Robust lessons learned from bank failures during the Great Financial Crisis

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Abstract:

Several empirical studies have identified unique characteristics of banks that subsequently failed during the Great Financial Crisis. The notion is that by identifying these risk characteristics we are better able to monitor and regulate the risks to banks during the next crisis. A concern is bank failure is a relatively rare event, therefore inferences based on a single model specification can be sensitive to the choice of variables. We re-examine three studies (DeYoung and Torna, 2013; Jin et al., 2011; Ng and Roychowdhury, 2014) of bank failures during the Great Financial Crisis to determine whether these authors' main findings are robust to accounting for uncertainty in the model's specification. Our results indicate their results are not robust and that the causes of bank failures during the Great Financial Crisis are similar to those of past periods of crisis and are driven by traditional measures of risk.

JEL Classifications: G17, G21, G28

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Introduction

It is a challenge to understand the underlying causes of an outcome that occurs rarely, so when there is an outbreak of acute events, it provides researchers and policy makers with an opportunity to identify characteristics that are precursors to the event. Studies of bank failure fit this pattern, as episodes of failures in the United States are relatively rare in most years following the Great Depression of the 1930s. However, the 322 bank failures during the Great Financial Crisis (GFC) of 2008-2010 prove banks remain at risk of failure and the previous outbreak of 2,325 failures during the Savings and Loan (S & L) crisis (1982-1993) was no mere anomaly. Banking is a highly regulated industry, so in the aftermath of the GFC, researchers have focused on whether there are any policy lessons that could be learned from these recent failures.

Studies (DeYoung and Torna, 2013; Jin et al., 2011; Ng and Roychowdhury, 2014) seem to suggest several new regulatory implications based on their findings. DeYoung and Torna (2013), for example, find evidence that pre-crisis exposure to non-traditional banking activities (insurance underwriting, securitization, investment banking, and venture capital) put banks at higher risk of failure during the GFC. The policy implication is regulators may need to either monitor these activities more closely or reconsider the decision (Financial Services Modernization Act) to allow commercial banks to engage in non-traditional bank activities. In their study, Ng and Roychowdhury (2014) find that the addition of loan loss reserves to regulatory capital increased, rather than decreased, banks' risk of failure. This result suggests loan loss reserves do not act as a buffer against bank failure and therefore should not be included in regulatory capital. The recent wave of failures also indicates greater regulatory oversight is needed to strengthen audit quality based on banks' choice of auditor (Jin et al., 2011).

The question this paper looks to examine is whether these policy lessons thought to have been learned during the GFC are sensitive to model risk and thus valid. Model risk (Berg and Koziol, 2017; Cont, 2006; Kerkhof et al., 2010) refers to the uncertainty associated with drawing inferences from a model specification that doesn't represent the true data generating process. Theoretically, the Federal Reserve (Cole et al., 1995) identifies approximately thirty financial variables, as most likely to affect the probability of bank failure. Regulators though have very little agreement to which factors are most important (Lane et al., 1986), which results in researchers using different sets of controls in their models. The issue, Campbell Harvey (2017) notes in his presidential address to the American Finance Association, is that researchers may therefore intentionally or unintentionally engage in data mining, where they report results from model specifications that support their hypotheses and ignore the rest. The effect is reported p-values then tend to overstate the evidence of an effect, which results in findings that are really false positives, i.e., results that will not be supported in subsequent analyses. Inferences based on a single model specification, may then be subject to model risk.

A solution to this issue that accounts for model risk is to use a Bayesian approach (Cont, 2006; Harvey 2017; Kerkhof et al., 2010), which incorporates uncertainty of the model's specification by averaging over a set of theoretically possible model specifications. By accounting for model risk in our inferences, we seek to improve our understanding of the factors that are robust predictors of bank failures during the Great Financial Crisis. Our results using Bayesian model averaging (BMA) find no evidence to indicate non-traditional activities measured by the share of bank income arising from stakeholder activities (e.g. investment banking, insurance underwriting) has an effect on failure during the Great Financial Crisis. Similarly, we find no evidence that either allowances included in regulatory capital, or choice of auditor, influences bank failure when accounting for model risk. Together our findings suggest a lack of regulatory oversight in these regards did not play a role in the crisis. Instead, we find strong evidence bank failures during the Great Financial Crisis are influenced by fundamentals found in CAMEL ratings similar to the S & L crisis (Cole and Gunther, 1998) and reflect a bank's underlying capital adequacy (equity), asset quality (loans past due, loans in nonaccrual, and share of consumer loans), and liquidity (brokered deposits).[1]

Model risk and Bayesian model averaging

After the Great Financial Crisis, the Basel Committee on Banking Supervision implemented revisions to the Basel II framework requiring banks to assess model risk to ensure

[1] Reliance on brokered deposits as a source of funds (liability) can create liquidity issues for a bank during a crisis due to the volatility of their withdrawal, relative to core deposits.

their valuation estimates are prudent and reliable (Bank for International Settlements BIS, 2009). Model risk is the risk associated with using a potentially incorrect model to make inferences. Previous studies have examined the effects of model risk on the pricing of derivatives (Cont, 2006) and determining the probability of loan default (Berg and Koziol, 2017) and value-at-risk (Kerkhof et al., 2010). Kerkhof et al. (2010) and Cont (2006) both discuss, model risk can be thought of in terms of ambiguity or model uncertainty, as to whether a model's prediction is correct when a class of alternative model specifications is specified. They each note there are two approaches to addressing model uncertainty. One approach is to consider the worst-case outcome under the set of all outcomes, and the other uses Bayesian model averaging (BMA) to average over the set of possible outcomes.

The choice of independent variables to include in a model's specification should be determined by theory. But what happens when theory identifies a large number of variables as potentially relevant to the outcome in question. In this case, researchers are left in the often-unavoidable position of choosing a set of variables to include in their models' specifications. The challenge is when there is no a priori reason to choose one set of variables over another. Researchers may then use different sets of variables in their models, which lead to different inferences as to the underlying effects and exposure to model risk. The choice of variables may be a result of p-hacking, where researchers use data mining to identify control variables that support their hypotheses.[2] In effect, by reporting only results supporting their hypothesis and ignoring the rest, these researchers overstate evidence in favor of rejecting the null. Even when researchers have good intentions and report the robustness of their findings in their entirety, one

[2] Harvey (2017) notes p-hacking may also involve choice of estimation method (e.g. logit vs survival model) and sample selection (e.g. observation exclusion).

is left uncertain as to results from specifications not considered. The consequence is statistically significant findings observed in one narrowly defined setting may not be robust predictors in subsequent outbreaks.

Part of the problem is p-values are not well suited to providing evidence with respect to a model's specification or hypothesis (Harvey, 2017; Raftery, 1995). A p-value measures the probability of observing an outcome in the data more extreme than what is assumed under the null hypothesis, and in a Bayesian sense represents the probability of observing the data given the hypothesis $P(D \mid H_0)$. A p-value of 0.05 indicates the null hypothesis is rejected 5% of the time, when it is in fact true, and yet it does not tell us the probability the null hypothesis is true $P(H_0 \mid D)$. As Harvey (2017, p. 1407) points out the p-value is calculated based on the explicit assumption the null is true. Edwards et al. (1963, pp. 221-222) highlight this point in relation to a typical two-tailed t-test with many degrees of freedom. Assuming the null is true, the t-statistic will lie 2% of the time between 1.96 and 2.58. A t-statistic observed within this interval appears to strongly favor the alternative. If when the null is false, the statistic were instead to lie uniformly between the values -20 and 20, then the statistic is 1.55% of the time between 1.96 and 2.58. The data one observes in this case actually favor the null based on the alternative.

A Bayesian perspective provides a more natural way (Harvey, 2017; Raftery, 1995) to compare the evidence in favor of one model specification relative to another. Consider two hypotheses with respect to model specifications, M_1 and M_2, where we have prior beliefs as to their validity given by $P(M_1)$ and $P(M_2)$. Assuming one of the two specifications is the true model, it can be shown using Bayes rule that the odds of M_1 relative to the alternative are given by:

$$\frac{P(M_1 \mid D)}{P(M_2 \mid D)} = \frac{P(D \mid M_1)}{P(D \mid M_2)} \frac{P(M_1)}{P(M_2)} \tag{1}$$

The posterior odds in favor of M_1 over M_2 is equal to the Bayes factor multiplied by the prior odds in favor of M_1, where the Bayes factor equals the ratio of integrated likelihoods. A posterior odds of 20 is interpreted as model specification M_1 being 20 times more likely than the alternative M_2, which corresponds to a 95% probability M_1 is the true model that generates the data $P(M_1 \mid D)$ and a 5% probability for the alternative specification $P(M_2 \mid D)$.[3]

We utilize this Bayesian perspective to incorporate the uncertainty in the choice of variables to include in the model's specification by using Bayesian model averaging (BMA). Predictions based on a single model specification are shown (Volinsky et al., 1997) to be sensitive to variable selection when outcomes are rare and there are many potential risk factors. Volinksy et al. (1997) demonstrate in this case that BMA outperforms single model specifications in terms of out-of-sample predictions (lower prediction errors) and that p-values from a single specification tend to overstate evidence of an effect because they ignore uncertainty. It has also been shown (Raftery et al., 1997) using simulated data, where the underlying causal relation between the data is known, that BMA is better able to determine the true model's specification relative to stepwise and other single model approaches that rely on p-values.

BMA incorporates uncertainty into the estimates by taking a weighted average of the estimates from the entire set of model specifications of interest, where weights are determined by

[3] The odds equal = $\Omega(H_0 \mid D) = \frac{P(H_0 \mid D)}{1 - P(H_0 \mid D)}$ therefore $P(H_0 \mid D) = \frac{\Omega(H_0 \mid D)}{1 + \Omega(H_0 \mid D)}$

the posterior probability of each model given the data. The posterior model probability (PMP) for a particular specification, M_k, when there are more than two models under consideration can be generalized from equation 1 and is given by

$$P(M_k \mid D) = \frac{P(D \mid M_k)P(M_k)}{\sum_{l=1}^{K} P(D \mid M_l)P(M_l)} \qquad (2)$$

The PMP is determined by each of the K models' likelihoods $P(D \mid M_k)$ and priors $P(M_k)$ for each model being the true model. Without strong a priori information we assume a uniform prior such that each specification is equally likely, which simplifies the PMP to

$$P(M_k \mid D) = \frac{P(D \mid M_k)}{\sum_{l=1}^{K} P(D \mid M_l)} \qquad (3)$$

Volinsky et al. (1997) show that the likelihoods for each of the models $P(D \mid M_k)$ can be approximated by a function of the Bayesian information criterion of model k (BIC_k) relative to the baseline model with only a constant (BIC_0).

$$\begin{aligned} P(D \mid M_k) &\approx \exp\left(-\frac{1}{2} BIC_k^{'}\right) \\ BIC_k^{'} &= BIC_k - BIC_0 = -LRT + p_k \log(N) \end{aligned} \qquad (4)$$

The difference of which is equal to the likelihood ratio statistic subtracted from the number of parameters in model k, p_k, multiplied by the natural log of the number of observations.[4]

Bayesian model averaging is implemented for the logit and Cox proportional hazards models used here by the R-package BMA (Raftery et al., 2018). The set of models we consider is quite large, in the neighborhood of 1 billion different specifications, so to increase the speed of

[4] For the logit model the number of observations is equal to the sample size, whereas the Cox proportional hazards model uses the number of events, i.e. failures.

estimation the routine narrows down the number of models to average over. Specifications where the odds are more than twenty to one in favor of another model specification receive little support from the data and are excluded. Excluding these specifications appeals to parsimony and has little impact on our inferences, while performing as well as averaging over all models (Raftery, 1995). Inferences are drawn based on the posterior means of the coefficients and statistical evidence of a non-zero effect is determined based on the coefficient's posterior effect probability (PEP). The PEP equals the probability that β_k is included in the model (i.e. is non-zero), which is given by

$$P(\beta_k \neq 0 \mid D) = \sum_{A_k} p(M_k \mid D) \tag{5}$$

where the summation of posterior model probabilities is over the set A_k of models that include β_k. The statistical evidence of a non-zero effect is considered to be strong and very strong, according to a commonly used rule of thumb (Raftery, 1995), based on Bayes factors of 20 and 150, which correspond to PEP values of 0.95, and 0.99 on the probability scale, respectively.

A re-analysis of bank failures during the Great Financial Crisis

The Great Financial Crisis resulted in unprecedented interventions by the Federal Reserve that included bailouts, the purchase of mortgage-backed securities via quantitative easing, and the creation of low-interest lending facilities. Efforts to stabilize the financial system were also supported by the U.S. Treasury Department's direct injection of capital into banks under the Troubled Assets Relief Program (TARP).[5] These actions raised widespread concerns about the adequacy of existing practices regarding bank risk management and the need for improved oversight by regulators to maintain the safety and soundness of banks.

[5] See Enkhtaivan and Lu (2021) for a thorough overview of TARP implementation.

The perception of some is the assessment of bank risk may have missed the mark, in part, due to a fundamental shift in banks' core activities from traditional banking activities to non-traditional, fee generating activities following passage of the Financial Services Modernization Act in 1999. Banks embraced their newfound ability to earn fee income by underwriting securities and issuing asset backed securities. Bessler and Kurmann (2014) observe this change in banks' core activities, in turn, altered their risk exposure over time. They find that U.S. banks' exposure to low-grade credit risk and real estate increased, while exposure to interest rate risk declined. The implication is multiple risk factors were important to the overall assessment of bank risk and this "requires controlling for factors that reflect both, traditional as well as emerging determinants of bank risk" (Bessler and Krumann, 2014, p. 165).

Banks ultimately failed, or were close to failure, due to having insufficient capital to cover their losses during the crisis. Capital injections under TARP provided a needed lifeline to keep many banks afloat that were previously considered well capitalized by regulators. Capital requirements account for different types of risk and differences in risk across asset classes, with different risk weights assigned to each. The challenge regulators face is to create capital requirements that reflect banks' complexity and the impacts on risk from their financial innovation. Analysis of the crisis reveals that different measures of bank capital resulted in different assessments of risk. Demirguc-Kunt and Huizinga (2010) examine variation in banks' stock returns and find higher quality forms of capital, Tier 1, are more relevant than lower forms (Tier 2) to the market's assessment of risk during the crisis. Results, such as these, suggest that the quality of capital, in addition to the quantity, are both important to assessing risk.

The crisis, though, also revealed model risk (BIS, 2009) played a role in the inability of banks' models to accurately price assets and assess risks. Inferences from models may be incorrect if a model is misused or its assumptions are invalid. For example, one might assume that the data analyzed are reported accurately and any missing data is random. If either measurement error or missing data is non-random, then inferences are likely to be biased. Mason et al. (2014) find evidence of both issues in data typically used to analyze the risk of residential mortgage backed securities. The lesson they suggest is big data is not necessarily complete data. Another source of model risk arises when different model specifications result in different predictions. Griffin et al. (2021) empirically examines competing explanations for the boom and bust observed for housing prices. Their analysis uses BMA to compare side-by-side the relative evidence for different theories based on the support alternative specifications receive in the data. Considering all the theoretically relevant variables in the data Griffin et al. (2021) note is beneficial in this approach as it allows for consistent comparisons, when testing alternative theories.

In the analysis that follows, we re-examine three studies (DeYoung and Torna, 2013; Jin et al., 2011; Ng and Roychowdhury, 2014) of bank failure in the United States to determine whether model risk impacts their main findings. Their findings seem to suggest bank failures during the crisis were influenced by non-traditional bank activities (DeYoung and Torna, 2013), the treatment of regulatory capital (Ng and Roychowdhury, 2014), and choice of auditor (Jin et al., 2011). Each of which have important regulatory implications.

