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Predicting Operational Loss Exposure Using Past Losses*

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Abstract

Operational risk models, such as the loss distribution approach, frequently use past internal losses to forecast operational loss exposure. However, the ability of past losses to predict exposure, particularly tail exposure, has not been thoroughly examined in the literature. In this paper, we test whether simple metrics derived from past loss experience are predictive of future tail operational loss exposure using quantile regression. We find evidence that past losses are predictive of future exposure, particularly metrics related to loss frequency.

JEL Classification: G21, G28, G32
Keywords: Banking Regulation, Risk Management, Operational Risk, Tail Risk, Quantile Regression

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1 Introduction

International regulatory capital rules (i.e., the Basel Accords) require internationally active banks to hold capital for operational risk.[1] In the US, large, internationally active bank holding companies (BHCs) are required to calculate their operational risk capital according to the Advanced Measurement Approach (AMA), which relies on banks' internal models to estimate exposure at the 99.9% confidence level.[2] As of the end of June 2015, the eleven US BHCs with approved AMA models held capital against operational risk that, on average, amounted to 27% of total risk-weighted assets. This amount is significant when compared to capital held against market and credit risk (8% and 65% of risk-weighted assets, respectively).[3,4] In addition, large US BHCs are required to estimate operational losses under stressed conditions for the annual Comprehensive Capital Analysis and Review (CCAR) required by the Federal Reserve.[5]

To estimate operational loss exposure for AMA and CCAR, bank holding companies typically use models that assume past operational losses are predictive of future operational loss exposure.[6] For this assumption to be sensible, past operational losses should proxy for the underlying factors driving operational loss exposure, such as risk management quality, risk appetite, business model, and size. Given the relative stability of the central moments of the operational loss distribution, such as the expected value, past averages are likely

[1] Basel Committee on Banking Supervision (2006), "International Convergence of Capital Measurement and Capital Standards."

[2] Board of Governors of the Federal Reserve System (2015a), Code of Federal Regulations, Title 12, Part 217, Subpart E.

[3] Risk-weighted assets is an international regulatory concept used to calculate how much loss-absorbing capital a bank needs to endure stressful markets. See Basel Committee on Banking Supervision (2006) for more details.

[4] These estimates are based on financial statement information (10-K, 10-Q, 6-K and 20-F) as of 2015Q2 for the following eleven bank holding companies: BNY Mellon, Citigroup, Goldman Sachs, HSBC, JPMorgan Chase, Morgan Stanley, Northern Trust, State Street, UBS, US Bancorp, and Wells Fargo.

[5] Board of Governors of the Federal Reserve System (2016), "Comprehensive Capital Analysis and Review 2016 Summary Instructions."

[6] For example, the loss distribution approach (LDA), frequently used by AMA banks, and regression techniques that use past losses to forecast future stressed losses, used by multiple CCAR banks.

good predictors of future average losses.[7] On the other hand, in the tail of the distribution, exposure is dominated by large and infrequent events; thus, estimates of tail exposure suffer from significant uncertainty. Besides uncertainty, estimation methods that rely heavily on past losses usually also suffer from significant instability as new large events are included in datasets. Moreover, the adequacy of past losses as proxies for the often idiosyncratic drivers of tail events is not obvious. So, whether past losses add value in forecasting tail exposure over other proxies, such as income or assets, should be assessed.

Using data from all US bank holding companies subject to CCAR, this paper studies whether past losses are predictive of tail exposure. To this end, we performed quantile regressions where the high quantiles of the industry distribution of banks' annual operational losses are forecasted using metrics calculated from past losses and other financial variables. We used a variety of alternative explanatory variables (such as controls for size, risk appetite, and risk management quality) and specifications, and we found that loss metrics help forecast tail operational loss exposure. In particular, we found that average loss frequency is a robust predictor of future losses; a one unit increase in average frequency of losses above \$100k is associated with approximately a \$4.6Mln increase in the 95^{th} quantile of future annual operational losses.

An extensive literature focuses on the performance of models relying on past loss experience in credit risk. Hillegeist et al. (2004) compare accounting-based models (Z-Score and O-Score) with market-based models (Black-Scholes-Merton model) for probability of default and find that market-based models perform better; while Agarwal and Taffler (2008) compare the Z-score model with the Merton model and find that that they have similar ability to predict default. Bharath and Shumway (2008) compare the Merton distance to default model with simpler alternatives and find that the Merton model does

[7] Analysis of this paper confirms that past average losses are good predictors of expected losses. See Table 3.

not significantly improve upon them. Altman and Sabato (2007) compare a distress prediction model specific to small and medium sized enterprises (SME) with a generic corporate model and find that the SME model outperforms the generic model. Gupton (2005) shows that Moody's LossCalc model for loss given default outperforms multiple benchmarks. Finally, Lopez and Saidenberg (2000) examine the challenges in validating and backtesting credit models and propose evaluations methods.

Likewise, an extensive literature focus on the performance of market risk models. Berkowitz and O'Brien (2002) evaluate the performance of banks' Value-at-Risk (VaR) models and find that VaR models do not outperform simple time-series models based on banks' trading P&L. Perignon et al. (2008) assess the VaR models of Canadian banks and find that these models systematically overestimate exposure. Bao et al. (2006) compare multiple VaR models, including Riskmetrics and EVT models, and find that EVT models perform best during crisis periods. Escanciano and Olmo (2011) discuss how model risk presents challenges for the backtesting of VaR models and show that block-bootstrapping techniques produce more accurate backtesting. Finally, Gaglianone et al. (2012) illustrate how backtesting of VaR models can be performed using quantile regression.

However, similar studies are lacking for operational risk. To our knowledge, this is the first article to show that metrics of past loss experience are predictive of operational loss exposure. By identifying the loss metrics that best predict exposure, this paper contributes to the literature on factors predictive of operational loss exposure. This literature includes Chernobai et al. (2011), who find that operational loss frequency is higher for younger, more complex, and more exposed to credit risk firms; Cope et al. (2012), who find that banks' likelihood of experiencing certain types of operational losses is highly correlated with constraints on executive power, insider trading, shareholder protection laws and supervisory power; Wang and Hsu (2013), who find that board size and the fraction of independent directions are negatively related with the likelihood of operational loss events;

and Abdymomunov et al. (2015), who find that banks suffer higher operational losses during weak macro environments.

Our study coincides with substantial revisions to the Basel framework for operational risk capital. In March 2016, the Basel Committee proposed to replace the previous standardized approaches and the AMA with a new standardized approach, the Standardized Measurement Approach (SMA). Under the SMA, large bank holding companies are required to calculate operational risk capital according to a fixed formula that relies on the Business Indicator, an income statement proxy for operational loss exposure, and on past losses. The results of this paper support the combination of size and loss metrics in the calculation of operational risk capital and can inform revisions to the SMA.

The remainder of this paper is organized as follows: Section 2 describes the data used; Section 3 describes the quantile regression methodology and presents the main empirical results; Section 4 provides multiple robustness checks; finally, Section 5 concludes.

2 Data

The analysis in this paper relies on operational loss event data, financial statements, and other supervisory information of 31 bank holding companies that participated in CCAR 2015.[8] Loss information, including loss amounts and counts, is used from 2000Q1 or as far back as available in the Federal Reserve's Y-14Q reports.[9] Liabilities, equity, total assets, net interest income, and total noninterest income are obtained from Y-9C reports when available and supplemented with data from Bloomberg otherwise.[10] Risk management and

[8] List provided in Appendix A.

[9] Some banks have reported losses before 2000Q1. However, such data is likely incomplete, and so we opted to start our sample in 2000Q1.

[10] Some firms in our sample, such as Goldman Sachs and Morgan Stanley, did not become bank holding companies until late in our sample period and so were not required to fill the Y-9C report for the earlier portion of our sample. Also, some non-bank holding companies (e.g., Countrywide Financial) merged with

internal controls ratings are obtained from confidential supervisory assessments. In addition to firm-specific information, a NBER recession indicator is used.

The dependent variable in the regressions of this paper is the total amount of operational losses suffered by a bank holding company over a calendar year. Banks provide multiple dates for their operational loss events on Y-14Q reports: occurrence date, discovery date, and accounting date; we rely on the accounting date because it reflects when losses enter the firms' financial statements and, thus, when capital is needed to cushion losses. In some cases, operational loss events result in multiple loss impacts through time, which are recorded separately in the Y-14Q report (for example, losses resulting from a litigation event may be spread through multiple years). However, reporting practices of losses with multiple impacts are not consistent across banks - some banks aggregate most impacts to one date, while others provide extensive temporal disaggregation; for consistency, we opted to aggregate all impacts of a loss event to its first accounting date.[11] Thus, our loss event dataset includes a single entry for each loss event, which sums all loss impacts of the loss event. Total operational losses for year t are the sum of the loss amounts of all events with a loss amount of at least \$20k and with the first accounting date in year t.

Multiple loss metrics are constructed to use as explanatory variables; in all cases, loss metrics for year t are calculated using bank data from the beginning of the sample until year t (e.g., 2012 average total annual losses for a bank whose loss history started in 2000 correspond to the average of annual total losses between 2000 and 2012), but we only calculate the metrics if at least three years are available (e.g., for a bank whose first year of

or were acquired by bank holding companies in our sample. For consistency between the loss datasets and the financial statement variables used for these companies, Y-9C data was augmented by Bloomberg data where appropriate.

