.770884	-0.001158	0.616187	-0.0014	0.107635	-0.003423	0.008093	-0.000213
	0.16		0.000***		0.015**		0.529		0.348	
rre_sa_chg	-0.000852	-0.00307	-0.891128	-0.00743	-0.030398	-0.005654	-0.052385	-0.019936	-0.049238	-0.005035
	0.101		0.000***		0.005***		0.356		0.343	
rre_mt_chg	0.000052	-0.00186	-0.609937	-0.00401	0.108498	-0.004171	0.016914	-0.008187	0.197813	-0.001867
	0.913		0.000***		0.017**		0.778		0.040**	
rre_pac_chg	-0.000033	-0.00235	-0.832219	-0.002623	0.391636	-0.001792	0.037389	-0.011572	0.109656	-0.005104
	0.919		0.000***		0.000***		0.346		0.004***	
rre_ne_chg	.	.	.	.	.	.	.	.	.	.
	.		.		.		.		.	
rre_enc_chg	-0.000593	-0.00481	-1.526128	-0.005876	0.219115	-0.004194	-0.008108	-0.014562	-0.031347	-0.00662
	0.235		0.000***		0.012**		0.938		0.009***	
rre_esc_chg	-0.001897	-0.00078	-1.111163	-0.003813	0.092830	-0.000922	-0.089620	-0.003256	0.071357	0.001133
	0.235		0.000***		0.722		0.666		0.657	
rre_wsc_chg	0.002331	0.00126	-2.095733	-0.00353	-0.729177	0.001401	0.155771	-0.003134	-0.060727	0.004845
	0.244		0.000***		0.015**		0.701		0.000***	
rre_wnc_chg	-0.000023	-0.00290	-1.303362	-0.008976	1.100744	-0.001268	0.012597	-0.010728	0.490705	-0.001599
	0.984		0.000***		0.020**		0.947		0.173	
tepr	-0.001603		-0.076523		-0.078425		-0.066407		-0.043452	
	0.000***		0.000***		0.001***		0.001***		0.004***	
llrpr	-0.001482		-0.073874		-0.236777		-0.398074		-0.650198	
	0.004***		0.128		0.014**		0.001***		0.001***	
roapr	-0.000181		-0.020026		-0.019869		0.024134		-0.072706	
	0.227		0.397		0.599		0.000***		0.019**	
npap_lnlsdebtr	0.000797		0.071905		0.086836		0.084761		0.091830	
	0.000***		0.000***		0.000***		0.000***		0.000***	
secpr	-0.000118		-0.009030		-0.019123		-0.009646		-0.010130	
	0.028**		0.137		0.055*		0.377		0.371	
bdpr	0.000016		0.006420		0.013079		0.005223		0.000480	
	0.721		0.115		0.032**		0.317		0.941	

lnsize	-0.000002	-0.000314	-0.000957	-0.001419	-0.001356
	0.379	0.429	0.148	0.037**	0.075*
cashduepr	-0.000035	-0.002778	-0.009775	-0.013747	-0.014887
	0.507	0.669	0.418	0.455	0.596
goodwillpr	0.000019	-0.170362	-0.015624	0.033282	-0.105702
	0.989	0.103	0.848	0.655	0.266
rer14pr	-0.000062	0.002740	0.003111	0.009849	0.010784
	0.063*	0.555	0.68	0.232	0.246
remulpr	-0.000055	0.017039	0.023973	0.046049	0.042256
	0.593	0.038**	0.109	0.000***	0.001***
reconpr	-0.000021	-0.002950	0.017353	0.039380	0.056987
	0.751	0.753	0.163	0.000***	0.000***
recompr	-0.000044	0.006020	0.022162	0.038345	0.051403
	0.248	0.221	0.004***	0.000***	0.000***
cipr	-0.000028	0.009402	0.007864	0.015065	0.011215
	0.714	0.249	0.536	0.181	0.396
conspr	-0.000324	-0.030984	-0.063606	-0.037708	-0.024760
	0.039**	0.149	0.120	0.244	0.407
Constant	4.519	-15.037	-1.471	-2.619	-2.936
	0.136	0.000***	0.301	0.183	0.028**
Pseudo R2	0.828	0.451	0.279	0.229	0.192
AIC by N	0.047	0.132	0.165	0.172	0.175
AIC	331.391	963	1,260	1,355	1,418
Chi Squared	80	1,132	411	404	417
Model Significance p	0	0	0	0	0
Failed & Technically "Failed" Banks	177	177	177	177	176
OBA Banks	0	0	0	0	0
Observations	6,993	7,283	7,621	7,898	8,111

Notes:

[1]Relative HPI Annual Change; p values on 2nd row; ***=1% **=5% *=10% Significance;

OBA is Open Bank Assistance & is included as Failed banks; Number of parameters is 25 & Model df is 24.

Constant is an Odds-Ratio estimate.

Table 6: Logistic Regression 2014 Failures Marginal Effects Estimation

Estimated Marginal Effects with Regression p Values

DV= failure, OBA's & technical failures in **2014**

Sample: Commercial Banks, Savings Banks and Savings & Loans

Independent Variable Estimation Date

	2013q4		**2012q4**		**2011q4**		**2010q4**		**2009q4**	
Variables	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]
rre_ma_chg	0.003166	0.00210	0.015279	0.00095	-0.002741	-0.00280	-1.670149	-0.00116	0.194465	-0.00140
	0.000***		0.668		0.603		0.000***		0.085*	
rre_sa_chg	0.001246	0.00958	0.005905	0.00614	-0.038182	-0.00307	-0.538284	-0.00743	-0.012796	-0.00565
	0.000***		0.416		0.418		0.000***		0.011**	
rre_mt_chg	0.000776	0.00549	-0.004139	0.00609	0.011802	-0.00186	-0.372216	-0.00401	0.045471	-0.00417
	0.000***		0.000***		0.788		0.000***		0.069*	
rre_pac_chg	0.000712	0.00697	-0.002175	0.00520	0.032044	-0.00235	-0.498861	-0.00262	0.156047	-0.00179
	0.000***		0.808		0.52		0.000***		0.035**	
rre_ne_chg	-0.000071	0.00103	.	.	.	.	.	.	.	.
	0.000***		.		.		.		.	
rre_enc_chg	0.001654	0.01118	0.004756	0.00586	-0.006477	-0.00481	-0.919622	-0.00588	0.081036	-0.00419
	0.000***		0.7		0.885		0.000***		0.093*	
rre_esc_chg	0.002371	0.00334	-0.016058	0.00251	0.162129	-0.00078	-0.596575	-0.00381	0.387390	-0.00092
	0.000***		0.382		0.31		0.000***		0.065*	
rre_wsc_chg	0.001439	0.00899	-0.009662	0.00792	-0.216124	0.00126	-1.143988	-0.00353	-0.596799	0.00140
	0.000***		0.3		0.206		0.000***		0.005***	
rre_wnc_chg	0.002048	0.01095	-0.013441	0.01044	0.246408	-0.00290	-0.688089	-0.00898	1.170508	-0.00127
	0.000***		0.265		0.064*		0.000***		0.004***	
tepr	-0.000889		-0.022909		-0.059392		-0.044716		-0.051121	
	0.000***		0.000***		0.000***		0.001***		0.000***	
llrpr	-0.000135		-0.021261		-0.045370		-0.088885		-0.127781	
	0.601		0.129		0.276		0.031**		0.013**	
roapr	-0.000005		-0.010169		0.008532		0.009583		0.013991	
	0.582		0.092*		0.608		0.002***		0.016**	
npap_lnlsdebtr	0.000328		0.008968		0.019130		0.033415		0.025199	
	0.000***		0.000***		0.000***		0.000***		0.000***	
secpr	-0.000050		0.000177		-0.003348		-0.000343		0.000833	
	0.064*		0.875		0.307		0.944		0.859	
bdpr	0.000006		0.001060		-0.001608		0.000043		-0.000472	
	0.904		0.477		0.78		0.994		0.904	