We first attempt to replicate the results from each study using our construction of the authors' samples and their control variables. Replication is an important part of scientific discovery, which Harvey (2017) notes in his presidential address to the American Finance Association is far too often ignored in the field of finance. The inability to replicate results may indicate a model has fundamental errors and is subject to model risk. Model risk, though, also occurs when different models provide different predictions. To account for the uncertainty in model specification we apply BMA to the data, where we include in the data a standard set of well-defined controls. The 26 variables we consider for inclusion in the BMA models are the call report items the Federal Reserve identified for consideration in their Financial Institutions Monitoring System (FIMS) model (Cole et al., 1995) to predict banks' risk of failure.[6] As Cole et al. (1995) note, these variables were theoretically selected based on the Fed's review of the literature and their use in examination reports. The variables are mostly financial ratios and reflect the areas of capital adequacy, asset quality, management, earnings, and liquidity (CAMEL).[7] Table 1 lists these variables and the applicable call report series. Each of the 26 variables is scaled by total assets, other than a bank's age and size.

[Insert Table 1 about here]

Several of these control variables are identified as strong predictors of bank failures observed during the S & L crisis. Cole and Gunther (1998) find that equity, past due loans, loans in nonaccrual, foreclosed real estate, net income, securities, and large CDS, each measured as a share of total assets, affect the probability a bank fails in each of the two time periods (1985 and 1987) they examine during the S & L crisis, where each of the variables is significant at the 1% level. In addition, Lane et al. (1986) also finds that the share of C & I loans increases the risk of bank failure in the years (1979-1983) of the crisis they examine. Operating expense, i.e. non-

[6] The FDIC uses similar variables in their statistical CAMELS off-site rating (SCOR) model to predict changes in CAMELS ratings (Collier et al., 2003).

[7] Lane et al. (1986) interpret that measures of loan composition reflect management quality. Collier et al. (2003), however, believe that management quality cannot be identified with any financial ratio. An alternative approach to identify differences in management quality is to use textual analysis to reveal differences in banks' culture, which Luu et al., (2023) observe influences bank stability. Differences in corporate governance measures have also been shown (Alzayed et al., 2023) to influence bank stability. It should be noted that these measures of bank culture and corporate governance are only available for very small samples of the population of US banks.

interest expense, is also shown (Lane et al., 1986; Whalen, 1991) to increase the risk of failure during the S & L crisis period. Similar measures have also been identified (Berger and Bouwman, 2013; Cleary and Hebb, 2016; Cole and White, 2012) to be relevant to failures during the Great Financial Crisis. Cole and White (2012) observe at year-end 2008 that equity, nonperforming assets (the sum of loans past due, nonaccrual loans, and foreclosed property), net income, securities, cash, intangible assets, and loan mix significantly affect whether a bank fails in 2009. The question we empirically explore is whether there are other unique factors that contribute to failures during the Great Financial Crisis, when considering for inclusion in the model a standard list of predictors and accounting for uncertainty in the model's specification.

Deregulation and non-traditional banking activities

Banking is a highly regulated industry, so when there is an outbreak of bank failures an obvious concern is whether regulations or a lack thereof played a role. Deregulation due to the passage of the Financial Services Modernization Act in 1999 allowed banks in the pre-crisis period to directly increase their involvement with non-traditional banking activities (e.g. insurance underwriting, investment banking, and asset securitization). Such activities were viewed to be contributing factors to failures during the Great Depression, which led to the separation of investment and commercial banks with passage of the Banking (Glass-Steagall) Act of 1933 (Preston, 1933).[8] DeYoung and Torna's (2013) hypothesis is higher exposure to these activities also contributed to greater risk of failure during the Great Financial Crisis. DeYoung and Torna (2013) measure a bank's risk exposure using their shares of income relative

[8] Wicker (1980), for example, discusses how the failure of the investment bank Caldwell and Company, the largest in the South, contributed directly to the closing of 120 banks affiliated with the firm in a two-week period in November and December of 1930. Wicker (1980) argues other failures in the period originated from the uncertainty caused by Caldwell's collapse. A result Wicker (1980) notes is due to Caldwell's heavy borrowing from bank affiliates, which was used to finance the purchase of municipal securities for trading purposes.

to total assets from traditional activities (e.g., fees and net interest) and non-traditional activities (e.g. stakeholder and fee-for-service). Stakeholder income is derived from investment banking, insurance underwriting, and revenue earned on trading, securitization, and venture capital, whereas fee-for-service income includes fees from securities brokerage, annuity and insurance sales, and loan servicing. Many of the sources of income from these non-traditional activities derive from off-balance sheet activities, which are associated with a bank's risk (Li et al., 2018). DeYoung and Torna predict a higher share of income from these sources increases the risk of failure during the financial crisis period (2008:Q3 – 2010:Q4).

The sample of commercial banks DeYoung and Torna (2013) use in their analysis excludes: 1. banks with more than 50% foreign ownership, 2. banks with loans less than 25% of total assets, 3. banks without deposits, 4. banks more than 100 billion in assets, 5. banks with stakeholder income to total assets greater than the 99.5 percentile of the distribution, and 6. banks with fee-for-service income to total assets greater than the 99.5 percentile of the distribution. DeYoung and Torna (2013) estimate a logit model with pooled quarterly call report data to predict failures during 2008:Q3 – 2010:Q4 with various lead times (1-8 quarters). The results they report in Table 4 (p. 410) indicate increasing stakeholder income via non-traditional banking activities increases the probability of bank failure in predictions made 1 to 6 quarters ahead, where the estimates are statistically significant at the 1% level for the 1, 2, and 5 quarter ahead predictions and at the 5% level for 3 and 4 quarters ahead.

The sample in our replication attempt consists of 62,823 quarterly bank observations for the period 2008:Q1 -2010:Q2, which is quite comparable to the 62,934 observations used in

DeYoung and Torna's (2013) analysis for the same period.[9] The summary statistics based on our construction of their variables also appear quite similar across the two samples.[10] In Table 2 we report the estimates from our attempt to replicate DeYoung and Torna's (2013) findings with respect to the effects of stakeholder income on bank failure in prediction intervals ranging from 1-quarter to 6-quarters ahead. Our estimates indicate that stakeholder income does not have a statistically significant effect on the probability of bank failure at the 10% level for the 1-3 quarters ahead prediction intervals. Our estimates though do reveal the effect is statistically significant at the 0.1% level for the 4-6 quarters ahead prediction intervals. Similar to DeYoung and Torna (2013), we report the odds from a one-standard deviation change in the covariates. For the 4-quarter ahead prediction, increasing stakeholder income by one-standard deviation increases the probability of failure by 17 percent, which is even stronger than the 7 percent effect observed by DeYoung and Torna (2013). We find the effects are similarly stronger in magnitude for the 5-quarter (23 percent) and 6-quarter (21 percent) ahead predictions as well.

It is unclear why in our sample stakeholder income in the 1-3 quarter ahead predictions was not statistically significant, while in DeYoung and Torna's (2013) sample it is significant. It is likely slight variation in construction of our sample and variables explains the difference in findings. In order to reduce the possibility variation in variable construction plays a role in our results and to more generally test the effects of model uncertainty, we re-examine the effects of non-traditional banking activities using the 4 separate components of income (stakeholder, fee-for-service, traditional fee, and net interest) and our set of 26 standard variables. With 30 control

[9] Torna (August 29, 2019) indicated in a personal communication that they (DeYoung and Torna, 2013) no longer had access to the data or the code needed to replicate exactly their sample and results.

[10] We report the series used to construct the relevant variables in Appendix Table 1 and a comparison of summary statistics in Appendix Table 2, which are available online.

variables this implies there are just over one billion different models (2^{30}) under consideration with BMA.

[Insert Table 2 about here]

The BMA estimates of the multi-period logit model for the 1-6 quarters ahead prediction intervals appear in Table 3. The number of specifications averaged over in the different prediction intervals range between 8 and 59 and the posterior model probability of the specification averaged over that is most likely the true model generating the data ranges between 0.08 and 0.52. The implication, for example, is that the best single model specification of the 23 averaged over for the 4-quarter ahead prediction is only 16% likely to be the model that generates the data, which implies there is a great deal of uncertainty in any single model's specification. The estimates indicate the measure of non-traditional banking income from stakeholders (i.e. stakeholder income) was not included in any of the models averaged (PEP = 0) over for the 1-4 quarter ahead prediction intervals. For the predictions 5-quarters and 6 quarters ahead, stakeholder income has a posterior effect probability that is less than 50%, which means the effect is more likely equal to zero than not. Non-traditional income from fee-for-services was not included in any of the models averaged over for any of the prediction intervals examined. Neither measure of non-traditional income receives support for having an effect on bank failure during the crisis, when we account for uncertainty in the model's specification.

The results though indicate very strong evidence that equity has an effect (PEP $\geq$ 99) on reducing bank failure for each prediction interval. Increasing the share of equity to total assets by one-standard deviation reduces the risk of failure within a quarter by 95% (1-0.048), and reduces the risk of failure within 6 quarters by 55% (1-0.449). Nonaccrual loans also received very strong support (PEP >=99) for increasing failures in the 2-6 quarter ahead predictions. For prediction intervals of 3-6 quarters ahead, there was very strong evidence (PEP $\geq$ 99) of failures increasing with loans past due 30-89 days, whereas failures decrease with the share of consumer loans. A few other measures received strong support (PEP $\geq$ 95) for having an effect in the various prediction intervals - volatile liability expense (1-quarter); net income (2-quarter); share of consumer loans (1-quarter), foreclosed real estate (6-quarters), and brokered deposits (4, 5, and 6-quarters).

[Insert Table 3 about here]

Our BMA estimates indicate there isn't evidence in the data to suggest that stakeholder income affects bank failure, when averaging over the space of models supported by a list of theoretically relevant and standardized controls. For the prediction 4-quarters ahead we observed for the 23 model specifications BMA averaged over that none included the stakeholder income measure. However, it is possible to find model specifications using subsets of the standard controls that are consistent with DeYoung and Torna's (2013) findings. Estimating bank failures 4-quarters ahead using the full set of controls, we observe (Table 4, column 1) that the estimate of the odds ratio for a one-standard deviation increase in stakeholder income is 1.15, which is statistically significant at the 1% level. A one-standard deviation increase in the share of stakeholder income increases the probability of failure by 15%. This result is not an anomaly. If we instead estimate the model using stepwise estimation with backward elimination and a p-value criterion of 0.10 for removal, we find a similar result (Table 4, column 2). For this specification, the estimate of the odds-ratio (1.15) for stakeholder income is again statistically significant at the 1% level. Limiting one's analysis to these two specifications, might lead one to conclude that the share of stakeholder income increased the likelihood of bank failure during the Great Financial Crisis.

The concern is whether either of these two model specifications are likely to reflect the true data generating process (DGP). If they do not, then relying on either models' estimates may result in inappropriate inferences. Resolving this concern requires one to assess the relative support that each specification receives from the data. We assess the relative strength here by comparing each model specification separately to the specification (M_{BIC}) that best fits the data according to the Bayesian information criterion (BIC). Griffin et al. (2021) also provide a similar comparison of the model selected based on BIC in relation to alternative specifications. This specification is indicated in Table 4, column 3, and does not include the stakeholder income variable. The basis for our comparison of models is the Bayes factor for specification M_{BIC} relative to M_k. For the model that includes all the controls, we find that the difference between the models' BIC values is large (180), which equates to a Bayes factor of 4.49×10^{38}. It is therefore extremely unlikely (0 to most computers' precision) that the model that includes all the controls is the model that generates our data, relative to model M_{BIC}. We draw a similar conclusion from the comparison with the model chosen by stepwise selection. Despite these two models' predictions that the share of stakeholder income increases bank failure, the evidence suggests neither model specification is supported by the data. Of the three models examined, the model supported by the data indicates that stakeholder income does not affect bank failure. The advantage of using BMA is that one is able to base inferences on the entire space of models, rather than a subset of results from separate model specification the researcher chooses to report.

[Insert Table 4 about here]

As an additional robustness check, we apply BMA to an alternative set of models implied by the list of variables used by DeYoung and Torna (2013) in their analysis. This allows us to determine whether stakeholder income, which is statistically significant in our replication using

DeYoung and Torna's specification and the 4-6 quarters ahead prediction intervals, has an effect when we average over the models implied by their choice of covariates. The results from BMA indicate there isn't strong evidence (PEP ≥ 95) to suggest that stakeholder income has an effect on bank failures during the Great Financial Crisis.[11] The posterior effect probability of stakeholder income is zero for the 4-quarter ahead prediction and is 65% and 78% for the 5-quarter and 6-quarter ahead predictions. Instead, loans past due 30-80 days, loans in non-accrual status, equity, brokered deposits, and construction and development loans, and home price growth all have a very strong (PEP ≥ 99) effect on the prediction failures at the 4-6 quarters ahead prediction intervals.

Treatment of allowances for loan loss reserves as regulatory capital

It is not surprising total equity capital plays an important role in reducing failures in the model estimated above, as it serves as a buffer to cover unexpected losses and keep banks solvent during cyclical periods of downturn. Regulatory capital, i.e. total risk-based capital, consists of tier 1 and tier 2 capital. Tier 1 capital is the most loss absorbing form of capital and is primarily a bank's total equity capital (i.e. the sum of common stock, surplus, and retained earnings) less the value of several items, such as goodwill, intangible assets, and deferred tax assets. Tier 2 capital is lower quality capital that is less quickly able to absorb losses and includes a bank's subordinated debt, preferred stock, and allowances for loan losses of up to 1.25% of the bank's gross risk-weighted assets.[12] Research (Alali and Jaggi, 2011) shows that banks use loan loss provisions, in part, to manipulate their earnings and this behavior is stronger among banks with riskier asset portfolios. Due to the difference in quality, tier 1 and tier 2

[11] These result appear in Appendix Table 3

[12] The allowances for loan losses counted for risk based purposes deduct the allocated transfer risk reserve and add allowances for credit losses on off-balance sheet credit exposures.

capital may therefore differ in their effect on bank failures. Ng and Roychowdhury (2014) examine this relation by identifying whether the inclusion of allowances for loan loss reserves reduces the quality of total regulatory capital, by increasing the risk of bank failure.

Ng and Roychowdhury (2014) use a cross-section of commercial banks to estimate a logit model to examine whether a bank fails at any point during the period 2008-2010. Their sample of 6,382 commercial banks consists of banks located in the 50 US states and the District of Columbia and is restricted to banks with positive values of total assets and total loans in both 2006 and 2007.[13] The control variables are derived using annual data and measured as of year-end 2007.[14] Separate measures for the different components of regulatory capital are included in the specification to test for their potentially heterogeneous effects on bank failure. These measures include tier 1 capital, tier 2 capital minus allowable allowances, and allowable allowances in tier 2 capital, where each is scaled by total risk-weighted assets. Ng and Roychowdhury (2014) find (Table 6, Panel A, Column 2) that allowable allowances included in tier 2 capital, which they refer to as addbacks, increase the probability of bank failure by 24.2 percent for a one-standard deviation change with the estimate statistically significant at the 5% level. This differs from the negative and statistically significant (p-value < 0.001) coefficient Ng and Roychowdhury (2014) observe for the tier 1 capital ratio, which provides evidence that capital of different quality has a heterogeneous effect on bank failures.

Ng and Roychowdhury (2014) observe that an increase in allowances, due to an increase in provisions, reduces tier 1 capital and adds to tier 2 capital when under the limit, such that total

[13] The restrictions are a result of the construction of the control variables, which in some cases use lagged and unlagged values, to avoid dividing by zero.