[11] This aggregation choice likely works against significance of the variables in our regression analysis because it results in lumpier and more volatile loss totals, which are likely harder to predict than smoother loss totals.

loss data is 2005, the first year explanatory loss metrics are available is 2007). We use the maximum available period to calculate the loss metrics to increase the stability of explanatory loss metrics. We construct four types of loss metrics: 1) average total annual losses only including losses above given thresholds or between two thresholds (e.g., average total annual losses only including loss events above \$20k, average total annual losses only including loss events between \$20k and \$1Mln; 2) average loss frequency only including loss events above given thresholds or between two thresholds (e.g., average frequency only including loss events above \$100k, average frequency only including loss events between \$100k and \$1Mln); 3) average loss severity only including loss events above a given threshold (only \$100k is used); and 4) estimates of the 95^{th} quantile of the operational loss distribution obtained through empirical bootstrapping.[12]

We also use financial statement metrics as explanatory variables: total equity, total liabilities, net interest income, and non-interest income. To increase stability, these metrics are calculated according to a rolling average of three calendar years. For total liabilities and equity, values at the end of the calendar year are averaged for three years (e.g., when using total equity to predict operational losses in 2013, we use the average of total equity at the end of 2012, 2011 and 2010); while for net-interest income and non-interest income, values of the full calendar year income statement are averaged for three years.

In addition to loss metrics and financial statement metrics, we also use supervisory assessments of the quality of management. Specifically, the rating constitutes an

[12] To estimate the 95^{th} quantile of the operational loss distribution of a bank using past losses, we use an empirical bootstrapping approach. The empirical bootstrap is recommended as a benchmark for operational risk capital models in US Advanced Measurement Approach guidance - see Board of Governors of the Federal Reserve System (2014), Basel Coordination Committee Bulletin 14-1. This approach follows the Loss Distribution Approach and, thus, loss severity and frequency are estimated separately. Frequency is assumed to follow a Poisson distribution; while severity is assumed to follow the historical empirical distribution. Loss events are pooled to a single unit of measure and annual loss distribution is obtained through Monte Carlo simulation convolution of the frequency and severity distributions. As loss histories usually do not exceed fifteen years, the empirical bootstrap likely constitutes an underestimate of operational loss exposure at the tail of the distribution because the observed years may not include the tail events that populate the tail.

assessment of the ability of BHCs' board of directors and senior management, as appropriate for their respective position, to identify, measure, monitor and control risk. The ratings range on a numeric scale from 1 to 5, with a rating of 1 being the strongest (good) and a rating of 5 being the weakest (bad).[13] Finally, we use an indicator of recession in the US economy, obtained from the NBER, as an explanatory variable.

Table 1 presents the descriptive statistics of the loss metrics, financial statement metrics, supervisory assessment of management quality, and the recession dummy. Each bank-year combination is an independent observation.

[Insert Table 1 here]

Operational risk is significant for large US BHCs. On average, large US BHCs face operational risk losses above $800Mln per year that represents almost 0.10% of their total assets. Once in ten years, BHCs in our sample, lose around $2Billion representing more than 0.22% of their total assets. Given that large US BHCs are highly leveraged, this can represent a significant hit to their capital base. On average, large US BHCs funded 8.8% of their total assets with tier 1 capital in 2014Q3.[14] Thus, once every ten years, a BHC in our sample suffered operational losses that would erode more than 2.5% of their capital base if their tier 1 to assets ratio stood at the industry average.

[13] A detailed description of the Bank Holding Company Rating System can be found at: http://www.federalreserve.gov/boarddocs/srletters/2004/sr0418.htm.

[14] Board of Governors of the Federal Reserve System (2015b), "Comprehensive Capital Analysis and Review 2015: Assessment Framework and Results."

3 Empirical Results

To test the predictive ability of past losses, we run several OLS and quantile regressions.[15] Losses from all CCAR bank holding companies are pooled in these regressions; however, due to the significant differences across banks in our sample, the conditional distribution of annual operational losses is likely heteroscedastic.[16] To mitigate the heteroscedasticity and increase estimation efficiency, we follow a methodology proposed by Jung et al. (2015): first, for each set of explanatory variables to be used in regressions, we calculate the 25^{th} quantile and 75^{th} quantile regressions; second, we calculate the fitted values of these 25^{th} and 75^{th} quantile regressions; third, we calculate the weight of each observation in our regression of interest, which corresponds to one divided by the fitted interquartile range (i.e., 1/(Fitted value of the 75^{th} quantile regression - Fitted value of the 25^{th} quantile regression);[17] finally, we multiply the dependent and the explanatory variables of each observation by their corresponding weight.[18]

Coefficient estimates are unlikely to be normally distributed in a small sample such as

[15] See Koenker and Bassett (1978), Koenker and Hallock (2001) and Koenker (2005) for descriptions of the theory and use of quantile regression.

[16] To reduce the heteroscedasticity of data, we considered scaling the dependent variable as well as some of the explanatory variables including the loss metrics, total equity, total liabilities, and income measures by total assets. However, we believe that such transformation inherently biases estimation towards finding statistically significant effects. For example, in a simple model of losses at time t as a function of average losses up to time t-1, if losses at time t are unrelated to losses at time t-1, but assets at time t are related to assets at time t-1, we would find a correlation after scaling, although there was no correlation prior to scaling. We have calculated the results using assets scaling instead of the methodology we employed in this paper to reduce heteroscedasticity, and generally effects are more likely to be statistically significant when scaling by total assets is used.

[17] In some cases the fitted 75^{th} quantile can be lower than the fitted 25^{th} quantile for observations at the extreme of the range of values of certain explanatory variables. Also, in other cases, weights can become very large, when the interquartile range is very close to zero. To avoid negative weights and extremely high weights, we employ a two-step procedure: first, we divide the interquartile range for all observations by the average interquartile range - this normalization does not affect relative weights, and so it has no direct impact on regression results; second, we floor the normalized interquartile range to 0.02. We have undertaken sensitivity analysis for this assumption by considering floors ranging from 0.01 to 0.1, and results are not significantly affected (see Appendix B).

[18] We check the robustness of our results by using the intertertile range and the range between the 10^{th} and the 90^{th} quantiles instead of the interquartile range to set the weights. Results are qualitatively similar (see Appendix C).

ours; thus, to appropriately test the significance of estimated effects, we use empirical bootstrapping.[19] We employ the (x,y)-pair bootstrap technique, whereby pairs of observations from the original sample are sampled with replacement and model parameters are re-estimated multiple times. To obtain coefficient p-values, first we calculate the proportion of coefficient estimates above and below zero; then, we multiply the smaller of these proportions by two to obtain the p-value for the two-sided test of statistical significance. Our p-value estimates are based on 10,000 re-samples.[20]

To assess whether past operational losses help predict future operational losses, we start by performing regressions that only include past loss metrics as explanatory variables. We consider seven alternative combinations of explanatory variables: 1) average total annual losses only including loss events above \$20k; 2) average frequency of loss events above \$100k; 3) average severity of losses only including loss events above \$100k; 4) the 95^{th} quantile of the operational loss distribution obtained through empirical bootstrapping; 5) average frequency of loss events above \$100k and average severity of losses only including loss events above \$100k; 6) average total annual losses only including loss events between \$20k and \$1Mln and average total annual losses only including loss events above \$1Mln; and 7) average frequency of loss events between \$100k and \$1Mln and average frequency of loss events above \$1Mln.

Average total annual losses jointly reflect the frequency and severity of operational losses experienced by banks and, so, are an intuitive starting point on a search for a

[19] The bootstrapped estimates often show significant asymmetry around the mean estimate and, thus, demonstrate the non-normality of regression coefficients.

[20] To further assess the statistical robustness of our results we use block bootstrapping, a technique that addresses dependence within clusters of observations by bootstrapping clusters of observations as a block, rather than independently (Cameron et al. (2008)). In our implementation of the block bootstrap procedure, in each replication we sampled with replacement from the 31 BHCs for which we have data, until the bootstrap sample included data for 31 firms. Given that the number of years of data available varies across firms, our final bootstrap samples have a variable number of observations but generally close to our total sample size of 220. The statistical significance of regression coefficients does not change significantly (see Appendix D for results).

summary metric of past losses; however, loss frequency and loss severity may be more predictive when considered as separate factors, and so we consider regressions where they are considered alone and together as separate factors. In addition, we consider the 95^{th} percentile of the operational loss distribution obtained through empirical bootstrapping to assess how a simplified LDA framework compares with other simpler metrics in predicting annual operational losses. Finally, we estimate regressions where we separate the effects of body losses and tail losses; in model 6, we do so by separating the average losses resulting from loss events between $20K and $1Mln and loss events above $1Mln; while in model 7, we do so by separating the average frequency resulting from losses events between $100K and $1Mln and loss events above $1Mln.

The loss metrics we use are significantly correlated, as pairwise correlations exceed 50% in all cases (see Table 2). For example, average total annual losses have a correlation of 89.9% with average loss frequency and a correlation of 97.5% with the 95^{th} quantile of the loss distribution measured from past losses. Nevertheless, we believe comparing the predictive ability of the different loss measures is relevant. So, to avoid multicollinearity that muddles regression results, we chose to not include multiple loss metrics in the same regression, except for cases where they measure a separate dimension of the loss distribution (e.g., average loss frequency and average loss severity, or average total annual losses only including loss events between $100K and $1Mln and average total annual losses only including loss events above $1Mln).