lnsize	-0.000007	-0.000231	-0.000783	-0.000950	-0.001008
	0.014**	0.021**	0.006***	0.018**	0.016**
cashduepr	-0.000075	-0.002103	-0.010281	-0.009024	0.002568
	0.028**	0.218	0.030**	0.218	0.679
goodwillpr	-0.000100	-0.103791	-0.064246	-0.191430	-0.211594
	0.857	0.154	0.463	0.179	0.216
rer14pr	-0.000059	-0.001044	-0.003009	-0.000406	-0.000315
	0.011**	0.423	0.383	0.934	0.952
remulpr	-0.000001	0.001025	0.006956	0.011869	0.009497
	0.973	0.683	0.225	0.118	0.3
reconpr	-0.000005	0.003096	0.008551	0.005561	0.014376
	0.923	0.124	0.139	0.496	0.050*
recompr	-0.000052	-0.000298	0.000476	0.006116	0.008176
	0.031**	0.803	0.891	0.222	0.118
cipr	-0.000035	0.001044	-0.001579	0.000894	0.000034
	0.434	0.591	0.8	0.912	0.997
conspr	-0.000027	0.001239	0.001781	-0.000589	-0.010395
	0.423	0.59	0.827	0.971	0.608
Constant	3.349	4.730	4.911	-10.000	0.916
	0.506	0.104	0.047**	0.000***	0.656
Pseudo R2	0.814	0.568	0.401	0.297	0.219
AIC by N	0.031	0.062	0.080	0.090	0.095
AIC	206	416	561	654	728
Likelihood Ratio Test	692	483	344	257	190
Likelihood Ratio p	0	0	0	0	0
Chi Squared	.	281	280	1,579	318
Model Significance p	.	0	0	0	0
Failed & Technically "Failed" Banks	78	78	78	78	78
OBA Banks	0	0	0	0	0
Observations	6,695	6,734	6,993	7,283	7,621

Notes:

[1]Relative HPI Annual Change; p values on 2nd row; ***=1% **=5% *=10% Significance;

OBA is Open Bank Assistance & is included as Failed banks.

Constant is an Odds-Ratio estimate.

Table 7: Out-of-Sample Tabulation -- Actual Failures vs Predicted Failures

One - Year Look-Ahead

One - Year Prediction Date: DV - 2010 Bank Failures using IV - 2009q4 Data

Predicted Actual Failures	Actual Failures		
	No Fail (0)	Fail (1)	Total
0	7,078 91.791	3 1.935	7,081 90.02
1	633 8.209	152 98.065	785 9.98
Total	7,711 100	155 100	7,866 100

Notes: Bottom cell level - column percentage;
Failure Cutoff: 0.05;
Prediction Date: DV - 2010 Failures using IV - 2009q4.

Table 8: Out-of-Sample Tabulation -- Actual Failures vs Predicted Failures

Two - Year Look–Ahead

Two - Year Prediction Date: DV - 2010 Bank Failures using IV - 2008q4 Data

Predicted Actual Failures	Actual Failures		
	No Fail (0)	Fail (1)	Total
0	6,197 77.501	13 8.442	6,210 76.196
1	1799 22.499	141 91.558	1,940 23.804
Total	7,996 100	154 100	8,150 100

Notes: Bottom cell level - column percentage;
Failure Cutoff: 0.05;
Prediction Date: DV - 2010 Failures using IV - 2008q4.

Table 9: Out-of-Sample Tabulation – Actual Failures vs Predicted Failures

Three - Year Look–Ahead

Three - Year Prediction Date: DV – 2010 Bank Failures using IV – 2007q4 Data

Predicted Actual Failures	Actual Failures No Fail (0)	Fail (1)	Total
0	5,808 70.7	58 37.662	5,866 70.092
1	2407 29.3	96 62.338	2503 29.908
Total	8,215 100	154 100	8,369 100

Notes: Bottom cell level - column percentage;
Failure Cutoff: 0.05;
Prediction Date: DV - 2010 Failures using IV - 2007q4.

Table 10: Out-of-Sample Tabulation – Actual-Technical Failures vs Predicted Failures

One - Year Look–Ahead

One - Year Prediction Date: DV – 2010 Bank Failures using IV – 2009q4 Data

Predicted Act-Tech Failures	Act-Tech Failures No Fail (0)	Fail (1)	Total
0	7,062 94.147	19 5.205	7,081 90.02
1	439 5.853	346 94.795	785 9.98
Total	7,501 100	365 100	7,866 100

Notes: Bottom cell level - column percentage;
Failure Cutoff: 0.05;
Prediction Date: DV - 2010 Failures using IV - 2009q4.

Table 11: Out-of-Sample Tabulation – Actual-Technical Failures vs Predicted Failures

Two - Year Look–Ahead

Two - Year Prediction Date: DV – 2010 Bank Failures using IV – 2008q4 Data

Predicted Act-Tech Failures	Act-Tech Failures No Fail (0)	Fail (1)	Total
0	6,176	34	6,210
	79.322	9.341	76.196
1	1610	330	1940
	20.678	90.659	23.804
Total	7,786	364	8,150
	100	100	100

Notes: Bottom cell level - column percentage;
Failure Cutoff: 0.05;
Prediction Date: DV - 2010 Failures using IV - 2008q4.

Table 12: Out-of-Sample Tabulation – Actual-Technical Failures vs Predicted Failures

Three - Year Look–Ahead

Three - Year Prediction Date: DV – 2010 Bank Failures using IV – 2007q4 Data

Predicted Act-Tech Failures	Act-Tech Failures No Fail (0)	Fail (1)	Total
0	5,748	118	5,866
	71.796	32.507	70.092
1	2258	245	2503
	28.204	67.493	29.908
Total	8,006	363	8,369
	100	100	100

Notes: Bottom cell level - column percentage;
Failure Cutoff: 0.05;
Prediction Date: DV - 2010 Failures using IV - 2007q4.