[14] The series we used to construct Ng and Roychowdhury's (2014) variables based on their descriptions appear in Appendix Table 4.

regulatory capital increases. In this case, Ng and Roychowdhury posit the effect of addbacks to tier 2 capital intensify the effect on bank failure. To test this notion, they add to their specification an indicator variable, CAPINC, for whether the addback of allowances are likely to increase total capital and an interaction term between this indicator and the ratio of allowances added to tier 2 capital. They find (Table 6, Panel A, Column 3) the coefficient of the interaction term in their logit model is positive and statistically significant at the 5% level, which indicates the positive relation between bank failures and allowable allowances included in tier 2 capital is stronger the more likely the allowances result in an increase of total regulatory capital. Ng and Roychowdhury (2014) also test the robustness of their results by using a Cox proportional hazards model, where they examine the time to failure through year-end 2010. The estimates from their hazard model (Table 6, Panel B) further support their conclusions.

We were again unable to exactly match the sample of 6,382 observations used by Ng and Roychowdhury (2014). The summary statistics from our sample of 6,486 observations though are for the most part quite similar.[15] The one significant difference is in the measure Ng and Roychowdhury (2014) use to evaluate the timeliness of loan loss provisions, which they note follows the specification used by Beatty and Liao (2011). The mean and standard deviation of the timeliness of provisions in our sample is 0.040 and 0.225 respectively, whereas they find a mean of 0.107 and a standard deviation of 0.123. The timeliness of loan loss provisions for a bank is measured by comparing the provision of loans conditioning on future loan performance relative to only conditioning on past performance, where the comparison is based on the difference in the adjusted R^2 from two regressions on the bank's quarterly provisions controlling for several factors over a period of three years. One potential source of the variation is from the

[15] See Appendix Table 5.

scaling of nonperforming loans. Ng and Roychowdhury (2014) indicate (p. 1252) they follow Beatty and Liao's (2011) specification, but also indicate they scale non-performing loans by lagged total assets, whereas Beatty and Liao (2011) scale using lagged total loans.[16] Using either measure has little impact on the mean and standard deviation for the timeliness of loan losses as indicated in Table 5. We are though able to closely replicate the summary statistics Ng and Roychowdhury (2014) report for their timeliness measure if we instead use the difference in the unadjusted R^2 from the two regressions. Table 5 provides a comparison of the results based on the alternative scaling measures and whether the adjusted or unadjusted R^2 is used. In the results reported below, we use the timely measure based on the adjusted R^2 and scaling of nonperforming loans as indicated by Beatty and Liao (2011).[17]

[Insert Table 5 about here]

Using our sample and construction of Ng and Roychowdhury's (2014) variables, we attempt to replicate the main findings from the models they report in columns 1-3 of Table 6. Their interest in the first model specification is to the effects of allowances for loan loss reserves and total regulatory capital on bank failure. Similar to Ng and Roychowdhury, we find (Table 6, column 1) the logit model's coefficient for loan loss reserves is positive and statistically significant (p-value 0.048). Based on our estimates, a one-standard deviation increase in loan loss reserves increases the probability of failure by 13.5%, when evaluated at the variables' mean values. For comparison, Ng and Roychowdhury (2014) find an effect of 12.5%.[18] Total equity

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[16] Roychowdhury (August 26, 2019) indicated in a personal communication they (Ng and Roychowdhury, 2014) no longer had access to the data or the code needed to replicate their data and results so it is unclear how their timely measure or dataset more generally was constructed.

[17] Using the difference in unadjusted R^2 did not materially affect our results.

[18] The marginal effect reported here and for the effect of equity are based on the authors' calculations using Ng and Roychowdhury's (2014) estimates and summary statistics.

capital has a negative and statistically significant (p-value < 0.001) on failure, where a one-standard deviation reduces failure by 92%. Ng and Roychowdhury observe a similarly sized marginal effect of 93.3%. Our estimates confirm the notion that total capital serves as a buffer against failure and higher loan loss reserves are associated with higher risk of failure.

Next we examine whether there is evidence of a heterogeneous effect of capital on bank failure by replacing total capital in the specification with the separate measures for tier 1 capital, tier 2 capital excluding allowable allowances, and allowable allowances in tier 2 capital, along with replacing allowances for loan loss reserves with the remainder not allowable as tier 2 capital. The results (Table 6, column 2) of our replication attempt are again similar to Ng and Roychowdhury's (2014) findings. Allowances for loan loss reserves added into tier 2 capital have a positive and statistically significant (p-value 0.040) effect on bank failure, whereas tier 1 capital has a negative and statistically significant effect (p-value < 0.001) on reducing failure. Using our estimates and data, a one-standard deviation increase in addbacks increases the risk of failure by 24.8 percent, whereas an increase in tier 1 capital reduces the risk of failure by 91.9 percent. These marginal effects are quite similar (24.2 and 93.3 percent) to those reported by Ng and Roychowdhury (2014). Lastly, we attempt to determine whether the effect of allowances on bank failure is affected by whether they likely increase a bank's total capital. The results in column 3 of Table 6 indicate allowances added to tier 2 capital are more likely to increase failure when they are more likely to increase regulatory capital based on the coefficient of the interaction term between addbacks and CAPINC, but we find the effect is only marginally statistically significant (p – value 0.099). Ng and Roychowdhury (2014), for comparison, find the interaction term is statistically significant at the 1% level.

[Insert Table 6 about here]

In Table 6 columns 4-6 we report the estimates from a Cox proportional hazard models where we model the time to failure using the same time-fixed covariates from the logit model. The results from the hazard model support the conclusions of the previous findings and largely replicate Ng and Roychowdhury's (2014) results. Noteworthy, we find the statistical significance for the coefficient on the interaction between allowances added to tier 2 capital and the indicator for an increase in capital increases (p-value 0.053) relative to what we found for the logit model (p-value 0.099).

We next turn our attention to determining the robustness of these inferences when we account for uncertainty in the model's specification. First, we re-consider the effects of allowances for loan loss reserves and total regulatory capital when the model space under consideration also includes the timeliness of loan loss provisions and 23 of the 26 standard controls. Equity and allowances for loan losses as a share of total assets are omitted from our standard controls due to the inclusion of total regulatory capital and allowances as a share of risk-weighted assets in the model. We also temporarily exclude provisions as a share of assets from consideration, given a subsequent specification we examine includes the indicator, CAPINC, which takes the value of 1 if the bank has made positive provisions, and has not reached the limit on loan loss reserves as of the previous year, and is not an S-corporation.

[Insert Table 7 about here]

The logit model estimates from BMA (Table 7, Panel A, Column 1) indicate there is a great deal of uncertainty, as 132 models are averaged over and the specification with the highest posterior model probability is 6% likely to be the model that generates our data. The posterior mean indicates total regulatory capital has a negative effect on bank failure, and there is very strong evidence of a non-zero effect (PEP $\geq$ 99). We do not find evidence that allowances for loan loss reserves have an effect on the probability of bank failure as the posterior effect probability (i.e. probability of a non-zero effect) is only 27%. This differs from Ng and Roychowdhury's (2014) estimates from their single model specification, where they find allowances are strongly associated with a higher probability of failure. In addition, none of the models that were averaged over included the measure of the timeliness of provisions, which indicates very strong evidence the measure does not have an effect.

To examine whether heterogeneity is evident with respect to the regulatory treatment of allowances as capital, we use the same 23 standard controls as before along with the separate components of total capital (tier 1, allowances in tier 2, other tier 2) and allowances split into those added back into tier 2 capital and those that are not added back. The estimates from BMA (Table 7, column 2) again indicate that tier 1 capital has a negative effect on bank failure and receives very strong support for a non-zero effect (PEP =100). We find that neither of the separate measures for allowances added to tier 2 capital and allowances not added to tier 2 capital receive support for a non-zero effect as each only has a posterior effect probability of 9% and 3%, respectively. We find no evidence allowances in the aggregate, or split into separate components, affects the probability of bank failure. While Tier 1 capital reduces the probability of bank failure, the components of tier 2 capital have no effect. As a final robustness check, we also added to the model space under consideration the indicator for whether allowances are likely to add to total regulatory capital and it's interaction with allowances added to tier 2 capital. Neither of these two variables receive any support for inclusion in the models we average over and thus we find the same estimates as the previous specification. Accounting for uncertainty, we find no evidence from the logit model to suggest that allowances, whether or not added into tier 2 capital, are associated with a higher risk of failure.

We further explore the robustness of these results by modelling the time to failure using a Cox proportional hazards model and accounting for uncertainty. The inferences based on the hazard model's estimates are quite similar to those from the logit model. Panel B of Table 7 reports estimates from the hazard model. Regulatory capital reduces the risk of bank failure and the probability the effect is non-zero is 100%. In the survival model, we though do find strong evidence that allowances increase the risk of failure (PEP = 95). When each of the separate capital components are added to the models under consideration, we find some evidence supporting a non-zero effect due to allowances included in tier 2 capital (PEP = 84) though the effect is not strong (Jeffreys, 1961; Raftery 1995). When we add to the model specification the indicator for an increase in capital and its interaction with allowances in tier 2 capital there is no longer any support for a non-zero effect from allowances in tier 2 capital and there is no support to indicate the interaction term has a non-zero effect. Each of the measures has a posterior effect probability less than 50%. Similar to the conclusions from the logit model, we do not find strong evidence to suggest that the allowances added to tier 2 capital which are most likely to increase capital contribute to the risk of bank failure when accounting for uncertainty in the model's specification using a standard list of controls.

Next, we again highlight the inferences drawn by Ng and Roychowdhury (2014) can be observed in specifications consisting of our standard controls. Here we focus on estimating the logit model and the effects capital added back has on predicting bank failure. Estimates of the model specification that include all the controls (Table 8, column 1) indicate allowances for loan loss reserves added into tier 2 capital has a positive coefficient (0.74) and statistically significant (p-value 0.093) effect on bank failure. A one-standard deviation increase in addbacks increases the risk of failure by 19.3 percent. The model specification chosen by stepwise selection (Table

8, column 2) also includes the variable controlling for addbacks. The coefficient for addbacks (0.73) is similar in magnitude as the model with the full set of controls and is statistically significant at the 10% level (p-value 0.097). However, we find the model specification that best fits the data according to the BIC criterion (M_{BIC}) does not include this variable (Table 8, column 3). Separate comparisons of the two specifications that include addbacks with model M_{BIC} reveals that neither of these two models are supported by the data. The Bayes factors comparing model M_{BIC} and the model with all the controls is 1.14×10^{26} and is equal to $8.80.3 \times 10^{6}$ for the stepwise model. The posterior probability that either alternative is the model that generates our data is mathematically equal to zero.

[Insert Table 8 about here]

As an additional robustness check, we apply BMA to the set of models implied by the list of variables Ng and Roychowdhury (2014) use in their analysis. The BMA estimates from the logit model indicate that allowances of loan loss reserves did not have an effect on failure, as the variable was not included in any of the 4 models averaged over. [19] Total capital reduces failure and the posterior effect is very strong (PEP $\geq$ 99). When we added the various separate components of capital to the models under consideration, we again find no evidence to suggest allowances included in tier 2 capital, i.e. addbacks, have an effect on failure as the posterior effect probability was 21%. When the indicator for whether the addition of allowances to capital were likely to increase total capital was added to the model space, along with its interaction with addbacks, the results were the same. Neither of the two variables was included in the models averaged over, therefore the models averaged over are identical. Our results were quite similar,

[19] These estimates are available in Appendix Table 6. Panel A has the logistic model estimates and panel B the hazard model estimates.

when BMA was applied to the set of hazard models implied by Ng and Roychowdhury's (2014) controls. Allowances for loan loss reserves did not receive support (PEP 12%) for having a non-zero effect in the baseline model. When the components of capital are split up, we find some support of an effect of addbacks on bank failure. The evidence similar to before is not strong as the probability the effect is non-zero (PEP) is only 80%. When we add the indicator and interaction term to the list of variables for inclusion in the model, the posterior effect probability of the interaction term is 32%, which suggests there isn't any evidence from the hazard model that allowances more likely to contribute to capital when added to tier 2 capital have any effect on bank failure.

What we find is more likely influencing the risk of bank failure than the regulatory treatment of allowances as capital is the bank's most recent provisions for loan losses. We omitted this measure from our standard list of controls as the value is used, in part, to construct Ng and Roychowdhury's (2014) indicator of whether addbacks are likely to increase capital. We though found no evidence to suggest the interaction with addbacks had any effect on bank risk. Similarly, we found no evidence that the timeliness of provisions as measured by Ng and Roychowdhury (2014) had any effect whatsoever on bank risk. When we include provisions in the space of models considered in Table 6, we find that provisions receive strong support for inclusion (PEP > 95) in both the logit and hazard model specifications and increase the risk of failure.[20] There is though strong evidence that allowances in the aggregate do not have any effect in either the logit or hazard models. Including provisions in the model space, we find no evidence that allowances used as tier 2 capital have an effect on bank failure, regardless of their

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[20] Estimates from the models that consider for inclusion provisions as a share of assets are available in Appendix Table 7. Panel A has the logistic model estimates and panel B the hazard model estimates.

effects on the likeliness of increasing capital. Provisions made prior to the period at risk of failure and not their timeliness or whether they are added to capital as part of allowances for loan loss reserves are what matters to predicting bank failure.

Choice of bank auditor and bank failure

Setting aside allowances for loan and lease loss reserves is a determination made by management that under generally accepted accounting principles (GAAP) allows for a high degree of judgement in estimating credit losses on currently impaired and likely to become impaired loans and leases in the portfolio.[21] Regulatory expectations are such that management will follow well developed and consistently applied policies, which include monitoring asset quality and updating policies when required to be consistent with GAAP. This suggests the quality of financial reporting may differ based on managements' judgements and their commitment to these principles. Banks may further manipulate their earnings by modifying the discretionary portion of their accruals, which may obfuscate their risk exposure (Yasuda et al., 2004). External auditors may then serve as an independent check on management by attesting to the quality of internal controls as it relates to financial reporting. Jin et al. (2011) posit the quality of a bank's financial reporting is influenced by the reputation of their auditor, such that banks whose auditor pre-crisis is part of the Big 4 (PWC, KPMG, Deloitte, and Ernst and Young) are likely to have higher quality financial data and are therefore less likely to fail during the Great Financial Crisis. The results from their logit model indicate that banks with a full-scope external audit by a Big 4 auditor in 2006 are less likely to fail in the period 2007-2010 – a result they find is statistically significant at the 5% level. Based on their coefficient estimates, and the means of their variables, a Big 4 auditor reduces the probability a bank fails by 2.74

[21] https://www.fdic.gov/regulations/laws/rules/5000-4700.html

percentage points.[22]

Data identifying the external auditor is drawn from bank holding company filings, therefore the sample used by Jin et al. (2011) in their analysis is restricted to commercial banks that are part of a bank holding company. In addition, Jin et al. (2011, p. 2813) eliminate banks from their sample if they in 2006 have either tier 1 capital less than 4%, loan loss provisions greater than 1%, or a return on assets less than -5%. Their estimation sample consists of 25,428 quarterly observations in 2006 that are drawn from 6437 commercial banks, where the unit of analysis is at the individual bank level, rather than the aggregate for the parent of the holding company.

Similar to the other two studies, we were unable to exactly replicate the sample used by Jin et al. (2011), as our sample consists of 23,623 quarterly observations from 5989 banks. The variables Jin et al. (2011) use for controls in their model specification of bank failure include several standard risk measures (e.g. tier 1 capital, non-performing loans, provisions for loan losses, size).[23] We were able to construct these four variables without issue and the summary statistics from our sample closely match those of Jin et al. (2011).[24] Our attempt to construct the remaining control variables though revealed a number of significant issues that we document below.

