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Working Paper

Statistical challenges of stress test financial stability assessments

AEI Economics Working Paper, No. 2020-15

Provided in Cooperation with:

American Enterprise Institute (AEI), Washington, DC

Suggested Citation: Kupiec, Paul H. (2020) : Statistical challenges of stress test financial stability assessments, AEI Economics Working Paper, No. 2020-15, American Enterprise Institute (AEI), Washington, DC

This Version is available at:

<https://hdl.handle.net/10419/280628>

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American Enterprise Institute

AEI Economics Working Paper 2020-15
December 2020

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Statistical Challenges of Stress Test Financial Stability Assessments

by

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Abstract

Banking system stress tests are a key component of IMF/World Bank financial stability assessments. The focus on stress tests is predicated on prior belief that there is a strong contemporaneous correlation between bank performance and stress scenario macro-financial variables. Using US data, I use latent factor analysis to show that the presumed correlations are weak at best. This shortcoming is addressed by introducing a novel macro-financial variable to measure system-wide bank performance and using shrinkage estimators to reduce the risk of overfitting. Bespoke stress test models are constructed for the largest 200 banks in the US as of 2008Q2 using alternative shrinkage estimators. Bank performance is forecast over the first three years of the financial crisis using actual economic conditions as the stress test scenario. Parsimonious models including the new banking macro-financial variable are shown to be most accurate, but none of the stress test models analyzed are accurate by any absolute standard. The deficit in forecast accuracy identified herein is likely to be magnified for stress tests forecasts derived from less comprehensive data.

Statistical Challenges of Stress Test Financial Stability Assessments

The sciences do not try to explain, they hardly even try to interpret, they mainly make models. By a model is meant a mathematical construct which, with the addition of certain verbal interpretations, describes observed phenomena. The justification of such a mathematical construct is solely and precisely that it is expected to work. —John von Neumann (1955, p. 15)

I. Introduction

Financial system stability assessments, like those conducted by the International Monetary Fund (IMF) and the World Bank in the context of their Financial Sector Assessment Program (FSAP), include an exercise designed to assess a banking sector's capacity to weather a severe economic recession.¹ Banking system stress tests are key component of these assessments. Bank stress test use econometric models to link individual banks' performance to variables that measure economic conditions (so-called macro-financial variables) during a multi-year hypothetical stressful scenario.

A stress scenario is designed to simulate a severe recession. The scenario is a dynamic path for the key macro-financial variables that are used to model bank performance. According to the IMF,

[A] scenario describes forward-looking, severe, consistent, and robust trajectories for a comprehensive set of macro-financial variables that react following the materialization of a shock. ... Real GDP is [typically] the anchor variable of the scenario because a recession typically defines the worst macro-financial environment for most financial institutions.²

Forecasts of individual banks' performance are constructed using a stress path for the macro-financial variables. These forecasts project individual bank profit, loss and capital positions throughout the stress scenario. The resilience of the banking system is judged by the

¹ According to the IMF (<https://www.imf.org/external/np/fsap/faq/index.htm#q1>), "Any country can request an FSAP assessment, whether or not it is borrowing from the Bank or the Fund. In September 2010, the IMF Board decided that 25 jurisdictions with financial sectors that have the greatest impact on global financial stability—or "systemically important" financial sectors— should undergo in-depth reviews of their financial health by the Fund every five years in the context of Fund surveillance under Article IV of the Fund's Articles."

² Adrian, et al., (2020, pp. 15-16).

banking system's capacity to remain adequately capitalized throughout the hypothetical stress simulation.

The econometric models used in stress tests are estimated using times series data on banks' historical performance along with historical data on macro-financial variables. According to Adrian, et al., (2020, p. 9), IMF stress tests use, "multiple satellite models to translate adverse scenario variables ... into balance sheet items and profits and losses that affect financial institutions capital and capital requirements."

Unlike regulatory stress test models that often make use of detailed confidential bank information, FSAP stress test typically rely on publicly available data when it is available, and in many cases, the staff of these multilateral agencies must construct proxies for stress test macro-financial variables when actual data are not available.³

The utility of financial sector stress testing depends, at least in part, on the accuracy of the forecasts produced by the stress test models used to project bank earnings under severe stress conditions. Stress test models that substantially overstate stress scenario losses may spur policies requiring unnecessarily large capital buffers or the introduction of new macroprudential regulations which can unnecessarily restrict beneficial financial intermediation.⁴ Similarly, stress test models that understate stress scenario losses may engender a false sense of security among regulators and financial market participants unintentionally encouraging imprudent risk-taking.

In this paper, I provide what is likely a best-possible-case assessment of the accuracy of system-wide bank stress tests. It is best case for a number of reasons. First, I use US data which

³ FSAPs commonly encounter severe data limitations which require the IMF team to create proxy variables for missing or unavailable data. See Annex 2 in Adrian, et. al., (2020).

⁴ According to Adrian et. al. (2020, p. 2), "Although recommendations [based on stress test results] could include the need to boost capital cushions, they can also include the adoption of other macro-prudential measures, such as targeting credit demand (debt to income and loan to value ratios), surcharges (countercyclical or risk specific surcharges), or liquidity requirements."

are uniformly of high quality and provide a long time series of data on macro-financial variables and individual bank performance.⁵ Second, I use the actual macroeconomic and financial market conditions of the US financial crisis as the stress test scenario so that any inaccuracies in stress test forecasts owe entirely to stress test model forecasting error because the macro-financial variable values during the stress scenario represent actual financial and economic data realizations which are internally consistent. And finally, I use several sophisticated econometric techniques to estimate bespoke bank stress test models which attenuate the “overfitting bias” that is the inherent in overly complex stress test modeling approaches. The time and computational demands of the models analyzed in this paper also likely exceed the time and computational stress testing resources available in a typical IMF FSAP exercise.^{6,7}

I identify an important impediment that impacts stress test model forecast accuracy. Using latent factor analysis, I show that the contemporaneous correlations between traditional stress test macro-financial variables and individual bank performance are weak, pointing to the need for employing parsimonious models to reduce the risk of overfitting. The finding also identifies a need to identify and include a macro-financial variable that is more closely linked with bank performance. I address the latter issue by introducing a variable that measures the quarterly weighted-average performance of all insured depository institutions (IDIs) and the former by employing shrinkage estimation methods to reduce the risk of overfitting.

⁵ I use quarterly data from 1993Q1 through 2011Q2.

⁶ Adrian, et, al state that FSAP stress test models are typically Excel-based so they are transparent and readily accessible to member country authorities. Many of the calculations required to estimate the stress test models used in this paper would be very difficult if not impossible to construct using only a standard Excel spreadsheet and imbedded functions.

⁷ The author has been personally involved in the IMF stress testing processes for many member countries over the course of more than a decade when he was employed by the IMF and subsequently, multiple times and in multiple countries, as an IMF stress testing consultant.

I track the actual performance of the 200 largest banks in the US over the first three years of the financial crisis and compare their actual performance to forecasts constructed using seven alternative stress test models.⁸ Each of the seven stress test models employs a different shrinkage technique to minimize the risk of overfitting the data. The stress test models attempt to predict bank pre-tax quarterly returns as measured by bank income before extraordinary items and taxes divided by bank assets at the end of the prior quarter (hereinafter *INBFTXEX* or bank returns).⁹ I estimate bespoke stress test models for each of the sample banks and construct stress test forecasts that correct for mergers consummated within the stress scenario time period. I compare actual stress scenario bank returns to the merger-adjusted stress test model forecasts of bank returns.

I construct bank equity-to-asset ratios implied by the merger-adjusted stress test forecasts and compare them to bank “baseline” equity-to-asset ratios. Baseline ratios adjust banks’ reported equity-to-asset ratios so that they corresponded to ratios constructed using the merger-adjusted bank return forecasts. Baseline equity-to-asset ratios remove the impact of dividends, share repurchases and external injections of capital like those associated with the Troubled Asset Relief Program. I assume a bank must maintain a 6 percent equity-to-asset ratio throughout the stress period in order to “pass” the stress test.

The results demonstrate the beneficial impact of using a parsimonious model specification that includes the weighted-average quarterly return on all IDIs as a new nontraditional macro-financial stress test variable. The simplest stress test model specifications— a 3-parameter model that includes a constant, lagged bank performance, and the

⁸ The aggregate asset holdings of these 200 banks in 2008Q2, the quarter prior to the start of the stress test, was \$10.88 trillion or approximately 82 percent of all assets in the banking system at that date.

⁹Models are fit in ratio form because bank quarterly income and assets both exhibit unit root characteristics.

average quarterly return among all system IDIs, and a 5-parameter model that adds two latent factors extracted from a large set of traditional macro-financial variables—produce the most accurate stress test results among the models considered.

Still, none of the stress test models is very accurate in an absolute sense. All of the stress test models underestimate the stress scenario losses experienced by a large number of banks. Depending on the stress test model, between 28 and 37 banks are forecast to pass the stress test when they fail to maintain 6-percent equity-to-asset ratios under baseline estimates. Similarly, all models exhibit high error rates when it comes to identifying banks that fail the stress test. Depending on the stress test model, between 10 and 19 banks that pass the stress test under baseline estimates are forecast to fail according to stress test model forecasts. Many of the stress test model failures include large overestimates of a bank's cumulative stress scenario loss. These overestimates of bank losses compound and cause each of the stress test models to substantially overstate the total equity shortfall in the banking system. Stress test model estimates of the additional equity needed to keep all banks from failing the stress test range from 2.4 to 5.7 times the magnitude of the true baseline capital shortfall.

The analysis highlights significant statistical challenges that impact the forecast accuracy of stress tests conducted under ideal conditions regarding data availability, stress scenario design and the time and resources devoted to calibrating individual bank stress test models. Less ideal conditions raise the potential for even larger stress testing errors. The potential for such errors should weigh prominently when evaluating policy recommendations based on stress test results.

II. Background

Banking system stress tests are predicated on the presumption that there is a stable predictable relationship between each bank's performance and an appropriate set of observable macro-financial variables. Typically, stress test model specifications are selected based on some

measure of the model goodness of fit over a single calibration sample.¹⁰ The abbreviated length of available time series data precludes the use of hold-out validation samples.¹¹ Even the most technically advanced banking regulatory agencies judge models according to their within-estimation-sample performance after they are satisfied with the “conceptual soundness” of their model development processes.¹² Out-of-sample forecast accuracy is rarely mentioned as a primary stress test model validation criterion despite the well-known fact that over-parameterized models will generally have excellent within-sample performance but poor out-of-sample forecasting accuracy.

Unfortunately, there is not a large body of research that supports the implicit presumption that bank performance has a stable and predictable relationship with contemporaneous macro-financial variables. Guerrieri and Welch (2012) found very large root-mean-square forecast errors when they attempted to project individual components of bank income using macro-financial explanatory variables. For decades, the US federal bank regulatory agencies have used models to predict future banks performance.¹³ It is notable that researchers at both the Federal Reserve Board and the Federal Deposit Insurance Corporation report that their attempts to

¹⁰ See for example the discussion in Hirtle et al., (2015).

¹¹ Regarding data availability, The US is among the countries with the highest quality and longest time series data available, and even in the US, detailed time series data on bank performance from uniform regulatory reports are only available from the mid-1980s. In addition, the past 40 years have seen large structural changes in financial markets and banking systems. These changes likely diminish the value of including early banking data when calibrating a stress test model for a contemporary bank.

¹² The Federal Reserve Board’s 2020 Dodd-Frank stress test methodology document discusses the model validation process employed by the Federal Reserve System Model Validation Group. “This group’s model validation process includes reviews of model performance, conceptual soundness, and the processes, procedures, and controls used in model development, implementation, and the production of results. For each model, the group annually assesses the model’s reliability based on its underlying assumptions, theory, and methods and determines whether any issues require remediation as a result of that assessment.” (p. 7).

¹³ Some regulatory models are designed to predict bank failure over a multi-year horizon while others predict bank regulatory ratings (so-called CAMELS ratings) changes.

include macro-financial variables failed to improve forecast accuracy over models with explanatory variables that include only measures of bank-specific characteristics.¹⁴

The paucity of research examining bank stress test model accuracy is easily explained. Because the time series available for building stress test models is short, there is insufficient data available to retain separate hold-out validation samples. This small sample problem is compounded by the fact that appropriate validation samples must include severe economic recessions to assess a model's ability to forecast under stressful conditions. Another reason is the way stress test models are employed. Stress test models are often used to forecast bank profit and losses over a hypothetical baseline scenario, and then again over a hypothetical stress scenario. In reality, neither scenario is ever realized, so actual bank performance is never observed in either case.

The few studies that have investigated the forecast accuracy of bank stress test models (Kupiec, 2018, 2020) have found that stress test models calibrated using data on a bank's own historical performance tend produce more accurate forecasts than forecasts from "representative bank" models calibrated using pooled bank data. Parsimonious single-equation models have been shown to produce more accurate forecasts than complex multi-equation models, and the methodology used to select explanatory variables and calibrate model parameters has been shown to have an important impact on stress test forecast accuracy.

In the analysis that follows, I focus on relatively simple single-equation stress test models. This choice is motivated by the aforementioned research and by the statistics literature that finds that excessive model complexity increases the risk of over-fitting the data and

¹⁴ For the Federal Reserve models, see Cole, Cornyn and Gunther (1995); For the Federal Deposit Insurance Corporation models, see Nuxoll (2003).

including spurious explanatory variables that reduce out-of-sample forecast accuracy.¹⁵

Overfitting is especially problematic when there are a large number of potential explanatory variables, a short time series available for estimation, and when the data have a weak underlying signal-to-noise ratio.

The explanatory variables included in stress test models are selected using some statistical methodology applied to the historical bank performance data and a set of macro-financial variables available for consideration. In many cases, there are a large number of macro-financial market variables that could be used to explain a bank's performance history, but little guidance as to which variables to include in the model. One way to address this problem is to include all potential explanatory variables using a Bayesian model averaging methodology.¹⁶ An alternative is to impose parsimony and limit the number of model explanatory variables to reduce the risk of overfitting historical data. Different approaches can be used to impose parsimony, but the general class of methods are called "shrinkage estimators" (Stock and Watson, 2012).¹⁷

One approach for reducing the number of explanatory variables in a model is sequential testing that eliminates variables judged to be superfluous. Backward stepwise regression is an example of a sequential testing algorithm. An alternative approach for reducing dimensionality is the use of latent factors. Stock and Watson (2002) suggest fitting an approximate factor model to the set of all possible explanatory variables and using the latent factor estimates as the explanatory variables in the forecasting model. The risk of overfitting historical data is reduced if the covariation of a large set of macro-financial variables can be accurately reproduced using a

¹⁵ See, for example, Malcolm and Sober (1994), Hawkins (2004), Green and Armstrong (2015), or the discussion in Hastie, Tibshirani, and Friedman (2008) Section 7.

¹⁶ Kupiec (2020) compares the forecast accuracy of stress test models calibrated using Bayesian model averaging to models calibrated using Lasso and finds that the Lasso produced more accurate forecasts.

¹⁷ Stock and Watson (2012) show that Bayesian model averaging can also be interpreted as shrinkage estimator.

small number of latent factors. Stock and Watson (2012) find that forecasts constructed using latent factors often perform as well or better than forecasts constructed from other shrinkage estimators.

Another strategy for attenuating the risk of overfitting is Tibshirani's (1996) least absolute shrinkage and selection (Lasso) algorithm for parameter estimation coupled with Akaike (1973) information criterion (AIC) for variable selection. The Lasso methodology includes a penalty function that "zeros out" variables of minimal importance. The magnitude of the Lasso penalty determines which variables remain in the model. The AIC criterion is employed to select the best model specification. Prior research suggests that the Lasso-AIC approach can improve stress-test forecast accuracy compared to models calibrated using backward stepwise regression.

The risk of overfitting stress test models is magnified when a modeler's prior beliefs presume the existence of a strong statistical links between contemporaneous measures of bank performance and variable that measure macro-financial conditions. When priors presume the existence of a strong relationship, it is natural to pursue a model selection strategy focused on generating large R-squared statistics within the historical estimation sample. The next section introduces statistical analysis that can help to inform research priors so they are more closely aligned with data realities and lead to better informed choice of the statistical modelling techniques used to calibrate stress test models. The following section introduces an approximate latent factor model that will be used to assess the strength of the contemporaneous relationship between a cross section of alternative macro-financial variables and individual bank returns.

Approximate Latent Factor Model

Quarterly data on macro-financial variables and individual bank performance can be modeled as separate approximate factor models. Let X_t represent a $(N \times 1)$ vector of mean-zero time series, F_t represent a $(k \times 1)$ vector of common latent factors, and e_t represent a $(N \times 1)$ vector of idiosyncratic disturbances. Using the approximate factor model, a set of variables of interest, X_t , are modelled as linearly dependent on a set of common latent factors,

$$X_t = \gamma F_t + e_t, \quad (1)$$

where γ is an $(N \times k)$ vector of factor loadings.