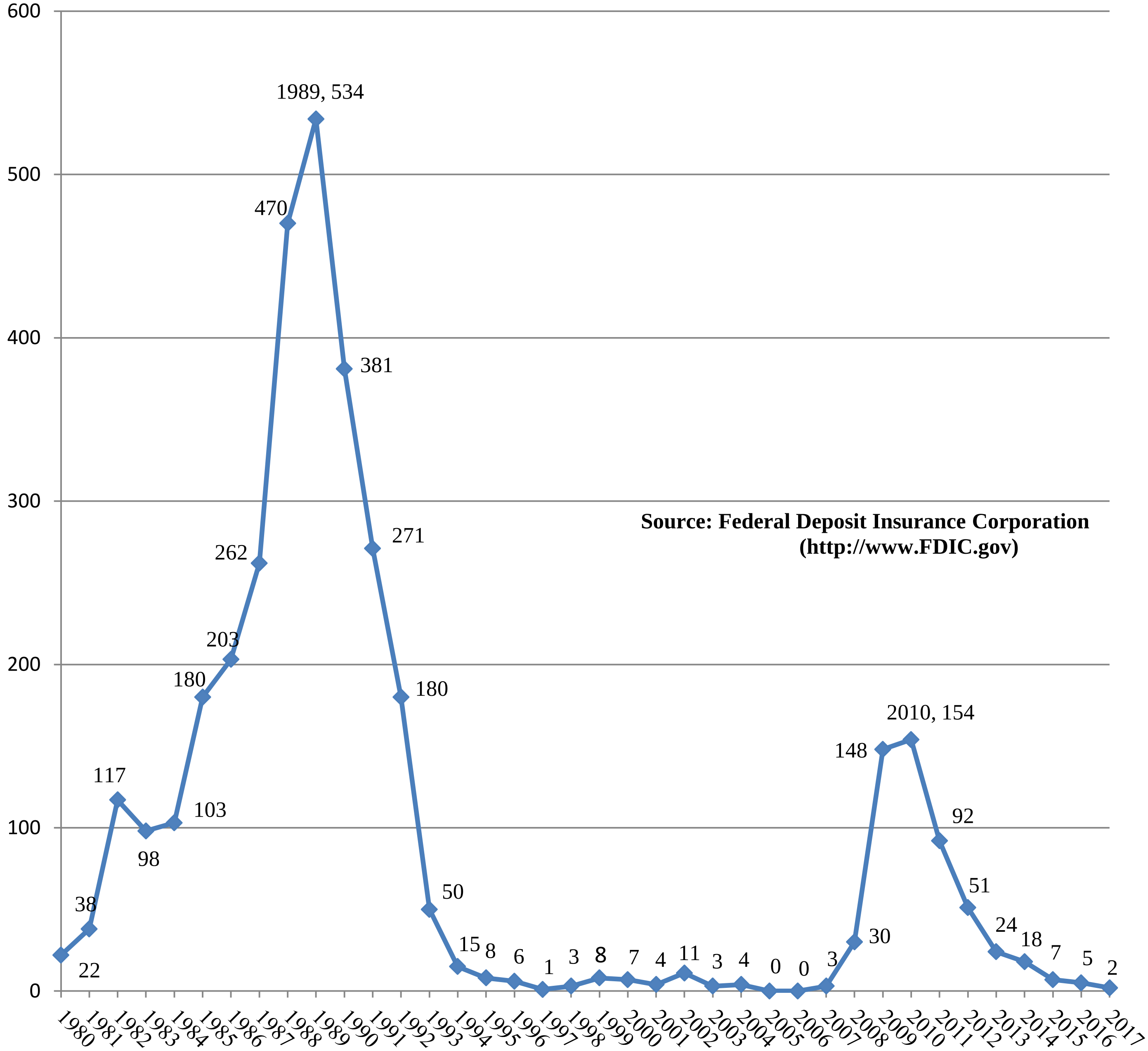
Table 13: Likelihood Ratio Test – Model Comparison

Regional Annual HPI Change & Call Report Model vs. Call Report Model

Failure Year	Independent Var. Lag	Independent Var. Date	Degrees of Freedom	Chi Squared	p Value	
2008	1-Year	2007q4	9	4.314	0.890	
2008	2-Year	2006q4	9	45.325	0.000	***
2008	3-Year	2005q4	9	12.931	0.166	
2008	4-Year	2004q4	9	21.293	0.011	**
2008	5-Year	2003q4	9	23.196	0.006	***
2009	1-Year	2008q4	9	24.762	0.003	***
2009	2-Year	2007q4	9	18.126	0.034	**
2009	3-Year	2006q4	9	86.180	0.000	***
2009	4-Year	2005q4	9	88.271	0.000	***
2009	5-Year	2004q4	9	83.044	0.000	***
2010	1-Year	2009q4	9	4.921	0.841	
2010	2-Year	2008q4	9	62.310	0.000	***
2010	3-Year	2007q4	9	36.146	0.000	***
2010	4-Year	2006q4	9	88.016	0.000	***
2010	5-Year	2005q4	9	86.766	0.000	***
2011	1-Year	2010q4	8	16.570	0.035	**
2011	2-Year	2009q4	8	44.191	0.000	***
2011	3-Year	2008q4	8	67.815	0.000	***
2011	4-Year	2007q4	8	39.058	0.000	***
2011	5-Year	2006q4	8	68.534	0.000	***
2012	1-Year	2011q4	8	8.500	0.386	
2012	2-Year	2010q4	8	22.285	0.004	***
2012	3-Year	2009q4	8	45.106	0.000	***
2012	4-Year	2008q4	8	61.723	0.000	***
2012	5-Year	2007q4	8	36.677	0.000	***
2013	1-Year	2012q4	9	4.998	0.834	
2013	2-Year	2011q4	9	17.976	0.035	**
2013	3-Year	2010q4	9	20.072	0.017	**
2013	4-Year	2009q4	9	37.757	0.000	***
2013	5-Year	2008q4	9	50.753	0.000	***
2014	1-Year	2013q4	9	7.350	0.601	
2014	2-Year	2012q4	8	21.923	0.005	***
2014	3-Year	2011q4	8	22.885	0.004	***
2014	4-Year	2010q4	8	20.029	0.010	**
2014	5-Year	2009q4	8	33.469	0.000	***
2015	1-Year	2014q4	8	12.299	0.138	
2015	2-Year	2013q4	9	8.772	0.459	
2015	3-Year	2012q4	8	18.139	0.020	**
2015	4-Year	2011q4	8	29.680	0.000	***
2015	5-Year	2010q4	8	20.111	0.010	***

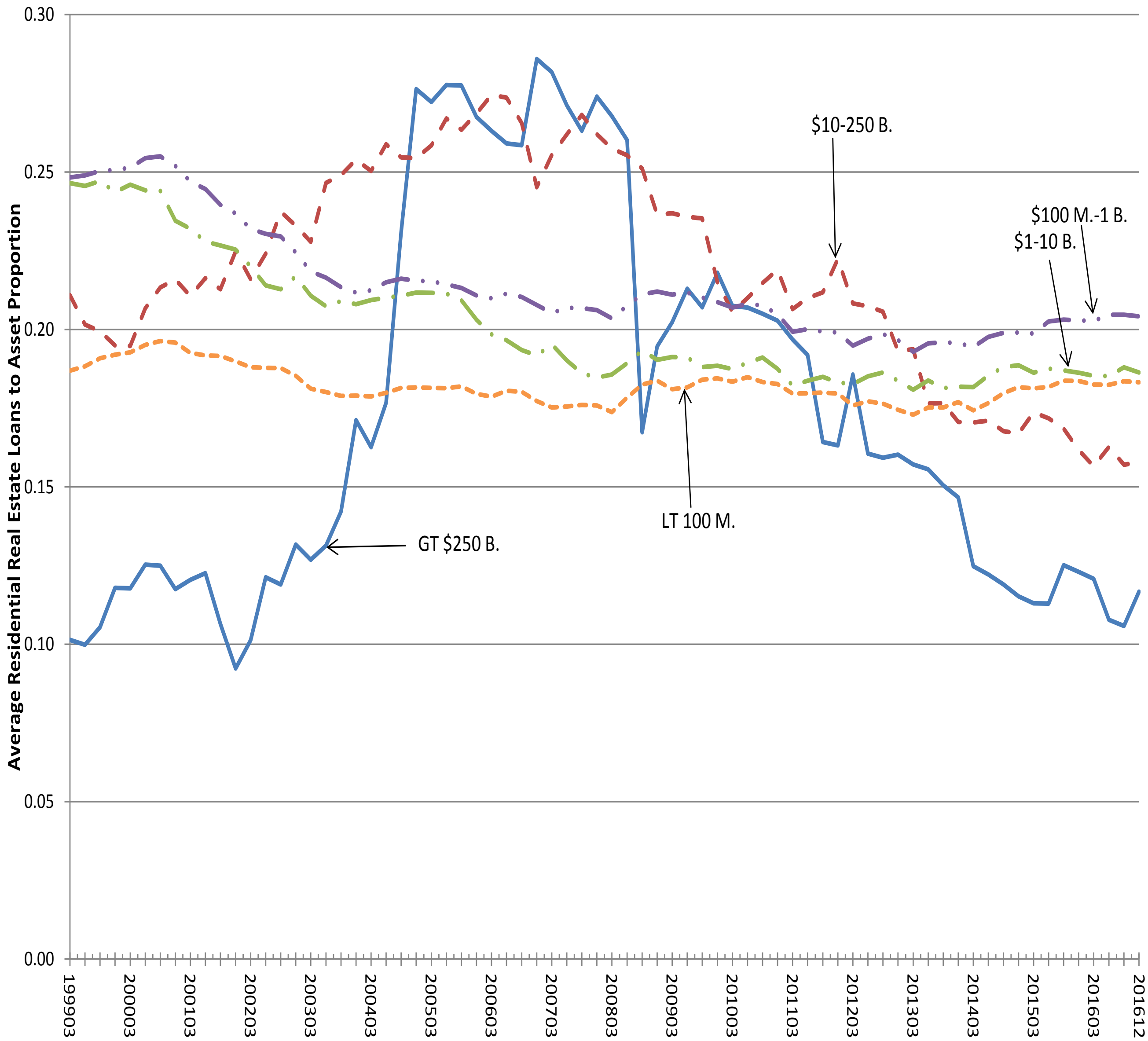
Notes: Comparison is performed by the Likelihood Ratio Test; Statistical significance Chi Squared p value symbols are *** is 1%, ** is 5%, and * is 10%.