The model specification used by Jin et al. (2011) includes three measures of quarterly loan growth scaled by assets at the end of the previous quarter (i.e. start of current quarter),

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[22] The marginal effect is based on our calculation using estimates and summary statistics reported by Jin et al. (2011), where we compare the difference in probabilities evaluated at the variables' mean values for a bank with and without a Big 4 auditor and first quarter data.

[23]The measures and call report series we used in their construction are included in Appendix Table 8.

[24]Summary statistics for the variables are available in Appendix 9.

which include the growth of total loans (GLOANS) and separate measures for the growth in real estate (GRESTATE) and commercial and industrial (GCOMM) loans. In our sample the average quarterly growth of loans as a share of assets for banks that fail (4.1%) is more than twice the value (1.7%) for banks that do not fail. For comparison, Jin et al. (2011) report quarterly loan growth values of 1.4% and 1.3% of total assets for banks that fail and do not fail, respectively. The loan growth we observe is primarily driven by growth in real estate loans, whereas growth for this category is negligible in the statistics Jin et al. (2011) report. Loan growth in their sample is instead primarily explained by the omitted loan categories, which include consumer and "other" loans. The statistics we report based on our construction of the loan growth measures though are consistent with aggregate data from the FDIC's quarterly banking profile (2006, Q4), which indicate quarterly loan growth in 2006 was driven by an increase in loans secured by real estate (71%), followed by C & I loans (25%), and with only negligible growth observed in the consumer and other loan categories. It is unclear what explains the significant difference in our measures for the growth of real estate loans, though the difference is unlikely due to differences in our samples and is more likely driven by variation in the series used in their construction.

Jin et al. (2011, p. 2815) also include in their model an indicator (PUBLIC) for whether a "bank is a publicly listed bank." No other details are provided for the measure's construction, so we similar to DeYoung and Li (2019) use the CRSP-FRB link table provided by the Federal Reserve Bank of New York to identify publicly-traded banks and bank holding companies in the Center for Research in Security Prices (CRSP) database.[25] Based on this definition, we find that 13% (21%) of our quarterly observations from non-failed (failed) banks are publicly traded,

[25] The link table is available at https://www.newyorkfed.org/research/banking_research/datasets.html .

which is higher than the statistics Jin et al. (2011) report of 4% (11%), respectively. For comparison, Kwan (2004) finds 26% of bank holding companies are publicly traded.

The biggest consternation with our replication attempt arises with the constructions of variables that Jin et al. (2011) refer to as LOAN_MIX and PSLOANS. Jin et al. (2011, p. 2813) explain LOAN_MIX is measured as "the proportion of heterogeneous loans such as commercial and industrial loans, direct lease financing, all other real estate loans, agriculture loans, and foreign loans to total loans." The measure of loan mix is seemingly the share of loans in these categories, yet the mean they report is equal to 0.004 and 0.003 for their samples of banks that respectively do not and do fail. Commercial and industrial loans, which are said to be included in the share, alone make up 0.15 (15%) of the typical bank's loan portfolio. The construction of loan mix though differs fundamentally from the description provided in the text and is instead the sum of the values of C & I loans past due 30-89 days (RCFD1606), C & I loans past due more than 90 days (RCFD1607), C & I loans in nonaccrual status (RCFD1608), restructured C & I loans (RCFD1609), loans to foreign governments (RCFD2081), loans to foreign governments past due 30-89 days (RCFD5389), and loans to foreign governments past due more than 90 days (RCFD5390), which is divided by total loans (RCON1400).[26] Using these seemingly random series, we are able to replicate the means of the LOAN_MIX measure Jin et al. (2011) report with our samples of failed and non-failed banks. The issue is the construction of the measure has no meaningful interpretation in relation to any standard measure of risk, yet is observed by Jin et al. (2011) to have a statistically significant (5% level) effect on reducing bank failure. This finding reminds us of the importance of theory, as blindly relying on p-values can lead us to

[26] Jin (August 3, 2019) in a personal communication provided the series Jin et al. (2011) use to construct LOAN_MIX. In Appendix Table 10 we provide the complete description of each of these series.

observe otherwise ad hoc relations in the data (Harvey, 2017).

Jin et al. (2011, p. 2813) include in their specification a variable PSLOAN, which is said to control for the role of securitized assets and they describe as "the proportion of securitized assets to total assets." Later in the text (p. 2814), the measure is described as securitized loans, scaled by total loans. The mean they report for their measure is 24% and 20% for their samples of failed and non-failed banks, which does not make sense based on the variable's description. Of the 8681 total commercial banks included in the FDIC's Quarterly Bank Profile (FDIC, 2006) in the fourth quarter of 2006, only 126 reported securitization activities. A ratio of securitized loans can be constructed with call report data. For example, Chen et al. (2017) use the share of assets sold and securitized with servicing retained or with recourse, relative to total assets.[27] As noted, for the vast majority of banks (98.5%) the ratio is zero due to their lack of securitization activities, therefore the mean of this measure is close to zero (0.0010) in our sample. Even among banks with securitization activities, the conditional mean is only 0.064. It is unclear what Jin et al. (2011) were trying to capture with their measure, as many of the series they indicated were used in the variable's construction do not exist in the call report data for the period examined.[28] The three series that exist (RCON5571, RCON5573, RCON5575) in the call reports are only reported for the June 30 report date prior to 2010 (i.e. are not available quarterly) and have no relation whatsoever to securitized loans.[29] Given we were unable to replicate or

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[27] The series (RCFDB705, RCFDB706, RCFDB707, RCFDB708, RCFDB709, RCFDB710, RCFDB711) are used to construct the numerator, which is scaled by total assets.

[28] Jin (August 3, 2019) in a personal communication provided the series Jin et al. (2011) use to construct the variable PSLOAN. In Appendix Table 11 we provide the complete description of each of these series.

[29] Series RCON5571 is defined in the Federal Reserve's Micro Data Reference Manual as "amount currently outstanding of commercial and industrial loans to U.S. addressees (in domestic offices) with original amounts of $100,000 or less". Source: https://www.federalreserve.gov/apps/mdrm/data-dictionary. The other two series (RCON5573, RCON5575) are also related to commercial and industrial (C & I) loans with loan amounts of more than $100,000 to $250,000 and more than $250,000.

understand the intent of the measure PSLOANS, we omit the variable from our replication attempt of Jin et al. (2011).

The typical multi-period logit model with panel data (e.g. DeYoung and Torna, 2013) conditions on the currently available data to predict whether failure occurs in a subsequent period, where with each period forward in time the data is updated and the prediction interval advances. Jin et al. (2011) instead use quarterly data from 2006 to predict failure in a fixed period of time (2007- 2010). The econometric issue this creates is quarterly observations for a given bank are no longer independent of each other, as a bank that is known to fail will have the same outcome for each of the four quarters. To remedy this issue, one can instead use a static logit model (e.g. Ng and Roychowdhury, 2014), where one predicts failures in 2007-2010 conditioning on controls from a single fixed point in time.

To allow for comparison to the original (Jin et al., 2011) findings we use quarterly data from 2006 to estimate a logistic regression model with their specification (excluding securitized loans) of whether a bank fails in the period 2007-2010. Our estimates (Table 9, Column 1) replicate Jin et al.'s finding that having a Big 4 auditor reduces the probability a bank fails in the period, where the result is statistically significant at the 1% level. Our estimates though indicate the magnitude of the marginal effect is 0.97 percentage points, which is less than the 2.74 percentage points implied by Jin et al.'s estimates. If one uses a static-logit model with independent observations, by limiting the data to quarter 4, then a Big 4 auditor still reduces the probability of failure and the result is statistically significant at the 5% level (Table 9, column 2) with a marginal effect of 0.81 percentage points.

The issues faced with the construction of the control variables used by Jin et al. (2011) highlight the need for researchers to use clearly defined and theoretically relevant variables in their model specifications. Using our standard list of controls and the sample restrictions of Jin et al. (2011), we estimate a static-logit model with BMA to determine whether having a Big 4 audit in 2006 has an effect on predicting the failures in the period in the period 2007-2010 and control variables drawn from December 31, 2006. The estimates reported in Table 10 indicate there is evidence against the hypothesis that having a Big 4 auditor has an effect on bank failure, as none of the 30 models averaged over include the variable. Our results indicate there is uncertainty in the true model's specification, as the model with the highest posterior model probability is only 22% likely to be the specification that generates our data. The variables that receive strong support (PEP >= 95%) for having an effect on failures include demand deposits, brokered deposits, provisions for loan losses, age, and the share of consumer loans. Several variables (e.g. loans past due 30-89 days, nonaccrual loans, charge offs) that reflect asset quality did not have an effect in the Jin et al. (2011) sample, which we found strong support of an effect for in Ng and Roychowdhury's (2014) sample of observations. This is a result of Ng and Roychowdhury's (2014) model using controls from 2007, i.e. at the start of the crisis when declining asset quality is more prevalent than in 2006.[30]

[Insert Table 10 about here]

Our results indicate that none of the 30 models that BMA averaged over included the indicator of whether a bank's auditor was part of the Big 4. We are again able to show it is possible to find a model specification that includes the variable, where the coefficient is statistically significant at the 10% level. For the model that includes all the standard controls, the coefficient of having a Big 4 auditor is negative but is statistically insignificant at the 10% level (Table 11, column 1). However, we find the model specification chosen by stepwise selection

[30] Charge-offs, for example, were almost twice as high in the fourth quarter 2007 than in 2006.

(Table 1, column 2) includes Big 4 auditor and the coefficient is statistically significant at the 10% level (p-value 0.093). Similar to our previous examples, the Bayes factors comparing the model specification (Table 11, column 3) chosen based on BIC (M_{BIC}) to the full model and stepwise models suggests that neither of these two models that include a control for having a Big 4 auditor generate our data.

[Insert Table 11 about here]

In our final robustness check we applied BMA to the set of models implied by the controls Jin et al. (2011) use in their analysis, where we exclude the measure of securitized loans given the issues with its construction. BMA averages over three different models, where the specification with the highest posterior model probability is 79% likely to be the model that generates our data.[31] The indicator for an audit by a Big 4 firm has a posterior effect probability of 15.4% and therefore we again find no strong evidence that a Big 4 auditor has an effect on bank failure, when one accounts for uncertainty in the model's specification.

Conclusions

This paper re-examines three studies (DeYoung and Torna, 2013; Jin et al., 2011; Ng and Roychowdhury, 2014) to assess whether certain policy lessons thought to have been learned during the Great Financial Crisis are sensitive to model risk and thus valid. Specifically, we examine whether regulators need to reconsider decisions to allow commercial banks to engage in non-traditional bank activities (e.g., investment banking) based on the empirical findings of DeYoung and Torna (2013) and for loan loss reserves to be included as regulatory capital based on Ng and Roychowdhury (2014). In addition, we examine whether a bank's choice of external auditor (Jin et al., 2011) effects their risk of failure.

[31] These estimates appear in Appendix 12.

Each of these three studies of bank failure base their inferences on the estimates from a single model specification. Such inferences, though, are subject to model risk when alternative model specifications are also considered. To account for model risk in drawing our inferences, we use BMA over the space of model specifications implied by the different linear combinations of a consistent set of control variables. Rather than base inferences on a single model specification, BMA uses a weighted average over each of the models' estimates. Our BMA estimates indicate that none of the three studies (DeYoung and Torna, 2013; Jin et al., 2011; Ng and Roychowdhury, 2014) findings of interest are robust when we account for model uncertainty. We find there isn't strong evidence to suggest non-traditional banking activities, the regulatory treatment of allowances as capital, or the choice of auditor has any effect on the risk of failure during the GFC.

Instead, we find bank failures during the GFC are explained by differences in fundamentals reflecting measures of capital adequacy, asset quality, and liquidity. Total equity capital is shown to reduce the risk of failure. Asset quality impairment, measured using loans past due and loans in nonaccrual, is shown to increase the likelihood of failure. Brokered deposits, a measure of bank liquidity, are purchased funds that are subject to higher and more variable interest expense than core deposits. We find a higher share of brokered deposits increases the likelihood of failure. Each of these same factors (equity, loans past due, loans in nonaccrual, brokered deposits) were also observed by Cole and Gunther (1998) to similarly affect bank failures during the S & L crisis. One difference we observe between the two crisis periods is that the share of consumer loans played a role in failures during the GFC and not the S & L crisis. Accounting for model risk, we find the robust lessons learned from the GFC are in large part similar to lessons learned from the previous S & L crisis.

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Table 1: Candidate variables for inclusion in the model specification

Variable	Description	Call Report Series
Loans past due 30-89 days	Loans past due 30-89 days and still accruing interest divided by assets	RCFD1406
Loans past due 90+ days	Loans past due 90 days or more and still accruing interest divided by assets	RCFD1407
Nonaccrual loans	Loans in nonaccrual status divided by assets	RCFD1403
Foreclosed real estate	Foreclosed real estate divided by assets	RCFD2150
Equity	Equity divided by assets	RCFD3210
Net income	Income before income taxes and discontinued operations divided by assets	RIAD4301
Securities	Available for sale and held to maturity securities divided by assets	RCFD1754 + RCFD1773
Loan loss reserves	Allowance for loan and lease losses divided by assets	RCFD3123
Jumbo CDs	CD greater than or equal to $100,000 divided by assets	RCON2604
Cash	Cash and balances due from depository institutions divided by assets	RCFD0010
Demand deposits	Total demand deposits divided by assets	RCON2210
Federal funds purchased	Federal funds purchased divided by assets	RCONB993 + RCONB995
Volatile liability expense	Interest paid on Federal funds purchased and large CDS divided by assets	RIAD4190 + RIADA517
Charge-offs	Charge-offs divided by assets	RIAD4635
Brokered deposits	Indicator variable equal to 1 if the ratio of brokered deposits to total assets is greater than 1% and equal to 0 otherwise	RCON2365
Non-interest expense	Non-interest expense divided by assets	RIAD4093
Insider loans	Loans to insiders divided by assets	RIAD4093
Dividends	Dividends divided by assets	RCFD6164
Age	Age of the bank in years	RSSD9950
Size	Natural log of assets	RCFD2170
Provisions for loan losses	Provisions for loan and lease losses divided by assets	RIAD4230
C & I loans	Commercial and industrial loans divided by assets	RCFD1766
Commercial real estate	Commercial real estate loans divided by assets	RCON1480
Consumer loans	Consumer loans divided by assets	RCFD1975
Agriculture loans	Agriculture loans divided by assets	RCFD1590
Federal funds sold	Federal funds sold loans divided by assets	RCONB987 + RCONB989

Series are divided by total assets (RCFD2170) where noted.