It is possible to identify and estimate the latent factors that represent the common “unseen” sources driving the variation in a large cross section of bank returns and similarly for a cross-section of macro-financial variables. The strength of the contemporaneous statistical relationship between the set of macro-financial variables and bank returns can be measured by the strength of the statistical relationship between the latent factors associated with the macro-financial variables and the latent factors that explain bank returns.

To extract the latent factors, I use the approximate factor model of Chamberlain and Rothschild (1983) first implemented by Connor and Korajczyk (1986, 1988, 1993). This approach has been generalized by Stock and Watson (2002) and others for purposes of estimating latent factors to use in constructing macroeconomic forecasts. When there are many potential explanatory variables that could be used in a forecasting model and a relatively short time series of observations, latent factor estimates can be estimated and used to reduce the dimensionality of the model selection process and the risk of overfitting the historical data.

Let X represent the $(T \times N)$ data matrix with the t^{th} row equal to the X'_t . The maximum rank of the cross product matrix of data $X'X$ is the $\min(N, T)$. Connor and Korajczyk (1986)

show that, when $N > T$, consistent estimates of k approximate latent factors are given by first k eigenvectors of XX' multiplied by \sqrt{T} . The corresponding factor loadings are given by,

$$\hat{\gamma} = X' \begin{bmatrix} \hat{F}'_1 \\ \vdots \\ \hat{F}'_T \end{bmatrix} T^{-1}, \text{ where } \hat{F}_t \text{ represents the consistent estimate of the factor vector at time } t. \text{ When}$$

$N < T$, Stock and Watson (2002) show that k factor loadings γ are consistently estimated the first k eigenvectors of $X'X$ multiplied by \sqrt{N} , while the factors are consistently estimated by,

$$\begin{bmatrix} \hat{F}'_1 \\ \vdots \\ \hat{F}'_T \end{bmatrix} = N^{-1}X\hat{\gamma}, \text{ where } \hat{\gamma} \text{ is the consistent estimate of the } (N \times k) \text{ factor loading matrix.}$$

Before extracting latent factors, it is first necessary to identify how many factors should be extracted. Let Ψ_k represent the k^{th} largest eigenvalue $(NT)^{-1}XX'$; Ψ_k is also equal to the k^{th} largest eigenvalue $(NT)^{-1}X'X$. Let $ER(k) = \frac{\Psi_k}{\Psi_{k+1}}$, $k = 1, 2, \dots, kmax$, where $kmax$ is a number in excess of the largest number of latent factors that could potentially be determining X_t .¹⁸ Ahn and Horenstein (2013) show that a consistent estimate of the number of latent factors determining the data, X , is given by the so-called eigenvalue ratio estimator, $\max_{1 \leq k \leq kmax} ER(k)$.

They also derive an alternative consistent estimate of the number of latent factors, the so-called growth ratio estimator. Let $m = \min(N, T)$, $V(k) = \sum_{j=k+1}^m \Psi_j$, and $GR(k) = \frac{\ln[V(k-1)/V(k)]}{\ln[V(k)/V(k+1)]}$.

The growth ratio estimator is, $\max_{1 \leq k \leq kmax} GR(k)$.

III. The Data

The data used in this analysis span the period 1993Q1 through 2011Q2. Bank data are taken from the quarterly regulatory filings, ‘‘Report on Conditions and Income’’ (Call reports),

¹⁸ Ahn and Horenstein (2013) show that a choice of $kmax$ that is much larger than the true number of latent factors in the data is not problematic.

that are publicly available.¹⁹ I identify the 200 largest banks by asset size as of 2008Q2, the last quarter before the start of the stress test forecasting period used in the analysis. The 200 largest banks measured by assets are listed in Table A1 in the Appendix along with their book assets, equity and equity-to-asset ratio as of 2008Q2. It so happens that two of the largest banks as of 2008Q2 are branches of foreign banks (Bank Hapoalin, B.M., and Bank of China). Foreign branches are not required to segregate and report branch-specific equity separate from their parent banks' accounts. These two banks do not report the data needed to construct stress test forecasts and must be excluded from the subsequent empirical analysis.

Several of these large banks operating as of 2008Q2 fail to survive as independent institutions through 2011Q2. All of the non-surviving banks were acquired by other banks, some after failing and passing through an FDIC receivership. If a bank failed or was acquired without failing within the period 2008Q3-2011Q2, the date of the failure and(or) acquisition is reported in Table A1.

For each of the remaining 198 banks in the sample, I construct merger-adjusted series by aggregating the respective merging bank series into the surviving bank's data series in the quarters prior to the date the merger was consummated.²⁰ This adjustment simulates "pooling of interest" merger accounting.²¹ It treats all merging banks as if they were part of the surviving bank from 1993Q1 onwards, or the earliest quarter in which the merged banks first filed a Call report. This merger-adjustment procedure removes jumps and discontinuities that occur in uncorrected series as a consequence of mergers.²² Summary statistics on the merger-adjusted

¹⁹ <https://cdr.ffiec.gov/public/>

²⁰ Historical merger and acquisition data is made publically available by the Federal Deposit Insurance Corporation, in their current institutions database, https://www7.fdic.gov/idasp/advSearch_warp_download_all.asp?intTab=1

²¹ Under pooling-of-interests accounting treatment, the target bank's assets, liabilities, and owner's equities are combined with those of the acquiring bank at book value.

²² See for example, <https://www.fdic.gov/bank/analytical/quarterly/2019-vol13-1/fdic-v13n1-4q2018-article.pdf>

bank data are reported in Table A2 in the Appendix. To economize on space, I report summary statistics on the pooled data grouped by different bank asset-size categories instead of reporting bank-by-bank statistics.

After the merger-adjustment process, 178 of the 198 banks have complete data series from 1993Q1 through 2008Q2. The remaining 20 banks have merger-adjusted histories that begin subsequent to 1993Q1. Five of the remaining 20 banks have fewer than 22 quarterly observations, too few observations to utilize four of the stress test calibration approaches considered subsequently.²³

I measure bank quarterly returns using the ratio of a bank's quarterly income before tax and extraordinary items to bank asset balances held at the end of the prior quarter. I measure performance in ratio form because both quarterly assets and income are likely follow unit root processes. Income before tax and extraordinary items is defined as net interest income plus non-interest income plus securities gains (or losses) less non-interest expense less loan and lease loss provisions.

The analysis introduces a novel macro-financial variable to measure banking system-wide performance. The variable is the weighted-average of all insured depository institutions (IDIs) ratio of income before tax and extraordinary items to assets at the end of the prior quarter, where the weights are the share of an IDI's assets in the system at the end of the prior quarter.²⁴ The average is taken across all IDIs reporting in a quarter. This series is plotted in Figure 1 and series summary statistics are reported in Table A2 in the Appendix.

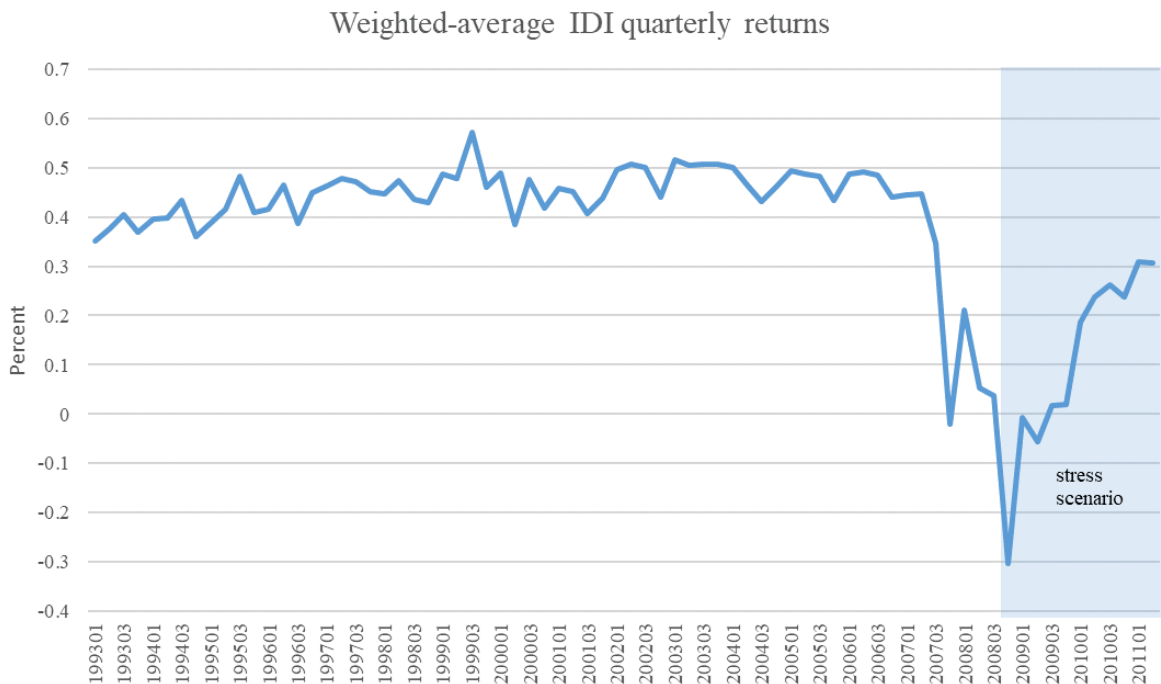
Quarterly data for 13 traditional macro-financial variables are constructed from data reported in the Federal Reserve Bank of Saint Louis FRED database. Data on real home prices

²³ Limited length of available times is yet another reason to prefer parsimonious stress test models.

²⁴ IDIs include all depositories that file regulatory Call reports.

are from the American Enterprise Institute Center for Housing Markets and Finance.²⁵ The macroeconomic and financial market explanatory variables included in stress test model regressions are reported in Table A2 along with summary statistics for these data.

Figure 1: Macro-financial variable measuring quarterly banking system performance



IV. Approximate Latent Factor Model Estimates

I use the quarterly returns on 178 banks with complete data histories and quarterly data on the 13 traditional macro-financial variables to estimate separate approximate latent factor models using data from 1993Q2 through 2008Q2. I estimate eigenvalues for the 13 macro-financial variables and again for the 178 bank returns and calculate Ahn and Horenstein (2013) $ER(k)$ and $GR(k)$ statistics to identify the number of latent factors driving the respective sets of variables.

For both the bank return data and the macro-financial data, the magnitude of the eigenvalues of the respective scaled cross-product matrices decline markedly beyond the second

²⁵ <http://www.aei.org/publication/national-housing-market-index-release-for-q2-2017/>

largest eigenvalue, and the magnitude of the remaining eigenvalues are small relative to the magnitude of the first two eigenvalues. This pattern is consistent with a small number of latent factors. I use $kmax = 5$ as the maximum possible number of common latent factors driving the respective series.

Table 1 reports the $ER(k)$ and $GR(k)$ statistics for the respective series. The macro-financial variables and bank return data generate $ER(k)$ and $GR(k)$ statistics that consistently show that there are 2 common latent factors driving each set of variables.²⁶

Table 1: Statistics that identify the number of latent factors

13 macro-financial variables			178 bank performance variables		
k	$ER(k)$	$GR(k)$	k	$ER(k)$	$GR(k)$
1	1.141	0.776	1	1.510	1.102
2	2.074	1.425	2	2.046	1.603
3	1.179	0.844	3	1.106	0.910
4	1.123	0.735	4	1.265	1.034
5	1.491	0.883	5	1.179	0.963

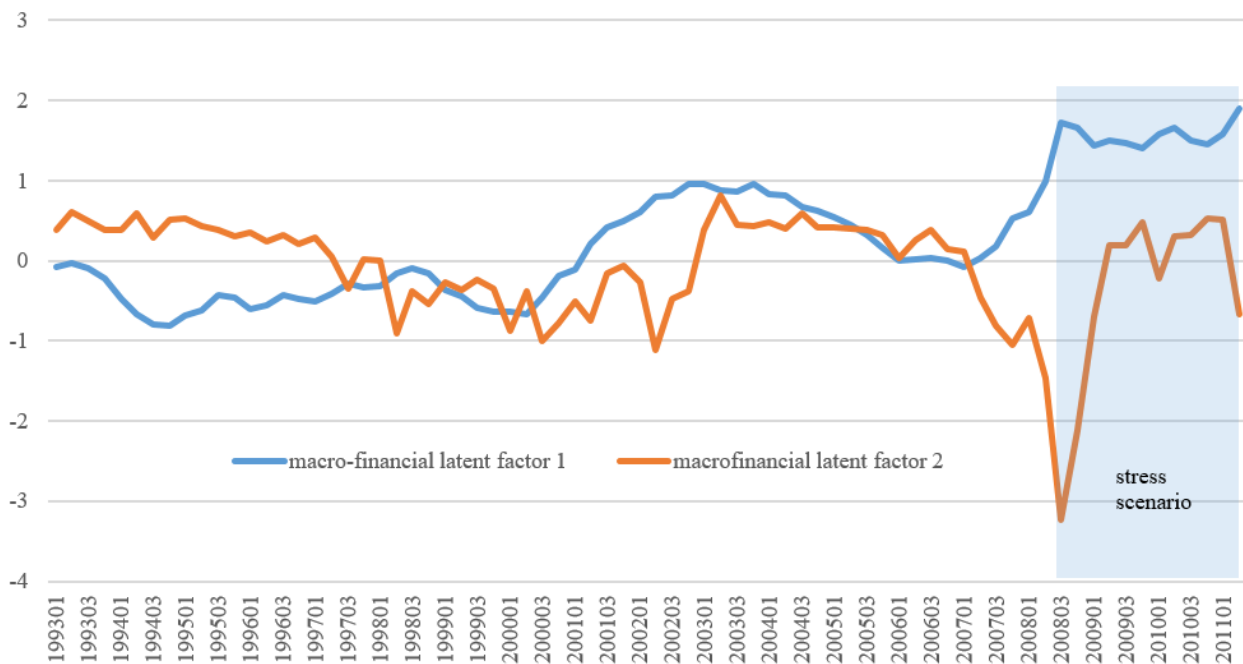
$ER(k)$ is the eigenvalue ratio statistic and $GR(k)$ is the growth ratio statistic from Ahn and Horenstein (2013).

Figure 2 plots the first two approximate latent factor estimates from for the 13 macro-financial series for the period 1993Q2 through 2011Q2. The latent factor estimates for the period 2008Q3-2011Q2, the estimates subsequently used as stress scenario macro-financial variables, are projected from the factor loading estimates derived using pre-stress scenario data (1993Q2-2008Q2). The bank return latent factor estimates for the period 1993Q2-2008Q2 are plotted in Figure 3.

²⁶ That is, $ER(k)$ and $GR(k)$ are largest for $k = 2$. The first two latent macro-financial factors explain 53 percent of the variation in the 13 macro-financial series while the first two bank performance latent factors explain a little over 30 percent of the total variation in 178 bank returns series.