Figure 1: Bank Failures from 1980 to 2017



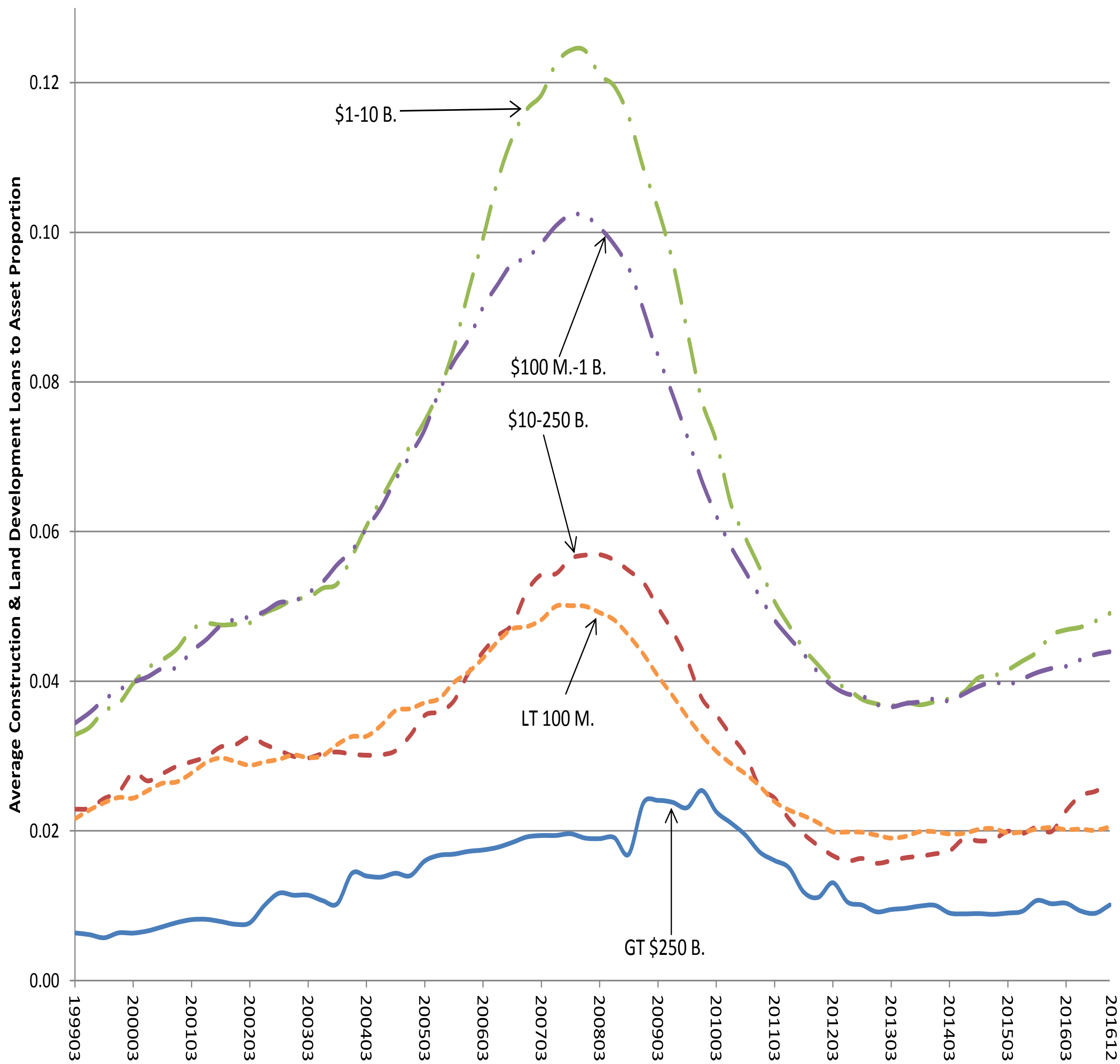
Source: Federal Deposit Insurance Corporation (http://www.FDIC.gov)

Figure 2: Average Residential Real Estate Loan to Asset Proportion by Asset-Size Group



Source: FDIC, Bank Reports of Income and Condition, various years.

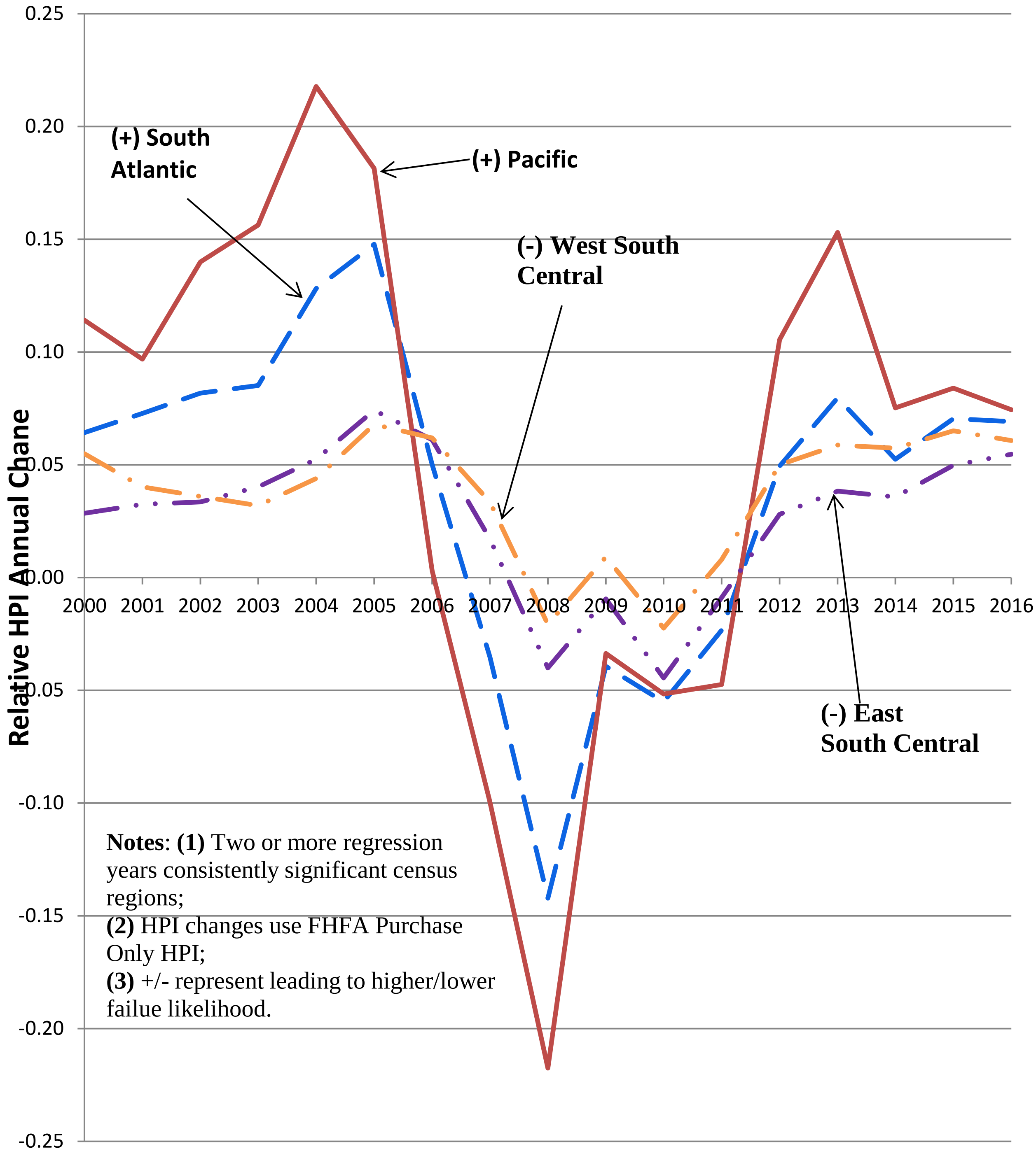
Figure 3: Average Construction & Land Development Loan to Asset Proportion by Asset-Size Group