Table 2: Replicating the effects of non-traditional bank activities on bank failure

	(1)		(2)		(3)		(4)		(5)		(6)	
	One quarter		Two quarters		Three quarters		Four quarters		Five quarters		Six quarters	
	Odds	p-value	Odds	p-value	Odds	p-value	Odds	p-value	Odds	p-value	Odds	p-value
Stakeholder	0.942	0.192	0.99	0.916	0.975	0.723	1.169	< 0.001	1.225	< 0.001	1.211	0.001
Fee-for-service	0.971	0.765	0.921	0.531	1.064	0.446	1.05	0.509	1.018	0.804	0.964	0.648
Traditional fee	0.986	0.873	0.973	0.799	0.942	0.594	0.865	0.352	0.82	0.499	0.761	0.276
Net interest	0.604	0.003	0.675	0.009	0.845	0.141	0.843	0.153	0.893	0.418	0.908	0.427
Liquidity	0.612	0.017	0.736	0.107	0.848	0.323	0.944	0.733	0.865	0.399	0.832	0.24
Loan concentration	0.725	0.213	0.772	0.331	0.958	0.856	1.092	0.636	1.056	0.729	1.115	0.381
Cost inefficiency	0.979	0.869	0.894	0.184	0.962	0.681	0.992	0.945	1.017	0.895	1.131	0.296
ROA	1.033	0.472	0.837	0.001	0.894	0.037	0.922	0.164	0.944	0.371	1.061	0.457
Nonperforming loan	1.104	0.082	1.158	0.007	1.271	< 0.001	1.295	< 0.001	1.33	< 0.001	1.361	< 0.001
Equity	0.04	< 0.001	0.045	< 0.001	0.054	< 0.001	0.089	< 0.001	0.111	< 0.001	0.168	< 0.001
Log (Assets)	0.957	0.734	0.88	0.329	0.864	0.16	0.909	0.317	0.925	0.43	0.96	0.677
MBHC	0.944	0.661	0.782	0.083	0.848	0.142	0.78	0.006	0.76	0.001	0.831	0.01
Log (Age)	1.141	0.176	1.11	0.284	1.11	0.272	1.108	0.245	1.091	0.306	1.048	0.558
Brokered deposits	1.048	0.561	1.072	0.361	1.136	0.08	1.152	0.031	1.178	0.007	1.231	0.001
Core deposits	1.004	0.977	0.997	0.979	1.039	0.76	0.977	0.838	0.934	0.513	0.888	0.227
Goodwill	2.951	< 0.001	3.08	< 0.001	2.878	< 0.001	2.526	< 0.001	2.312	< 0.001	2.097	< 0.001
CRE loans	1.31	0.027	1.264	0.062	1.194	0.136	1.124	0.307	1.101	0.376	0.984	0.867
C&D loans	1.307	0.019	1.539	< 0.001	1.68	< 0.001	1.79	< 0.001	1.88	< 0.001	1.782	< 0.001
Multifamily mort.	1.181	0.009	1.215	0.001	1.206	< 0.001	1.176	< 0.001	1.147	0.002	1.136	0.001
Business loans	1.051	0.78	1.042	0.824	1.148	0.41	1.332	0.02	1.255	0.035	1.2	0.037
Income growth	0.643	0.068	1.02	0.933	0.939	0.734	0.759	0.059	0.907	0.577	0.816	0.12
Unemployment rate	1.042	0.802	1.186	0.285	1.357	0.058	1.65	0.001	1.694	0.001	1.495	0.011
Home price growth	1.052	0.676	0.992	0.937	0.84	0.04	0.83	0.009	0.741	< 0.001	0.716	< 0.001
Number of banks	6530		6576		6647		6708		6785		6861	
Observations	62439		62823		63254		63696		64195		64742	

The pooled logit model uses a panel of quarterly bank data to predict failures in the quarter ahead indicated for the period 2007:Q3 - 2010:Q4. The odds reported correspond to a one-standard deviation change in the indicated variable. P-values reported are based on whether the estimated coefficient is different than zero and standard errors clustered at the bank level. The specifications include time indicators that are not reported.

Table 3: Model risk and the effects of non-traditional bank activities on bank failure

	(1)		(2)		(3)		(4)		(5)		(6)	
	One quarter		Two quarters		Three quarters		Four quarters		Five quarters		Six quarters	
	Odds	PEP	Odds	PEP	Odds	PEP	Odds	PEP	Odds	PEP	Odds	PEP
Stakeholder	—	—	—	—	—	—	—	—	1.054	30.9	1.088	49.8
Fee-for-service	—	—	—	—	—	—	—	—	—	—	—	—
Traditional fee	—	—	—	—	—	—	0.820	42.2	0.863	28.4	0.985	3.6
Net interest	0.962	12.3	0.748	80	—	—	—	—	—	—	—	—
Loans past due 30-89 days	1.006	5	1.026	17.9	1.311	100	1.401	100	1.281	100	1.327	100
Loans past due 90+ days	—	—	—	—	—	—	—	—	—	—	1.001	0.9
Nonaccrual loans	1.171	91.8	1.220	100	1.347	100	1.305	100	1.357	100	1.315	100
Foreclosed real estate	1.033	33.5	1.003	2.9	—	—	1.069	70.4	1.101	94.4	1.119	100
Equity	0.048	100	0.070	100	0.097	100	0.184	100	0.225	100	0.449	100
Net income	—	—	0.749	100	0.929	52.3	0.989	9.6	0.996	3.5	—	—
Securities	0.775	51.4	0.716	68.5	—	—	—	—	0.800	58.1	0.887	33.3
Loan loss reserves	—	—	—	—	—	—	—	—	—	—	—	—
Jumbo CDs	—	—	—	—	—	—	—	—	1.002	1.1	—	—
Cash	—	—	—	—	—	—	—	—	0.889	39.9	0.903	33.3
Demand deposits	—	—	—	—	—	—	0.931	18.5	0.848	39.1	0.725	66.3
Federal funds purchased	—	—	—	—	—	—	—	—	—	—	—	—
Volatile liability expense	1.226	100	—	—	1.038	27.1	—	—	—	—	—	—
Charge-offs	—	—	—	—	1.053	45.3	1.075	70.5	—	—	—	—
Brokered deposits	—	—	—	—	1.374	90.6	1.615	100	1.752	100	1.712	100
Non-interest expense	—	—	0.783	100	—	—	—	—	—	—	—	—
Insider loans	—	—	—	—	—	—	—	—	—	—	—	—
Dividends	—	—	—	—	—	—	0.968	5.7	—	—	—	—
Age	—	—	—	—	—	—	—	—	0.959	17.3	0.731	98.9
Size	—	—	—	—	1.021	7.5	1.310	80.4	1.220	60.5	1.180	50.1
Provisions for loan losses	—	—	—	—	1.002	2.3	—	—	—	—	—	—
C & I loans	—	—	—	—	—	—	—	—	—	—	—	—
Consumer loans	0.325	100	0.859	24.4	0.431	100	0.388	100	0.341	100	0.372	100
Commercial real estate	—	—	—	—	—	—	—	—	0.999	0.5	0.933	28.4
Agriculture loans	—	—	—	—	—	—	—	—	—	—	—	—
Federal funds sold	—	—	—	—	—	—	—	—	—	—	—	—
Banks	6530		6576		6647		6708		6785		6861	
Observations	62439		62823		63254		63696		64195		64742	
Models averaged over	8		9		8		23		59		34	
Posterior model probability	0.33		0.52		0.34		0.16		0.08		0.17	

The pooled logit model uses a panel of quarterly bank data to predict failures in the indicated quarter ahead during 2007:Q3 - 2010:Q4. BMA estimates reported include the odds and posterior effect probabilities (PEP) based on the variables averaged over. The odds are determined by taking the exponential of the product of the coefficient's posterior mean and the variable's standard deviation. Variables considered for inclusion in the model and not averaged over are indicated with "—".

Table 4: Comparing model specifications with non-traditional bank activities

	(1)		(2)		(3)	
	Full model		Stepwise		BIC	
	Odds	p-value	Odds	p-value	Odds	p-value
Stakeholder	1.149	0.001	1.146	0.001	—	—
Fee-for-service	1.039	0.580	—	—	—	—
Traditional fee	0.914	0.587	—	—	—	—
Net interest	1.162	0.218	—	—	—	—
Loans past due 30-89 days	1.322	< 0.001	1.350	< 0.001	1.410	< 0.001
Loans past due 90+ days	1.062	0.074	1.073	0.031	—	—
Nonaccrual loans	1.241	< 0.001	1.258	< 0.001	1.290	< 0.001
Foreclosed real estate	0.009	0.010	1.073	0.022	1.100	< 0.001
Equity	0.203	< 0.001	0.204	< 0.001	0.185	< 0.001
Net income	0.730	< 0.001	0.714	< 0.001	—	—
Securities	0.752	0.038	0.733	0.017	—	—
Loan loss reserves	1.090	0.173	—	—	—	—
Jumbo CDs	1.077	0.317	—	—	—	—
Cash	0.886	0.238	—	—	—	—
Demand deposits	0.870	0.274	—	—	—	—
Federal funds purchased	0.927	0.403	—	—	—	—
Volatile liability expense	1.097	< 0.001	1.098	< 0.001	—	—
Charge-offs	1.180	0.003	1.151	< 0.001	1.107	< 0.001
Brokered deposits	1.521	< 0.001	1.568	< 0.001	1.623	< 0.001
Non-interest expense	0.767	0.040	0.762	0.011	—	—
Insider loans	0.992	0.931	—	—	—	—
Dividends	0.600	0.110	—	—	—	—
Age	0.861	0.119	0.841	0.049		
Size	1.426	0.001	1.399	< 0.001	1.389	< 0.001
Provisions for loan losses	0.754	0.001	0.782	0.001	—	—
C & I loans	0.999	0.994	—	—	—	—
Consumer loans	0.405	< 0.001	0.431	< 0.001	0.382	< 0.001
Commercial real estate	0.788	0.013	0.803	0.016	—	—
Agriculture loans	1.058	0.761	—	—	—	—
Federal funds sold	1.028	0.769	—	—	—	—
Observations	63582		63582		63582	
BIC	-701039		-701165		-701217	
Bayes Factor	4.49×10^{38}		1.96×10^{11}			

The logit model specifications reported for the four quarter ahead predictions of bank failure are based on (1) the full set of standard controls, (2) the model chosen by stepwise selection, and (3) the model chosen by the Bayesian information criterion (BIC). The odds reported indicate the effect of a one-standard deviation change in a given variable. Variables not included in a given specification are indicated by "—". The Bayes factor reported compares the model chosen based on BIC, relative to either the full model (1) or stepwise model (2).

Table 5: A comparison of the timeliness of loan loss provisions measures

Scaling NPL with Total Assets	Observations	Mean	SD	P25	Median	P75
Timely (adjusted R^2)	6486	0.040	0.225	-0.077	0	0.116
Timely (R^2)	6486	0.113	0.129	0.022	0.066	0.158
Scaling NPL with Total Loans						
Timely (adjusted R^2)	6486	0.041	0.226	-0.077	0	0.115
Timely (R^2)	6486	0.113	0.129	0.022	0.066	0.158
Ng and Roychowdhury (2014)	6382	0.107	0.123	0.020	0.063	0.149

The table reports the mean and standard deviation (SD), along with the 25th (P25), 50th (median), and 75th (P75) percentiles for the distribution of the timeliness of provisions.

Table 6: Replicating the effects of allowances as regulatory capital on bank failure

	(1)	(2)	(3)	(4)	(5)	(6)
Allowance for loan loss (ALL)	0.200**			0.179**		
	(0.101)			(0.080)		
Total Capital	-0.253***			-0.236***		
	(0.034)			(0.030)		
ALL in tier 2 capital		0.933**	0.296		1.015**	0.306
		(0.454)	(0.602)		(0.427)	(0.564)
ALL not in tier 2		0.079	0.097		0.077	0.100
		(0.124)	(0.122)		(0.099)	(0.095)
Tier 1 capital		-0.251***	-0.248***		-0.238***	-0.234***
		(0.0340)	(0.034)		(0.030)	(0.030)
Other tier 2 capital		-0.021	-0.031		0.009	-0.014
		(0.174)	(0.176)		(0.150)	(0.152)
CAPINC			-1.441			-1.551*
			(0.969)			(0.899)
ALL in tier 2 X CAPINC			1.427*			1.531*
			(0.864)			(0.790)
Non-performing loans	0.217***	0.216***	0.221***	0.167***	0.165***	0.174***
	(0.036)	(0.036)	(0.036)	(0.029)	(0.029)	(0.029)
Change in NPL	0.038	0.033	0.025	0.015	0.014	0.006
	(0.041)	(0.041)	(0.041)	(0.031)	(0.031)	(0.030)
Timely	0.268	0.210	0.200	0.382	0.321	0.324
	(0.319)	(0.323)	(0.323)	(0.277)	(0.282)	(0.282)
ROA	-0.009	-0.014	-0.007	0.053	0.044	0.055
	(0.056)	(0.057)	(0.055)	(0.039)	(0.039)	(0.038)
Real estate loan	0.017	0.013	0.013	0.020**	0.016*	0.016*
	(0.010)	(0.010)	(0.010)	(0.009)	(0.008)	(0.008)
Loan concentration	0.027***	0.030***	0.030***	0.019**	0.022***	0.023***
	(0.010)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)
Uninsured deposit	0.026***	0.024***	0.024***	0.020***	0.019***	0.018***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Liquidity	-0.147***	-0.147***	-0.145***	-0.166***	-0.163***	-0.155***
	(0.039)	(0.040)	(0.039)	(0.037)	(0.037)	(0.037)
Overhead	-0.037	-0.035	-0.032	0.012	0.012	0.010
	(0.072)	(0.071)	(0.070)	(0.035)	(0.038)	(0.038)
Insider loan	-0.013	-0.014	-0.016	-0.026	-0.028	-0.030
	(0.052)	(0.052)	(0.052)	(0.047)	(0.047)	(0.046)
Total assets	-0.007	-0.014	-0.014	-0.006	-0.013	-0.012
	(0.017)	(0.020)	(0.020)	(0.015)	(0.018)	(0.018)
Midwest Region	1.434***	1.392***	1.400***	1.333***	1.297***	1.320***
	(0.454)	(0.455)	(0.458)	(0.432)	(0.432)	(0.433)
South Region	1.249***	1.199***	1.195***	1.150***	1.099**	1.091**
	(0.450)	(0.451)	(0.454)	(0.429)	(0.429)	(0.430)
West Region	2.238***	2.200***	2.193***	2.055***	2.012***	2.003***
	(0.462)	(0.463)	(0.466)	(0.436)	(0.436)	(0.437)
FED	0.216	0.211	0.210	0.006	0.005	-0.026
	(0.228)	(0.228)	(0.229)	(0.202)	(0.202)	(0.203)
OCC	0.376*	0.370*	0.366*	0.381**	0.366**	0.365**
	(0.193)	(0.194)	(0.194)	(0.172)	(0.173)	(0.172)
Intercept	-6.102***	-6.968***	-6.320***			
	(0.888)	(0.967)	(1.075)			

Columns 1-3 report estimates of coefficients and their standard errors in parentheses from a logit model and columns 4-6 report estimates from a Cox hazards model. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively. There are 6486 observations in the sample.