[Insert Table 2 here]

Table 3 presents coefficients from the regression of operational losses at year t on loss metrics at year $t-1$. We have chosen to use explanatory variables for one year prior to the dependent variable because we want for our regression to show the ability of loss metrics and other control variables to predict operational losses. Panel A reports OLS estimates according to the following regression:

$$OL_{i,t} = \alpha + \sum_j \beta^j LossMetric^j_{i,t-1} + \epsilon_{i,t}, \tag{1}$$

Where $OL_{i,t}$ is the operational risk loss of bank i in year t and $LossMetric^j_{i,t-1}$ are the j^{th} loss metric of firm i calculated at $t-1$. Panel B regressions estimate the following conditional quantile functions:

$$Quant^\theta(OL_{i,t}|LossMetrics) = \alpha^\theta + \sum_j \beta^{\theta,j} LossMetric^j_{i,t-1}, \tag{2}$$

Where $Quant^\theta(OL_{i,t})$ is the θ^{th} quantile of the distribution of annual operational losses of bank i in year t and $LossMetric^j_{i,t-1}$ is the j^{th} loss metric of firm i calculated at $t-1$. Panel B presents the 95^{th} quantile estimates.[21]

[Insert Table 3 here]

Regression results are generally intuitive: when used as the single explanatory variable, an increase in average total annual losses, average frequency, or average severity is associated with a statistically significant increase in expected future losses and in the 95^{th}

[21] We use 95^{th} quantile regressions to illustrate the predictive ability of loss metrics and other control variables over future tail losses. This choice of quantile is arbitrary; nevertheless, we believe that using the 95^{th} quantile is sensible because it can be intuitively interpreted as 1 in 20 years losses. To demonstrate the robustness of our results, we provide the results of the 90^{th} and the 99^{th} quantile regressions on Appendix E. Results are consistent in most cases.

quantile of the distribution of future losses. When average frequency and average severity are considered together in a regression, an increase in average frequency is associated with a statistically significant increase in expected future losses and in 95^{th} quantile of future losses, while the coefficient associated with average severity is weakly significant on the OLS regression and not significant in the 95^{th} quantile regression. The coefficients associated with average frequency are of similar magnitude when average severity is accounted for and when it is not, suggesting that average frequency is more revealing of future exposure than average severity when losses are the only explanatory variables used.

When small losses are separated from large losses (i.e., loss events above $1Mln are categorized as large) in predicting future losses, both loss metrics become not statistically significant in most cases (with the exception of average total annual large losses in the OLS regression). Nevertheless, regression coefficients are positive in almost all cases.

Finally, the regressions where the 95^{th} quantile of loss distribution measured from past losses is used to predict future expected losses and the 95^{th} quantile of future losses, unsurprisingly, show a positive and statistically significant relation between past 95^{th} quantile and future losses. In the quantile regression predicting the 95^{th} quantile, the coefficient associated with the 95^{th} quantile measured from past loss data is 1.29, which implies that the 95^{th} quantile of losses is increasing as time passes in our sample.

The regression results discussed so far demonstrate that, when used without additional covariates, past loss metrics are predictive of loss exposure. To further establish the usefulness of past losses, we assess whether past loss metrics remain predictive of exposure when other variables that proxy for riskiness are considered. We consider three types of variables to proxy for banks riskiness: financial statement variables, supervisory assessments, and a macroeconomic indicator of recession.

Two financial statement variables are considered: total debt and total equity. When summed, total debt and total equity equal total assets; thus, they jointly proxy for bank size. We have chosen to consider debt and equity separately because their mix reflects leverage and risk appetite. Also, we use the Risk Management (R) rating of the Bank Holding Company Rating System to proxy for risk management quality in our regressions; however, risk management quality is unlikely to have the same absolute effect on operational loss totals in a small and a large bank, and so we also include the management rating times total assets interaction term in the regression. Finally, to account for the effect of macroeconomic shocks on total operational losses, we include an indicator variable that assumes the value of one when the US is in a recession and zero otherwise. Similar to risk management quality, we do not believe the absolute effect of a recession in operational losses is likely to be the same for small and large banks, and so we also include an interaction term between the recession indicator and total assets in our regressions.

Some of these variables are highly correlated with loss metrics (see Table 2). For example, bilateral correlations between total equity and average total annual losses or between total equity and average loss frequency are close to 90%; the correlations between total liabilities and these loss metrics are similarly high. These high correlations raise the question of whether past loss metrics are predictive of exposure even when other risk proxies are considered. Table 4 presents the results of regressions including loss metrics and the other proxy variables described in the previous paragraph as explanatory variables. Panel A reports according to the following regression:

$$OL_{i,t} = \alpha + \sum_j \beta^j LossMetric^j_{i,t-1} + \sum_k \beta^k ControlVariable^k_{i,t-1} + \epsilon_{i,t}, \qquad (3)$$

Where $OL_{i,t}$ is the operational risk loss of bank i in year t, $LossMetric^j_{i,t-1}$ is the j^{th} loss metric of firm i calculated at $t-1$, and $ControlVariable^k_{i,t-1}$ is the kth control variable for firm i at time $t-1$. Panel B regressions estimate the following conditional quantile functions:

$$Quant^{\theta}(OL_{i,t}|LossMetrics, ControlVariables) = \alpha^{\theta} + \sum_{j} \beta^{\theta,j} LossMetric^{j}_{i,t-1} + \sum_{k} \beta^{\theta,k} ControlVariable^{k}_{i,t-1}, \quad (4)$$

Where $Quant^{\theta}(OL_{i,t})$ is the θ^{th} quantile of the distribution of annual operational losses of bank i in year t, $LossMetric^{j}_{i,t-1}$ is the j^{th} loss metric of firm i calculated at $t-1$, and $ControlVariable^{k}_{i,t-1}$ is the kth control variable for firm i at time $t-1$. Panel B presents the 95th quantile estimates.

[Insert Table 4 here]

When considered together with other risk proxies, average loss frequency remains a statistically significant predictor of future total operational losses. A unit increase in the average frequency of losses above \$100K is associated with approximately a \$1.9Mln increase in future expected losses and a \$4.6Mln increase in the 95th quantile of the distribution of future operational loss distribution. On the other hand, average total losses, average loss severity, and the 95th quantile of the operational loss distribution measured from past losses are not statistically predictive of future expected losses or of the 95th quantile of the distribution of future losses when other risk factors are taken into account. The superiority of average frequency measures relative to measures based on total losses (such as the average total annual losses or the 95th quantile of the operational loss distribution based on past losses) is likely due to frequency being a more stable proxy for risk exposure, as it does not fluctuate significantly when new tail losses are incurred.[22]

When average loss frequency and severity are included in the same regression, the coefficient associated with average loss frequency remains positive and statistically significant both in the OLS and the 95^{th} quantile regressions, while the coefficient associated with average loss severity is not statistically significant in either regression. The magnitude of the coefficients associated with average loss frequency is similar in the OLS and the 95^{th} quantile regressions that include average loss severity to the coefficients obtained in the regressions that only include average loss frequency as a loss metric.

When average frequency of large losses (i.e., loss events above $1Mln) is separated from the average frequency of small losses (i.e., loss events between $100K and $1Mln), neither of them is a statistically significant predictor in the OLS regression; on the other hand, in the 95^{th} quantile regression the frequency of small losses is positively associated with future losses while the frequency of large losses is negatively associated with future losses. A possible explanation for the negative association between the frequency of large losses and future losses is mean reversion, as banks that suffer large losses may then become less likely to experience similar large losses in the future. Similarly, when average total annual losses resulting from large loss loss events are separated from the average total annual losses resulting from small loss events, an increase in average total annual losses resulting from small loss events is associated with an increase in the future expected losses and 95^{th} quantile of the operational loss distribution; however, in this case, an increase in the average total losses resulting from large loss events does not significantly predict the future 95^{th} quantile (and still does not predict future expected losses).

High levels of total equity are negatively associated with smaller operational loss

[22] The higher stability of average frequency is demonstrated by its lower coefficient of variation: the coefficient of variation for average frequency above $100K is approximately 152%, while the coefficient of variation of average total annual losses is approximately 214% and the coefficient of variation of the 95^{th} quantile of operational loss distribution measured from past losses is approximately 206%.

exposure in the future; this relation is consistent across all specifications we tried both for the OLS and the 95^{th} quantile regressions and statistically significant in all cases. On the other hand, total liabilities are positively associated with future loss exposure in some of the OLS and 95^{th} quantile regressions; however, total liabilities fail to reach statistical significance when paired with loss frequency measures, which indicates that loss frequency metrics are more reliable predictors of operational loss exposure than liability levels. Taken together, the coefficients associated with total equity and total liabilities indicate that more leveraged, riskier banks are exposed to more operational risk.

Except for one regression, the risk management rating given by regulators to banks has no predictive ability over future losses when other factors such as losses, liabilities, and equity are controlled for. This finding suggests that these ratings may be backward-looking, rather than forward-looking. Finally, when the recession dummy and the interaction term between the recession dummy and total assets are jointly taken into account, a recession leads to an increase in operational losses in the ensuing year for all but the smallest banks in our sample; the potential effect of a crisis is largest for the largest banks.

4 Robustness Checks

To assess the robustness of our results, we conduct a variety of alternative regressions.