Source: FDIC, Bank Reports of Income and Condition, various years.

Figure 4: Census Regions

Figure 5: Consistently Significant FHFA Census Region HPI Change Values



1. Source: Federal Housing Finance Agency, https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index.aspx

Figure 6: In-Sample ROC Curve Model Comparison

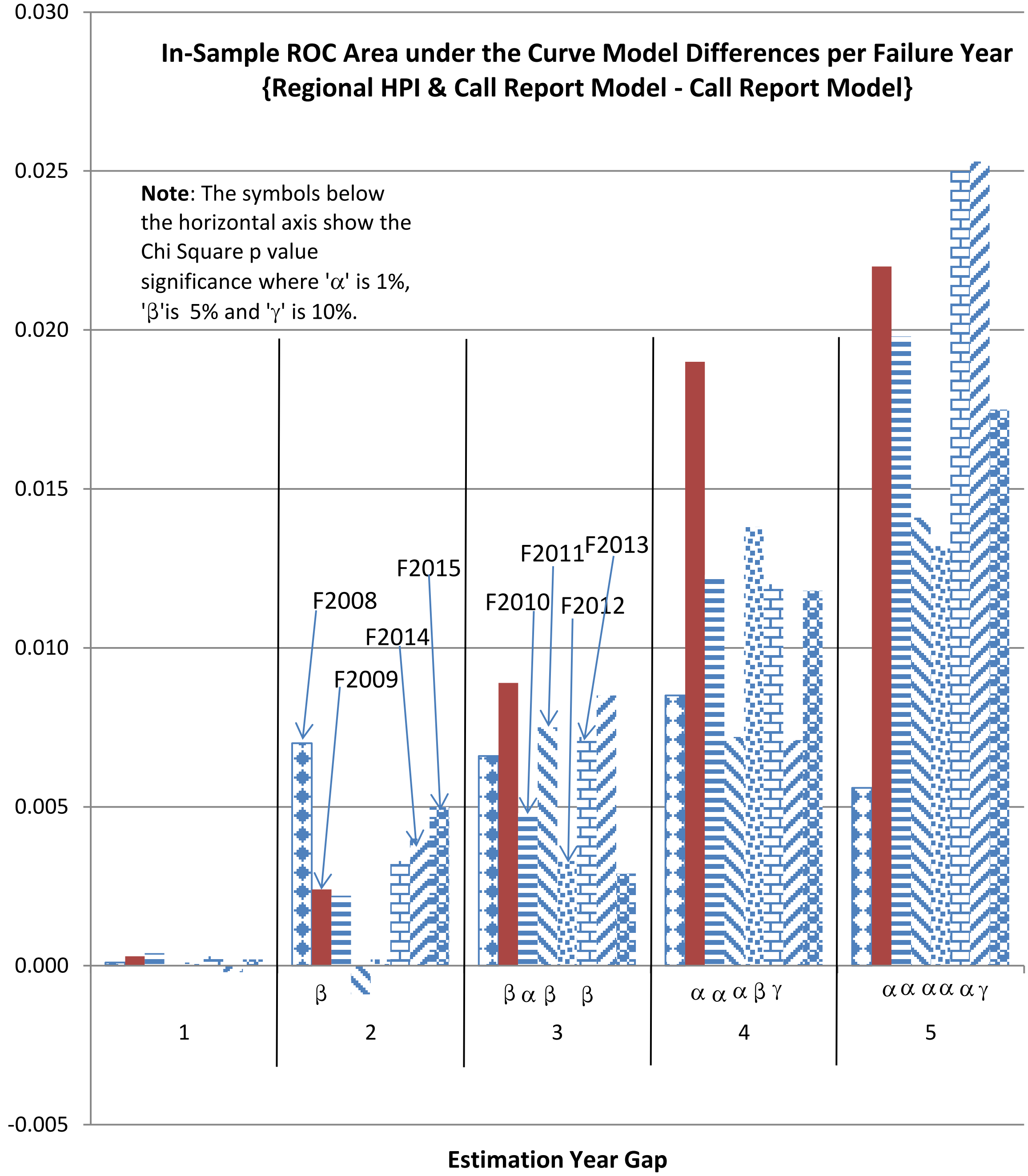
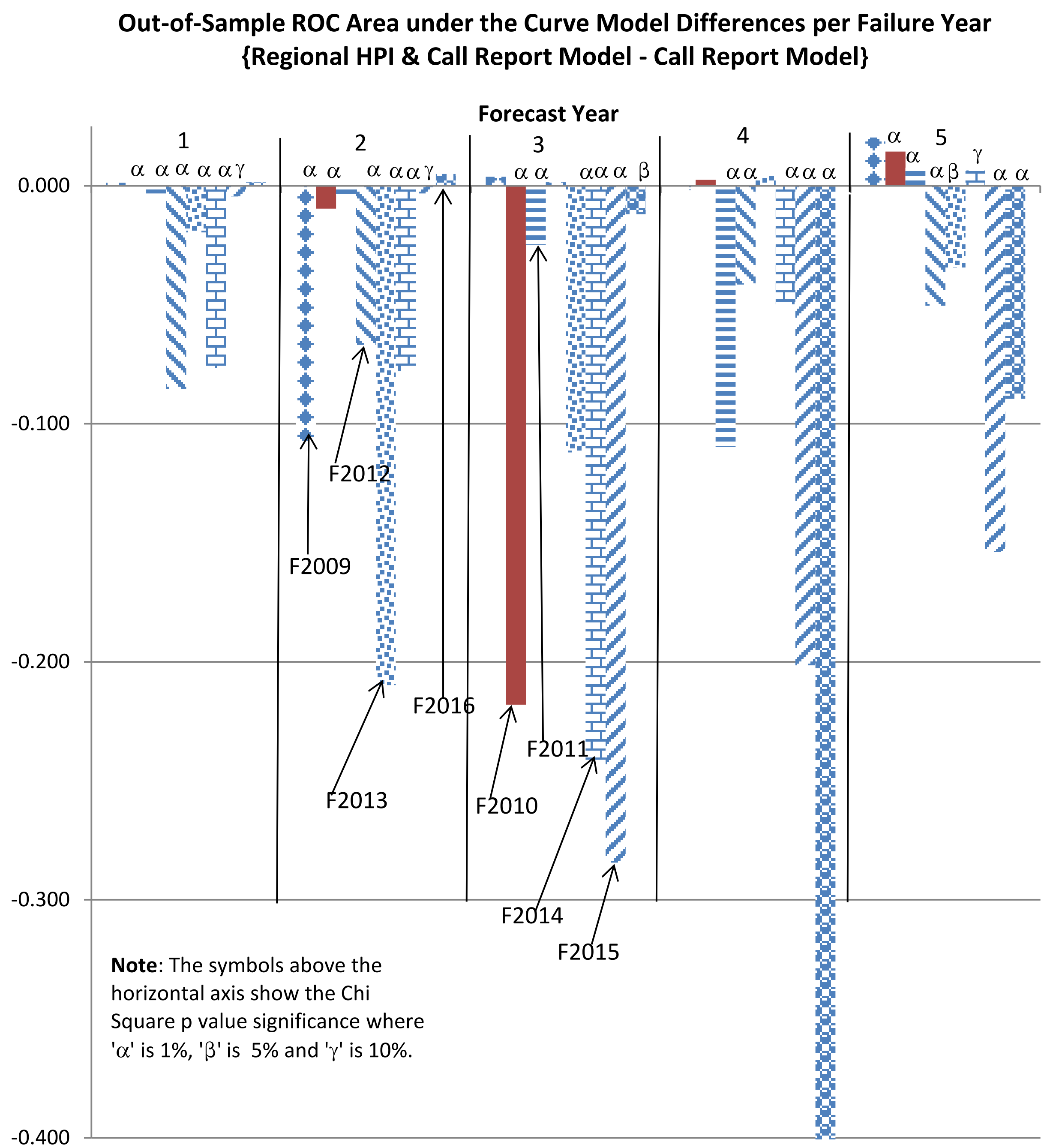