Table 7: Model risk and the effects of allowances on bank failure

Panel A: Logistic regression

	(1)			(2)			(3)		
	Coef	SE	PEP	Coef	SE	PEP	Coef	SE	PEP
Allowance for loan loss (ALL)	—	—	—						
Total Capital	-0.164	0.034	100						
ALL in tier 2 capital				—	—	—	—	—	—
ALL not in tier 2				—	—	—	—	—	—
Tier 1 capital				-0.168	0.033	100	-0.168	0.033	100
Other tier 2 capital				—	—	—	—	—	—
CAPINC							—	—	—
ALL in tier 2 X CAPINC							—	—	—
Timely	—	—	—	—	—	—	—	—	—
Loans past due 30-89 days	37.796	5.768	100	37.962	5.759	100	37.962	5.759	100
Loans past due 90+ days	3.646	11.490	10.8	3.508	11.341	10.3	3.508	11.341	10.3
Nonaccrual loans	18.450	5.810	97.4	18.447	5.919	97.4	18.447	5.919	97.4
Foreclosed real estate	0.161	1.881	0.9	0.149	1.815	0.8	0.149	1.815	0.8
Net income	0.348	2.162	3.2	0.308	2.022	2.9	0.308	2.022	2.9
Securities	-0.027	0.237	1.6	-0.014	0.168	0.9	-0.014	0.168	0.9
Jumbo CDs	0.416	0.914	19.7	0.506	0.996	23.4	0.506	0.996	23.4
Cash	-5.217	7.081	40.1	-6.234	7.388	47.2	-6.234	7.388	47.2
Demand deposits	-3.540	3.414	57.2	-2.974	3.333	49.2	-2.974	3.333	49.2
Federal funds purchased	—	—	—	—	—	—	—	—	—
Volatile liability expense	—	—	—	—	—	—	—	—	—
Charge-offs	-92.702	25.091	100	-88.092	28.060	97.8	-88.092	28.060	97.8
Brokered deposits	1.212	0.199	100	1.210	0.199	100	1.210	0.199	100
Non-interest expense	—	—	—	—	—	—	—	—	—
Insider loans	-0.454	2.402	4.3	-0.355	2.134	3.4	-0.355	2.134	3.4
Dividends	—	—	—	—	—	—	—	—	—
Age	-0.008	0.002	99.1	-0.008	0.002	98.8	-0.008	0.002	98.8
Size	0.005	0.033	3	—	—	—	—	—	—
Provisions for loan losses	108.723	23.432	100	103.506	26.846	98.8	103.506	26.846	98.8
C & I loans	-0.020	0.218	1.1	-0.044	0.331	2.1	-0.044	0.331	2.1
Consumer loans	-20.318	4.139	100	-20.552	4.136	100	-20.552	4.136	100
Commercial Real Estate	-2.047	1.406	74.5	-2.218	1.383	78.6	-2.218	1.383	78.6
Agriculture loans	-3.791	3.391	62.4	-4.089	3.318	67.7	-4.089	3.318	67.7
Federal funds sold	0.029	0.358	0.8	—	—	—	—	—	—
Intercept	-0.853	0.810	100	-0.902	0.592	100	-0.902	0.592	100

Observations	6466	6466	6466
Models Averaged over	44	40	40
Posterior model probability	13%	14%	14%

Table 7 continued

Panel B: Cox proportional hazard model

	(1)			(2)			(3)		
	Coef	SE	PEP	Coef	SE	PEP	Coef	SE	PEP
Allowance for loan loss (ALL)	0.000	0.011	0.7						
Total Capital	-0.178	0.030	100						
ALL in tier 2 capital				0.170	0.375	21.7	0.159	0.365	20.3
ALL not in tier 2				-0.003	0.031	1.9	-0.003	0.030	1.8
Tier 1 capital				-0.182	0.030	100	-0.182	0.030	100
Other tier 2 capital				0.000	0.012	0.6	0.000	0.011	0.6
CAPINC							-0.086	0.397	5.9
ALL in tier 2 X CAPINC							0.073	0.340	5.6
Timely	0.005	0.053	1.8	0.004	0.045	1.4	0.003	0.043	1.3
Loans past due 30-89 days	23.275	3.806	100	23.417	3.801	100	23.396	3.797	100
Loans past due 90+ days	28.427	7.701	99.4	27.853	7.885	99	27.835	7.854	99
Nonaccrual loans	17.675	3.329	100	17.456	3.347	100	17.432	3.348	100
Foreclosed real estate	1.934	4.979	16.5	1.802	4.821	15.4	1.742	4.748	14.9
Net income	2.191	3.862	28.7	2.000	3.736	26.3	1.908	3.669	25.2
Securities	-0.232	0.623	16	-0.130	0.472	9.6	-0.122	0.458	9
Jumbo CDs	0.100	0.353	10.1	0.122	0.392	11.6	0.118	0.387	11.3
Cash	-7.434	5.798	72.5	-7.835	5.714	75.9	-7.957	5.699	76.7
Demand deposits	-1.611	2.247	40.6	-1.275	2.061	33.7	-1.248	2.048	33
Federal funds purchased	0.000	0.119	0.7	0.000	0.110	0.6	0.000	0.107	0.5
Volatile liability expense	-0.022	0.287	1.5	-0.019	0.264	1.2	-0.018	0.256	1.2
Charge-offs	-62.688	14.369	100	-60.753	14.751	100	-60.593	14.762	100
Brokered deposits	1.172	0.181	100	1.162	0.180	100	1.161	0.180	100
Non-interest expense	0.019	0.348	0.9	0.017	0.325	0.7	0.016	0.314	0.7
Insider loans	-9.829	6.470	80.1	-9.474	6.514	78.1	-9.615	6.478	79.1
Dividends	0.004	1.698	1.5	0.001	1.525	1.2	0.001	1.475	1.2
Age	-0.008	0.002	100	-0.008	0.002	100	-0.008	0.002	100
Size	0.002	0.016	2.6	0.000	0.006	0.7	0.000	0.006	0.7
Provisions for loan losses	60.339	11.894	100	57.752	12.556	100	57.421	12.623	100
C & I loans	-0.034	0.240	3.4	-0.048	0.286	4.3	-0.045	0.277	4
Consumer loans	-18.356	3.639	100	-18.559	3.649	100	-18.573	3.648	100

Commercial real estate	-2.891	0.693	100	-2.938	0.694	100	-2.944	0.694	100
Agriculture loans	-6.123	1.991	100	-6.048	1.976	100	-6.070	1.979	100
Federal funds sold	0.098	0.572	4.4	0.071	0.478	3.4	0.066	0.463	3.2
Observations	6466			6466			6466		
Models Averaged over	66			89			98		
Posterior model probability	11%			9%			8%		

Panel A contains estimates from a static logit model of bank failure in the period 2008-2010 based on controls from year-end 2007. The models averaged over in columns 2 and 3 are the same as the indicator variable (CAPINC) and its interaction with allowances in tier 2 capital are not included in the models averaged over in column 3. Panel B contains estimates from a Cox proportional hazard model, where time to failure in the period 2008-2010 is measured as of year-end 2007 and time invariant covariates measured at year-end 2007 are used. BMA estimates reported include the posterior mean (Coef), standard deviation (SE), and effect probabilities (PEP) of the variables averaged over. Variables considered for inclusion in the model and not averaged over are indicated with "—".

Table 8: Comparing model specifications with capital components

	(1) Full model	(2) Stepwise	(3) BIC
ALL in tier 2 capital	0.7448*	0.7299*	—
	(0.4435)	(0.4404)	—
ALL not in tier 2	0.3148*	0.2986*	—
	(0.1824)	(0.1727)	—
Tier 1 capital	-0.1932***	-0.1729***	-0.1897***
	(0.0378)	(0.0328)	(0.0318)
Other tier 2 capital	-0.0507	—	—
	(0.1794)	—	—
Timely	0.3193	—	—
	(0.3299)	—	—
Loans past due 30-89 days	30.6803***	31.8027***	40.3342***
	(6.0317)	(5.9789)	(5.3275)
Loans past due 90+ days	34.1780**	34.1287**	—
	(14.2823)	(14.2235)	—
Nonaccrual loans	20.8754***	20.2455***	29.4379***
	(5.4086)	(5.2768)	(4.3306)
Foreclosed real estate	14.4181	—	—
	(9.2605)	—	—
Net income	9.2895	—	—
	(7.3570)	—	—
Securities	-1.7934*	-2.2849**	—
	(0.9964)	(0.9480)	—
Jumbo CDs	2.0453**	2.2640***	—
	(0.8532)	(0.8184)	—
Cash	-10.5412**	-11.9860***	-14.1636***
	(4.6652)	(4.4802)	(4.6361)
Demand deposits	-2.9527	—	—
	(2.0483)	—	—
Federal funds purchased	0.3042	—	—
	(1.4414)	—	—
Volatile liability expense	-1.2551	—	—
	(2.9902)	—	—
Charge-offs	-7.7450	—	—
	(17.3027)	—	—
Brokered deposits	1.1466***	1.1448***	1.2767***
	(0.1992)	(0.1950)	(0.1906)
Non-interest expense	3.3457	—	—
	(3.5329)	—	—

Insider loans	-9.5592*	-9.8022*	—
	(5.4422)	(5.3737)	—
Dividends	-10.5579	—	—
	(14.2222)	—	—
Age	-0.0089***	-0.0093***	-0.0090***
	(0.0023)	(0.0022)	(0.0021)
Size	0.0953	0.1290*	—
	(0.0819)	(0.0688)	—
C & I loans	-1.8097*	-2.0711**	—
	(0.9924)	(0.9681)	—
Consumer loans	-20.0556***	-21.1395***	-21.5559***
	(3.9533)	(3.8866)	(3.8996)
Commercial Real Estate	-3.2305***	-3.5905***	-3.1876***
	(0.8291)	(0.8065)	(0.7748)
Agriculture loans	-5.3423**	-5.6699***	-6.0966***
	(2.0981)	(2.0626)	(2.0351)
Federal funds sold	2.4435	—	—
	(1.8101)	—	—
Intercept	-1.9704	-2.4215*	-0.2950
	(1.4214)	(1.2559)	(0.4877)
Observations	6466	6466	6466
BIC	-55200	-55288	-55320
Bayes Factor	1.14×10^{26}	8.89×10^{6}	

The static logit model specifications of bank failure are based on (1) the full set of standard controls, (2) the model chosen by stepwise selection, and (3) the model chosen by the Bayesian information criterion (BIC). Controls from year-end 2007 are used to predict whether a bank fails in the period 2008-2010. Variables not included in a given specification are indicated by "—". The Bayes factor reported compares the model chosen based on BIC, relative to the either the full model (1) or stepwise model (2). ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 9: Replicating the effects of a Big 4 auditor on bank failure

	(1)	(2)
Big 4 Auditor (BIG4)	-0.534***	-0.608**
	(0.139)	(0.287)
Tier 1 capital (CAP)	-16.483***	-15.784***
	(1.507)	(3.088)
Nonperforming loans (NPL)	15.860***	27.063***
	(3.550)	(6.289)
Provisions for loan losses (LLP)	339.897***	276.482***
	(28.659)	(42.296)
Growth in C & I loans (GCOMM)	10.311***	19.409***
	(3.043)	(5.955)
Growth in real estate loans (GRESTATE)	10.943***	8.435
	(2.512)	(5.184)
Growth in total loans (GLOANS)	-5.297**	-5.644
	(2.305)	(4.565)
LOAN_MIX	-46.325***	-78.784***
	(10.238)	(21.878)
SIZE	0.274***	0.290***
	(0.032)	(0.064)
PUBLIC	-0.121	0.057
	(0.107)	(0.212)
Intercept	-4.930***	-5.698***
	(0.481)	(0.971)
Quarter fixed effects	YES	NO
Log-likelihood	-3086	-754
Pseudo-R2	0.11	0.13
# of observations	23626	5813

Logit model estimates of whether a bank fails in the period 2007 - 2010. Column 1 uses controls from each of the four quarters in 2006, i.e. observations that are not independent for a given bank, similar to Jin et al. (2011). In column 2 we use controls from only quarter 4, i.e. observations that are independent. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 10: Model risk and the effects of auditor on bank failure

	(1)		
	Coef	SE	PEP
Big 4 Auditor (BIG4)	—	—	—
Loans past due 30-89 days	—	—	—
Loans past due 90+ days	0.860	6.257	2.4
Nonaccrual loans	2.146	7.868	8.1
Foreclosed real estate	—	—	—
Equity	—	—	—
Net income	30.299	13.007	90.7
Securities	-0.602	1.140	25
Loan loss reserves	—	—	—
Jumbo CDs	1.697	1.273	70.3
Cash	—	—	—
Demand deposits	-6.862	2.137	96.8
Federal funds purchased	—	—	—
Volatile liability expense	-1.179	5.026	6.4
Charge-offs	—	—	—
Brokered deposits	1.081	0.205	100
Non-interest expense	—	—	—
Insider loans	-0.165	1.360	1.9
Dividends	-0.950	5.957	3.2
Age	-0.009	0.002	100
Size	0.022	0.069	10.2
Provisions for loan losses	247.561	49.005	100
C & I loans	-0.050	0.410	1.7
Commercial real estate	-0.657	1.115	29.5
Consumer loans	-21.390	3.976	100
Agriculture loans	-0.639	1.688	15
Federal funds sold	—	—	—
Intercept	-3.307	0.945	100
Observations	5804		
Models Averaged over	30		
Posterior model probability	0.22		

BMA estimates of the static logit model for whether a bank fails in the period 2007 - 2010, using controls from year-end 2006. BMA estimates reported include the posterior mean (Coef), standard deviation (SE), and effect probabilities (PEP) of the variables averaged over. Variables considered for inclusion in the model and not averaged over are indicated with "—".

Table 11: Comparing model specifications with a Big 4 auditor

	(1)	(2)	(3)
	Full model	Stepwise	BIC
Big 4 Auditor (BIG4)	-0.3537	-0.4647*	—
	(0.2811)	(0.2765)	—
Loans past due 30-89 days	-4.7977	—	—
	(10.4559)	—	—
Loans past due 90+ days	39.1000*	35.7166*	—
	(21.0084)	(19.1792)	—
Nonaccrual loans	29.3917**	28.8837**	—
	(12.3887)	(11.4933)	—
Foreclosed real estate	24.0413	—	—
	(25.7790)	—	—
Equity	-4.1417	—	—
	(2.7966)	—	—
Net income	32.4416***	26.7171***	33.5924***
	(10.9934)	(9.4850)	(8.7054)
Securities	-3.2571***	-3.3356***	—
	(0.9363)	(0.8956)	—
Loan loss reserves	23.9653	—	—
	(32.6019)	—	—
Jumbo CDs	2.3444***	2.3322***	2.3464***
	(0.8231)	(0.8092)	(0.7392)
Cash	-7.4096*	-6.5760*	—
	(3.9133)	(3.7708)	—
Demand deposits	-4.2881**	-3.8292**	-7.1841***
	(1.8598)	(1.8347)	(1.6480)
Federal funds purchased	2.2967*	2.4418*	—
	(1.3558)	(1.3835)	—
Volatile liability expense	-23.0870**	-22.2046**	—
	(9.9212)	(9.4595)	—
Charge-offs	-82.4110	—	—
	(63.4463)	—	—
Brokered deposits	0.8227***	0.8711***	1.0616***
	(0.2010)	(0.2002)	(0.1917)
Non-interest expense	8.0335	—	—
	(5.8608)	—	—
Insider loans	-6.6667	—	—
	(4.9857)	—	—
Dividends	-21.7049	—	—
	(16.4021)	—	—

Age	-0.0085***	-0.0091***	-0.0088***
	(0.0023)	(0.0022)	(0.0021)
Size	0.1526*	0.1676**	—
	(0.0844)	(0.0794)	—
Provisions for loan losses	213.8735***	188.4704***	249.4749***
	(59.9248)	(49.7367)	(44.3209)
C & I loans	-1.9980*	-2.1136**	—
	(1.0812)	(1.0695)	—
Commercial real estate	-3.4310***	-3.3530***	—
	(0.8374)	(0.8168)	—
Consumer loans	-20.8339***	-21.1245***	-20.8427***
	(4.0117)	(3.8634)	(3.8377)
Agriculture loans	-3.9375**	-4.1824**	—
	(1.8456)	(1.8247)	—
Federal funds sold	-2.8823	-3.2391*	—
	(1.8128)	(1.7559)	—
Intercept	-2.6058*	-3.0070***	-3.4889***
	(1.3485)	(1.1464)	(0.3271)
Observations	5804	5804	5804
BIC	-48777	-48836	-48883
Bayes Factor	1.04×10^{23}	1.61×10^{10}	

The static logit model specifications of bank failure are based on (1) the full set of standard controls, (2) the model chosen by stepwise selection, and (3) the model chosen by the Bayesian information criterion (BIC). Controls from year-end 2006 are used to predict whether a bank fails in the period 2007-2010. Variables not included in a given specification are indicated by "—". The Bayes factor reported compares the model chosen based on BIC, relative to the either the full model (1) or stepwise model (2). ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Appendix Table 1: Series used to construct the control variables for the non-traditional income model