To assess the strength of the contemporaneous statistical relationship between the latent factors that explain bank returns and the latent factors that drive the common variation in the macro-financial variables, I use simple regressions of the bank latent factor estimates on the macro-financial latent factor estimates. I retain the constant so that the R^2 statistic has the standard interpretation.²⁷

Figure 2: Traditional macro-financial latent factor estimates

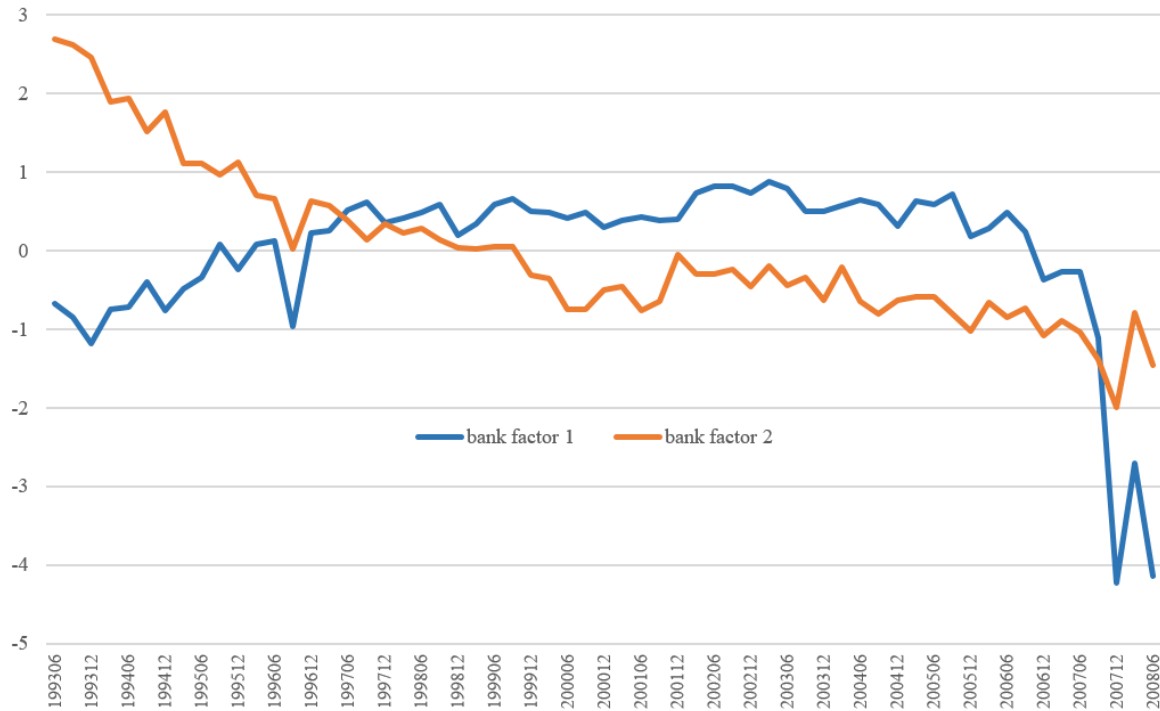


The regression estimates reported in Table 2 show that the variation in the latent bank factors have only a weak relationship with the latent factors extracted from macro-financial variables. While the individual macro-financial latent factors coefficient estimates are statistically significant at conventional levels, these factors explain very little of the total variation in the quarterly bank latent factors. A constant and the two macro-financial latent factors explain only 3 percent of the total variation in the first bank factor, and about 38 percent

²⁷ That is, the percentage of the overall variation of the dependent variable explained by the linear regression.

of the variation in the second bank factor. Since the two bank factors themselves explain only about 33 percent of the common covariation in the 178 bank quarterly returns, these results foreshadow the likelihood of achieving only limited forecast accuracy from regression models that include only a subset of these 13 macro-financial variables.

Figure 3: Latent factor estimates derived from the quarterly returns on 178 banks



As a check on the robustness of these latent factor regression results, I regress weighted-average IDI quarterly returns on the two latent macro-financial factor estimates. The results, also reported in Table 2, show that the two macro-financial factors together are able to explain only about 9 percent of the quarterly variation in weighted-average IDI returns.

These results have several implications for the construction of stress test forecast models. First, the set of 13 traditional macro-financial explanatory variables analyzed are unlikely to spawn highly accurate stress test model forecasts. Additional explanatory variables will be needed to reproduce the variation in quarterly bank returns that is orthogonal to this traditional

set of macro-financial variables. Second, because the number of time series observations are limited and the data exhibit a low signal-to-noise ratio, stress test models that are calibrated to include a large number of these traditional macro-financial variables are likely to include spurious variables that will reduce forecasting accuracy relative to more parsimonious model specifications.

Table 2: Relationship between macro-financial latent factor estimates, bank return latent factor estimates, and system-wide IDI returns

dependent variable	constant	macro-financial latent factor 1	macro-financial latent factor 2	R ²
latent bank factor 1	2.5x10 ⁻¹⁶ (0.13)	0.15 (0.24)	0.30 (0.26)	0.03
latent bank factor 2	-3.1x10 ⁻¹⁶ (0.10)	-0.84** (0.19)	0.85** (0.21)	0.38
weighted-average IDI income-to-asset ratio	9.3x10 ⁻¹⁷ (0.12)	0.06 (0.23)	0.60* (0.25)	0.09

Regressions based on 61 observations. All variables are standardized. Coefficient standard error estimates appear in parenthesis below coefficient estimates. * indicates statistical significance at the 5 percent level. ** indicates statistical significance at the one percent level.

In the remainder of this paper, I estimate and assess the forecast accuracy of seven alternative stress test model specifications. The models are constructed using three shrinkage approaches: backward stepwise regression, approximate latent factors, and Lasso methods.²⁸ All of the model specifications potentially include a lagged dependent variable but differ in the other variables used in calibration process. Some models include the 13 macro-financial variables as potential explanatory variables and use shrinkage methods to impose parsimony. Others include

²⁸ All of the modeling approaches in this paper can be interpreted as a shrinkage approach that pull some ordinary least squares regression coefficients toward zero. See for example the discussion in Stock and Watson (2012).

the two dominate latent factor estimates extracted from the 13 macro-financial series. While others augment the set of potential explanatory variables with weighted-average IDI returns.²⁹

The direct use of bank latent factor estimates as explanatory variables in stress tests is problematic. Latent factor stress scenario realizations are weighted averages of the performance of the specific individual banks undergoing stress testing. Consequently, stress scenario latent factor realizations require an estimate of the performance of all 178 banks in each stress test quarter as an input. In contrast, stress scenario weighted-average IDI returns can be specified independent of knowing any individual bank’s return and used as a practical replacement for latent bank factors. Table 3 reports the results of a regression of weighted-average IDI returns on estimates of the two latent factors derived from individual bank returns. The regression results show that the two latent bank factors explain 90 percent of the overall variation in the weighted-average IDI bank performance measure.

Table 3: Relationship between the weighted-average IDI returns and bank latent factors

dependent variable	constant	bank latent factor 1	bank latent factor 2	R ²
weighted-average IDI returns	-1.1.x10 ⁻¹⁶	0.94**	0.11*	0.90
	(0.04)	(0.04)	(0.04)	

Regressions based on 61 observations. All variables are standardized. Coefficient standard error estimates appear in parenthesis below coefficient estimates. * indicates statistical significance at the 5 percent level. ** indicates statistical significance at the one percent level.

The historical characteristics of the system-wide IDI return measure can be analyzed as a separate macro-financial factor and added to the traditional set of macro-financial variables used to characterize the state of the economy in the stress scenario. The same techniques currently

²⁹ The inclusion of the weighted average performance of all banks as an explanatory variable is analogous to the market factor in the so-called “market model” commonly used to analyze the expected returns on a cross-section of traded equities.

used in stress scenario design can be adapted to ensure that the stress scenario variation in the weighted average IDI returns are consistent with the variation of other macro-financial variables in the stress scenario.³⁰

V. Stress Test Methodology

1. The models

I estimate seven different approaches for calibrating stress test model. I use quarterly data from 1993Q1 through 2008Q2 for model calibration. For each bank and modeling approach, I construct stress test forecasts for the period 2008Q3 through 2011Q2.

The calibration methods differ in the approaches taken to enforce parsimony. Some directly restrict the number of explanatory variables used in the specification while others use a large potential set of explanatory variables and shrinkage techniques (stepwise regression or Lasso) to reduce the dimensionality of the final stress test model. The seven alternative stress test modeling approaches are summarized in Table 4.

The three-, four- and five-parameter stress test model are estimated using ordinary least squares. The 3-parameter model is the simplest model. It uses weighted-average IDI returns as its only macro-financial variable. The 4-parameter model closely follows the Stock and Watson (2002) methodology using macro-financial latent factor estimates to reduce the dimensionality of the model. The 5-parameter model adds weighted-average IDI returns as an additional explanatory variable.

The 15- and 16-parameter stepwise models are estimated using backward stepwise regression. The procedure begins with OLS estimates and all explanatory variables included in the model. The constant is retained at all steps of the process. At each step of the algorithm, the

³⁰ See, for example, the discussion in Adrian, et.al., (2020), pp. 17-19. In the current analysis, consistency is ensured because the stress test scenario uses the actual realized values of a macro-financial variables used in the analysis.

variable with the least statistical significance³¹ is omitted and the model is re-estimated with ordinary least squares. The process is repeated until the regression model's adjusted-R² statistic achieves a maximum.

The 14- and 15-parameter Lasso models are estimated using Tibshirani's (1996) least absolute distance and selection operator (Lasso) and the AIC criterion. Lasso minimizes the model's means square error while simultaneously imposing a penalty on the sum of the absolute values of the model's coefficient estimates. If y_t represents an observation on the dependent variable, x_{it} represents an observation on the i^{th} explanatory variable and β_i represents the coefficient on the i^{th} explanatory variable, Zou, Hastie and Tibshirani (2007) show that the Lasso coefficient estimates satisfy,

$$\hat{\beta} = \arg \min_{\beta} [(\sum_{t=1}^T (y_t - \sum_{i=1}^p x_{it}\beta_i)) + \delta \sum_{i=1}^p |\beta_i|] \quad (2)$$

The Lasso penalty on the L^1 norm of the coefficients, δ , sets coefficient estimates to zero unless the estimate's absolute value exceeds a threshold set by the penalty rate. If the penalty rate is set to zero, Lasso produces ordinary least squares estimates. If the penalty rate is set too high, Lasso will set all coefficient estimates to zero.

I estimate the Lasso model using the Wu and Lange (2008) coordinate decent algorithm over the global grid of relevant Lasso penalty rates. I calculate the AIC estimate following Zou, Hastie and Tibshirani (2007) and select the Lasso penalty rate and corresponding Lasso coefficient estimates that minimize the AIC.

2. *Baseline Performance Estimates*

I construct a baseline estimate of each bank's equity-to-asset ratio that corrects a bank's reported equity-to-asset ratio for a number of factors over the stress scenario horizon. It uses the

³¹ That is, the largest probability that the coefficient estimate is not different from zero.

Table 4: Potential explanatory variables included in each alternative stress test model

Potential set of stress test model explanatory variables	3-parameter model	4 parameter model	5 parameter model	15-parameter stepwise model	16-parameter stepwise model	14-parameter Lasso model	15-parameter Lasso model
constant	x	x	x	x	x		
lagged dependent variable	x	x	x	x	x	x	x
approximate latent macro factor 1		x	x				
approximate latent macro factor 2		x	x				
banking system weighted-average equity-to-asset ratio	x		x		x		x
Nominal Quarterly GDP growth rate, SAAR				x	x	x	x
civilian unemployment rate, unadjusted				x	x	x	x
10-year Treasury yield				x	x	x	x
3-month Treasury yield				x	x	x	x
Moody's AAA yield				x	x	x	x
Moody's Baa yield				x	x	x	x
Federal funds rate				x	x	x	x
Wilshire quarterly market index return				x	x	x	x
Wilshire daily return standard deviation				x	x	x	x
Kansas City Fed Financial Stability Index (FSI) quarterly average				x	x	x	x
VIX daily average				x	x	x	x
VIX quarterly percent change				x	x	x	x
Change in Real House Price Index				x	x	x	x

Notes: The 3-, 4- and 5-parameter models are estimated using OLS. The 14-, 15- and 16-parameter stepwise and Lasso models begin the calibration process with the indicated variables. The number of explanatory variables in the final stress test model specifications for these models differs by bank and are determined by the outcome of the shrinkage estimation algorithm.

bank's reported quarterly return ($INBFTXEX_t$) to dynamically adjust the bank's June 2008 reported equity-to-asset ratio. Under the assumption that the bank forgoes making any capital distributions (dividends or share buybacks), does not raise any new external capital, pay taxes or receives tax refunds, and reinvests any profits and absorbs any losses by scaling up or down its existing equity, investments and operations, the bank's equity-to-asset ratio will evolve dynamically as,

$$\frac{equity_t}{assets_t} = \left(\frac{equity_{t-1}}{assets_{t-1}} + INBFTXEX_t \right) / (1 + INBFTXEX_t) \quad (3)$$

The baseline estimation approach begins with a bank's June 2008 equity-to-asset ratio and dynamically adjusts the ratio using the bank's reported $INBFTXEX_t$ value. Baseline estimates are free from any distortion that might be introduced by capital injections from government assistance programs like TARP.³² Mergers that take place during the stress period do not augment or diminish the bank's baseline equity-to-asset ratio except through their impact on $INBFTXEX_t$. Stress test model forecasts are merger-adjusted so the forecasts take into account the impact that a merger has on a bank's reported $INBFTXEX_t$.

To pass the stress test, I assume that a bank must maintain an equity-to-asset of at least 6 percent over the period 2008Q2-2011Q2. Under this pass-fail criterion, a bank that takes no losses over the stress scenario will still fail the stress test if its 2008Q2 equity-to-asset ratio is less than 6 percent.³³ I report the details of each bank's stress test results in the Appendix, so an interested reader can assess the implications of choosing a different minimum equity-to-asset ratio as the criterion for passing the stress test.

³² TARP capital injections were made at the holding company level, not at the bank level. However, the bank holding company could, if needed or deemed desirable, pass some (or all) of the new TARP capital down to the bank.

³³ There are banks with 2008Q2 equity-to-asset ratios below 4 percent, so setting a lower minimum stress test capital of 4-percent would still result in at least one bank failing based on their 2008Q2 equity position.

3. Stress Test Forecast Construction

Forecasts are constructed for the first 12-quarters of the 2008 financial crisis (2008Q3-2011Q2) using the actual quarterly values of the macro-financial explanatory variables and associated macro-financial latent factor estimates. The forecasts are true out-of-sample forecasts. Lagged dependent variables are initially set equal to June 2008 values. In subsequent quarters lagged dependent variables are set equal to lagged forecast values.

4. Merger Adjustments

Mergers involving sample banks occurred over the first 12 quarters of the financial crisis. When an acquired bank is merged, the acquiring institution's Call report data are augmented to reflect the income, deposits, loans, securities and other characteristics of the newly-merged institution. A forecast based on information solely from an acquiring bank's June 2008 call report data cannot be expected to accurately forecast the bank's INBFTXEX at a subsequent quarter should the bank acquire the income producing assets and liability expenses from a merging institution. Forecasts must be corrected to account for merger-related impacts on banks' reported INBFTXEX values.

Consider an example in which a bank consummates its first and only merger within the stress scenario in December 2008. A 12-quarter stress test forecast of the resulting institution must be constructed from two different stress scenario forecasts. First, a 12-quarter forecast is constructed for the acquiring bank using the bank's actual June 2008 data as the initial conditions. Second, the historical data for the acquiring bank is merger-adjusted to include the newly acquired bank and its stress test model parameters are re-estimated assuming the two banks were combined throughout their pre-2008Q3 history. Third, a 12-quarter forecast is constructed using June 2008 merger-adjusted initial conditions and the new merger-adjusted parameter estimates. Finally, the 12-quarter merger-adjusted forecast is constructed as the

September 2008 projection from the first forecast and 11-quarterly projections from the second forecast beginning in December 2008.

Alternatively, if the bank's first merger was delayed until March 2009, the 12-quarter merger-adjusted forecast would be constructed as the September and December 2008 projections from the first forecast with the subsequent 10 quarterly projections taken from the second forecast beginning in March 2009. If the bank experiences a merger or mergers in each of the 12 stress scenario quarters, the merger-adjusted forecast must be assembled from 12 different forecasts, each of which would use a different set of merger-adjusted stress test model estimates and merger-adjusted June 2008 initial conditions.

5. *Stress Test Scenario Capital Shortfall Estimates*

Each bank's equity-to-asset ratio is forecast throughout the stress scenario using the bank's initial 2008Q2 equity-to-asset ratio, merger-adjusted forecasts of *INBFTXEX* and equation (3). If a bank's 2008Q2 or forecasted equity-to-asset ratio falls below 6-percent in any stress test quarter, the bank's 2008Q2 equity is supplemented in \$100,000 increments until the bank's forecasted equity-asset ratio satisfies a minimum 6-percent lower bound throughout the stress test period. The total increment to a bank's 2008Q2 equity is an estimate of the additional equity the bank needs to pass the stress test where the equity is injected in the form of a debt-for-equity swap.³⁴

VI. Stress Test Results

Table 5 reports summary statistics on the distribution of the merger-adjusted actual and forecasted values of banks' quarterly stress scenario returns (*INBFTXEX*) from each stress

³⁴ This algorithm simulates a bank's equity-to-asset ratio throughout the stress scenario after the bank raises equity in \$100,000 increments and uses the proceeds to retire outstanding bank debt. The simulated equity injection does not alter the bank's 2008Q2 asset holdings.

testing approach over the period 2008Q3-2011Q2. The summary statistics give some indication of the magnitude of the forecast errors of the respective stress test models. The standard deviation of forecasts from the 3- and 5-parameter models are a little more than twice the standard deviation of the distribution of actual outcomes whereas the distributions of the stepwise and Lasso model forecasts are between 5 and 7 times as large as the standard deviation of actual outcomes.