Figure 7: Out-of-Sample ROC Curve Model Comparison



Appendix A
Table A1: Logistic Regression 2010 Failures Marginal Effects Estimation

Estimated Marginal Effects with Regression p Values

DV= failure, OBA's & technical failures in **2010**

Sample: Commercial Banks, Savings Banks and Savings & Loans

	Independent Variable Estimation Date									
	2009q4		2008q4		2007q4		2006q4		2005q4	
Variables	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]
rre_ma_chg	-0.004094	-0.00136	0.152718	-0.00332	0.070194	-0.00021	0.079343	0.00162	-0.027448	0.00639
	0.039**		0.266		0.77		0.691		0.333	
rre_sa_chg	-0.012183	-0.00548	0.011035	-0.01932	-0.141654	-0.00488	0.287522	0.00653	0.094411	0.01978
	0.000***		0.809		0.617		0.000***		0.000***	
rre_mt_chg	0.005862	-0.00404	0.072643	-0.00793	0.084455	-0.00181	-0.002413	0.00364	0.003615	0.00976
	0.414		0.13		0.658		0.970		0.892	
rre_pac_chg	0.012715	-0.00174	0.037861	-0.01121	-0.021579	-0.00495	1.741819	0.00014	0.031555	0.00807
	0.309		0.217		0.627		0.179		0.19	
rre_ne_chg	0.115670	-0.00058	0.353818	-0.00217	1.149952	-0.00071	1.414523	-0.00058	-0.462620	0.00199
	0.008***		0.033**		0.078*		0.098*		0.064*	
rre_enc_chg	0.021996	-0.00406	0.128440	-0.01411	-0.043464	-0.00642	-0.245441	-0.00030	-0.008183	0.00637
	0.129		0.134		0.105		0.934		0.942	
rre_esc_chg	-0.006062	-0.00089	0.331928	-0.00316	-0.103765	0.00110	-0.077770	0.00477	-0.021155	0.00560
	0.000***		0.063*		0.000***		0.388		0.220	
rre_wsc_chg	-0.031530	0.00136	0.852233	-0.00304	-0.096529	0.00470	-0.255113	0.00891	-0.215357	0.00980
	0.551		0.012**		0.003***		0.004***		0.007***	
rre_wnc_chg	0.092309	-0.00123	0.254625	-0.01040	0.664080	-0.00155	-0.058864	0.00463	-0.135569	0.01166
	0.168		0.093*		0.375		0.003***		0.125	
tepr	-0.055862		-0.162298		-0.087013		0.008653		0.020913	
	0.000***		0.000***		0.002***		0.537		0.185	
llrpr	-0.053904		-0.152202		-0.450799		-0.845218		-0.638334	
	0.000***		0.195		0.097*		0.003***		0.020**	
roapr	-0.026322		0.040063		-0.083380		-0.066618		-0.189008	
	0.000***		0.000***		0.126		0.007***		0.096*	
npap_lnlsdebtr	0.033807		0.137554		0.140342		0.275504		0.328944	
	0.000***		0.000***		0.000***		0.000***		0.000***	
secpr	-0.002041		-0.020993		-0.016147		-0.031516		-0.036824	
	0.426		0.102		0.402		0.035**		0.004***	
bdpr	0.001793		0.021013		0.031864		0.033623		0.000839	
	0.098*		0.000***		0.002***		0.000***		0.010**	

lnsize	-0.000206	-0.002069	-0.001778	-0.000901	-0.000278
	0.018**	0.003***	0.075*	0.377	0.787
cashduepr	-0.002998	-0.009487	0.009021	0.009791	-0.031702
	0.186	0.697	0.782	0.652	0.243
goodwillpr	0.029401	0.077675	-0.029036	-0.199889	-0.421789
	0.387	0.336	0.735	0.016**	0.000***
rer14pr	0.000381	0.009818	0.026222	-0.001071	-0.002559
	0.833	0.321	0.080*	0.926	0.809
remulpr	0.004554	0.051060	0.078425	0.075148	0.061243
	0.076*	0.000***	0.000***	0.000***	0.000***
reconpr	0.006774	0.078653	0.126038	0.110265	0.094025
	0.006***	0.000***	0.000***	0.000***	0.000***
recompr	0.001295	0.033305	0.067514	0.042352	0.038803
	0.522	0.001***	0.000***	0.000***	0.001***
cipr	-0.000012	0.011275	0.017335	0.025878	0.026232
	0.996	0.35	0.386	0.117	0.081*
conspr	-0.003267	-0.028550	-0.043564	-0.080389	-0.102158
	0.458	0.346	0.299	0.056*	0.020**
Constant	0.971	-0.447	-3.471	-3.723	-3.603
	0.608	0.764	0.003***	0.000***	0.000***
Pseudo R2	0.720	0.359	0.268	0.254	0.219
AIC by N	0.111	0.240	0.267	0.266	0.262
AIC	877	1,958	2,237	2,261	2,269
Likelihood Ratio Test	2,127	1,067	801	751	622
Likelihood Ratio p	0	0	0	0	0
Chi Squared	491	577	570	631	594
Model Significance p	0	0	0	0	0
Failed & Technically "Failed" Banks	365	364	363	357	336
OBA Banks	0	0	0	0	0
Observations	7,866	8,150	8,369	8,501	8,647

Notes:

[1]Relative HPI Annual Change; p values on 2nd row; ***=1% **=5% *=10% Significance;

OBA is Open Bank Assistance & is included as Failed banks.

Constant is an Odds-Ratio estimate.