4.1 Firm Fixed Effects

Table 5 presents the results when firm fixed effects are added to the loss metrics and the other control variables discussed in the previous section. Panel A reports OLS estimates according to the following regression:

$$OL_{i,t} = \alpha_i + \sum_j \beta^j LossMetric^j_{i,t-1} + \sum_k \beta^k ControlVariable^k_{i,t-1} + \epsilon_{i,t}, \tag{5}$$

Where $OL_{i,t}$ is the operational risk loss of bank i in year t, $LossMetric^j_{i,t-1}$ is the j^{th} loss metric of firm i calculated at $t-1$, $ControlVariable^k_{i,t-1}$ is the kth control variable for firm i at time $t-1$, and α_i is the bank i fixed effect. Panel B regressions estimate the following conditional quantile functions:

$$\begin{aligned} &Quant^{\theta}(OL_{i,t}|LossMetrics, ControlVariables, FixedEffects) = \\ &\qquad \alpha_i^{\theta} + \sum_j \beta^{\theta,j} LossMetric^j_{i,t-1} + \sum_k \beta^{\theta,k} ControlVariable^k_{i,t-1}, \end{aligned} \tag{6}$$

Where $Quant^{\theta}(OL_{i,t})$ is the θ^{th} quantile of the distribution of annual operational losses of bank i in year t, $LossMetric^j_{i,t-1}$ is the j^{th} loss metric of firm i calculated at $t-1$, $ControlVariable^k_{i,t-1}$ is the kth control variable for firm i at time $t-1$, and α_i is the bank i fixed effect. Panel B presents the 95^{th} quantile estimates.

[Insert Table 5 here]

In the 95^{th} quantile regressions that include one loss metric, the loss metric is always statistically significant; however, perhaps surprisingly, in the fixed effects regressions average total annual losses, average severity, and the 95^{th} quantile of the operational loss distribution measured from past losses are negatively associated with future losses. This result is likely explained by mean reversion: average total annual losses, average severity, and the 95^{th} quantile measured from past losses are all driven by large loss events, which are unlikely to occur multiple times in our short sample. Thus, when stable differences in exposure between banks are controlled for by firm fixed effects, these loss metrics become associated with lower future losses because after a bank experiences a large tail loss, it is less likely to experience another such loss in the remainder of our sample. On the other hand, even when firm fixed effects are used, an increase in average loss frequency remains associated with an increase in future losses, with a coefficient close in magnitude to the coefficient obtained when fixed effects were not used. These results reinforce the reliability of average frequency as an indicator of future exposure.

When two loss metrics are combined in a 95^{th} quantile regression, we see again a pattern that can be explained by mean reversion: in the regression combining average loss frequency and average loss severity, average loss frequency is positively associated with future losses while average loss severity is negatively associated with future losses; in the regression where average total annual losses from small loss events are controlled separately from average total annual losses from large events, average total annual losses from small loss events are positively associated with future losses while average total annual losses from large loss events are negatively associated with future losses; finally, in the regression where average frequency of small loss events is controlled separately from average frequency of large loss events, average frequency of small loss events is positively associated with future losses while average frequency of large loss events is negatively associated with future losses.

In the OLS regressions loss metrics are not statistically significant in most cases, except for the positive association of average frequency, average total annual losses from small loss events (when average total annual losses from large loss events are controlled for), and average frequency of small loss events (when average frequency of large loss events is controlled for) with future losses. These significant coefficients are consistent with the 95^{th}

quantile regressions.

4.2 Controlling for Income

Gross income was used as a proxy for operational loss exposure in the Basel II standardized approaches for operational risk capital. However, as far as we are aware, the efficacy of gross income as an operational risk proxy has not been directly researched in the literature. The 2014 Basel Committee consultative paper on changes to the standardized approaches for operational risk capital calculation introduced a new operational risk proxy, the Business Indicator, within which sub-components of gross income are treated differently. The data available to us does not allow reliable estimation of the Business Indicator and its subcomponents back beyond 2010, but nevertheless we are interested in assessing whether the major components of gross income relate differently to future operational losses and whether metrics driven by loss history remain significant when measures of income are considered. Thus, we introduce net-interest income and non-interest income as explanatory variables in the regressions of this subsection.

The income measures we use are highly correlated with total liabilities and total equity, and so regression results become very noisy when all four metrics are used. Thus, to research the validity of income metrics as proxies for operational risk and to assess whether loss metrics remain significant when income measures are used as controls, we exclude total liabilities and total equity from the regressions in this subsection. Table 6 presents the regression results.

[Insert Table 6 here]

Net-interest income is significant at the 10% level or less in the 95^{th} quantile regressions that include one loss metric, and the size of its coefficient varies between 0.015 and 0.082; in the 95^{th} quantile regressions that include two loss metrics, net-interest income is not statistically significant. Coefficient estimates for non-interest income in the 95^{th} quantile regressions are much noisier than net-interest income estimates, and so non-interest income is not statistically significant in any of the 95^{th} quantile regressions. These results question the usefulness of non-interest income as a proxy for tail operational loss exposure.

In the OLS regressions, net-interest income is positively associated with future losses in all but one regression, although it is only statistically significant in three of the seven specifications. For these regressions, the positive association between non-interest income and future losses is more consistent, as the coefficient of non-interest income is positive in all seven regressions and only fails to reach significance at the 10% level in two of them.

The statistical relation between the loss metrics under study and future losses in these regressions is generally consistent with the relation found in the regressions that included total liabilities and total equity instead of income metrics. In the OLS and the 95th quantile regressions that only include one loss metric, the only loss metric to achieve statistical significance is average frequency, and it does so with coefficients similar to the obtained when total liabilities and total equity were used as controls instead of income metrics. Similarly, in the 95^{th} quantile regressions that combine two loss metrics average frequency of small losses, average total annual losses resulting from small losses, and average frequency (when average severity is controlled for) are positively associated with future losses; this was already the case when total liabilities and total equity were used as control variables.

5 Conclusion

Operational risk practitioners have typically relied on past operational losses to model the distribution of future operational losses. In this paper we provide evidence that past operational losses are a useful metric to predict operational loss exposure, including tail exposure. Metrics associated with loss frequency prove the most robust in forecasting exposure, likely because they are more stable proxies for risk exposure as they do not fluctuate significantly when new tail losses are incurred. However, financial regulators should interpret these findings with caution. Requiring the use of frequency metrics to measure exposure can lead to undesirable incentives, as breaking loss events into smaller loss events or aggregating them into larger loss events would have capital implications.

Loss metrics that are significantly affected by large loss events, such as average total annual losses, average loss severity, and the 95^{th} quantile of the operational loss distribution measured from past losses, have an inconsistent relation with future losses. In particular, these variables are positively associated with future exposure when used in a stand-alone basis, are not statistically significant when combined with other proxies for riskiness, but become negatively associated with future exposure when taken together with firm fixed effects. The negative association in the fixed effects case is likely the result of mean reversion, as banks are unlikely to experience multiple large loss events in our small sample. Also, these findings are particularly problematic for the use of LDA models to forecast exposure, as the 95^{th} quantile of operational loss distribution measured according to a simplified LDA framework proved less predictive of future tail exposure than a simpler average frequency metric.

Finally, our analysis shows that increased leverage is associated with increase operational loss exposure and that economic crises lead to an increase in operational loss exposure. On the other hand, we do not find evidence that supervisory assessments of the quality of management are statistically significant predictors of operational loss exposure.

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Table 1: **Descriptive Statistics**

This table presents descriptive statistics. The sample includes 240 bank-year observations. In Panel A, yearly statistics are reported for loss metrics. In Panel B, averages from the beginning of the sample are reported for loss metrics. $Yearly\ Loss$ is the sum of the gross amounts of loss events. $Yearly\ Loss$ > \$1M is the sum of the gross amounts of loss events greater than \$1 Million. $Count$ > \$100K is the number of loss events greater than \$100K. $Count$ > \$1M is the number of loss events greater than \$1 Million. $Severity$ > \$100K is the average severity of loss events greater than \$100K. $Individual\ Bootstrap$ 95^{th} is the estimate of the 95^{th} quantile of the unconditional distribution using empirical bootstrap. In Panel C, yearly statistics are reported for BHCs characteristics. In Panel D, 3 years rolling averages are reported for BHCs characteristics. $Total\ Assets$ is the value of total assets at the end of the year. $Equity$ is value of equity at the end of the year. $Liabilities$ is the value of the liabilities at the end of the year. $Net\ Interest\ Income$ is the value of net-interest income for the calendar year. $Non-Interest\ Income$ is the value of non-interest income for the calendar year. $Risk$ is the value of the risk management rating given by the Federal Reserve System to BHCs. $Crisis\ Indicator$ is a binary variable that assumes the value of one if the US is deemed to be in recession for at least one month in the year according to the NBER.

Panel A: Yearly loss metrics - \$ values are in thousands

Yearly Observation	N	Mean	Std. Dev.	10^{th}	50^{th}	90^{th}	Coeff. Var.
Yearly Loss	240	831,354	2,754,760	13,394	114,309	1,939,477	3.31
Yearly Loss > \$1M	240	746,078	2,689,181	4,714	64,778	1,611,642	3.60
Count > \$100K	240	240	345	20	86	712	1.44
Count > \$1M	240	28	44	2	10	91	1.59
Severity > \$100K	240	2,174	3,557	344	1,034	4,220	1.64

Panel B: Loss metrics from sample beginning to year t - \$ values are in thousands

Average from beginning	N	Mean	Std. Dev.	10^{th}	50^{th}	90^{th}	Coeff. Var.
Yearly Loss	240	677,252	1,448,146	17,582	106,439	2,407,447	2.14
Yearly Loss > \$1M	240	611,810	1,354,834	8,974	82,819	2,217,184	2.21
Count > \$100K	240	183	278	15	69	636	1.52
Count > \$1M	240	21	31	2	7	85	1.48
Severity > \$100K	240	2,256	2,419	491	1,390	6,228	1.07
Individual Bootstrap 95^{th}	240	2,446,753	5,041,653	60,895	373,151	9,645,042	2.06