Table 5: Summary statistics on the distribution of actual and forecasted values of banks' income-to-asset ratios over the stress scenario

	actual income-to- asset ratio	3-param stress model forecast	4-param stress test model forecast	5-param stress test model forecast	15-param stepwise stress test model forecast	16-param stepwise stress test model forecast	14-param Lasso model forecast	15-param Lasso stress test model forecast
mean	-0.0004	0.0011	0.0051	0.0023	-0.0007	-0.0061	-0.0009	-0.0037
standard deviation	0.0103	0.0227	0.0355	0.0225	0.0597	0.0719	0.0511	0.0690
.01 quantile	-0.0393	-0.0307	-0.0671	-0.0572	-0.1939	-0.2998	-0.2429	-0.2924
.05 quantile	-0.0151	-0.0124	-0.0087	-0.0134	-0.0143	-0.0176	-0.0105	-0.0122
.10 quantile	-0.0074	-0.0073	-0.0012	-0.0062	-0.0054	-0.0084	-0.0043	-0.0052
.25 quantile	-0.0009	-0.0007	0.0018	-0.0004	0.0001	-0.0005	0.0005	-0.0002
.5 quantile	0.0011	0.0020	0.0039	0.0022	0.0031	0.0029	0.0030	0.0026
.75 quantile	0.0033	0.0037	0.0057	0.0043	0.0057	0.0055	0.0051	0.0047
.90 quantile	0.0053	0.0053	0.0109	0.0080	0.0095	0.0089	0.0101	0.0090
.95 quantile	0.0082	0.0076	0.0175	0.0149	0.0147	0.0130	0.0157	0.0147
.99 quantile	0.0173	0.0415	0.0740	0.0652	0.0710	0.0264	0.0457	0.0580

Notes: The actual income-to-asset distribution, and the distributions of this ratio as forecast by the 3-, 4-, and 5-parameter models are based on 198 quarterly bank observations over the period 2008Q3-2011Q2. The distribution of the ratios forecast by the 15- and 16-parameter stepwise models and the 14- and 15-parameter Lasso models are based on quarterly observations on 192 banks over the same time period.

A comparison of model-specific estimates of the 1 and 99 percent quantiles of the respective return distributions show large differences in the forecast range of outcomes. The 3-, 4- and 5-parameter stress test models show modest deviations of their forecast distribution tail quantile values compared to the tail quantiles of the actual distribution. The stepwise and Lasso stress test models exhibit much larger deviations, especially in the negative tail of the return distribution. The characteristics of the distribution of the forecasts produced by the 3-parameter

model most closely track the characteristics of the actual distribution of bank returns over the stress scenario.

Table 6 reports the results of regression models in which merger-adjusted stress test forecasts are regressed on a constant and actual merger-adjusted bank returns over the stress scenario (2008Q3-2011Q2). An ideal stress test model would have forecasts that equal actual outcomes. The regression would generate a constant of zero, a coefficient estimate of 1 on actual outcomes, and a regression R^2 statistic equal to 1. The scatter plot of actual and corresponding forecast values would fall along the 45-degree line.

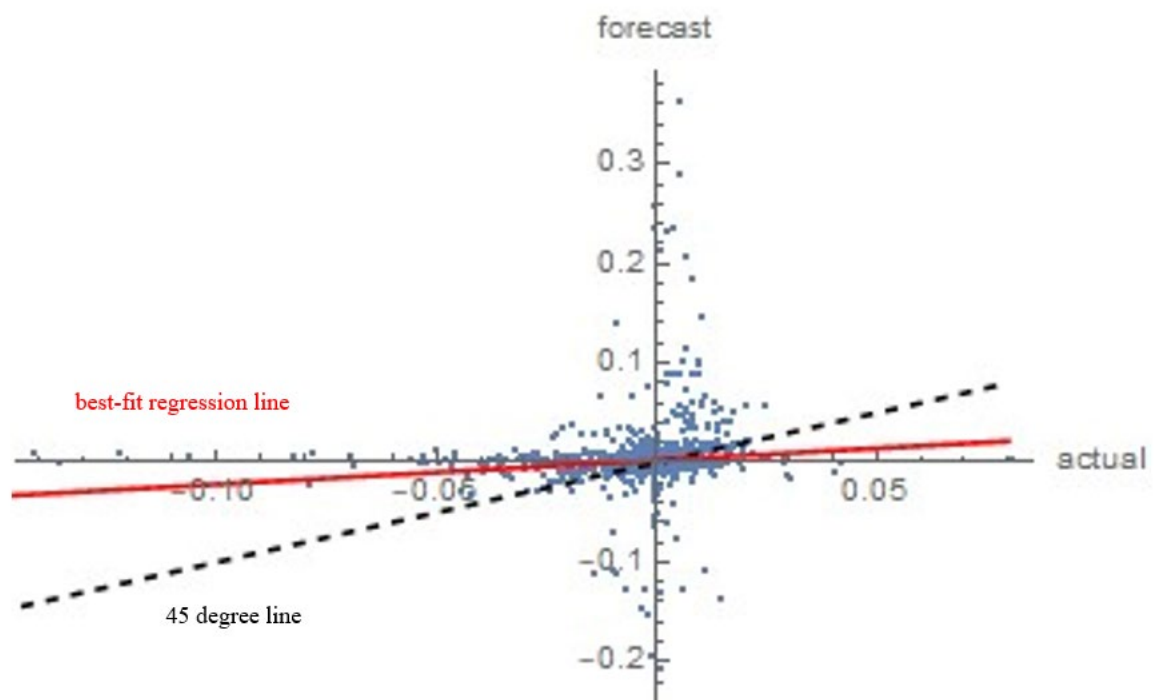
Table 6: Regression of merger-adjusted quarterly forecasts on actual bank returns

model forecast	intercept	coefficient estimate on actual bank returns	regression R^2
3-parameter	0.0012** (.0005)	0.1864** (.0452)	0.007
4-parameter	0.0053** (.0007)	0.2342** (.0708)	0.005
5-parameter	0.0024** (.0005)	0.2413** (.0447)	0.012
15-parameter stepwise	-0.0006 (.0012)	0.2918* (.1238)	0.002
16-parameter stepwise	-0.0059** (.0015)	0.3886** (.1490)	0.003
14-parameter Lasso	-0.0007 (.0011)	0.3163** (.1060)	0.004
15-parameter Lasso	-0.0036* (.0014)	0.2336 (.1431)	0.001

Notes: Coefficient standard error estimates appear in parenthesis below coefficient estimates. The 3-, 4-, and 5-parameter regressions are based on 2376 observations. The stepwise and Lasso model regressions are based on 2304 observations. The symbols * and ** indicate, respectively, statistically different from 0 at the 5 percent and 1 percent level.

The regression results reported in Table 6 show that all the stress test models fall short of the ideal forecast model. All of the models have coefficient estimates on actual bank returns far below 1. Six model have intercepts that are statistically different from 0, and the best-fitting model (5-parameter) has an R^2 statistic of only 1.2 percent. Figure 4 plots the forecast and actual realizations for the 5-parameter model along with the 45-degree line and the fitted regression from Table 6.

Figure 4: Actual and forecast values of the 5-parameter stress test model, 2008Q3-2011Q2



The detailed results of the stress test equity-to-asset ratio forecasts for each bank are reported in Tables A2 and A3 in the Appendix. Table 7 provides an overview. Of the 200 largest insured depository institutions (IDIs) as of 2008Q2, two were foreign branches that lack the data necessary for stress testing. Of the remaining 198 IDIs, 132 passed the stress test according to baseline equity-to-asset ratio estimates. Of the 66 banks that failed the stress test under baseline capitalization estimates, 17 began the stress test with equity to-asset ratios of less than 6 percent

and would fail the stress test regardless of their performance in the stress scenario since I have assumed that 6 percent is the minimum acceptable equity-to-asset ratio.

Table 7: Summary of stress test pass/fail results

Total number of IDIs	200							
less foreign branches	2							
Total number of domestic IDIs	198							
<i>of which:</i>								
	pass stress test under:	pass baseline and pass under:	false passes	fail stress test under:	fail baseline and fail under:	false fails	fails baseline, 2008Q2 capital < .06	baseline failures correctly identified by the model
baseline	132			66				
3-param model	150	121	29	48	35	13	17	18
4- param model	161	124	37	37	27	10	17	10
5-param model	145	117	28	53	38	15	17	21
15-param stepwise model	148	113	35	44	28	16	15	13
16-param stepwise model	147	110	37	45	26	19	15	11
14-param Lasso model	156	119	37	36	26	10	15	11
15-param Lasso model	153	118	35	39	28	11	15	13

Notes: the 14-, 15-, and 16- parameter models include estimates for only 192 IDIs. These approaches are not viable for 6 banks because of an insufficient number of degrees of freedom in the estimation sample.

The results reported in Table 7 show that all of the stress test modeling approaches over-estimate the number of banks that pass the test. Not only does each stress test model underestimate the number of baseline bank failures, but they also identify as “fails” many banks that pass the stress test under the baseline. The best approach for accurately identifying failures is the 3-parameter model. It identifies 53 percent of the banks that actually fail the stress test. Moreover, the statistics show that among the banks that are correctly identified as failing, more than half can be identified as failing by looking at the 2008Q2 equity-to-capital ratio alone. Only the 3-parameter model produces dynamic forecasts that correctly identify more failing banks than can be identified by examining each banks 2008Q2 equity-to-asset ratio in isolation without doing *any* econometric modeling or forecasting.

Table 8 provides an alternative perspective for analyzing the results. It decomposes the stress test forecasts according to the actual outcomes each bank experienced during the stress scenario period. Of the 198 domestic IDIs, 157 remained as independent open and operating

through 2011Q2. Of the remaining IDIs, 24 were acquired by another IDI before 2011Q2 without failing while 17 IDIs failed and were resolved in an FDIC resolution. Of the 157 independent surviving IDIs, 44 failed the stress test under baseline estimates but fewer than half of these banks were correctly identified by any of the stress test modeling approaches. Of the 24 banks acquired while open and operating, 8 failed the stress test under baseline estimates. Five of these 8 institutions were correctly identified by the 3-parameter model and the 15-parameter Lasso model. Of the 17 institutions taken into an FDIC receivership, 14 failed the stress test under baseline equity-to-asset ratio estimates. Fully 10 of these were correctly identified by the 3-parameter model.

Table 8: Actual bank outcomes and stress test estimates

Total number of IDIs	200				
less foreign branches	2				
Total number of domestic IDIs	198				
<i>of which:</i>					
Survive stress scenario as independent IDIs	157				
Are acquired during the stress scenario without failing			24		
fail and enter FDIC receivership during the stress scenario					17
<i>of which fail under:</i>					
baseline	44	<i>of which fail baseline and under:</i>	8	<i>of which fail baseline and under:</i>	14
3-parm model	28	20	8	5	12
4- parm model	22	16	6	4	9
5-parm model	34	24	8	5	11
15-parm stepwise model	28	17	7	4	9
16-parm stepwise model	29	16	8	4	8
14-parm Lasso model	20	15	7	4	9
15-parm Lasso model	22	16	8	5	9

Notes: the 14-, 15-, and 16- parameter models include estimates for only 192 IDIs. These approaches are not viable for 6 banks because of an insufficient number of degrees of freedom in the estimation sample.

Figure 5 shows the number of banks that are estimated to pass the stress test, both under baseline estimates and the forecasts from each model, as banks add additional equity to their 2008Q2 capital structures.³⁵ The plot shows that 132 banks pass under baseline estimates with no additional equity while the 3-parameter model passes 150 banks with no additional equity, and the remaining models pass even more banks. If all banks increased their 2008Q2 equity-to-asset ratios by 5 percentage points, 178 banks would pass baseline estimates³⁶ and also pass under 3-parameter model forecasts. The remaining six stress test models would incorrectly pass more than 178 banks. With an additional 20 percentage points of equity, baseline estimates indicate that all 198 banks would pass the stress test. But even if all banks had 20 percentage points of additional equity in 2008Q2, the forecasts from the seven stress test models would still fail between 2 and 6 banks.

Figures 6 and 7 illustrate the bank-specific variation among the alternative stress test model forecasts. The baseline estimates and stress test models are unanimous for 104 banks, all of which pass the stress test without any additional equity. There are 27 banks that require no extra equity to pass the stress test under baseline estimates, but require additional equity to pass the stress test under at least one of the stress test model forecasts. Figure 6 shows the minimum, maximum and median estimate of the additional equity needed to pass the stress test under the seven alternative stress test model forecasts.³⁷ The remaining 61 banks need additional equity under the baseline to pass the stress test. Figure 7 shows baseline estimates of the additional equity needed to pass the stress test along with the minimum, median and maximum estimate of

³⁵ Equity is assumed to be added in the form of a debt-for-equity swap.

³⁶ 132 banks pass with no additional equity. With an additional 5 percentage points of equity in 2008Q2, 46 additional banks pass the stress test.

³⁷ One bank is excluded from Figure 5 because the bank did not have enough observations to estimate all seven stress test models. 5 banks that fail under the baseline are excluded from Figure 6 because they had an insufficient number of observations to estimate all seven stress test models.

additional equity needed to pass the stress test under the seven alternative stress test models. Figures 6 and 7 show that the different stress test models often produce a wide range estimates of the the equity shortfall, and the range of stress test model estimates is not monotonically related to the magnitude of the baseline shortfall estimate.

Table 9 provides estimates of the total additional equity needed to ensure that all banks pass the stress test under the baseline and respective stress test model forecasts. The simplest model estimates, those from the 3-, 4- and 5-parameter models, are based on 198 banks. The estimates from the 14-, 15- and 16 parameter models, include only 192 banks because of data limitations.³⁸ All of the stress test models overestimate the amount of additional equity required to ensure that all banks maintain a 6 percent equity-to-asset ratio throughout the stress scenario. The stress test model equity shortfall estimate closest to the baseline estimate (14-parameter Lasso model) more than doubles the amount of equity actually needed.

The universal tendency to over-estimate the system-wide capital shortfall may not be specific to this stress scenario or the stress test models used in this analysis. The stress testing process includes an asymmetry which creates a tendency for stress test to overstate the capital shortfall in a banking system. The mechanism is transparent in the following example.

Assume a system has several banks, each with 6-percent equity-to-asset ratios at the start of the stress test. The stress scenario lasts 1 period. Let each bank's actual return be 0, so all banks' baseline equity-to-asset ratios remain unchanged at 6 percent. Now assume the stress test models for each bank produce unbiased forecasts with symmetric errors around the mean earnings forecast of 0. Any bank that has a forecast error realization that indicates a loss will cause the bank fail the stress test and add to the capital shortfall estimate for the system as a

³⁸ In total, the 6 omitted banks require an additional \$422.1 million to pass the stress test under baseline estimates.

whole. In contrast, positive forecast errors do not reduce the systemwide capital shortfall estimate. In practice, stress model forecasts are unlikely to be unbiased and their forecast errors may not be symmetric, so stress tests could understate or overstate the system capital shortfall. Still the asymmetry of the pass/fail criterion will interact with model forecast error to produce an overestimate of the additional equity a banks needs to pass the stress test.

Table 9: Estimates of the total additional equity capital in required to ensure that all banks maintain 6 percent equity-to-asset ratios throughout the stress scenario

Estimation method	additional equity (\$000)	additional equity as percentage of 2008Q2 total assets
baseline	44,412,900	0.41
3-parameter model	143,720,500	1.32
4-parameter model	252,982,100	2.32
5-parameter model	149,120,200	1.37
15-parameter stepwise model	119,371,500	1.10
16-parameter stepwise model	159,331,000	1.46
14-parameter Lasso model	107,034,600	0.98
15-parameter Lasso model	125,823,600	1.16

Notes: The baseline, 3-,4- and 5-parameter model estimates of additional equity capital are based on 198 banks. The 14-, 15- and 16-parameter model estimates exclude 6 banks because they lack a sufficient number of observations to estimate the models. The percentage measures of additional equity uses the total assets of all 198 banks as the base.

To summarize the results, all of the stress test models examined pass too many banks relative to baseline estimates. When they fail banks, they tend to overestimate the amount of additional equity needed to maintain a minimum 6 percent equity-to-asset requirement. In terms of a stress test model’s ability to correctly identify banks with passing and failing baseline stress test results, the 3-parameter and 5-parameter models outperform the other models. The 3-parameter’s overall accuracy rate—the total number of correctly identified passing and failing

banks divided by 198— is 78.79 percent, just slightly higher than the 5-parameter model’s accuracy rate of 78.28 percent.