Table A2: Logistic Regression 2011 Failures Marginal Effects Estimation

Estimated Marginal Effects with Regression p Values

DV= failure, OBA's & technical failures in **2011**

Sample: Commercial Banks, Savings Banks and Savings & Loans

	Independent Variable Estimation Date									
	2010q4		**2009q4**		**2008q4**		**2007q4**		**2006q4**	
Variables	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]
rre_ma_chg	-0.061620	-0.00116	0.284442	-0.0014	-0.066200	-0.00342	0.024882	-0.00021	-0.022590	0.00167
	0.000***		0.212		0.759		0.082*		0.760	
rre_sa_chg	-0.018001	-0.00743	-0.062726	-0.005654	-0.092813	-0.01994	-0.084114	-0.00504	0.258044	0.00674
	0.000***		0.000***		0.212		0.633		0.000***	
rre_mt_chg	-0.013348	-0.00401	0.040772	-0.004171	-0.034861	-0.00819	0.173133	-0.00187	-0.003870	0.00376
	0.000***		0.356		0.649		0.254		0.945	
rre_pac_chg	-0.017038	-0.00262	0.363213	-0.001792	0.018837	-0.01157	0.128675	-0.00510	-2.636924	0.00014
	0.000***		0.001***		0.708		0.014**		0.064*	
rre_ne_chg	.	.	.	.	.	.	.	.	.	.
	.		.		.		.		.	
rre_enc_chg	-0.031168	-0.00588	0.174348	-0.004194	-0.062546	-0.01456	0.099014	-0.00662	0.031835	-0.00031
	0.000***		0.088*		0.650		0.408		0.345	
rre_esc_chg	-0.022718	-0.00381	-0.050106	-0.000922	-0.129180	-0.00326	0.022137	0.00113	0.040981	0.00493
	0.000***		0.000***		0.634		0.292		0.523	
rre_wsc_chg	-0.044544	-0.00353	-0.900753	0.001401	0.190250	-0.00313	-0.087703	0.00485	-0.150671	0.00920
	0.000***		0.004***		0.719		0.003***		0.032**	
rre_wnc_chg	-0.026847	-0.00898	0.948968	-0.001268	-0.065877	-0.01073	0.900411	-0.00160	-0.041539	0.00478
	0.000***		0.054*		0.788		0.164		0.020**	
tepr	-0.006664		-0.144020		-0.083848		-0.047007		0.021487	
	0.000***		0.000***		0.001***		0.011**		0.067*	
llrpr	-0.003383		-0.164267		-0.465812		-1.129100		-0.551926	
	0.000***		0.14		0.006***		0.000***		0.048**	
roapr	-0.000049		-0.022105		0.021112		-0.142422		-0.057153	
	0.909		0.607		0.327		0.000***		0.012**	
npap_lnlsdebtr	0.002932		0.118052		0.112350		0.121024		0.177104	
	0.000***		0.000***		0.000***		0.000***		0.000***	
secpr	-0.000093		-0.005520		-0.000849		-0.003998		-0.003184	
	0.616		0.662		0.954		0.801		0.813	
bdpr	0.000184		0.012013		0.004533		0.007318		0.007749	
	0.127		0.126		0.478		0.429		0.399	

lnsize	0.000009	-0.000697	-0.000958	-0.000756	-0.001221
	0.267	0.339	0.217	0.396	0.175
cashduepr	-0.000283	0.004766	-0.016144	-0.004246	0.004685
	0.149	0.745	0.523	0.896	0.863
goodwillpr	0.005780	-0.136470	-0.026647	-0.135915	-0.132080
	0.000***	0.369	0.805	0.142	0.066*
rer14pr	-0.000007	0.012616	0.019881	0.019967	0.015091
	0.966	0.241	0.073*	0.126	0.169
remulpr	0.000225	0.020229	0.053607	0.066849	0.073102
	0.434	0.384	0.002***	0.000***	0.000***
reconpr	0.000143	0.060441	0.085640	0.102275	0.094553
	0.543	0.000***	0.000***	0.000***	0.000***
recompr	0.000084	0.041762	0.062368	0.078313	0.069651
	0.613	0.000***	0.000***	0.000***	0.000***
cipr	0.000316	0.031219	0.044192	0.043281	0.049889
	0.201	0.030**	0.001***	0.008***	0.001***
conspr	0.000077	-0.022044	0.002120	-0.019681	-0.043962
	0.834	0.518	0.948	0.602	0.281
Constant	-17.256	-3.472	-5.192	-4.437	-5.005
	0.000***	0.009***	0.005***	0.000***	0.000***
Pseudo R2	0.823	0.339	0.263	0.216	0.207
AIC by N	0.062	0.208	0.225	0.233	0.229
AIC	453	1,585	1,779	1,894	1,889
Likelihood Ratio Test	1,895	790	616	509	481
Likelihood Ratio p	0	0	0	0	0
Chi Squared	.	447	491	493	508
Model Significance p	.	0	0	0	0
Failed & Technically "Failed" Banks	269	269	269	268	262
OBA Banks	0	0	0	0	0
Observations	7,283	7,621	7,898	8,111	8,232

Notes:

[1]Relative HPI Annual Change; p values on 2nd row; ***=1% **=5% *=10% Significance;

OBA is Open Bank Assistance & is included as Failed banks.

Constant is an Odds-Ratio estimate.

Table A3: Logistic Regression 2013 Failures Marginal Effects Estimation

Estimated Marginal Effects with Regression p Values

DV= failure, OBA's & technical failures in **2013**

Sample: Commercial Banks, Savings Banks and Savings & Loans

	Independent Variable Estimation Date									
	2012q4		2011q4		2010q4		2009q4		2008q4	
Variables	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]
rre_ma_chg	0.023406	0.00092	-0.000262	-0.00270	-1.968739	-0.00112	0.319041	-0.00136	0.059697	-0.00332
	0.000***		0.975		0.000***		0.030**		0.575	
rre_sa_chg	0.006517	0.00594	-0.036497	-0.00297	-0.629230	-0.00719	-0.025339	-0.00548	-0.029289	-0.01932
	0.000***		0.144		0.000***		0.000***		0.416	
rre_mt_chg	0.002421	0.00589	-0.006693	-0.00180	-0.447816	-0.00388	0.042704	-0.00404	0.007093	-0.00793
	0.000***		0.49		0.000***		0.102		0.853	
rre_pac_chg	0.002670	0.00503	0.041207	-0.00228	-0.575753	-0.00254	0.254120	-0.00174	0.031294	-0.01121
	0.000***		0.278		0.000***		0.004***		0.234	
rre_ne_chg	0.047094	0.00024	0.006121	-0.00071	-1.374061	-0.00073	0.360126	-0.00058	0.057953	-0.00217
	0.000***		0.936		0.000***		0.166		0.577	
rre_enc_chg	0.009697	0.00566	-0.007937	-0.00465	-1.081528	-0.00569	0.115160	-0.00406	-0.004298	-0.01411
	0.000***		0.747		0.000***		0.041**		0.948	
rre_esc_chg	0.010571	0.00243	-0.007820	-0.00075	-0.768479	-0.00369	0.134651	-0.00089	-0.019973	-0.00316
	0.000***		0.935		0.000***		0.514		0.882	
rre_wsc_chg	0.006028	0.00766	0.053180	0.00122	-1.510797	-0.00342	-0.293217	0.00136	0.074408	-0.00304
	0.000***		0.552		0.000***		0.138		0.772	
rre_wnc_chg	0.006881	0.01009	0.154204	-0.00281	-0.861314	-0.00869	1.287314	-0.00123	0.094877	-0.01040
	0.000***		0.064*		0.000***		0.002***		0.445	
tepr	-0.001620		-0.042192		-0.039776		-0.056208		-0.035196	
	0.029**		0.000***		0.000***		0.000***		0.012**	
llrpr	-0.000763		-0.036060		-0.059729		-0.156949		-0.317801	
	0.469		0.197		0.068*		0.007***		0.000***	
roapr	-0.000184		0.003531		0.011655		0.020173		0.005687	
	0.020**		0.806		0.014**		0.020**		0.716	
npap_lnlsdebtr	0.001221		0.032486		0.049007		0.048029		0.052902	
	0.000***		0.000***		0.000***		0.000***		0.000***	
secpr	0.000130		0.000683		0.003593		0.000576		0.011143	
	0.123		0.84		0.482		0.930		0.171	
bdpr	0.000064		0.002738		0.006490		0.009965		0.002935	
	0.434		0.393		0.030**		0.015**		0.441	