Panel C: Yearly BHCs characteristics - \$ values are in millions

Yearly Observation	N	Mean	Std. Dev.	10^{th}	50^{th}	90^{th}	Coeff. Var.
Total Assets	240	518,950	692,101	63,501	173,866	1,869,269	1.33
Equity	240	44,832	57,669	6,440	20,433	153,368	1.28
Liabilities	240	472,539	635,600	55,903	153,270	1,688,600	1.35
Net Interest Income	240	17,346	25,504	1,883	6,182	62,674	1.47
Non-Interest Income	240	11,329	14,672	817	4,656	37,569	1.30
Risk	220	2.33	0.55	2.00	2.00	3.00	0.24
Crisis Indicator	240	0.29	0.46	0.00	0.00	1.00	1.56

Panel D: 3 years rolling average BHCs characteristics - \$ values are in millions

3 years rolling average	N	Mean	Std. Dev.	10^{th}	50^{th}	90^{th}	Coeff. Var.
Total Assets	240	499,060	669,525	60,034	172,184	1,801,439	1.34
Equity	240	41,794	54,097	6,199	19,520	134,898	1.30
Liabilities	240	455,225	616,035	52,965	149,070	1,641,487	1.35
Net Interest Income	240	17,241	25,104	1,986	6,155	62,436	1.46
Non-Interest Income	240	10,754	13,531	819,759	5,018	36,044	1.26
Risk	220	2.33	0.55	2.00	2.00	3.00	0.24
Crisis Indicator	240	0.29	0.46	0.00	0.00	1.00	1.56

Table 2: **Correlations**

This table presents correlations estimates and the p-values. In Panel A, correlation estimates between yearly observations are presented. In Panel B, correlation between loss metrics' averages from the beginning and financial's three year rolling window average are presented. *Yearly Loss* is the sum of the gross amounts of loss events. *Count* > \$100K is the number of loss events greater than \$100K. *Severity* > \$100K is the average severity of loss events greater than \$100K. *Yearly Loss* > \$1M is the sum of the gross amounts of loss events greater than \$1 Million. *Individual Bootstrap* 95^{th} is the estimate of the 95^{th} quantile of the unconditional distribution using empirical bootstrap. *Yearly Loss* \$0-\$1Mln is the sum of the gross amounts of loss events between \$0 and \$1Mln. *Yearly Loss* > \$1Mln is the sum of the gross amounts of loss events greater than \$1Mln. *Count* \$100K-\$1Mln is the number of loss events between \$100K and \$1Mln. *Count* > \$1Mln is the number of loss events greater than \$1Mln. *Equity* is value of equity of BHCs at the end of the year. *Liabilities* is the value of the liabilities at the end of the year. *Net Interest Income* is the value of net-interest income for the calendar year. $Non-Interest\ Income$ is the value of non-interest income for the calendar year. *Risk* is the value of the risk management rating given by the Federal Reserve System to BHCs. *Crisis Indicator* is a binary variable that assumes the value of one if the US is deemed to be in recession for at least one month in the year according to the NBER.

Panel A: Yearly loss metrics - Yearly BHCs characteristics

	Variable													
Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 - Yearly Loss	1.000													
2 - Count > \$100K	0.489	1.000												
	(0.00)													
3 - Severity > \$100K	0.783	0.234	1.000											
	(0.00)	(0.00)												
4 - Individual Bootstrap 95^{th}	0.665	0.722	0.460	1.000										
	(0.00)	(0.00)	(0.00)											
5 - Yearly Loss \$0-\$1Mln	0.528	0.989	0.266	0.758	1.000									
	(0.00)	(0.00)	(0.00)	(0.00)										
6 - Yearly Loss > \$1Mln	0.999	0.454	0.790	0.645	0.494	1.000								
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)									
7 - Count \$100K-\$1Mln	0.572	0.947	0.305	0.772	0.982	0.539	1.000							
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)								
8 - Count > \$1Mln	0.500	0.872	0.275	0.742	0.865	0.471	0.824	1.000						
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)							
9 - Equity	0.532	0.852	0.329	0.866	0.880	0.504	0.883	0.835	1.000					
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)						
10- Liabilities	0.605	0.857	0.391	0.888	0.887	0.577	0.896	0.830	0.968	1.000				
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)					
11- Net Interest Income	0.599	0.804	0.392	0.867	0.846	0.574	0.868	0.742	0.894	0.938	1.000			
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)				
12- Non-Interest Income	0.364	0.785	0.225	0.702	0.797	0.335	0.782	0.764	0.881	0.876	0.783	1.000		
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)			
13- Risk	0.014	0.073	0.092	0.143	0.048	0.013	0.012	0.101	0.119	0.066	0.035	0.047	1.000	
	(0.83)	(0.28)	(0.18)	(0.04)	(0.48)	(0.85)	(0.86)	(0.14)	(0.08)	(0.33)	(0.60)	(0.49)		
14- Crisis Indicator	0.145	-0.044	0.183	0.032	-0.026	0.150	-0.008	-0.007	-0.043	0.006	0.064	-0.080	-0.010	1.000
	(0.03)	(0.51)	(0.01)	(0.63)	(0.71)	(0.03)	(0.90)	(0.92)	(0.52)	(0.93)	(0.35)	(0.24)	(0.88)	

Panel B: Loss metrics from sample beginning - 3 years rolling average BHCs characteristics

	Variable													
Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 - Yearly Loss	1.000													
2 - Count > \$100K	0.899	1.000												
	(0.00)													
3 - Severity > \$100K	0.722	0.556	1.000											
	(0.00)	(0.00)												
4 - Individual Bootstrap 95^{th}	0.975	0.866	0.723	1.000										
	(0.00)	(0.00)	(0.00)											
5 - Yearly Loss \$0-\$1Mln	0.908	0.995	0.564	0.877	1.000									
	(0.00)	(0.00)	(0.00)	(0.00)										
6 - Yearly Loss > \$1Mln	0.999	0.885	0.729	0.975	0.894	1.000								
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)									
7 - Count \$100K-\$1Mln	0.891	0.999	0.536	0.858	0.995	0.876	1.000							
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)								
8 - Count > \$1Mln	0.917	0.956	0.681	0.892	0.946	0.908	0.944	1.000						
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)							
9 - Equity	0.895	0.916	0.674	0.875	0.922	0.886	0.907	0.936	1.000					
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)						
10- Liabilities	0.901	0.921	0.718	0.897	0.920	0.893	0.911	0.954	0.973	1.000				
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)					
11- Net Interest Income	0.894	0.887	0.657	0.894	0.897	0.887	0.882	0.884	0.919	0.945	1.000			
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)				
12- Non-Interest Income	0.785	0.850	0.660	0.785	0.845	0.775	0.839	0.899	0.922	0.920	0.850	1.000		
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)			
13- Risk	0.163	0.135	0.155	0.143	0.114	0.165	0.134	0.138	0.122	0.095	0.089	0.026	1.000	
	(0.02)	(0.05)	(0.02)	(0.04)	(0.09)	(0.01)	(0.05)	(0.04)	(0.07)	(0.16)	(0.19)	(0.70)		
14- Crisis Indicator	0.022	-0.022	-0.001	0.032	-0.012	0.025	-0.021	-0.021	-0.037	0.023	0.079	-0.076	-0.010	1.000
	(0.74)	(0.75)	(0.99)	(0.63)	(0.86)	(0.72)	(0.75)	(0.76)	(0.58)	(0.73)	(0.24)	(0.27)	(0.88)	

Table 3: **Loss Metrics alone**

This table presents coefficient estimates from the regression of operational losses at year t on loss metrics at year $t-1$. Panel A presents OLS estimates while Panel B presents estimates from the 95^{th} quantile regressions. *Yearly Loss* is the sum of the gross amounts of loss events. *Count* > \$100K is the number of loss events greater than \$100K. *Severity* > \$100K is the average severity of loss events greater than \$100K. *Individual Bootstrap* 95^{th} is the estimate of the 95^{th} quantile of the unconditional distribution using empirical bootstrap. *Yearly Loss* \$0-\$1Mln is the sum of the gross amounts of loss events between \$0 and \$1Mln. *Yearly Loss* > \$1Mln is the sum of the gross amounts of loss events greater than \$1Mln. *Count* \$100K-\$1Mln is the number of loss events between \$100K and \$1Mln. *Count* > \$1Mln is the number of loss events greater than \$1Mln. P-values are presented in parentheses.

Panel A: OLS regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Yearly Loss	1.50^{***}						
	(0.00)						
Count > \$100K (*1,000)		$1{,}706^{*}$			$2{,}758^{***}$		
		(0.09)			(0.00)		
Severity > \$100K			389.32^{***}		38.51^{*}		
			(0.00)		(0.05)		
Individual Bootstrap 95^{th}				0.36^{***}			
				(0.00)			
Yearly Loss \$0-\$1Mln						-1.91	
						(0.78)	
Yearly Loss > \$1Mln						1.43^{***}	
						(0.00)	
Count \$100K-\$1Mln (*1,000)							148
							(0.89)
Count > \$1Mln (*1,000)							43,719
							(0.22)
N	240	240	240	240	240	240	240

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Panel B: 95^{th} quantile regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Yearly Loss	3.37^{***}						
	(0.00)						
Count > \$100K (*1,000)		$11{,}261^{***}$			$9{,}992^{***}$		
		(0.00)			(0.00)		
Severity > \$100K			$1{,}390^{***}$		66.09		
			(0.00)		(0.57)		
Individual Bootstrap 95^{th}				1.29^{***}			
				(0.00)			
Yearly Loss \$0-\$1Mln						3.00	
						(0.68)	
Yearly Loss > \$1Mln						3.50	
						(0.33)	
Count \$100K-\$1Mln (*1,000)							9,921
							(0.32)
Count > \$1Mln (*1,000)							46,870
							(0.94)
N	240	240	240	240	240	240	240

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4: **Loss metrics plus control variables**

This table presents coefficients estimates from regression of operational losses at year t on loss metrics and BHCs characteristics at year $t-1$. Panel A presents OLS estimates while Panel B presents estimates from the 95^{th} quantile regressions. $Yearly\ Loss$ is the sum of the gross amounts of loss events. $Count$ > \$100K is the number of loss events greater than \$100K. *Severity* > \$100K is the average severity of loss events greater than \$100K. *Individual Bootstrap* 95^{th} is the estimate of the 95^{th} quantile of the unconditional distribution using empirical bootstrap. $Yearly\ Loss$ \$0-\$1Mln is the sum of the gross amounts of loss events between \$0 and \$1Mln. $Yearly\ Loss$ > \$1Mln is the sum of the gross amounts of loss events greater than \$1Mln. *Count* \$100K-\$1Mln is the number of loss events between \$100K and \$1Mln. *Count* > \$1Mln is the number of loss events greater than \$1Mln. *Equity* is the value of equity at the end of the year. *Liabilities* is the value of the liabilities at the end of the year. *Risk* is the value of the risk management rating given by the Federal Reserve System to BHCs. TA is the value of BHCs total assets at the end of the year. *Crisis Indicator* is a binary variable that assumes the value of one if the US is deemed to be in recession for at least one month in the year according to the NBER. P-values are presented in parentheses.