VII. Summary and Conclusions

This analysis provides a rigorous assessment of the accuracy of several stress test modeling approaches similar to those that might be used to assess the resilience of a nation’s banking system in an IMF/World Bank FSAP exercise. The results represent estimates of the stress test modeling accuracy that might be achieved under highly favorable conditions meaning: (1) a long time series of accurate data on bank performance is available on a large cross section of important banks; (2) a similiarly long time series is avaiable on an identical frequency for many variables that accurately measure macoeconomic and financial market conditions; (3) there are no data inconsistencies in the specified stress scenario; and (4) bespoke stress test models are estimated for each individual bank, a process that is more accurate and resource instensive than “representative bank models” that estimate stress test model paramters using pooled bank data.

Using the approximate latent factor aproch of Connor and Korajczyk (1986, 1988, 1993) and Stock and Watson (2002), I demonstrate that the latent factors that explain the common quarterly covariation in the performance of 178 of the largest banks in the US are only weakly correlated with the latent factors that explain the common covariation in 13 macro-financial variables traditionally used to characterize stress test scenarios. The weak signal-to-noise ratio in these respective data series indicates the need to use modeling methods that minimize the risk of overfitting the macro-financial variables. The results also suggest a need to include additional explanatory variables that are more highly correlated with bank performance.

To address these issues, I introduce a new stress test model explanatory variable—the quarterly pre-tax return on assets for the entire banking system and consider seven alternative stress test modeling approaches for imposing parameter parsimony. The approaches include

Stock and Watson (2002) latent factor methods in addition to approached that select among many variables using alternative shrinkage estimation techniques.

I compare the actual performance of 198 banks with their stress test model forecasts over the first 3 years of the financial crisis after controlling for the effects of mergers, dividends, share repurchases and external capital injections. I use the realized values of macro-financial variables and latent factors as the stress scenario and assume that, in order to pass the stress test, a bank must maintain a 6 percent equity-to-asset ratio from 2008Q2 to 2011Q2.

The results show that the simplest stress test model specification— the 3-parameter model that includes a constant, lagged bank returns, and the weighted-average return on all IDIs— is the most accurate model in terms of identifying banks that pass and fail the stress test under baseline estimates. The 3-parameter model classifies 78.8 percent of the banks accurately on a pass/fail basis, but it substantially overestimates the system-wide equity shortfall that must be added to ensure that every bank maintains a minimum 6-percent equity-to-asset ratio throughout the stress scenario.

None of the stress test models is very accurate when comparing individual bank stress test forecasts with realized bank returns during the stress scenario. All of the stress test models underestimate stress scenario losses on a large number of banks. Depending on the model, between 29 and 37 banks are estimated to have passed the stress test when they actually failed under baseline estimates. Similarly, all of the stress test models overestimate stress test losses. Depending on the model, between 10 and 19 banks are estimated to have failed the stress test when they actually pass under baseline estimates. In instances where stress test models overestimate a bank's stress scenario losses and fail the bank, the magnitudes of the loss over-

estimates are typically substantial as evidenced by each model's inflated estimate of the system's overall capital shortfall.

The implications of these results for system-wide bank stress testing and financial stability analysis depend on the perceived costs of misclassifying individual banks and the social welfare consequences of over-estimating system-wide capital shortfalls. The stress testing estimates uniformly overestimate the additional equity need to achieve a system-wide 6-percent equity-to-asset ratio target by substantial amounts. The tendency to overestimate capital shortfalls may not be unique to this stress scenario or the models estimated in this analysis, but could well be an endemic feature of stress testing given the asymmetric way loss overestimates interact with the stress test objective function.

When assessing the resilience of a financial system based on the results of system-wide bank stress tests, the potential impact of stress test model forecast errors should be an important consideration. The analysis highlights significant statistical challenges that impact stress test forecasting accuracy even under ideal conditions regarding data availability, stress scenario design and the time and resources devoted to calibrating individual bank stress test models. Less ideal conditions raise the potential for even larger stress testing errors and the potential for such errors should weigh prominently when evaluating policy prescriptions based on stress test results.

Figure 5: Number of banks that pass the stress test with indicated amount of additional equity in 2008Q2

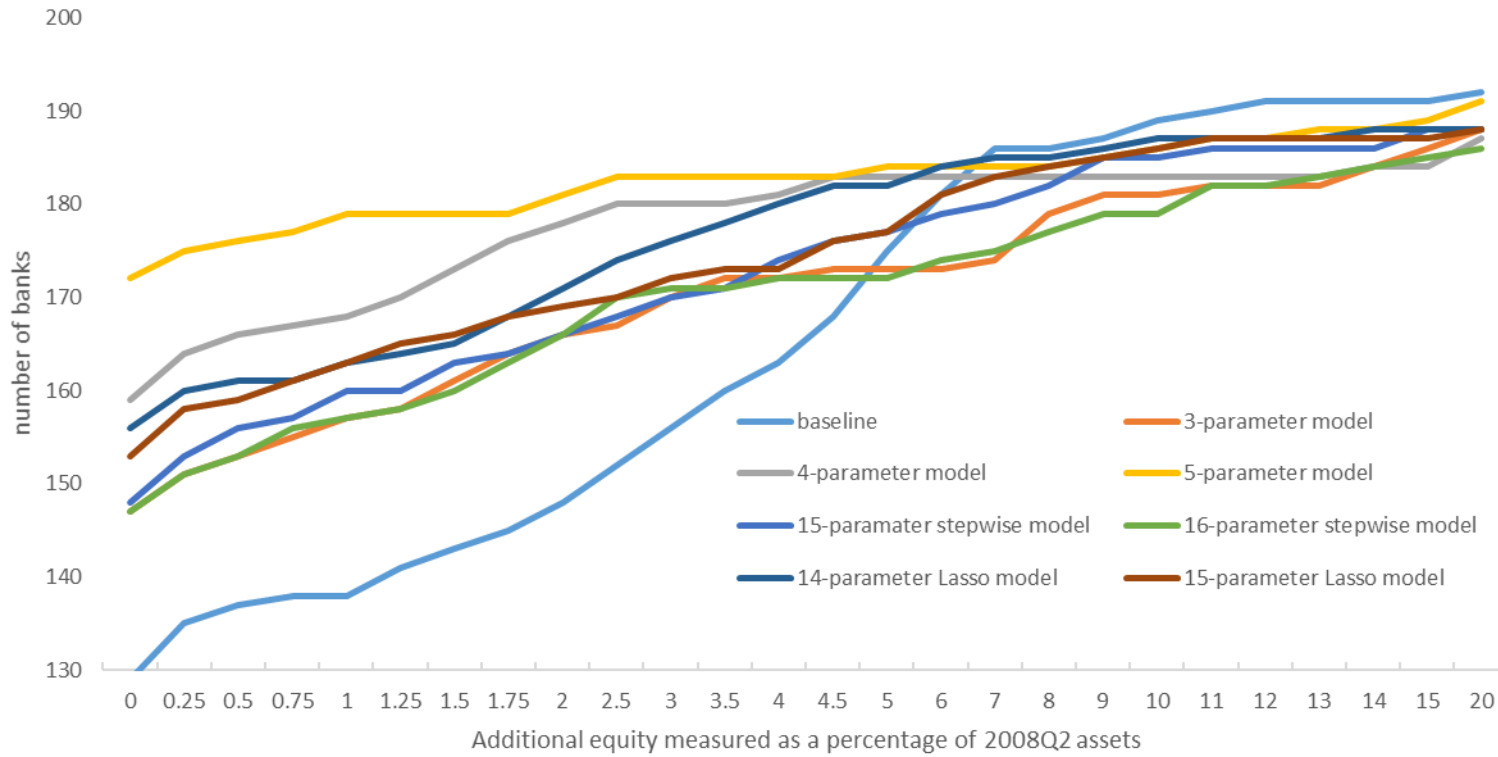


Figure 6: Capital shortfall estimates for IDIs with positive stress test capital shortfall estimates but no baseline capital shortfall

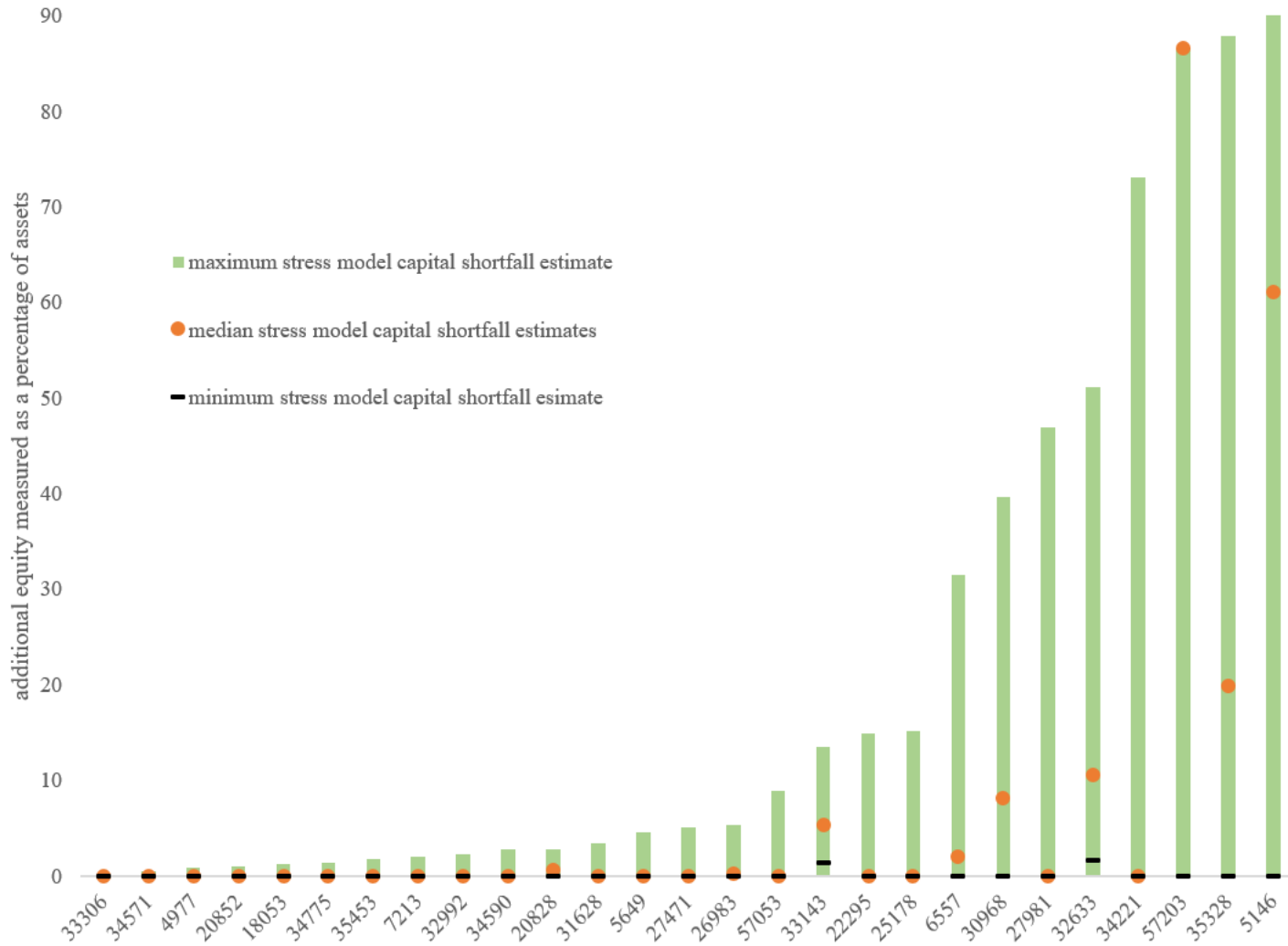
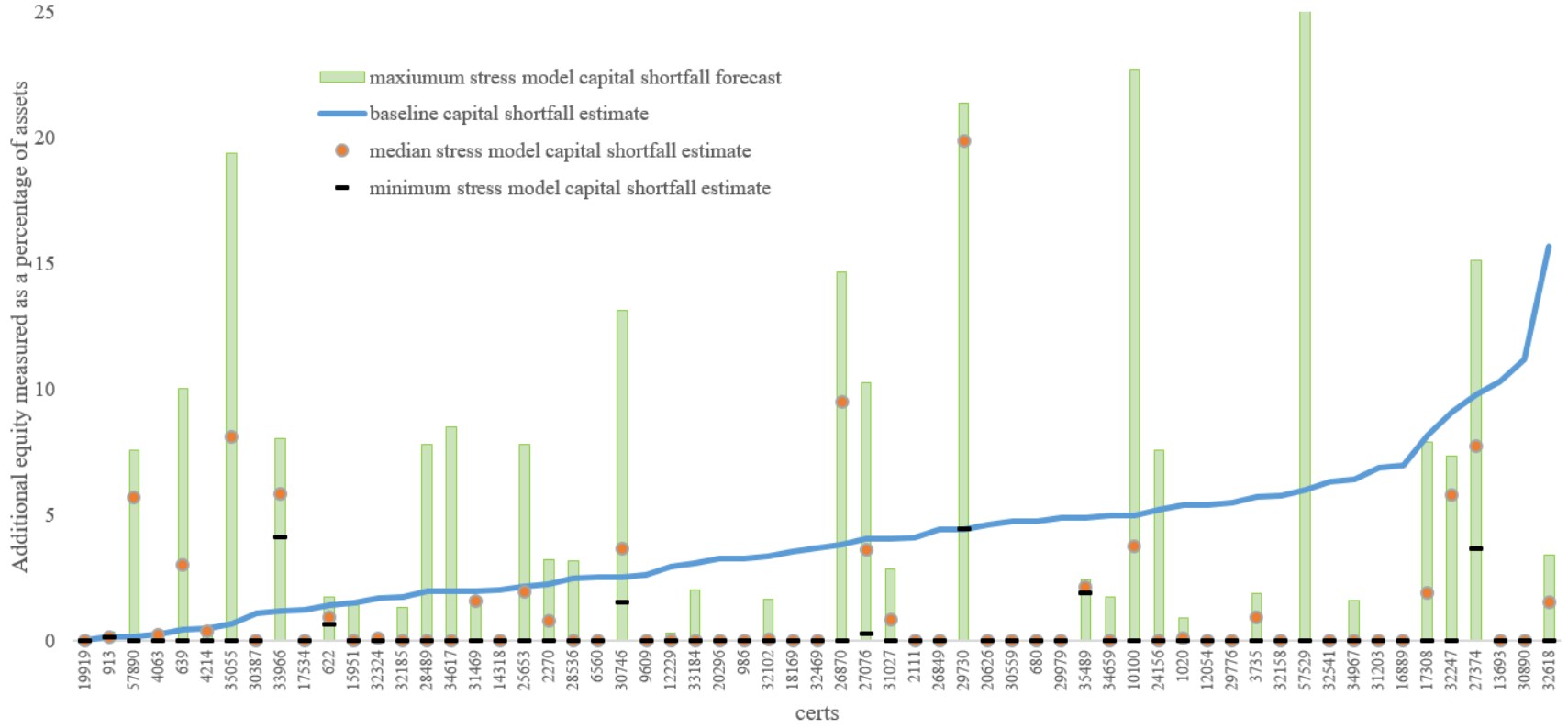


Figure 7: Capital shortfall estimates for IDIs with positive baseline capital shortfalls



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Table A1: Banks included in the analysis by asset size in descending order

rank by asset size 2008Q2	cert	name	2008Q2 total assets (000s)	2008Q2 total equity (000s)	2008Q2 equity-to- asset ratio	date bank fails	date bank is acquired
1	628	JPMorgan Chase Bank, National Association	1,378,468,000	108,929,000	7.90%		
2	3510	Bank of America, National Association	1,327,429,079	108,738,653	8.19%		
3	7213	Citibank, National Association	1,228,445,000	95,587,000	7.78%		
4	33869	Wachovia Bank, National Association	670,639,000	69,798,000	10.41%		4/1/10
5	3511	Wells Fargo Bank, National Association	503,327,000	43,942,000	8.73%		
6	32633	Washington Mutual Bank	307,021,614	24,379,747	7.94%	9/25/08	9/30/08
7	6548	U.S. Bank National Association	242,307,928	21,541,832	8.89%		
8	57890	HSBC Bank USA, National Association	177,466,246	12,421,503	7.00%		
9	867	SunTrust Bank	171,500,853	19,302,570	11.26%		
10	33318	FIA Card Services, National Association	165,349,652	42,566,553	25.74%		
11	6557	National City Bank	151,164,598	18,412,517	12.18%		12/9/09
12	12368	Regions Bank	139,353,930	20,678,723	14.84%		
13	14	State Street Bank and Trust Company	138,858,742	12,618,871	9.09%		
14	9846	Branch Banking and Trust Company	132,884,104	13,705,386	10.31%		
15	57957	RBS Citizens, National Association	132,050,955	18,018,737	13.65%		
16	639	The Bank of New York	130,062,000	8,510,000	6.54%		
17	6384	PNC Bank, National Association	128,348,405	12,080,577	9.41%		
18	33143	Countrywide Bank, FSB	116,384,145	7,222,288	6.21%		5/20/09
19	4297	Capital One, National Association	108,520,315	20,785,374	19.15%		
20	18409	TD Bank, National Association	98,855,014	19,081,319	19.30%		
21	17534	KeyBank National Association	98,047,883	7,693,362	7.85%		
22	35489	ING Bank, fsb	79,464,958	3,241,017	4.08%		
23	29950	Sovereign Bank	79,189,002	8,564,333	10.82%		
24	27076	Wachovia Mortgage, FSB	76,795,109	4,715,425	6.14%		12/9/09
25	23360	Citibank (South Dakota), N.A.	75,004,087	11,544,849	15.39%		
26	23702	Chase Bank USA, National Association	74,462,629	22,791,285	30.61%		
27	15407	LaSalle Bank National Association	68,378,716	14,915,318	21.81%		11/7/08
28	6672	Fifth Third Bank	67,272,497	5,431,743	8.07%		
29	983	Comerica Bank	65,961,348	5,724,869	8.68%		