lnsize	-0.000007	-0.000344	-0.000622	-0.001224	-0.001248
	0.101	0.088*	0.062*	0.015**	0.021**
cashduepr	0.000041	0.002785	0.004609	0.002819	0.011188
	0.652	0.46	0.438	0.741	0.312
goodwillpr	-0.006547	-0.083350	-0.202769	-0.050080	-0.072101
	0.339	0.252	0.049**	0.577	0.301
rer14pr	0.000114	0.004476	0.008701	0.008323	0.013353
	0.045**	0.144	0.051*	0.146	0.059*
remulpr	0.000074	0.009816	0.017904	0.023175	0.038079
	0.491	0.039**	0.008***	0.021**	0.000***
reconpr	-0.000020	0.005432	0.003195	0.014725	0.031522
	0.844	0.282	0.689	0.095*	0.000***
recompr	0.000115	0.007711	0.013232	0.020850	0.033894
	0.085*	0.012**	0.005***	0.000***	0.000***
cipr	0.000120	0.002732	0.010499	0.007493	0.015400
	0.25	0.6	0.149	0.433	0.112
conspr	0.000091	0.001555	-0.026951	-0.057976	-0.020371
	0.737	0.883	0.148	0.042**	0.415
Constant	-15.466	-2.831	-15.722	-1.069	-3.760
	0.000***	0.267	0.000***	0.507	0.115
Pseudo R2	0.828	0.522	0.376	0.256	0.220
AIC by N	0.038	0.089	0.110	0.125	0.127
AIC	261	642	829	987	1,039
Likelihood Ratio Test	1,018	646	469	322	279
Likelihood Ratio p	0	0	0	0	0
Chi Squared	391	267	1,604	373	355
Model Significance p	0	0	0	0	0
Failed & Technically "Failed" Banks	122	122	122	122	122
OBA Banks	0	0	0	0	0
Observations	6,965	7,232	7,525	7,866	8,150

Notes:

[1]Relative HPI Annual Change; p values on 2nd row; ***=1% **=5% *=10% Significance;

OBA is Open Bank Assistance & is included as Failed banks.

Constant is an Odds-Ratio estimate.

Table A4: Logistic Regression 2015 Failures Marginal Effects Estimation

Estimated Marginal Effects with Regression p Values

DV= failure, OBA's & technical failures in **2015**

Sample: Commercial Banks, Savings Banks and Savings & Loans

	Independent Variable Estimation Date									
	2014q4		2013q4		2012q4		2011q4		2010q4	
Variables	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]	ME/p	HPI change[1]
rre_ma_chg	0.723342	0.00166	0.029907	0.00210	0.111459	0.00095	0.090233	-0.00280	0.179484	-0.00116
	0.047**		0.203		0.266		0.002***		0.127	
rre_sa_chg	0.589366	0.00626	0.010864	0.00958	0.025021	0.00614	0.152525	-0.00307	0.049537	-0.00743
	0.003***		0.176		0.261		0.000***		0.1	
rre_mt_chg	0.173017	0.00280	0.001365	0.00549	-0.003995	0.00609	0.165753	-0.00186	0.075308	-0.00401
	0.332		0.855		0.010**		0.000***		0.009***	
rre_pac_chg	0.107313	0.00354	0.003664	0.00697	-0.015423	0.00520	0.114392	-0.00235	0.098308	-0.00262
	0.402		0.554		0.759		0.001***		0.009***	
rre_ne_chg	.	.	-0.002516	0.00103	.	.	.	.	.	.
	.		0.007***		.		.		.	
rre_enc_chg	0.372261	0.00904	0.009386	0.01118	0.019411	0.00586	0.166723	-0.00481	0.126886	-0.00588
	0.044**		0.411		0.612		0.000***		0.023**	
rre_esc_chg	0.663961	0.00330	0.011158	0.00334	0.010402	0.00251	0.482691	-0.00078	0.082204	-0.00381
	0.010***		0.533		0.819		0.000***		0.051*	
rre_wsc_chg	0.197269	0.00904	-0.003338	0.00899	-0.009819	0.00792	-0.641925	0.00126	0.225142	-0.00353
	0.476		0.848		0.707		0.000***		0.008***	
rre_wnc_chg	-0.080980	0.00984	-0.003541	0.01095	-0.041513	0.01044	0.602777	-0.00290	0.193047	-0.00898
	0.000***		0.000***		0.273		0.000***		0.003***	
tepr	-0.550820		-0.021931		-0.020651		-0.026368		-0.028211	
	0.000***		0.000***		0.079*		0.000***		0.002***	
llrpr	0.336716		-0.031997		-0.023930		-0.031502		-0.050521	
	0.172		0.271		0.402		0.170		0.051*	
roapr	-0.488913		-0.000413		0.002591		0.007708		0.007496	
	0.000***		0.312		0.543		0.000***		0.000***	
npap_lnlsdebtr	0.436323		0.014823		0.023606		0.014971		0.017858	
	0.000***		0.000***		0.000***		0.000***		0.000***	
secpr	0.031909		-0.001714		0.000398		-0.001755		-0.000119	
	0.358		0.273		0.862		0.488		0.974	
bdpr	-0.004323		0.001856		0.005013		0.003843		0.005891	
	0.853		0.412		0.001***		0.015**		0.001***	

lnsize	-0.001986	-0.000295	-0.000443	-0.000615	-0.000832
	0.192	0.169	0.119	0.003***	0.005***
cashduepr	0.050193	-0.003455	-0.003397	-0.004984	-0.002754
	0.219	0.11	0.449	0.218	0.624
goodwillpr	0.692863	0.029035	0.028601	0.026027	0.030448
	0.155	0.000***	0.225	0.281	0.261
rer14pr	0.106954	-0.000815	-0.001497	-0.001987	0.000217
	0.016**	0.538	0.565	0.463	0.953
remulpr	-0.196829	-0.005107	-0.013863	-0.008416	-0.003664
	0.007***	0.403	0.11	0.359	0.635
reconpr	-0.016331	0.000072	0.001962	0.002675	0.002338
	0.736	0.979	0.691	0.581	0.699
recompr	0.091343	0.000179	0.000044	0.001253	0.005399
	0.038**	0.912	0.986	0.656	0.14
cipr	0.167384	0.000414	0.002821	-0.000114	0.002356
	0.001***	0.868	0.403	0.977	0.672
conspr	0.059297	-0.002446	-0.002447	-0.001738	0.003575
	0.689	0.233	0.512	0.737	0.566
Constant	-17.485	3.977	0.563	8.246	4.443
	0.042**	0.345	0.881	0.011**	0.161
Pseudo R2	0.877	0.560	0.447	0.368	0.279
AIC by N	0.019	0.044	0.052	0.057	0.061
AIC	115	292	352	398	443
Likelihood Ratio Test	476	308	246	204	152
Likelihood Ratio p	0	0	0	0	0
Chi Squared	75	284	245	233	394
Model Significance p	0	0	0	0	0
Failed & Technically "Failed" Banks	46	46	46	46	45
OBA Banks	0	0	0	0	0
Observations	6,184	6,695	6,734	6,993	7,283

Notes:

[1]Relative HPI Annual Change; p values on 2nd row; ***=1% **=5% *=10% Significance;

OBA is Open Bank Assistance & is included as Failed banks.

Constant is an Odds-Ratio estimate.