Variable	Call report series or description
Stakeholder Income	((RIADA220 + RIADC888 + RIADC386 + RIADB491 +RIADB493) x 4/quarter)/RCFD2170 x 1000
Fee-for-Service Income	((RIADC886 + RIADC387 + RIADB492) x 4/quarter)/RCFD2170 x 1000
Traditional Fee Income	((RIADC887 + RIAD4070 + RIAD4080 + RIAD5416 + RIAD5415 + RIADB496 + RIADB497) x 4/quarter)/RCFD2170 x 1000
Net Interest Income	(RIAD4074 x 4/quarter)/RCFD2170 x 1000
Liquidity	(RCFD1754 + RCFD1773 + RCFD0010)/RCFD2948
Loan Concentration	$(RCFD1410/RCFD2122)^2 + (RCFD1766/RCFD2122)^2 + (RCFD1590/RCFD2122)^2 + (RCFD1288/RCFD2122)^2 + (RCFD1975/RCFD2122)^2 + (RCFD2081/RCFD2122)^2$
Cost Inefficiency	(RIAD4093 x 4/QUARTER)/RCFD2170
ROA	(RIAD4340 x 4/QUARTER)/RCFD2170
Nonperforming Loan	(RCFD1407 + RCFD1403)/RCFD2170
Equity	RCFD3210/RCFD2170
Assets	LN(RCFD2170)
MBHC	1 if bank is member of multi-bank holding company
Age	Based on establishment date (RSSD9950). Natural log is used of age.
Brokered Deposits	RCON2365/RCFD2170
Core Deposits	(RCFD2200 - RCON2604 - RCON2343)/RCFD2170
Goodwill	RCFD3163/RCFD2170
CRE Loans	RCON1480/RCFD2170
C&D Loans	RCON1415/RCFD2170
Multifamily Mortgage	RCON1460/RCFD2170
Business Loans	RCFD1766/RCFD2170
Income Growth†	Quarterly growth in state-level personal income (seasonally adjusted). Source: Bureau of Economic Analysis
Unemployment†	Quarterly state-level unemployment rate (seasonally adjusted). Source: Bureau of Labor Statistics.
Home Price Growth†	Quarterly growth in state-level home prices (seasonally adjusted). Source: Federal Housing Finance Agency

†Torna (September 5, 2019) indicated in a personal communication the macro series DeYoung and Torna (2013) use are the residuals from a state-level regression of the series in question on four quarterly indicators. The regressions we use are over the period 1990-2010 for income and unemployment, and 1991-2010 for the home price. Quarterly housing price data from the Federal Housing Finance Agency quarterly data begin in 1991.

Appendix Table 2: Summary statistics of the non-traditional income samples (All banks)

	Replication Sample	
	Mean	Std. Dev.
Stakeholder Income	0.039	0.316
Fee-for-Service Income	0.422	0.967
Traditional Fee Income	6.804	11.140
Net Interest Income	35.112	8.712
Liquidity	0.290	0.158
Loan Concentration	0.587	0.180
Cost Inefficiency	0.031	0.013
ROA	0.005	0.016
Nonperforming Loan	0.016	0.022
Equity	0.105	0.034
Assets	486343	2193155
MBHC	0.178	0.383
Age	74.711	41.286
Brokered Deposits	0.035	0.075
Core Deposits	0.640	0.117
Goodwill	0.004	0.013
CRE Loans	0.162	0.113
C&D Loans	0.065	0.075
Multifamily Mortgage	0.015	0.026
Business Loans	0.092	0.068
Income Growth	-0.917	1.902
Unemployment	1.998	1.994
Home Price Growth	-1.718	1.856
Observations	62823	

Summary statistics of the quarterly observations from 2008:Q1 - 2010:Q2 from our replication of DeYoung and Torna (2013).

Appendix Table 3: BMA estimates of non-traditional banking activities using an alternative set of controls.

	(1)		(2)		(3)	
	Four quarters		Five quarters		Six quarters	
	Odds	PEP	Odds	PEP	Odds	PEP
Stakeholder	—	—	1.123	64.6	1.150	77.8
Fee-for-service	—	—	—	0	—	—
Traditional fee	—	—	0.991	2.4	—	—
Net interest	—	—	—	0	—	—
Liquidity	—	—	0.996	1.3	—	—
Loan concentration	—	—	—	0	—	—
Cost inefficiency	—	—	—	0	—	—
ROA	0.997	3.6	—	0	—	—
Nonperforming loan	1.373	100	1.396	100	1.365	100
Equity	0.084	100	0.106	100	0.186	100
Log (Assets)	—	—	—	—	—	—
MBHC	—	—	0.990	5.2	—	—
Log (Age)	—	—	—	—	—	—
Brokered deposits	1.194	100	1.245	100	1.304	100
Core deposits	—	—	—	—	—	—
Goodwill	2.482	100	2.263	100	1.996	100
CRE loans	—	—	—	—	—	—
C&D loans	1.677	100	1.767	100	1.808	100
Multifamily mort.	1.123	78.4	1.056	42.3	1.113	79.2
Business loans	1.008	4	—	—	—	—
Income growth	0.992	19.5	—	—	—	—
Unemployment rate	1.002	6	1.009	22	—	—
Home price growth	0.955	100	0.937	100	0.932	100
Number of banks	6708		6785		6861	
Observations	63696		64195		64742	
Models averaged over	14		21		3	
Posterior model probability	0.26		0.16		0.57	

The pooled logit model uses a panel of quarterly bank data to predict failures in the indicated quarter ahead during 2007:Q3 - 2010:Q4. BMA estimates reported include the odds and posterior effect probabilities (PEP) based on the variables averaged over. The odds are determined by taking the exponential of the product of the coefficient's posterior mean and the variable's standard deviation. Variables considered for inclusion in the model and not averaged over are indicated with "—". The specification also considered for inclusion the quarterly time indicators that are not reported.

Appendix Table 4 : Call report series used to construct variables for the addbacks to loan loss model

Variable	Call report series
LLR	RCFD3123/RCFDA223
ADDBACK	RCFD5310/RCFDA223
OTHERLLR	(RCFD3123 - RCFD5310)/RCFDA223
TOTAL CAPITAL	(RCFD3792)/RCFDA223
TIER1	RCFD8274/RCFDA223
OTHER TIER2	(RCFD8275 - RCFD5310)/RCFDA223
NPL	(RCFD1407 + RCFD1403 + RCFD1406)/RCFD2122
CH_NPL	NPL - L.NPL
TIMELY*	See text.
ROA	RIAD4301/((RCFD2170 + L.RCFD2170)/2)
REAL ESTATE LOAN	RCFD1410/RCFD2122
LOAN CONCENTRATION	$[(RCFD1410/RCFD2122)^2 + (RCFD1766/RCFD2122)^2 + (RCFD1590/RCFD2122)^2 + (RCFD1288/RCFD2122)^2 + (RCFD1288/RCFD2122)^2 + (RCFD2081/RCFD2122)^2]*100$
UNINSURED DEPOSIT	RCONF051 + RCONF047)/(RCONF051 + RCONF047 + RCONF049 + RCONF045)
LIQUIDITY	(RCFD0010)/RCFD2200
OVERHEAD	RIAD4093/RCFD2170
INSIDER LOAN	RCFD6164/RCFD2170
TOTAL ASSETS	RCFD2170/1000000
NORTHEAST	RSSD9200 {CT ME MA NH RI VT NJ NY PA}
MIDWEST	RSSD9200 { IN IL MI OH WI IA KS MN MO NE ND SD}
SOUTH	RSSD9200 {DE DC FL GA MD NC SC VA WV AL KY MS TN AR LA OK TX}
WEST	RSSD9200 {AZ CO ID NM WA MT UT NV WY AK CA HI OR}

Ng and Roychowdhury (2014) indicate they create the TIMELY variable using the specification used by Beatty and Liao (2011). Beatty and Liao (2011 scale nonperforming loans by total loans, whereas Ng and Roychowdhury (2014) indicate they scale by total assets. As we also note in the text it appeared possible that Ng and Roychowdhury (2014) used the difference in R2 in calculating the TIMELY variable, rather than the adjusted R2 used by Beatty and Liao (2011). The measure used here is based on scaling nonperforming loans by total loans and the difference in adjusted R2.

Appendix Table 5 : Summary statistics of loan loss reserve sample

	Replication Sample	
	Mean	Std. Dev.
FAIL	0.035	0.185
Allowance for loan loss (LLR)	1.205	0.634
ALL in tier 2 capital (ADDBACK)	1.039	0.238
ALL not in tier 2 (OTHERLLR)	0.165	0.518
TOTAL CAPITAL	16.062	10.005
TIER1	14.958	10.021
OTHER TIER2	0.065	0.407
Nonperforming loans (NPL)	2.809	2.730
Change in NPL (CH_NPL)	0.633	2.476
TIMELY	0.041	0.254
ROA	1.249	1.354
REAL ESTATE LOAN	68.668	19.071
LOAN CONCENTRATION	0.576	0.179
UNINSURED DEPOSIT	40.059	15.209
LIQUIDITY	19.124	743.095
OVERHEAD	3.126	4.305
INSIDER LOAN	1.358	1.524
TOTAL ASSETS	1.657	30.394
NORTHEAST	0.089	0.285
MIDWEST	0.436	0.496
SOUTH	0.367	0.482
WEST	0.108	0.311
FDIC	0.662	0.473
FED	0.121	0.326
OCC	0.217	0.412
Number of Observations	6486	

Summary statistics of the annual observations from year-end 2007 from our replication attempt of Ng and Roychowdhury (2014). The variable FAIL refers to a bank that fails in the period 2008-2010.

Appendix Table 6: Effects of loan losses with alternative controls

Panel A: Logistic regression

	(1)			(2)			(3)		
	Coef	SE	PEP	Coef	SE	PEP	Coef	SE	PEP
Allowance for loan loss (ALL)	—	—	—						
Total Capital	-0.255	0.032	100						
ALL in tier 2 capital				0.227	0.478	21.4	0.227	0.478	21.4
ALL not in tier 2				—	—	—	—	—	—
Tier 1 capital				-0.256	0.031	100	-0.256	0.031	100
Other tier 2 capital				—	—	—	—	—	—
CAPINC							—	—	—
ALL in tier 2 X CAPINC							—	—	—
Nonperforming loans	0.261	0.019	100	0.256	0.020	100	0.256	0.020	100
Change in NPL	—	—	—	—	—	—	—	—	—
Timely	—	—	—	—	—	—	—	—	—
ROA	—	—	—	—	—	—	—	—	—
Real estate loan	0.004	0.011	12.8	0.005	0.013	16.2	0.005	0.013	16.2
Loan concentration	0.033	0.011	91.7	0.031	0.013	88.1	0.031	0.013	88.1
Uninsured deposit	0.025	0.005	100	0.024	0.005	100	0.024	0.005	100
Liquidity	-0.154	0.038	100	-0.154	0.038	100	-0.154	0.038	100
Overhead	—	—	—	—	—	—	—	—	—
Insider loan	—	—	—	—	—	—	—	—	—
Total assets	—	—	—	—	—	—	—	—	—
Midwest Region	0.125	0.421	9.0	0.097	0.374	6.9	0.097	0.374	6.9
South Region	0.114	0.386	9.0	0.087	0.342	6.9	0.087	0.342	6.9
West Region	1.111	0.406	100	1.085	0.370	100	1.085	0.370	100
FED	—	—	—	—	—	—	—	—	—
OCC	—	—	—	—	—	—	—	—	—
Intercept	-4.121	0.773	100	-4.581	0.866	100	-4.581	0.866	100
Observations	6466			6466			6466		
Models Averaged over	4			6			6		
Posterior model probability	78%			58%			58%		

Appendix Table 6 continued

Panel B: Cox proportional hazard model

	(1)			(2)			(3)		
	Coef	SE	PEP	Coef	SE	PEP	Coef	SE	PEP
Allowance for loan loss (ALL)	0.018	0.061	11.9						
Total Capital	-0.232	0.029	100						
ALL in tier 2 capital				0.864	0.568	80.1	0.628	0.619	58.5
ALL not in tier 2				0.000	0.014	2	0.000	0.012	1.7
Tier 1 capital				-0.233	0.028	100	-0.231	0.028	100
Other tier 2 capital				0.000	0.016	1.2	0.000	0.016	1.2
CAPINC							-0.548	0.965	29.9
ALL in tier 2 X CAPINC							0.528	0.896	32.2
Nonperforming loans	0.184	0.013	100	0.176	0.013	100	0.176	0.013	100
Change in NPL	0.000	0.005	2.5	0.000	0.005	2.1	0.000	0.005	1.8
Timely	0.052	0.170	11.8	0.033	0.135	8.5	0.032	0.133	8.2
ROA	0.000	0.005	2.3	0.001	0.010	3.3	0.001	0.008	2.7
Real estate loan	0.006	0.011	31	0.008	0.011	46.3	0.005	0.009	37.2
Loan concentration	0.029	0.010	93.6	0.027	0.011	92.6	0.029	0.009	96.8
Uninsured deposit	0.018	0.004	100	0.017	0.004	100	0.017	0.004	100
Liquidity	-0.158	0.036	100	-0.156	0.036	100	-0.153	0.036	100
Overhead	0.000	0.007	2.3	0.000	0.007	1.9	0.000	0.007	1.7
Insider loan	0.000	0.007	2.2	0.000	0.006	1.4	0.000	0.006	1.3
Total assets	0.000	0.003	2.9	-0.001	0.006	5.2	-0.001	0.005	4.7
Midwest Region	1.089	0.633	84.2	0.909	0.676	74.8	0.946	0.670	76.9
South Region	0.960	0.596	81.7	0.784	0.628	69.7	0.806	0.621	72
West Region	1.890	0.584	100	1.722	0.615	100	1.742	0.610	100
FED	-0.001	0.030	2.2	-0.001	0.024	1.3	-0.001	0.026	1.4
OCC	0.157	0.217	41	0.111	0.191	30.7	0.115	0.193	31.8
Observations	6466			6466			6466		
Models Averaged over	35			59			93		
Posterior model probability	18%			10%			7%		

Panel A contains estimates from a static logit model of bank failure in the period 2008-2010 based on controls from year-end 2007. The models averaged over in columns 2 and 3 are the same as the indicator variable (CAPINC) and its interaction with allowances in tier 2 capital are not included in the models averaged over in column 3. Panel B contains estimates from a Cox proportional hazard model, where time to failure in the period 2008-2010 is measured as of year-end 2007 and time invariant covariates measured at year-end 2007 are used. BMA estimates reported include the posterior mean (Coef), standard deviation (SE), and effect probabilities (PEP) of the variables averaged over. Variables considered for inclusion in the model and not averaged over are indicated with "—".