Panel A: OLS regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Yearly Loss	0.36						
	(0.12)						
Count > \$100K (*1,000)		1,856***			1,722***		
		(0.00)			(0.01)		
Severity > \$100K			-5.36		-4.56		
			(0.57)		(0.72)		
Individual Bootstrap 95^{th}				0.04			
				(0.21)			
Yearly Loss \$0-\$1Mln						2.87*	
						(0.05)	
Yearly Loss > \$1Mln						0.25	
						(0.10)	
Count \$100K-\$1Mln (*1,000)							1,520
							(0.35)
Count > \$1Mln (*1,000)							-10,269
							(0.77)
Equity	-0.008***	-0.007***	-0.008***	-0.007***	-0.007***	-0.004**	-0.007**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.03)
Liabilities	0.002*	-0.000	0.002***	0.001*	0.000	0.001**	-0.001
	(0.08)	(0.98)	(0.00)	(0.06)	(0.46)	(0.03)	(0.71)
1,000*Risk	11,516	-50,333	-9,610	-19,592	-20,873	33,247**	-137,056
	(0.72)	(0.51)	(0.79)	(0.55)	(0.65)	(0.01)	(0.51)
Risk*TA	-0.0001	0.0005	0.0001	0.0002	0.0002	-0.0001*	0.0008
	(0.64)	(0.46)	(0.68)	(0.65)	(0.59)	(0.08)	(0.51)
1,000*Crisis	-62,431**	-95,007*	-41,881	-50,343**	-82,155**	-52,720*	-55,401
	(0.02)	(0.06)	(0.10)	(0.05)	(0.04)	(0.07)	(0.45)
Crisis*TA	0.0006***	0.0011**	0.0005*	0.0005**	0.0010***	0.0009***	0.0006
	(0.01)	(0.01)	(0.07)	(0.02)	(0.01)	(0.01)	(0.24)
Bank Fixed Effects	No	No	No	No	No	No	No
N	220	220	220	220	220	220	220

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Panel B: 95^{th} quantile regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Yearly Loss	1.30						
	(0.43)						
Count > \$100K (*1,000)		4,629*			3,610*		
		(0.06)			(0.07)		
Severity > \$100K			-7.42		-31.26		
			(0.95)		(0.87)		
Individual Bootstrap 95^{th}				0.02			
				(0.95)			
Yearly Loss \$0-\$1Mln						13.22***	
						(0.01)	
Yearly Loss > \$1Mln						-0.21	
						(0.76)	
Count \$100K-\$1Mln (*1,000)							6,479***
							(0.00)
Count > \$1Mln (*1,000)							-232,244*
							(0.06)
Equity	-0.033***	-0.025***	-0.034***	-0.034***	-0.025***	-0.021***	-0.032***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Liabilities	0.005**	0.002	0.008***	0.007***	0.002*	0.004**	0.002
	(0.02)	(0.10)	(0.00)	(0.00)	(0.08)	(0.02)	(0.15)
1,000*Risk	-32,262	-12,710	5,411	-21,891	-41,984	90,148	-142,737
	(0.88)	(0.93)	(0.91)	(0.69)	(0.80)	(0.36)	(0.42)
Risk*TA	0.0001	0.0005	-0.0002	0.0000	0.0007	-0.0003	0.0013
	(0.84)	(0.79)	(0.74)	(0.91)	(0.77)	(0.69)	(0.26)
1,000*Crisis	-258,807**	-256,503**	-293,428*	-273,677**	-278,617**	-149,305**	-132,772*
	(0.02)	(0.04)	(0.06)	(0.01)	(0.01)	(0.02)	(0.08)
Crisis*TA	0.0014*	0.0023**	0.0022	0.0018*	0.0024**	0.0014**	0.0013**
	(0.07)	(0.04)	(0.17)	(0.10)	(0.02)	(0.03)	(0.04)
Bank Fixed Effects	No	No	No	No	No	No	No
N	220	220	220	220	220	220	220

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 5: **Loss metrics plus control variables and bank fixed effects**

This table presents coefficients estimates from regression of operational losses at year t on loss metrics and BHCs characteristics at year $t-1$ with bank fixed effects. Panel A presents OLS estimates while Panel B presents estimates from the 95^{th} quantile regressions. *Yearly Loss* is the sum of the gross amounts of loss events. *Count* > \$100K is the number of loss events greater than \$100K. *Severity* > \$100K is the average severity of loss events greater than \$100K. *Individual Bootstrap* 95^{th} is the estimate of the 95^{th} quantile of the unconditional distribution using empirical bootstrap. *Yearly Loss* \$0-\$1Mln is the sum of the gross amounts of loss events between \$0 and \$1Mln. *Yearly Loss* > \$1Mln is the sum of the gross amounts of loss events greater than \$1Mln. *Count* \$100K-\$1Mln is the number of loss events between \$100K and \$1Mln. *Count* > \$1Mln is the number of loss events greater than \$1Mln. *Equity* is the value of equity at the end of the year. *Liabilities* is the value of the liability at the end of the year. *Risk* is the value of the risk management rating given by the Federal Reserve System to BHCs. *TA* is the value of BHCs total assets at the end of the year. *Crisis Indicator* is a binary variable that assumes the value of one if the US is deemed to be in recession for at least one month in the year according to the NBER.

Panel A: OLS regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Yearly Loss	-0.25						
	(0.26)						
Count > \$100K (*1,000)		2,927**			2,552**		
		(0.03)			(0.04)		
Severity > \$100K			-8.28		-62.42		
			(0.67)		(0.11)		
Individual Bootstrap 95^{th}				-0.09			
				(0.12)			
Yearly Loss \$0-\$1Mln						12.17***	
						(0.01)	
Yearly Loss > \$1Mln						-0.52	
						(0.24)	
Count \$100K-\$1Mln (*1,000)							3,568**
							(0.04)
Count > \$1Mln (*1,000)							-48,997
							(0.38)
Equity	-0.014	-0.014**	-0.012	-0.017	-0.011	-0.018**	-0.017**
	(0.29)	(0.04)	(0.18)	(0.22)	(0.13)	(0.04)	(0.02)
Liabilities	0.005***	0.004***	0.005*	0.006***	0.004***	0.004***	0.003***
	(0.00)	(0.00)	(0.07)	(0.00)	(0.01)	(0.01)	(0.01)
Risk (*1,000)	93,855***	86,680**	45,402	76,429***	83,180**	79,742***	62,067**
	(0.01)	(0.01)	(0.63)	(0.00)	(0.03)	(0.01)	(0.04)
Risk*TA	-0.0011***	-0.0010***	-0.0009	-0.0008***	-0.0011***	-0.0009***	-0.0007***
	(0.00)	(0.01)	(0.21)	(0.00)	(0.00)	(0.00)	(0.00)
Crisis (*1,000)	-43,410**	-42,949	-108,542**	-40,833**	-29,128	-24,420	-11,786
	(0.01)	(0.13)	(0.03)	(0.02)	(0.23)	(0.18)	(0.34)
Crisis*TA	0.0005**	0.0005	0.0014**	0.0004**	0.0005	0.0002	0.0003
	(0.05)	(0.17)	(0.02)	(0.03)	(0.15)	(0.31)	(0.31)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	220	220	220	220	220	220	220

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Panel B: 95^{th} quantile regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Yearly Loss	-5.06***						
	(0.00)						
Count > \$100K (*1,000)		2,676**			3,031***		
		(0.03)			(0.01)		
Severity > \$100K			-227.10**		-358.98**		
			(0.01)		(0.02)		
Individual Bootstrap 95^{th}				-0.96***			
				(0.00)			
Yearly Loss \$0-\$1Mln						43.74***	
						(0.00)	
Yearly Loss > \$1Mln						-5.60***	
						(0.00)	
Count \$100K-\$1Mln (*1,000)							6,714***
							(0.00)
Count > \$1Mln (*1,000)							-371,170*
							(0.06)
Equity	-0.051	-0.068***	-0.084***	-0.041	-0.055***	-0.064***	-0.064***
	(0.14)	(0.00)	(0.00)	(0.11)	(0.00)	(0.00)	(0.00)
Liabilities	0.016***	0.010***	0.012***	0.015***	0.006***	0.008***	0.006***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Risk (*1,000)	59,599	106,637	57,410	61,545*	185,378**	104,025*	90,057
	(0.17)	(0.13)	(0.37)	(0.05)	(0.04)	(0.07)	(0.14)
Risk*TA	-0.0010**	-0.0006	-0.0003	-0.0009**	-0.0007	-0.0008	-0.0003
	(0.04)	(0.41)	(0.33)	(0.02)	(0.20)	(0.10)	(0.57)
Crisis (*1,000)	-63,776	-76,609	-118,604	-67,364	15,380	-5,651	22,469
	(0.41)	(0.23)	(0.28)	(0.30)	(0.57)	(0.42)	(0.50)
Crisis*TA	-0.0002	0.0006	0.0007	0.0001	0.0003	0.0003	0.0004
	(0.67)	(0.26)	(0.48)	(0.72)	(0.29)	(0.13)	(0.20)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	220	220	220	220	220	220	220