Table A1: continued: Banks included in the analysis by asset size in descending order

rank by asset size 2008Q2	cert	name	2008Q2 total assets (000s)	2008Q2 total equity (000s)	2008Q2 equity-to- asset ratio	date bank fails	date bank is acquired
30	913	The Northern Trust Company	65,199,779	3,817,135	5.85%		
31	588	Manufacturers and Traders Trust Company	65,079,643	7,060,191	10.85%		
32	3514	Bank of the West	63,262,439	8,786,998	13.89%		
33	19048	Compass Bank	61,067,148	13,412,201	21.96%		
34	22826	Union Bank of California, National Association	60,227,793	4,711,067	7.82%		
35	27374	Merrill Lynch Bank USA	58,042,116	3,300,435	5.69%		9/25/09
36	1020	M&I Marshall and Ilsley Bank	57,680,687	5,226,070	9.06%		
37	6560	The Huntington National Bank	54,842,484	5,664,014	10.33%		
38	993	Fifth Third Bank	54,160,865	6,449,840	11.91%		10/5/09
39	13074	Hudson City Savings Bank	49,149,097	4,269,938	8.69%		
40	30746	E*TRADE Bank	46,708,354	3,004,463	6.43%		
41	623	Deutsche Bank Trust Company Americas	46,071,000	8,510,000	18.47%		
42	33891	Washington Mutual Bank FSB	46,048,007	29,229,987	63.48%		10/8/08
43	16571	Harris National Association	41,592,254	3,837,709	9.23%		
44	7946	Mellon Bank, National Association	39,476,494	4,800,259	12.16%		
45	58032	Bank of America, Rhode Island, National Association	39,211,041	2,143,731	5.47%		
46	32992	Morgan Stanley Bank	38,530,000	3,702,000	9.61%		
47	57282	Citizens Bank of Pennsylvania	38,174,843	4,516,482	11.83%		
48	22488	LaSalle Bank Midwest National Association	37,642,708	5,922,973	15.73%		11/7/08
49	4977	First Tennessee Bank, National Association	35,286,528	3,182,059	9.02%		
50	57803	GMAC Bank	31,935,992	3,464,738	10.85%		
51	32188	USAA Federal Savings Bank	31,539,259	2,783,371	8.83%		
52	33954	Capital One Bank (USA), National Association	31,301,809	4,252,477	13.59%		
53	33184	RBC Bank (USA)	31,262,175	4,004,123	12.81%		
54	34571	Merrill Lynch Bank & Trust Co., FSB	31,094,658	4,155,628	13.36%		11/18/09
55	29730	IndyMac Bank, F.S.B.	30,698,512	1,143,344	3.72%	7/11/08	
56	5649	Discover Bank	30,501,647	3,685,250	12.08%		
57	5146	Wells Fargo Bank South Central, National Association	29,769,000	1,926,000	6.47%		
58	16022	New York Community Bank	29,006,619	4,077,485	14.06%		

Table A1: continued: Banks included in the analysis by asset size in descending order

rank by asset size 2008Q2	cert	name	2008Q2 total assets (000s)	2008Q2 total equity (000s)	2008Q2 equity-to- asset ratio	date bank fails	date bank is acquired
59	33966	Wachovia Bank, FSB	27,992,417	1,804,898	6.45%		11/10/09
60	57565	UBS Bank USA	27,316,033	1,950,377	7.14%		
61	34968	Banco Popular de Puerto Rico	26,101,000	1,869,000	7.16%		
62	9609	Colonial Bank	25,986,562	2,477,297	9.53%	8/14/09	8/18/09
63	57485	Goldman Sachs Bank USA	25,726,832	2,450,100	9.52%		
64	27471	American Express Centurion Bank	25,348,661	2,827,387	11.15%		
65	35328	American Express Bank, FSB.	25,024,015	2,840,507	11.35%		
66	5296	Associated Bank, National Association	22,059,071	2,550,182	11.56%		
67	57450	Charles Schwab Bank	21,608,387	1,268,501	5.87%		
68	29805	Astoria Federal Savings and Loan Association	21,598,603	1,567,748	7.26%		
69	2270	Zions First National Bank	20,195,316	1,075,619	5.33%		
70	18708	Citicorp Trust Bank, fsb	19,634,564	1,417,602	7.22%		
71	25178	Bank of America California, National Association	19,469,401	1,238,106	6.36%		
72	27334	People's United Bank	18,734,368	3,649,567	19.48%		
73	30387	Firstbank of Puerto Rico	17,841,107	1,422,132	7.97%		
74	18221	Webster Bank, National Association	17,351,831	1,933,106	11.14%		
75	33947	TD Bank USA, National Association	17,329,254	1,219,805	7.04%		
76	31027	Westernbank Puerto Rico	16,988,265	888,568	5.23%	4/30/10	5/3/10
77	28330	TCF National Bank	16,468,963	1,029,355	6.25%		
78	34617	State Farm Bank, F.S.B.	16,161,983	1,182,985	7.32%		
79	4214	Bank of Oklahoma, National Association	16,092,004	903,809	5.62%		
80	17281	City National Bank	15,970,869	1,493,917	9.35%		
81	32618	Guaranty Bank	15,937,098	758,376	4.76%	8/21/09	8/24/09
82	29776	AmTrust Bank	15,898,116	1,253,445	7.88%	12/4/09	12/7/09
83	24998	Commerce Bank, National Association	15,592,314	1,323,632	8.49%		
84	27314	GE Money Bank	15,357,129	3,594,315	23.40%		
85	32324	Chevy Chase Bank, F.S.B.	14,913,528	879,071	5.89%		10/14/09
86	32541	Flagstar Bank, FSB	14,567,785	987,235	6.78%		
87	13718	Wells Fargo Bank Northwest, National Association	14,470,000	1,192,000	8.24%		

Table A1: continued: Banks included in the analysis by asset size in descending order

rank by asset size 2008Q2	cert	name	2008Q2 total assets (000s)	2008Q2 total equity (000s)	2008Q2 equity-to- asset ratio	date bank fails	date bank is acquired
88	4063	MidFirst Bank	14,217,588	818,828	5.76%		
89	32247	BankUnited, FSB	14,180,593	1,065,227	7.51%	5/21/09	
90	26849	Carolina First Bank	13,937,707	1,610,288	11.55%		10/4/10
91	5510	The Frost National Bank	13,796,772	1,690,929	12.26%		
92	11063	First-Citizens Bank & Trust Company	13,539,818	1,328,669	9.81%		
93	11813	BancorpSouth Bank	13,394,684	1,361,641	10.17%		
94	17985	First Hawaiian Bank	13,026,627	2,518,325	19.33%		
95	9396	Valley National Bank	12,965,879	1,028,320	7.93%		
96	34967	Banco Popular North America	12,871,285	1,444,692	11.22%		
97	32469	United Commercial Bank	12,851,854	1,371,034	10.67%	11/6/09	11/9/09
98	35453	Bank of America Oregon, National Association	12,721,850	1,049,581	8.25%		
99	30968	Downey Savings and Loan Association, F.A.	12,630,056	1,008,642	7.99%	11/21/08	11/25/08
100	986	Citizens Bank	12,372,252	1,097,800	8.87%		
101	32158	Sterling Savings Bank	12,215,752	1,374,308	11.25%		
102	24107	Amegy Bank National Association	12,135,590	2,163,097	17.82%		
103	22295	Mellon Trust of New England, National Association	11,865,883	1,648,990	13.90%		8/27/08
104	28088	Washington Federal Savings and Loan Association	11,794,035	1,379,351	11.70%		
105	31628	East West Bank	11,770,445	1,406,530	11.95%		
106	12054	Emigrant Bank	11,474,415	724,629	6.32%		
107	24185	Northern Trust, National Association	11,004,765	967,626	8.79%		10/7/11
108	18538	Whitney National Bank	10,998,827	1,119,003	10.17%		
109	30890	Lehman Brothers Bank, FSB	10,801,401	1,725,344	15.97%		
110	18503	Cathay Bank	10,796,543	1,097,396	10.16%		
111	12229	First Bank	10,779,679	1,149,347	10.66%		
112	680	Wilmington Trust Company	10,646,093	881,983	8.28%		
113	13675	Firstmerit Bank, National Association	10,549,921	767,734	7.28%		
114	18053	Bank of Hawaii	10,347,508	750,883	7.26%		
115	30012	Third Federal Savings and Loan Association of Cleveland	10,318,492	1,380,961	13.38%		
116	20852	California Bank & Trust	10,258,822	1,054,750	10.28%		

Table A1: continued: Banks included in the analysis by asset size in descending order

rank by asset size 2008Q2	cert	name	2008Q2 total assets (000s)	2008Q2 total equity (000s)	2008Q2 equity-to- asset ratio	date bank fails	date bank is acquired
117	8728	Arvest Bank	9,895,268	941,436	9.51%		
118	5452	First National Bank of Omaha	9,737,381	687,910	7.06%		
119	19629	International Bank of Commerce	9,363,209	959,399	10.25%		
120	4988	Trustmark National Bank	9,181,105	983,473	10.71%		
121	19977	Israel Discount Bank of New York	9,123,478	619,913	6.79%		
122	7414	National Penn Bank	9,028,303	1,140,721	12.63%		
123	16004	First Niagara Bank	9,003,460	1,418,278	15.75%		
124	13693	Corus Bank, National Association	8,984,088	923,676	10.28%	9/11/09	9/14/09
125	23364	Rabobank, National Association	8,886,091	1,854,702	20.87%		
126	32102	Doral Bank	8,821,964	526,915	5.97%		
127	20828	Banco Santander Puerto Rico	8,658,754	612,480	7.07%		
128	7551	Fulton Bank	8,566,184	773,971	9.04%		
129	3628	MB Financial Bank, National Association	8,390,715	1,028,229	12.25%		
130	57529	Capmark Bank	8,349,376	943,043	11.29%		
131	17266	Umpqua Bank	8,342,510	1,446,941	17.34%		
132	33893	Raymond James Bank, FSB	8,340,970	510,772	6.12%		
133	3709	First Midwest Bank	8,266,581	896,452	10.84%		
134	16889	United Community Bank	8,258,437	931,594	11.28%		
135	18261	NewAlliance Bank	8,249,306	1,289,168	15.63%		6/9/11
136	32712	Fifth Third Bank, National Association	8,125,621	2,190,723	26.96%		10/5/09
137	27981	Capitol Federal Savings Bank	7,917,676	790,866	9.99%		
138	7888	First National Bank of Pennsylvania	7,904,823	1,036,140	13.11%		
139	16068	Apple Bank for Savings	7,760,909	701,598	9.04%		
140	35055	Metlife Bank, National Association	7,739,725	413,196	5.34%		
141	8273	UMB Bank, National Association	7,693,747	603,833	7.85%		
142	57203	Barclays Bank Delaware	7,670,217	1,016,411	13.25%		
143	18169	Pacific Capital Bank, National Association	7,477,211	768,683	10.28%		
144	3832	Old National Bank	7,453,304	695,371	9.33%		
145	32185	R-G Premier Bank of Puerto Rico	7,221,383	538,389	7.46%	4/30/10	

Table A1: continued: Banks included in the analysis by asset size in descending order

rank by asset size 2008Q2	cert	name	2008Q2 total assets (000s)	2008Q2 total equity (000s)	2008Q2 equity-to- asset ratio	date bank fails	date bank is acquired
146	28536	First Federal Bank of California, a Federal Savings Bank	7,179,442	690,976	9.62%	12/18/09	
147	28178	Northwest Savings Bank	6,987,020	710,878	10.17%		
148	7579	Susquehanna Bank PA	6,805,340	1,147,843	16.87%		
149	32773	Eastern Bank	6,802,175	747,121	10.98%		
150	16835	Prosperity Bank	6,791,800	1,273,934	18.76%		
151	24735	Silicon Valley Bank	6,673,145	634,139	9.50%		
152	34659	California National Bank	6,662,621	635,393	9.54%	10/30/09	11/3/09
153	19919	Banco Bilbao Vizcaya Argentaria Puerto Rico	6,576,376	531,691	8.08%		
154	21716	Citizens Business Bank	6,444,904	527,120	8.18%		
155	58009	Lehman Brothers Commercial Bank	6,418,255	982,178	15.30%		
156	28892	Investors Savings Bank	6,409,275	722,137	11.27%		
157	30559	BankAtlantic	6,369,215	549,991	8.64%		
158	57053	Signature Bank	6,369,088	426,250	6.69%		
159	12010	The Provident Bank	6,368,939	891,911	14.00%		
160	7468	First Commonwealth Bank	6,196,770	613,150	9.89%		
161	15504	First Citizens Bank and Trust Company, Inc.	6,181,738	596,181	9.64%		
162	15951	Provident Bank of Maryland	6,166,361	428,171	6.94%		6/18/09
163	34351	USAA Savings Bank	6,138,309	2,579,857	42.03%		
164	22953	MERCANTIL COMMERCEBANK, NATIONAL ASSOCIATION	6,035,838	472,681	7.83%		
165	34775	EverBank	6,022,498	400,844	6.66%		
166	26983	Wells Fargo Financial Bank	5,987,531	834,649	13.94%		3/16/09
167	33306	The PrivateBank and Trust Company	5,794,290	569,538	9.83%		
168	33686	Bank Hapoalim B.M.	5,781,018		0.00%		
169	873	Columbus Bank and Trust Company	5,764,431	813,317	14.11%		
170	1081	Southwest Bank, An M&I Bank	5,729,321	840,636	14.67%		7/15/10
171	31469	Oriental Bank and Trust	5,700,657	262,023	4.60%		
172	25653	Fremont Investment & Loan	5,657,341	229,735	4.06%		
173	17308	Central Pacific Bank	5,637,327	589,930	10.46%		

Table A1: continued: Banks included in the analysis by asset size in descending order

rank by asset size 2008Q2	cert	name	2008Q2 total assets (000s)	2008Q2 total equity (000s)	2008Q2 equity-to- asset ratio	date bank fails	date bank is acquired
174	32526	American Savings Bank, FSB	5,585,285	567,666	10.16%		
175	26870	Franklin Bank, S.S.B.	5,572,332	424,802	7.62%	11/7/08	11/14/08
176	32245	Dollar Bank, FSB	5,562,572	524,737	9.43%		
177	19842	Bank Leumi USA	5,560,103	466,687	8.39%		
178	31203	Bank of North Georgia	5,550,947	662,027	11.93%		6/14/10
179	34590	U.S. Bank National Association ND	5,534,282	611,085	11.04%		
180	34221	Morgan Stanley Trust	5,398,160	404,751	7.50%		
181	7230	NBT Bank, National Association	5,288,473	456,407	8.63%		
182	10100	Irwin Union Bank and Trust Company	5,285,370	491,071	9.29%	9/18/09	
183	1105	First Interstate Bank	5,284,160	416,469	7.88%		
184	33778	GE Capital Financial Inc.	5,266,326	1,275,787	24.23%		
185	803	Wesbanco Bank, Inc.	5,253,231	699,101	13.31%		
186	33653	Bank of China	5,240,563		0.00%		
187	20626	National Bank of Arizona	5,217,406	586,262	11.24%		
188	3735	Amcore Bank, National Association	5,133,355	335,556	6.54%	4/23/10	4/26/10
189	20296	Johnson Bank	5,091,300	351,500	6.90%		
190	21726	Sterling Bank	4,909,571	570,198	11.61%		7/29/11
191	2111	The National Bank of South Carolina	4,891,151	439,211	8.98%		6/15/10
192	29979	AnchorBank, fsb	4,891,017	434,566	8.88%		
193	24156	Ocean Bank	4,848,194	496,596	10.24%		
194	21674	Bank of Texas. National Association	4,713,906	653,125	13.86%		1/5/11
195	34383	Texas Capital Bank, National Association	4,652,370	426,958	9.18%		
196	6989	Community Bank, National Association	4,637,151	521,516	11.25%		
197	11677	Park National Bank	4,605,578	479,999	10.42%	10/30/09	11/3/09
198	14318	First National Bank	4,588,576	320,717	6.99%		
199	28489	Banner Bank	4,470,893	442,128	9.89%		
200	622	Amalgamated Bank	4,457,398	238,266	5.35%		