Appendix Table 7: The uncertain effects of allowances on bank failure

Panel A: Logistic regression

	(1)			(2)			(3)		
	Coef	SE	PEP	Coef	SE	PEP	Coef	SE	PEP
Allowance for loan loss (ALL)	—	—	—						
Total Capital	-0.164	0.034	100						
ALL in tier 2 capital				—	—	—	—	—	—
ALL not in tier 2				—	—	—	—	—	—
Tier 1 capital				-0.168	0.033	100	-0.168	0.033	100
Other tier 2 capital				—	—	—	—	—	—
CAPINC							—	—	—
ALL in tier 2 X CAPINC							—	—	—
Timely	—	—	—	—	—	—	—	—	—
Loans past due 30-89 days	37.796	5.768	100	37.962	5.759	100	37.962	5.759	100
Loans past due 90+ days	3.646	11.490	10.8	3.508	11.341	10.3	3.508	11.341	10.3
Nonaccrual loans	18.450	5.810	97.4	18.447	5.919	97.4	18.447	5.919	97.4
Foreclosed real estate	0.161	1.881	0.9	0.149	1.815	0.8	0.149	1.815	0.8
Net income	0.348	2.162	3.2	0.308	2.022	2.9	0.308	2.022	2.9
Securities	-0.027	0.237	1.6	-0.014	0.168	0.9	-0.014	0.168	0.9
Jumbo CDs	0.416	0.914	19.7	0.506	0.996	23.4	0.506	0.996	23.4
Cash	-5.217	7.081	40.1	-6.234	7.388	47.2	-6.234	7.388	47.2
Demand deposits	-3.540	3.414	57.2	-2.974	3.333	49.2	-2.974	3.333	49.2
Federal funds purchased	—	—	—	—	—	—	—	—	—
Volatile liability expense	—	—	—	—	—	—	—	—	—
Charge-offs	-92.702	25.091	100	-88.092	28.060	97.8	-88.092	28.060	97.8
Brokered deposits	1.212	0.199	100	1.210	0.199	100	1.210	0.199	100
Non-interest expense	—	—	—	—	—	—	—	—	—
Insider loans	-0.454	2.402	4.3	-0.355	2.134	3.4	-0.355	2.134	3.4
Dividends	—	—	—	—	—	—	—	—	—
Age	-0.008	0.002	99.1	-0.008	0.002	98.8	-0.008	0.002	98.8
Size	0.005	0.033	3	—	—	—	—	—	—
Provisions for loan losses	108.723	23.432	100	103.506	26.846	98.8	103.506	26.846	98.8
C & I loans	-0.020	0.218	1.1	-0.044	0.331	2.1	-0.044	0.331	2.1
Consumer loans	-20.318	4.139	100	-20.552	4.136	100	-20.552	4.136	100

Commercial Real Estate	-2.047	1.406	74.5	-2.218	1.383	78.6	-2.218	1.383	78.6
Agriculture loans	-3.791	3.391	62.4	-4.089	3.318	67.7	-4.089	3.318	67.7
Federal funds sold	0.029	0.358	0.8	—	—	—	—	—	—
Intercept	-0.853	0.810	100	-0.902	0.592	100	-0.902	0.592	100
Observations	6466			6466			6466		
Models Averaged over	44			40			40		
Posterior model probability	13%			14%			14%		

Appendix Table 7 continued

Panel B: Cox proportional hazard model

	(1)			(2)			(3)		
	Coef	SE	PEP	Coef	SE	PEP	Coef	SE	PEP
Allowance for loan loss (ALL)	0.000	0.011	0.7						
Total Capital	-0.178	0.030	100						
ALL in tier 2 capital				0.170	0.375	21.7	0.159	0.365	20.3
ALL not in tier 2				-0.003	0.031	1.9	-0.003	0.030	1.8
Tier 1 capital				-0.182	0.030	100	-0.182	0.030	100
Other tier 2 capital				0.000	0.012	0.6	0.000	0.011	0.6
CAPINC							-0.086	0.397	5.9
ALL in tier 2 X CAPINC							0.073	0.340	5.6
Timely	0.005	0.053	1.8	0.004	0.045	1.4	0.003	0.043	1.3
Loans past due 30-89 days	23.275	3.806	100	23.417	3.801	100	23.396	3.797	100
Loans past due 90+ days	28.427	7.701	99.4	27.853	7.885	99	27.835	7.854	99
Nonaccrual loans	17.675	3.329	100	17.456	3.347	100	17.432	3.348	100
Foreclosed real estate	1.934	4.979	16.5	1.802	4.821	15.4	1.742	4.748	14.9
Net income	2.191	3.862	28.7	2.000	3.736	26.3	1.908	3.669	25.2
Securities	-0.232	0.623	16	-0.130	0.472	9.6	-0.122	0.458	9
Jumbo CDs	0.100	0.353	10.1	0.122	0.392	11.6	0.118	0.387	11.3
Cash	-7.434	5.798	72.5	-7.835	5.714	75.9	-7.957	5.699	76.7
Demand deposits	-1.611	2.247	40.6	-1.275	2.061	33.7	-1.248	2.048	33
Federal funds purchased	0.000	0.119	0.7	0.000	0.110	0.6	0.000	0.107	0.5
Volatile liability expense	-0.022	0.287	1.5	-0.019	0.264	1.2	-0.018	0.256	1.2

Charge-offs	-62.688	14.369	100	-60.753	14.751	100	-60.593	14.762	100
Brokered deposits	1.172	0.181	100	1.162	0.180	100	1.161	0.180	100
Non-interest expense	0.019	0.348	0.9	0.017	0.325	0.7	0.016	0.314	0.7
Insider loans	-9.829	6.470	80.1	-9.474	6.514	78.1	-9.615	6.478	79.1
Dividends	0.004	1.698	1.5	0.001	1.525	1.2	0.001	1.475	1.2
Age	-0.008	0.002	100	-0.008	0.002	100	-0.008	0.002	100
Size	0.002	0.016	2.6	0.000	0.006	0.7	0.000	0.006	0.7
Provisions for loan losses	60.339	11.894	100	57.752	12.556	100	57.421	12.623	100
C & I loans	-0.034	0.240	3.4	-0.048	0.286	4.3	-0.045	0.277	4
Consumer loans	-18.356	3.639	100	-18.559	3.649	100	-18.573	3.648	100
Commercial real estate	-2.891	0.693	100	-2.938	0.694	100	-2.944	0.694	100
Agriculture loans	-6.123	1.991	100	-6.048	1.976	100	-6.070	1.979	100
Federal funds sold	0.098	0.572	4.4	0.071	0.478	3.4	0.066	0.463	3.2
Observations	6466			6466			6466		
Models Averaged over	66			89			98		
Posterior model probability	11%			9%			8%		

Panel A contains estimates from a static logit model of bank failure in the period 2008-2010 based on controls from year-end 2007. The models averaged over in columns 2 and 3 are the same as the indicator variable (CAPINC) and its interaction with allowances in tier 2 capital are not included in the models averaged over in column 3. Panel B contains estimates from a Cox proportional hazard model, where time to failure in the period 2008-2010 is measured as of year-end 2007 and time invariant covariates measured at year-end 2007 are used. BMA estimates reported include the posterior mean (Coef), standard deviation (SE), and effect probabilities (PEP) of the variables averaged over. Variables considered for inclusion in the model and not averaged over are indicated with "—".

Appendix Table 8: Call report series used to construct variables for the auditor choice model

Variable	Call report series or description
BIG4*	TEXTC703 {DELOITTE & TOUCHE; ERNST & YOUNG; KPMG; PWC}
CAP	RCFD8274/RCFDA223
NPL	(RCFD1406 + RCFD1407 + RCFD1403)/L.RCFD2170
LLP	(RIAD4230)/L.RCFD2170
GCOMM	RCFD1766 - L.RCFD1766)/L.RCFD2170
GRESTATE	(RCFD1410 - L.RCFD1410)/L.RCFD2170
GLOANS	(RCFD2122 - L.RCFD2122)/L.RCFD2170
LOAN_MIX	(RCFD1600 + RCFD1606 + RCFD1607 + RCFD1608 + RCFD1609 + RCFD2081 + RCFD5389 + RCFD5390)/ RCON1400
SIZE	LN (RCFD2170)
PUBLIC	Bank or parent holding company is publicly traded based on New York Fed's RSSD to PERMCO link

* Variations of the names of the Big 4 were also used, e.g. DELOITTE, DELLOITTE AND TOUCHE, DELOITTE AND TOUCHE, LLC.

Appendix Table 9 : Comparison of auditor choice samples

	Jin et al. (2011)				Replication sample			
	Failed		Non failed		Failed		Non failed	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
BIG4	0.081	0.273	0.066	0.248	0.106	0.307	0.085	0.278
CAP	0.123	0.053	0.159	0.077	0.113	0.035	0.149	0.103
PSLOANS	0.240	0.428	0.201	0.401				
NPL	0.016	0.019	0.014	0.014	0.014	0.014	0.012	0.011
LLP	0.002	0.003	0.001	0.002	0.002	0.001	0.001	0.001
GCOMM	0.006	0.02	0.004	0.026	0.006	0.020	0.002	0.017
GRESTATE	0.0002	0.001	0.0001	0.001	0.034	0.051	0.013	0.034
GLOANS	0.014	0.051	0.013	0.102	0.041	0.059	0.017	0.043
LOAN_MIX	0.003	0.006	0.004	0.014	0.003	0.006	0.004	0.006
SIZE	12.515	1.289	11.827	1.285	12.696	1.253	11.948	1.316
PUBLIC	0.105	0.307	0.039	0.194	0.214	0.410	0.133	0.339
Observations	778		24650		796		22827	

Summary statistics of the quarterly observations from 2006 comparing the sample of Jin et al. (2011) and our replication attempt.   Failed banks refer to the sample of quarterly observations for a bank that failed in the period 2007-2010.

Appendix Table 10: Series used in the construction of LOAN_MIX

Series	Description	Reporting Forms
RCFD1600	COMMERCIAL AND INDUSTRIAL LOANS (TOTAL LOANS OUTSTANDING)	FR 2886b
RCFD1606	COMMERCIAL AND INDUSTRIAL LOANS - PAST DUE 30-89 DAYS AND STILL ACCRUING	FFIEC 002 & 031
RCFD1607	COMMERCIAL AND INDUSTRIAL LOANS - PAST DUE 90 DAYS OR MORE AND STILL ACCRUING	FFIEC 002 & 031
RCFD1608	COMMERCIAL AND INDUSTRIAL LOANS - NONACCRUAL	FFIEC 002 & 031
RCFD1609	COMMERCIAL AND INDUSTRIAL LOANS: RESTRUCTURED AND IN COMPLIANCE WITH MODIFIED TERMS	FFIEC 002 & 031
RCFD2081	LOANS TO FOREIGN GOVERNMENTS AND OFFICIAL INSTITUTIONS	FFIEC 002 & 031, FR 2886b
RCFD5389	LOANS TO FOREIGN GOVERNMENTS AND OFFICIAL INSTITUTIONS - PAST DUE 30 THROUGH 89 DAYS AND STILL ACCRUING	FFIEC 031
RCFD5390	LOANS TO FOREIGN GOVERNMENTS AND OFFICIAL INSTITUTIONS - PAST DUE 90 DAYS OR MORE AND STILL ACCRUING	FFIEC 031

The series listed were used to construct the numerator of the measure LOAN_MIX. Series descriptions and reporting forms for the analysis period are taken from the Data Dictionary in the Federal Reserve's Micro Data Reference Manual available at https://www.federalreserve.gov/data/mdrm.htm

Appendix Table 11: Series used in the construction of PSLOAN

Series	Description	Reporting Forms	Start Date	End Date
RCON1218	CREDIT CARDS AND RELATED PLANS - PAST DUE 30-89 DAYS AND STILL ACCRUING	FFIEC 033 & 034	3/31/1984	12/31/2000
RCON1219	CREDIT CARDS AND RELATED PLANS - PAST DUE 90 DAYS OR MORE AND STILL ACCRUING	FFIEC 033 & 034	3/31/1984	12/31/2000
RCON1220	CREDIT CARDS AND RELATED PLANS - NONACCRUAL	FFIEC 033 FFIEC 034	3/31/1984 6/30/1985	12/31/2000 12/31/2000
RCON1221	CREDIT CARDS AND RELATED PLANS - RENEGOTIATED "TROUBLED" DEBT	FFIEC 033 FFIEC 034	3/31/1984 6/30/1985	3/31/1986 3/31/1986
RCON1990	LOANS TO PURCHASE PRIVATE PASSENGER AUTOMOBILES ON INSTALLMENT BASIS	FFIEC 010	6/10/1959	12/31/1983
RCON2008	CREDIT CARDS AND RELATED PLANS	FFIEC 033 & 034	12/31/1967	12/31/2000
RCON3288	AVERAGE OF CREDIT CARDS AND RELATED PLANS	FFIEC 033 & 034	3/31/1984	12/31/2000
RCON5430	REAL ESTATE LOANS: SECURED BY 1-4 FAMILY RESIDENTIAL PROPERTIES: REVOLVING, OPEN-END LOANS SECURED BY 1-4 FAMILY RESIDENTIAL PROPERTIES AND EXTENDED UNDER LINES OF CREDIT - PAST DUE 30 THROUGH 89 DAYS AND STILL ACCRUING	FFIEC 033 & 034	3/31/1991	12/31/2000
RCON5431	REAL ESTATE LOANS: SECURED BY 1-4 FAMILY RESIDENTIAL PROPERTIES: REVOLVING, OPEN-END LOANS SECURED BY 1-4 FAMILY RESIDENTIAL PROPERTIES AND EXTENDED UNDER LINES OF CREDIT - PAST DUE 90 DAYS OR MORE AND STILL ACCRUING	FFIEC 033 & 034	3/31/1991	12/31/2000
RCON5432	REAL ESTATE LOANS: SECURED BY 1-4 FAMILY RESIDENTIAL PROPERTIES: REVOLVING, OPEN-END LOANS SECURED BY 1-4 FAMILY RESIDENTIAL PROPERTIES AND EXTENDED UNDER LINES OF CREDIT - NONACCRUAL	FFIEC 033 & 034	3/31/1991	12/31/2000
RCON5571	AMOUNT CURRENTLY OUTSTANDING OF COMMERCIAL AND INDUSTRIAL LOANS TO U.S. ADDRESSEES (IN DOMESTIC OFFICES) WITH ORIGINAL AMOUNTS OF $100,000 OR LESS	FFIEC 002, 031, & 041	3/31/2001	12/31/9999
RCON5573	AMOUNT CURRENTLY OUTSTANDING OF COMMERCIAL AND INDUSTRIAL LOANS TO U.S. ADDRESSEES (IN DOMESTIC OFFICES) WITH ORIGINAL AMOUNTS OF MORE THAN $100,000 THROUGH $250,000	FFIEC 002, 031, & 041	3/31/2001	12/31/9999
RCON5575	AMOUNT CURRENTLY OUTSTANDING OF COMMERCIAL AND INDUSTRIAL LOANS TO U.S. ADDRESSEES (IN DOMESTIC OFFICES) WITH ORIGINAL AMOUNTS OF MORE THAN $250,000 THROUGH $1,000,000	FFIEC 002, 031, & 041	3/31/2001	12/31/9999

These are the series Jin indicated were used in the construction of PSLOANS. The first ten series listed are not available for the analysis period (2006) and two (italics) are confidential when collected. The other three series, which are available for the analysis period and indicated in bold type are only available in the 2nd quarter (June 30). Series descriptions and their years of availability are taken from the Data Dictionary in the Federal Reserve's Micro Data Reference Manual available at https://www.federalreserve.gov/data/mdrm.htm

Appendix Table 12: Effects of auditor choice with alternative controls

	(1)		
	Coef	SE	PEP
Big 4 Auditor (BIG4)	-0.096	0.250	15.4
Tier 1 capital (CAP)	-15.768	3.071	100
Nonperforming loans (NPL)	27.060	6.276	100
Provisions for loan losses (LLP)	284.968	42.111	100
Growth in C & I loans (GCOMM)	15.173	5.094	94.6
Growth in real estate loans (GRESTATE)	—	—	—
Growth in total loans (GLOANS)	0.203	0.883	5.4
LOAN_MIX†	-81.905	21.978	100
SIZE	0.245	0.059	100
PUBLIC	—	—	—
Intercept	-5.141	0.930	100
Observations	5813		
Models Averaged over	3		
Posterior model probability	79%		

BMA estimates of the static logit model for whether a bank fails in the period 2007 - 2010, using controls from year-end 2006. BMA estimates reported include the posterior mean (Coef), standard deviation (SE), and effect probabilities (PEP) of the variables averaged over. Variables considered for inclusion in the model and not averaged over are indicated with "—".