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 6: **Regressions with income controls**

This table presents coefficients estimates from regression of operational losses at year t on loss metrics and BHCs characteristics at year $t-1$. Panel A presents OLS estimates while Panel B presents estimates from the 95^{th} quantile regressions. $Yearly\ Loss$ is the sum of the gross amounts of loss events. $Count >$ \$100K is the number of loss events greater than \$100K. $Severity >$ \$100K is the average severity of loss events greater than \$100K. $Individual\ Bootstrap\ 95^{th}$ is the estimate of the 95^{th} quantile of the unconditional distribution using empirical bootstrap. $Yearly\ Loss$ \$0-\$1Mln is the sum of the gross amounts of loss events between \$0 and \$1Mln. $Yearly\ Loss >$ \$1Mln is the sum of the gross amounts of loss events greater than \$1Mln. $Count$ \$100K-\$1Mln is the number of loss events between \$100K and \$1Mln. $Count >$ \$1Mln is the number of loss events greater than \$1Mln. $Interest\ Income$ is the value of the interest income at the end of the year. $Net\ Interest\ Income$ is the value of net-interest income for the calendar year. $Non-Interest\ Income$ is the value of non-interest income for the calendar year. $Risk$ is the value of the risk management rating given by the Federal Reserve System to BHCs. TA is the value of BHCs total assets at the end of the year. $Crisis\ Indicator$ is a binary variable that assumes the value of one if the US is deemed to be in recession for at least one month in the year according to the NBER.

Panel A: OLS regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Yearly Loss	0.08						
	(0.52)						
Count > \$100K (*1,000)		1,313**			778		
		(0.02)			(0.23)		
Severity > \$100K			-13.17		-11.77		
			(0.23)		(0.16)		
Individual Bootstrap 95^{th}				-0.01			
				(0.91)			
Yearly Loss \$0-\$1Mln						3.54*	
						(0.08)	
Yearly Loss > \$1Mln						-0.02	
						(0.92)	
Count \$100K-\$1Mln (*1,000)							-848
							(0.83)
Count > \$1Mln (*1,000)							11,617
							(0.72)
Net Interest Income	0.018**	0.005	0.015**	0.020**	0.003	0.006	-0.006
	(0.03)	(0.33)	(0.03)	(0.02)	(0.52)	(0.27)	(0.88)
Non-Interest Income	0.017**	0.015***	0.011	0.026**	0.016***	0.015***	0.019
	(0.02)	(0.00)	(0.18)	(0.02)	(0.01)	(0.01)	(0.11)
Risk (*1,000)	-12,253	-11,171	-28,987	-174	-21,417	-15,334	-127,930
	(0.37)	(0.66)	(0.21)	(0.81)	(0.50)	(0.54)	(0.32)
Risk*TA	0.0000	0.0000	0.0002	-0.0001	0.0001	0.0000	0.0004
	(0.94)	(0.93)	(0.43)	(0.85)	(0.62)	(0.90)	(0.44)
Crisis (*1,000)	-51,586**	-68,713**	-25,758	-50,143**	-86,152**	-71,029***	-28,151
	(0.03)	(0.01)	(0.33)	(0.04)	(0.04)	(0.01)	(0.44)
Crisis*TA	0.0008**	0.0010***	0.0005*	0.0007**	0.0015***	0.0011***	0.0008**
	(0.03)	(0.00)	(0.08)	(0.04)	(0.01)	(0.00)	(0.03)
Bank Fixed Effects	No	No	No	No	No	No	No
N	220	220	220	220	220	220	220

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Panel B: 95^{th} quantile regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Yearly Loss	1.32						
	(0.65)						
Count > $100K (*1,000)		3,952***			3,865**		
		(0.01)			(0.02)		
Severity > $100K			-13.14		-39.85		
			(0.56)		(0.18)		
Individual Bootstrap 95^{th}				-0.15			
				(0.23)			
Yearly Loss $0-$1Mln						14.59**	
						(0.04)	
Yearly Loss > $1Mln						-0.46	
						(0.57)	
Count $100K-$1Mln (*1,000)							2,918*
							(0.09)
Count > $1Mln (*1,000)							16,674
							(0.98)
Net Interest Income	0.015*	0.031*	0.049**	0.082***	0.025	0.018	0.033
	(0.05)	(0.08)	(0.02)	(0.00)	(0.15)	(0.11)	(0.14)
Non-Interest Income	0.083	0.043	0.076	0.068	0.039	0.043	0.047
	(0.31)	(0.20)	(0.23)	(0.35)	(0.27)	(0.53)	(0.32)
Risk (*1,000)	-37,953	22,326	-50,774	-82,372	-8,428	-43,288	11,457
	(0.47)	(0.81)	(0.58)	(0.26)	(0.92)	(0.42)	(0.74)
Risk*TA	-0.0001	-0.0002	0.0000	0.0001	-0.0001	-0.0001	-0.0003
	(0.94)	(0.39)	(0.90)	(0.58)	(0.65)	(0.81)	(0.83)
Crisis (*1,000)	-85,779	-186,911*	-94,671	-90,789	-259,256*	-155,531*	-228,543*
	(0.14)	(0.09)	(0.21)	(0.15)	(0.07)	(0.08)	(0.09)
Crisis*TA	0.0011	0.0026*	0.0011	0.0007	0.0045*	0.0027*	0.0028**
	(0.18)	(0.05)	(0.20)	(0.17)	(0.06)	(0.07)	(0.03)
Bank Fixed Effects	No	No	No	No	No	No	No
N	220	220	220	220	220	220	220

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Appendix A

Table 7: **Bank Holding Companies**
This table presents the list of all the Bank Holding Companies that were considered in our study

Bank Holding Company Name
Ally Financial Inc.
American Express Company
Bank of America Corporation
The Bank of New York Mellon Corporation
BB&T Corporation
BBVA Compass Bancshares, Inc.
BMO Financial Corporation
Capital One Financial Corporation
Citigroup Inc.
Citizens Financial Group, Inc.
Comerica Inc.
Deutsche Bank Trust Corporation
Discover Financial Services
Fifth Third Bancorp.
The Goldman Sachs Group, Inc.
HSBC North America Holdings, Inc.
Huntington Bancshares Inc.
JPMorgan Chase & Co.
KeyCorp
M&T Corporation
Morgan Stanley
MUFG Americas Holding Corporation
Northern Trust Corporation
The PNC Financial Services Group, Inc.
Regions Financial Corporation
Santander Holdings USA, Inc.
State Street Corporation
SunTrust Banks, Inc.
U.S. Bancorp.
Wells Fargo &Co.
Zions Bancorp.

Appendix B

Table 8: **Loss Metrics plus control variables - Minimum interquantile range for each observation increased to 0.1**

This table presents coefficients estimates from regression of operational losses at year t on loss metrics and BHCs characteristics at year $t-1$. Panel A presents OLS estimates while Panel B presents estimates from the 95^{th} quantile regressions. $Yearly\ Loss$ is the sum of the gross amounts of loss events. $Count$ > \$100K is the number of loss events greater than \$100K. *Severity* > \$100K is the average severity of loss events greater than \$100K. $Individual\ Bootstrap$ 95^{th} is the estimate of the 95^{th} quantile of the unconditional distribution using empirical bootstrap. $Yearly\ Loss$ \$0-\$1Mln is the sum of the gross amounts of loss events between \$0 and \$1Mln. $Yearly\ Loss$ > \$1Mln is the sum of the gross amounts of loss events greater than \$1Mln. $Count$ \$100K-\$1Mln is the number of loss events between \$100K and \$1Mln. $Count$ > \$1Mln is the number of loss events greater than \$1Mln. *Equity* is the value of equity at the end of the year. *Liabilities* is the value of the liabilities at the end of the year. *Risk* is the value of the risk management rating given by the Federal Reserve System to BHCs. TA is the value of BHCs total assets at the end of the year. $Crisis$ $Indicator$ is a binary variable that assumes the value of one if the US is deemed to be in recession for at least one month in the year according to the NBER. P-values are presented in parentheses.