Table A2: Selected summary statistics for the data used in the analysis

Variables Used in the Analysis	Mean	Standard deviation	.05 Quantile	.10 Quantile	.25 Quantile	.5 Quantile	.75 Quantile	.90 Quantile	.95 Quantile
Quarterly returns, banks > \$100 bil in assets, 1993Q1-2008Q2 (pct)	0.47	0.35	0.03	0.21	0.38	0.47	0.56	0.72	0.87
Quarterly returns, banks > \$100 bil in assets, 2008Q3-2011Q2 (pct)	0.06	1.05	-0.92	-0.29	0.01	0.18	0.35	0.50	0.68
Quarterly returns, banks \$10bil < assets < \$100 bil, 1993Q1-2008Q2 (pct)	0.55	4.15	0.01	0.14	0.32	0.45	0.60	0.89	1.37
Quarterly returns, banks \$10 bil < assets < \$100 bil, 2008Q3-2011Q2 (pct)	0.00	1.04	-1.52	-0.80	-0.17	0.17	0.42	0.67	1.13
Quarterly returns, banks < \$10 bil assets, 1993Q1-2008Q2 (pct)	0.63	4.59	-0.01	0.10	0.29	0.40	0.52	0.74	1.23
Quarterly returns, banks < \$10 bil assets, 2008Q3-2011Q2 (pct)	-0.06	0.98	-1.79	-0.91	-0.13	0.16	0.32	0.49	0.70
Weighted-average quarterly return on all IDIs, 1993Q1-2008Q2 (pct)	0.42	0.14	0.05	0.36	0.41	0.45	0.48	0.50	0.51
Weighted-average quarterly return on all IDIs, 2008Q3-2011Q2 (pct)	0.18	0.15	-0.06	-0.01	0.02	0.24	0.26	0.31	0.38
Nominal quarterly GDP growth rate, SAAR (pct)	4.67	2.87	-0.50	1.20	3.80	4.90	6.40	7.70	8.80
civilian unemployment rate, unadjusted (pct) +	5.87	1.69	4.00	4.30	4.70	5.50	6.20	9.10	9.50
10-year Treasury yield (pct)*	4.91	1.29	2.81	3.35	4.03	4.85	5.94	6.59	7.14
3-month Treasury yield (pct)*	3.20	2.06	0.06	0.14	1.17	3.52	5.12	5.51	5.91
Moody's AAA yield (pct)*	6.31	1.05	4.92	5.14	5.47	6.31	7.24	7.59	7.99
Moody's Baa yield (pct)*	7.11	1.07	5.19	5.81	6.31	7.22	8.01	8.32	8.72
Federal funds rate (pct)*	3.36	2.14	0.12	0.18	1.25	4.06	5.30	5.69	5.99
Wilshire quarterly market index return (pct)	2.31	8.94	-15.14	-11.03	-1.91	2.86	7.78	12.42	16.78
Wilshire daily return standard deviation (pct)	1.05	0.65	0.44	0.50	0.66	0.87	1.37	1.76	2.18
Kansas City Fed Financial Stability Index (FSI) quarterly average	0.13	1.12	-0.81	-0.75	-0.62	-0.23	0.56	1.01	2.24
VIX daily average	20.92	8.07	12.12	12.47	13.73	20.15	25.38	29.94	33.02
VIX quarterly change (pct)	5.24	36.61	-37.68	-26.36	-13.87	-0.43	13.05	46.40	70.20
Change in Real House Price Index (pct)	0.29	2.08	-4.64	-2.49	-0.31	0.80	1.48	2.17	3.00

Notes: Quarterly data for the period March 1993 through June 2011 unless otherwise indicated. All banking data is derived from quarterly regulatory reports and is merger-adjusted to include all mergers consummated through 2008Q2. Summary data for banks categorized by asset size references bank asset size as of 2008Q2. Bank quarterly returns are defined as bank income before taxes and extraordinary items divided by beginning of quarter asset balances. Macro-financial data except the change in the real house price index are from the Federal Reserve Bank of St. Louis economic research department public database <https://fred.stlouisfed.org/>. The change in the real house price index is the American Enterprise Institute International Center on Housing Risk calculated quarterly as FHFA's all-transaction house price index divided by BEA's price index for personal consumption expenditures. + Indicates unemployment rate on the first day following quarter-end. * Indicates interest yield on the first day of each quarter.

Table A3: Estimates of the additional equity need to pass the stress test as a percentage of 2008Q2 assets

Additional 2008Q2 equity, measured as a percentage of 2008Q2 assets, required to maintain a 6 percent stress test minimum in all quarters 2008Q2 through 2011Q2 under baseline estimates and stress test model forecasts

rank by asset size 2008Q2	cert	baseline capital estimate	3- parameter model	4- parameter model	5- parameter model	15-parameter stepwise model	16-parameter stepwise model	14- parameter Lasso model	parameter Lasso model
1	628	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	3510	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	7213	0.00	2.08	0.00	1.77	0.00	0.00	0.00	0.00
4	33869	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	3511	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	32633	0.00	14.07	51.12	14.90	10.63	10.60	1.71	5.94
7	6548	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	57890	0.15	1.14	0.00	0.94	7.44	7.58	6.01	5.68
9	867	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10	33318	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
11	6557	0.00	2.55	31.56	2.31	0.00	0.53	2.06	0.03
12	12368	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
13	14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
14	9846	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
15	57957	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
16	639	0.43	0.00	0.00	0.53	3.87	10.02	3.01	4.32
17	6384	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
18	33143	0.00	13.50	1.43	4.57	5.37	10.23	2.85	5.49
19	4297	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
20	18409	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
21	17534	1.22	0.00	0.00	0.13	0.00	0.00	0.00	0.00
22	35489	4.91	1.92	2.16	1.92	2.15	2.15	2.42	2.33
23	29950	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
24	27076	4.05	10.27	0.29	10.15	0.82	2.02	3.60	8.25
25	23360	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
26	23702	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
27	15407	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
28	6672	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
29	983	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
30	913	0.15	0.15	0.15	0.15	0.15	0.34	0.15	0.15
31	588	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
32	3514	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
33	19048	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
34	22826	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
35	27374	9.80	15.13	3.65	15.04	7.74	5.74	5.40	10.78
36	1020	5.39	0.00	0.08	0.07	0.34	0.91	0.00	0.00
37	6560	2.54	0.00	0.00	0.00	0.00	0.00	0.00	0.00
38	993	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
39	13074	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
40	30746	2.54	13.13	1.51	12.91	3.65	3.93	2.08	3.00

Table A3: Estimates of the additional equity need to pass the stress test as a percentage of 2008Q2 assets

Additional 2008Q2 equity, measured as a percentage of 2008Q2 assets, required to maintain a 6 percent stress test minimum in all quarters 2008Q2 through 2011Q2 under baseline estimates and stress test model forecasts

rank by asset size 2008Q2	cert	baseline capital estimate	3- parameter model	4- parameter model	5- parameter model	15-parameter stepwise model	16-parameter stepwise model	14- parameter Lasso model	15- parameter Lasso model
41	623	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
42	33891	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
43	16571	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
44	7946	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
45	58032	0.53	0.53	0.53	0.53	0.00	0.00	0.00	0.00
46	32992	0.00	0.00	0.00	0.00	2.31	1.93	0.00	1.08
47	57282	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
48	22488	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
49	4977	0.00	0.84	0.00	0.46	0.00	0.00	0.00	0.00
50	57803	0.00	0.00	2.24	2.37	0.00	0.00	0.00	0.00
51	32188	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
52	33954	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
53	33184	3.08	0.00	0.00	2.02	0.00	0.00	0.00	0.00
54	34571	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00
55	29730	4.45	20.81	4.44	21.37	20.90	13.93	13.11	19.89
56	5649	0.00	0.00	0.00	0.00	4.55	0.00	1.40	0.00
57	5146	0.00	0.00	18.68	15.18	61.08	63.27	90.78	69.53
58	16022	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
59	33966	1.16	8.05	4.39	8.05	6.03	5.85	4.12	4.47
60	57565	0.00	0.00	0.00	0.15	0.00	0.00	0.00	0.00
61	34968	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
62	9609	2.63	0.00	0.00	0.00	0.00	0.00	0.00	0.00
63	57485	0.00	5.54	44.57	45.25	0.00	0.00	0.00	0.00
64	27471	0.00	4.47	0.00	0.00	5.15	1.30	0.00	0.00
65	35328	0.00	0.00	19.85	9.36	0.00	82.97	84.61	87.86
66	5296	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
67	57450	0.13	0.13	0.13	0.13	0.00	0.00	0.00	0.00
68	29805	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
69	2270	2.27	0.67	0.67	0.73	3.23	2.43	2.68	0.78
70	18708	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
71	25178	0.00	0.00	0.00	0.00	14.18	15.20	0.00	0.00
72	27334	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
73	30387	1.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00
74	18221	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
75	33947	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
76	31027	4.07	2.84	0.77	4.20	0.85	1.61	0.80	2.68
77	28330	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
78	34617	1.98	8.50	1.24	0.00	0.00	0.00	0.00	0.00
79	4214	0.49	0.38	0.38	0.38	0.38	0.38	0.38	0.38
80	17281	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table A3: Estimates of the additional equity need to pass the stress test as a percentage of 2008Q2 assets

Additional 2008Q2 equity, measured as a percentage of 2008Q2 assets, required to maintain a 6 percent stress test minimum in all quarters 2008Q2 through 2011Q2 under baseline estimates and stress test model forecasts

rank by asset size 2008Q2	cert	baseline capital estimate	3- parameter model	4- parameter model	5- parameter model	15-parameter stepwise model	16-parameter stepwise model	14- parameter Lasso model	15- parameter Lasso model
81	32618	15.69	2.89	1.55	3.06	1.33	1.45	3.13	3.40
82	29776	5.48	0.00	0.00	0.00	0.00	0.00	0.00	0.00
83	24998	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
84	27314	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
85	32324	1.68	0.17	0.11	0.11	0.11	0.11	0.11	0.11
86	32541	6.35	0.00	0.00	0.00	0.00	0.00	0.00	0.00
87	13718	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
88	4063	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24
89	32247	9.13	6.29	2.37	7.30	4.10	7.35	5.80	6.09
90	26849	4.43	0.00	0.00	0.00	0.00	0.00	0.00	0.00
91	5510	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
92	11063	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
93	11813	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
94	17985	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
95	9396	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
96	34967	6.42	1.58	0.00	1.84	0.00	0.00	0.00	0.00
97	32469	3.69	0.00	0.00	0.00	0.00	0.00	0.00	0.00
98	35453	0.00	0.00	1.82	0.69	0.00	0.00	0.00	0.00
99	30968	0.00	21.98	39.69	23.20	8.17	12.70	4.28	4.44
100	986	3.26	0.00	0.00	0.00	0.00	0.00	0.00	0.00
101	32158	5.76	0.00	0.00	0.00	0.00	0.00	0.00	0.00
102	24107	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
103	22295	0.00	0.00	0.00	0.00	14.91	14.91	0.00	0.00
104	28088	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
105	31628	0.00	3.45	0.00	2.07	0.00	1.51	0.00	0.00
106	12054	5.42	0.00	0.00	0.00	0.00	0.00	0.00	0.00
107	24185	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
108	18538	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
109	30890	11.19	0.00	0.00	0.00	0.00	0.00	0.00	0.00
110	18503	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
111	12229	2.92	0.30	0.00	0.25	0.00	0.00	0.00	0.00
112	680	4.77	0.00	0.00	0.00	0.00	0.00	0.00	0.00
113	13675	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
114	18053	0.00	0.00	0.00	0.00	1.27	0.00	0.00	0.00
115	30012	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
116	20852	0.00	0.00	0.00	0.00	0.00	1.03	0.00	0.00
117	8728	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
118	5452	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
119	19629	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
120	4988	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table A3: Estimates of the additional equity need to pass the stress test as a percentage of 2008Q2 assets

Additional 2008Q2 equity, measured as a percentage of 2008Q2 assets, required to maintain a 6 percent stress test minimum in all quarters 2008Q2 through 2011Q2 under baseline estimates and stress test model forecasts

rank by asset size 2008Q2	cert	forecasts							
		baseline capital estimate	3-parameter model	4- parameter model	5- parameter model	15-parameter stepwise model	16-parameter stepwise model	14- parameter Lasso model	15- parameter Lasso model
121	19977	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
122	7414	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
123	16004	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
124	13693	10.32	0.00	0.00	0.00	0.00	0.00	0.00	0.00
125	23364	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
126	32102	3.34	1.64	0.03	0.74	0.03	0.03	0.03	0.94
127	20828	0.00	0.00	0.00	0.00	2.84	2.70	1.56	0.66
128	7551	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
129	3628	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
130	57529	6.01	0.00	0.00	0.00	82.88	88.70	81.34	84.79
131	17266	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
132	33893	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
133	3709	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
134	16889	6.99	0.00	0.00	0.00	0.00	0.00	0.00	0.00
135	18261	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
136	32712	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
137	27981	0.00	0.00	0.00	0.00	0.00	46.97	0.00	0.00
138	7888	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
139	16068	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
140	35055	0.66	7.52	19.41	9.50	8.61	8.61	8.13	7.73
141	8273	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
142	57203	0.00	17.25	77.32	71.90	86.68	86.68	86.69	86.69
143	18169	3.55	0.00	0.00	0.00	0.00	0.00	0.00	0.00
144	3832	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
145	32185	1.72	1.34	0.00	1.48	0.77	0.00	0.00	0.00
146	28536	2.46	3.19	0.00	1.31	0.00	0.00	0.00	0.00
147	28178	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
148	7579	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
149	32773	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
150	16835	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
151	24735	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
152	34659	4.97	1.74	0.00	0.00	0.00	0.00	0.00	0.00
153	19919	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00
154	21716	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
155	58009	2.88	0.00	0.00	0.00	0.00	0.00	0.00	0.00
156	28892	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
157	30559	4.75	0.00	0.00	0.63	0.00	0.00	0.00	0.00
158	57053	0.00	0.00	0.00	0.00	8.59	8.99	0.00	0.61
159	12010	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
160	7468	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table A3: Estimates of the additional equity need to pass the stress test as a percentage of 2008Q2 assets

Additional 2008Q2 equity, measured as a percentage of 2008Q2 assets, required to maintain a 6 percent stress test minimum in all quarters 2008Q2 through 2011Q2 under baseline estimates and stress test model forecasts

rank by asset size 2008Q2	cert	baseline capital estimate	3- parameter model	4- parameter model	5- parameter model	15-parameter stepwise model	16-parameter stepwise model	14- parameter Lasso model	15- parameter Lasso model
161	15504	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
162	15951	1.50	1.39	0.00	0.64	0.00	0.00	0.00	0.13
163	34351	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
164	22953	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
165	34775	0.00	0.00	0.00	0.00	1.45	0.00	0.00	0.00
166	26983	0.00	0.00	0.00	3.15	0.19	0.19	1.97	5.32
167	33306	0.00	0.11	0.00	0.00	0.00	0.00	0.00	0.00
168	33686	0.00	0.00	0.00	6.00	0.00	0.00	0.00	0.00
169	873	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
170	1081	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
171	31469	1.99	1.41	1.41	1.52	1.73	1.73	1.56	1.56
172	25653	2.15	7.79	1.94	2.83	1.94	1.94	1.94	1.94
173	17308	8.20	7.91	1.19	8.19	1.90	1.97	1.88	4.69
174	32526	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
175	26870	3.82	14.66	13.83	15.82	4.49	6.46	9.52	9.68
176	32245	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
177	19842	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
178	31203	6.87	0.00	0.00	0.00	0.00	0.00	0.00	0.00
179	34590	0.00	0.00	0.00	0.00	2.81	2.29	0.00	0.00
180	34221	0.00	73.11	0.00	0.00	0.00	54.56	0.00	0.00
181	7230	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
182	10100	4.99	20.12	22.75	20.16	3.77	0.72	3.61	6.03
183	1105	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
184	33778	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
185	803	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
186	33653	0.00	0.00	0.00	6.00	0.00	0.00	0.00	0.00
187	20626	4.59	0.00	0.00	0.00	0.00	0.00	0.00	0.00
188	3735	5.71	1.88	1.35	3.11	0.00	0.00	0.93	1.38
189	20296	3.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00
190	21726	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
191	2111	4.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00
192	29979	4.89	0.00	0.00	0.00	0.00	0.00	0.00	0.00
193	24156	5.23	7.56	0.00	8.23	0.00	0.00	0.00	0.00
194	21674	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
195	34383	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
196	6989	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
197	11677	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
198	14318	2.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00
199	28489	1.98	7.81	0.00	5.45	0.30	0.00	0.00	1.61
200	622	1.43	0.94	1.74	2.34	0.66	0.66	1.03	1.03

Notes: Additional capital measured to the nearest \$100,000 expressed as a percentage of bank assets in 2008Q2. Entries recorded "na" (not applicable) cannot be reported for two reasons: (1) two branches of foreign banks (certs 33656 and 33686) do not report equity values and must be excluded from the stress modeling exercise; and (2), the stepwise and Lasso models for certs 58032, 57803, 57485, 57450, 57565 and 58009 cannot be estimated because their are an insufficient number of observations prior to 2008Q3 given the number of parameters in these models.

Table A4: Estimates of the dollar amount of additional equity needed to pass the stress test

Additional 2008Q2 equity (in 000s) required to maintain a 6 percent stress test minimum in all quarters 2008Q2 through 2011Q2 under baseline estimates and stress test model forecasts

rank by asset size 2008Q2	cert	baseline capital estimate	3- parameter model	4- parameter model	5- parameter model	15- parameter stepwise model	16- parameter stepwise model	14- parameter Lasso model	15- parameter Lasso model
1	628	0	0	0	0	0	0	0	0
2	3510	0	0	0	0	0	0	0	0
3	7213	0	25,522,100	0	21,684,400	0	0	0	0
4	33869	0	0	0	0	0	0	0	0
5	3511	0	0	0	0	0	0	0	0
6	32633	0	43,191,800	156,943,800	45,754,900	32,646,300	32,534,000	5,244,700	18,247,900
7	6548	0	0	0	0	0	0	0	0
8	57890	273,400	2,014,500	0	1,675,900	13,201,600	13,457,000	10,658,400	10,087,300
9	867	0	0	0	0	0	0	0	0
10	33318	0	0	0	0	0	0	0	0
11	6557	0	3,848,200	47,709,400	3,490,000	0	802,400	3,121,500	42,000
12	12368	0	0	0	0	0	0	0	0
13	14	0	0	0	0	0	0	0	0
14	9846	0	0	0	0	0	0	0	0
15	57957	0	0	0	0	0	0	0	0
16	639	565,400	0	0	683,800	5,033,800	13,035,700	3,910,000	5,624,700
17	6384	0	0	0	0	0	0	0	0
18	33143	0	15,716,000	1,666,600	5,314,500	6,249,700	11,901,400	3,313,500	6,388,000
19	4297	0	0	0	0	0	0	0	0
20	18409	0	0	0	0	0	0	0	0
21	17534	1,194,500	0	0	126,300	0	0	0	0
22	35489	3,899,900	1,526,900	1,718,900	1,526,900	1,707,000	1,707,000	1,923,900	1,853,500
23	29950	400	0	0	0	0	0	0	0
24	27076	3,108,000	7,884,000	222,600	7,793,400	627,100	1,548,200	2,766,400	6,336,600
25	23360	0	0	0	0	0	0	0	0
26	23702	0	0	0	0	0	0	0	0
27	15407	0	0	0	0	0	0	0	0
28	6672	0	0	0	0	0	0	0	0
29	983	0	0	0	0	0	0	0	0
30	913	94,900	94,900	94,900	94,900	94,900	221,200	94,900	94,900
31	588	0	0	0	0	0	0	0	0
32	3514	0	0	0	0	0	0	0	0
33	19048	0	0	0	0	0	0	0	0
34	22826	0	0	0	0	0	0	0	0
35	27374	5,689,800	8,783,400	2,118,700	8,727,400	4,493,500	3,332,700	3,132,700	6,257,800
36	1020	3,110,200	0	45,400	40,400	196,000	525,000	0	0
37	6560	1,393,700	0	0	0	0	0	0	0
38	993	0	0	0	0	0	0	0	0
39	13074	0	0	0	0	0	0	0	0
40	30746	1,188,700	6,134,200	704,900	6,029,300	1,705,600	1,836,100	971,800	1,400,900

Table A4: Estimates of the dollar amount of additional equity needed to pass the stress test

Additional 2008Q2 equity (in 000s) required to maintain a 6 percent stress test minimum in all quarters 2008Q2 through 2011Q2 under baseline estimates and stress test model forecasts

rank by asset size 2008Q2		baseline capital estimate	3-parameter model	4-parameter model	5-parameter model	15-parameter stepwise model	16-parameter stepwise model	14-parameter Lasso model	15-parameter Lasso model
cert									
41	623	0	0	0	0	0	0	0	0
42	33891	0	0	0	0	0	0	0	0
43	16571	0	0	0	0	0	0	0	0
44	7946	0	0	0	0	0	0	0	0
45	58032	209,000	209,000	209,000	209,000	na	na	na	na
46	32992	0	0	0	0	891,800	745,200	0	414,500
47	57282	0	0	0	0	0	0	0	0
48	22488	0	0	0	0	0	0	0	0
49	4977	0	297900	0	163,300	0	0	0	0
50	57803	0	0	714700	757,300	na	na	na	na
51	32188	0	0	0	0	0	0	0	0
52	33954	0	0	0	0	0	0	0	0
53	33184	964,000	0	0	631,700	631,700	0	0	0
54	34571	0	156,500	0	0	0	0	0	0
55	29730	1,365,000	6,388,100	1,363,900	6,561,200	6,561,200	4,275,600	4,025,400	6,107,400
56	5649	0	0	0	0	0	0	426,100	0
57	5146	0	0	5,560,400	4,520,300	4,520,300	18,835,800	27,025,600	20,697,700
58	16022	0	0	0	0	0	0	0	0
59	33966	326,100	2,252,100	1,227,500	2,254,100	2,254,100	1,636,200	1,153,000	1,251,400
60	57565	0	0	0	39,700	39,700	na	na	na
61	34968	0	0	0	0	0	0	0	0
62	9609	684,300	0	0	0	0	0	0	0
63	57485	0	1,426,000	11,466,600	11,641,200	11,641,200	na	na	na
64	27471	0	1,132,400	0	0	0	329,300	0	0
65	35328	0	0	4,968,100	2,343,400	2,343,400	20,763,200	21,171,900	21,986,800
66	5296	0	0	0	0	0	0	0	0
67	57450	28,100	28,100	28,100	28,100	28,100	na	na	na
68	29805	0	0	0	0	0	0	0	0
69	2270	457,800	136,100	136,100	147,900	147,900	490,500	541,100	158,300
70	18708	0	0	0	0	0	0	0	0
71	25178	0	0	0	0	0	2,960,300	0	0
72	27334	0	0	0	0	0	0	0	0
73	30387	191,100	0	0	0	0	0	0	0
74	18221	0	0	0	0	0	0	0	0
75	33947	0	0	0	0	0	0	0	0
76	31027	691,600	482,100	130,800	713,600	713,600	273,000	135,400	454,500
77	28330	0	0	0	0	0	0	0	0
78	34617	320,400	1,374,000	200,800	0	0	0	0	0
79	4214	79,200	61,800	61,800	61,800	61,800	61,800	61,800	61,800
80	17281	0	0	0	0	0	0	0	0

Table A4: Estimates of the dollar amount of additional equity needed to pass the stress test

Additional 2008Q2 equity (in 000s) required to maintain a 6 percent stress test minimum in all quarters 2008Q2 through 2011Q2 under baseline estimates and stress test model forecasts

rank by asset size 2008Q2	cert	baseline capital estimate	3- parameter model	4- parameter model	5- parameter model	15- parameter stepwise model	16- parameter stepwise model	14- parameter Lasso model	15- parameter Lasso model
81	32618	2,500,200	460,000	247,200	487,000	487,000	231,400	499,000	541,800
82	29776	871,000	0	0	0	0	0	0	0
83	24998	0	0	0	0	0	0	0	0
84	27314	0	0	0	0	0	0	0	0
85	32324	250,000	25,800	15,800	15,800	15,800	15,800	15,800	15,800
86	32541	924,800	0	0	0	0	0	0	0
87	13718	100	0	0	0	0	0	0	0
88	4063	34,300	34,300	34,300	34,300	34,300	34,300	34,300	34,300
89	32247	1,294,100	892,500	336,200	1,035,600	1,035,600	1,042,000	822,400	864,000
90	26849	617,100	0	0	0	0	0	0	0
91	5510	0	0	0	0	0	0	0	0
92	11063	0	0	0	0	0	0	0	0
93	11813	0	0	0	0	0	0	0	0
94	17985	0	0	0	0	0	0	0	0
95	9396	0	0	0	0	0	0	0	0
96	34967	826,000	203,900	0	237,100	237,100	0	0	0
97	32469	474,100	0	0	0	0	0	0	0
98	35453	0	0	231,200	88,100	88,100	0	0	0
99	30968	0	2,775,600	5,012,800	2,930,500	2,930,500	1,604,100	541,000	560,200
100	986	403,200	0	0	0	0	0	0	0
101	32158	703,700	0	0	0	0	0	0	0
102	24107	0	0	0	0	0	0	0	0
103	22295	0	0	0	0	1,769,500	1,769,500	0	0
104	28088	0	0	0	0	0	0	0	0
105	31628	0	405,900	0	243,400	0	177,600	0	0
106	12054	621,400	0	0	0	0	0	0	0
107	24185	0	0	0	0	0	0	0	0
108	18538	0	0	0	0	0	0	0	0
109	30890	1,209,000	0	0	0	0	0	0	0
110	18503	0	0	0	0	0	0	0	0
111	12229	315,200	31,900	0	26,700	0	0	0	0
112	680	508,000	0	0	0	0	0	0	0
113	13675	0	0	0	0	0	0	0	0
114	18053	0	0	0	0	131,200	0	0	0
115	30012	0	0	0	0	0	0	0	0
116	20852	0	0	0	0	0	105,200	0	0
117	8728	0	0	0	0	0	0	0	0
118	5452	0	0	0	0	0	0	0	0
119	19629	0	0	0	0	0	0	0	0
120	4988	0	0	0	0	0	0	0	0

Table A4: Estimates of the dollar amount of additional equity needed to pass the stress test

Additional 2008Q2 equity (in 000s) required to maintain a 6 percent stress test minimum in all quarters 2008Q2 through 2011Q2 under baseline estimates and stress test model forecasts

rank by asset size 2008Q2	cert	baseline capital estimate	3- parameter model	4- parameter model	5- parameter model	15- parameter stepwise model	16- parameter stepwise model	14- parameter Lasso model	15- parameter Lasso model
121	19977	0	0	0	0	0	0	0	0
122	7414	0	0	0	0	0	0	0	0
123	16004	0	0	0	0	0	0	0	0
124	13693	927,400	0	0	0	0	0	0	0
125	23364	0	0	0	0	0	0	0	0
126	32102	294,800	144,500	2,500	65,300	2,500	2,500	2,500	83,300
127	20828	0	0	0	0	245,800	233,600	134,900	57,300
128	7551	0	0	0	0	0	0	0	0
129	3628	0	0	0	0	0	0	0	0
130	57529	501,900	0	0	0	6,919,900	7,406,100	6,791,200	7,079,300
131	17266	0	0	0	0	0	0	0	0
132	33893	0	0	0	0	0	0	0	0
133	3709	0	0	0	0	0	0	0	0
134	16889	577,600	0	0	0	0	0	0	0
135	18261	0	0	0	0	0	0	0	0
136	32712	0	0	0	0	0	0	0	0
137	27981	0	0	0	0	0	3,718,600	0	0
138	7888	0	0	0	0	0	0	0	0
139	16068	0	0	0	0	0	0	0	0
140	35055	51,200	581,800	1,502,000	735,500	666,600	666,600	629,100	598,100
141	8273	0	0	0	0	0	0	0	0
142	57203	0	1,323,000	5,930,400	5,514,700	6,648,900	6,648,900	6,649,600	6,649,400
143	18169	265,100	0	0	0	0	0	0	0
144	3832	0	0	0	0	0	0	0	0
145	32185	124,100	96,500	0	106,900	55,500	0	0	0
146	28536	176,600	229,300	0	93,800	0	0	0	0
147	28178	0	0	0	0	0	0	0	0
148	7579	0	0	0	0	0	0	0	0
149	32773	0	0	0	0	0	0	0	0
150	16835	0	0	0	0	0	0	0	0
151	24735	0	0	0	0	0	0	0	0
152	34659	331,000	116,000	0	0	0	0	0	0
153	19919	2,600	0	0	0	0	0	0	0
154	21716	0	0	0	0	0	0	0	0
155	58009	185,000	0	0	0	na	na	na	na
156	28892	0	0	0	0	0	0	0	0
157	30559	302,800	0	0	40,100	0	0	0	0
158	57053	0	0	0	0	546,900	572,300	0	38,900
159	12010	0	0	0	0	0	0	0	0
160	7468	0	0	0	0	0	0	0	0

Table A4: Estimates of the dollar amount of additional equity needed to pass the stress test

Additional 2008Q2 equity (in 000s) required to maintain a 6 percent stress test minimum in all
quarters 2008Q2 through 2011Q2 under baseline estimates and stress test model forecasts

rank by asset size 2008Q2	cert	baseline	3-	4-	5-	15-	16-	14-	15-
		capital estimate	parameter model	parameter model	parameter model	parameter stepwise model	parameter stepwise model	parameter Lasso model	parameter Lasso model
161	15504	0	0	0	0	0	0	0	0
162	15951	92,200	86,000	0	39,600	0	0	0	7,800
163	34351	0	0	0	0	0	0	0	0
164	22953	0	0	0	0	0	0	0	0
165	34775	0	0	0	0	87,600	0	0	0
166	26983	0	0	0	188,500	11,600	11,600	117,900	318,400
167	33306	0	6,200	0	0	0	0	0	0
168	33686	na	na	na	346,900	na	na	na	na
169	873	0	0	0	0	0	0	0	0
170	1081	0	0	0	0	0	0	0	0
171	31469	113,300	80,100	80,100	86,400	98,500	98,500	88,700	88,700
172	25653	121,800	440,800	109,800	159,900	109,800	109,800	109,800	109,800
173	17308	462,400	445,700	67,300	461,500	107,200	111,200	105,700	264,300
174	32526	0	0	0	0	0	0	0	0
175	26870	213,100	816,800	770,500	881,300	250,200	360,200	530,300	539,500
176	32245	0	0	0	0	0	0	0	0
177	19842	0	0	0	0	0	0	0	0
178	31203	381,600	0	0	0	0	0	0	0
179	34590	0	0	0	0	155,700	127,000	0	0
180	34221	0	3,946,500	0	0	0	2,945,100	0	0
181	7230	0	0	0	0	0	0	0	0
182	10100	263,800	1,063,300	1,202,200	1,065,500	199,500	38,300	190,700	318,500
183	1105	0	0	0	0	0	0	0	0
184	33778	0	0	0	0	0	0	0	0
185	803	0	0	0	0	0	0	0	0
186	33653	na	na	na	314,500	na	na	na	na
187	20626	239,600	0	0	0	0	0	0	0
188	3735	293,300	96,500	69,200	159,600	0	0	47,900	70,600
189	20296	165,700	0	0	0	0	0	0	0
190	21726	0	0	0	0	0	0	0	0
191	2111	200,300	0	0	0	0	0	0	0
192	29979	239,300	0	0	0	0	0	0	0
193	24156	253,700	366,500	0	398,900	0	0	0	0
194	21674	0	0	0	0	0	0	0	0
195	34383	0	0	0	0	0	0	0	0
196	6989	0	0	0	0	0	0	0	0
197	11677	0	0	0	0	0	0	0	0
198	14318	92,600	0	0	0	0	0	0	0
199	28489	88,600	349,100	0	243,600	13,400	0	0	71,900
200	622	63,800	41,900	77,600	104,500	29,200	29,200	45,700	45,700

Notes: Entries recorded "na" (not applicable) cannot be reported for two reasons: (1) two branches of foreign banks (certs 33656 and 33686) do not report equity values and must be excluded from the stress modeling exercise; and (2), the stepwise and Lasso models for certs 58032, 57803, 57485, 57450, 57565 and 58009 cannot be estimated because their are an insufficient number of observations prior to 2008Q3 given the number of parameters in these models.