Panel A: OLS regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Yearly Loss	0.32						
	(0.26)						
Count > \$100K (*1,000)		1,364***			1,320**		
		(0.00)			(0.03)		
Severity > \$100K			-2.67		5.72		
			(0.80)		(0.51)		
Individual Bootstrap 95^{th}				0.03			
				(0.23)			
Yearly Loss \$0-\$1Mln						4.26***	
						(0.00)	
Yearly Loss > \$1Mln						0.00	
						(0.87)	
Count \$100K-\$1Mln (*1,000)							1,579***
							(0.00)
Count > \$1Mln (*1,000)							6,516
							(0.77)
Equity	-0.010***	-0.007***	-0.009***	-0.010***	-0.007**	-0.008***	-0.006**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
Liabilities	0.003***	0.002**	0.002***	0.003***	0.002**	0.002***	0.002**
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.04)
Risk (*1,000)	10,685	6,573	-20,152	-16,589	-4,607	27,456	14,889
	(0.99)	(0.87)	(0.53)	(0.45)	(0.93)	(0.15)	(0.68)
Risk*TA	-0.0005	-0.0001	0.0000	-0.0002	-0.0001	-0.0002	-0.0001
	(0.23)	(0.53)	(0.67)	(0.53)	(0.68)	(0.16)	(0.57)
Crisis (*1,000)	-75,701***	-73,432**	-60,535*	-67,536**	-72,033**	-79,258***	-68,011**
	(0.00)	(0.02)	(0.06)	(0.02)	(0.01)	(0.00)	(0.02)
Crisis*TA	0.0006**	0.0007***	0.0006**	0.0006**	0.0008***	0.0009***	0.0008***
	(0.04)	(0.00)	(0.04)	(0.03)	(0.00)	(0.00)	(0.00)
Bank Fixed Effects	No	No	No	No	No	No	No
N	220	220	220	220	220	220	220

*p < 0.10, **p < 0.05, ***p <0.01

Panel B: 95^{th} quantile regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Yearly Loss	1.04						
	(0.63)						
Count > \$100K (*1,000)		2,768*			3,296*		
		(0.06)			(0.10)		
Severity > \$100K			-0.29		26.36		
			(0.86)		(0.88)		
Individual Bootstrap 95^{th}				0.03			
				(0.95)			
Yearly Loss \$0-\$1Mln						11.79**	
						(0.01)	
Yearly Loss > \$1Mln						-0.04	
						(0.66)	
Count \$100K-\$1Mln (*1,000)							5,356***
							(0.00)
Count > \$1Mln (*1,000)							-47,862
							(0.32)
Equity	-0.030**	-0.027***	-0.035**	-0.035**	-0.034***	-0.022***	-0.023***
	(0.03)	(0.00)	(0.03)	(0.01)	(0.00)	(0.00)	(0.00)
Liabilities	0.008**	0.004*	0.008**	0.008***	0.006**	0.005**	0.002*
	(0.01)	(0.06)	(0.02)	(0.00)	(0.03)	(0.02)	(0.06)
Risk (*1,000)	20,326	10,433	26,350	18,368	25,472	107,194	-10,872
	(0.96)	(0.61)	(0.76)	(0.98)	(0.77)	(0.45)	(0.87)
Risk*TA	-0.0008	0.0001	-0.0004	-0.0003	-0.0003	-0.0005	0.0006
	(0.54)	(0.68)	(0.46)	(0.65)	(0.75)	(0.71)	(0.74)
Crisis (*1,000)	-171,531	-239,118**	-261,178	-250,453	-266,641*	-191,440**	-240,502
	(0.16)	(0.05)	(0.14)	(0.21)	(0.06)	(0.01)	(0.15)
Crisis*TA	0.0010	0.0016*	0.0018	0.0016	0.0015*	0.0021**	0.0022*
	(0.43)	(0.06)	(0.37)	(0.47)	(0.05)	(0.04)	(0.08)
Bank Fixed Effects	No	No	No	No	No	No	No
N	220	220	220	220	220	220	220

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 9: **Loss Metrics plus control variables - Minimum interquantile range for each observation decreased to 0.01**

This table presents coefficients estimates from regression of operational losses at year t on loss metrics and BHCs characteristics at year $t-1$. Panel A presents OLS estimates while Panel B presents estimates from the 95^{th} quantile regressions. $Yearly\ Loss$ is the sum of the gross amounts of loss events. $Count$ > \$100K is the number of loss events greater than \$100K. $Severity$ > \$100K is the average severity of loss events greater than \$100K. *Individual Bootstrap* 95^{th} is the estimate of the 95^{th} quantile of the unconditional distribution using empirical bootstrap. $Yearly\ Loss$ \$0-\$1Mln is the sum of the gross amounts of loss events between \$0 and \$1Mln. $Yearly\ Loss$ > \$1Mln is the sum of the gross amounts of loss events greater than \$1Mln. $Count$ \$100K-\$1Mln is the number of loss events between \$100K and \$1Mln. $Count$ > \$1Mln is the number of loss events greater than \$1Mln. *Equity* is the value of equity at the end of the year. *Liabilities* is the value of the liabilities at the end of the year. *Risk* is the value of the risk management rating given by the Federal Reserve System to BHCs. TA is the value of BHCs total assets at the end of the year. *Crisis* $Indicator$ is a binary variable that assumes the value of one if the US is deemed to be in recession for at least one month in the year according to the NBER. P-values are presented in parentheses.

Panel A: OLS regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Yearly Loss	0.38						
	(0.13)						
Count > \$100K (*1,000)		2,575***			2,329***		
		(0.00)			(0.00)		
Severity > \$100K			-9.47		-6.64		
			(0.49)		(0.61)		
Individual Bootstrap 95^{th}				0.03			
				(0.43)			
Yearly Loss \$0-\$1Mln						0.95	
						(0.31)	
Yearly Loss > \$1Mln						0.41*	
						(0.07)	
Count \$100K-\$1Mln (*1,000)							458
							(0.86)
Count > \$1Mln (*1,000)							20,771
							(0.63)
Equity	-0.005***	-0.009**	-0.007***	-0.008**	-0.008**	-0.000	-0.009*
	(0.00)	(0.03)	(0.00)	(0.01)	(0.03)	(0.41)	(0.08)
Liabilities	0.001	-0.001	0.001	0.000	0.000	0.000	-0.002
	(0.19)	(0.51)	(0.16)	(0.79)	(0.99)	(0.14)	(0.58)
Risk (*1,000)	558	-76,559	-19,656	-59,708	-49,404	23,740*	-313,092
	(0.96)	(0.30)	(0.66)	(0.29)	(0.58)	(0.07)	(0.32)
Risk*TA	0.0002	0.0007	0.0004	0.0007	0.0004	-0.0001	0.0015
	(0.78)	(0.16)	(0.47)	(0.23)	(0.44)	(0.17)	(0.34)
Crisis (*1,000)	-50,326*	-142,631*	-45,707	-30,265	-106,059	-30,071	-66,174
	(0.08)	(0.06)	(0.20)	(0.24)	(0.10)	(0.53)	(0.66)
Crisis*TA	0.0006**	0.0015**	0.0006*	0.0003	0.0014**	0.0008	0.0008
	(0.03)	(0.01)	(0.08)	(0.18)	(0.02)	(0.19)	(0.49)
Bank Fixed Effects	No	No	No	No	No	No	No
N	220	220	220	220	220	220	220

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Panel B: 95^{th} quantile regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Yearly Loss	1.30						
	(0.33)						
Count > \$100K (*1,000)		3,895*			3,624**		
		(0.07)			(0.03)		
Severity > \$100K			-6.84		-34.75		
			(0.88)		(0.69)		
Individual Bootstrap 95^{th}				0.03			
				(0.85)			
Yearly Loss \$0-\$1Mln						13.24***	
						(0.00)	
Yearly Loss > \$1Mln						-0.13	
						(0.73)	
Count \$100K-\$1Mln (*1,000)							6,120***
							(0.00)
Count > \$1Mln (*1,000)							-263,573**
							(0.05)
Equity	-0.027***	-0.028***	-0.032***	-0.025***	-0.026***	-0.020***	-0.033***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Liabilities	0.005**	0.002	0.007***	0.004**	0.002	0.004**	0.002
	(0.02)	(0.29)	(0.00)	(0.04)	(0.14)	(0.04)	(0.18)
Risk (*1,000)	14,912	-60,414	12,737	-61,125	-47,073	99,197	-184,433
	(0.70)	(0.62)	(0.95)	(0.42)	(0.60)	(0.28)	(0.33)
Risk*TA	0.0001	0.0007	-0.0002	0.0005	0.0007	-0.0004	0.0016
	(0.88)	(0.47)	(0.98)	(0.54)	(0.60)	(0.70)	(0.23)
Crisis (*1,000)	-221,703**	-266,511**	-269,922**	-195,224***	-288,008***	-135,069**	-90,490*
	(0.04)	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)	(0.09)
Crisis*TA	0.0014*	0.0022***	0.0019*	0.0014**	0.0024**	0.0013**	0.0009*
	(0.07)	(0.01)	(0.09)	(0.04)	(0.02)	(0.02)	(0.05)
Bank Fixed Effects	No	No	No	No	No	No	No
N	220	220	220	220	220	220	220

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Appendix C

Table 10: **Loss metrics plus control variables - intertertile range used for weighting**
This table presents coefficients estimates from regression of operational losses at year t on loss metrics and BHCs characteristics at year $t-1$. Panel A presents OLS estimates while Panel B presents estimates from the 95^{th} quantile regressions. *Yearly Loss* is the sum of the gross amounts of loss events. *Count* > \$100K is the number of loss events greater than \$100K. *Severity* > \$100K is the average severity of loss events greater than \$100K. *Individual Bootstrap* 95^{th} is the estimate of the 95^{th} quantile of the unconditional distribution using empirical bootstrap. *Yearly Loss* \$0-\$1Mln is the sum of the gross amounts of loss events between \$0 and \$1Mln. *Yearly Loss* > \$1Mln is the sum of the gross amounts of loss events greater than \$1Mln. *Count* \$100K-\$1Mln is the number of loss events between \$100K and \$1Mln. *Count* > \$1Mln is the number of loss events greater than \$1Mln. *Equity* is the value of equity at the end of the year. *Liabilities* is the value of the liabilities at the end of the year. *Risk* is the value of the risk management rating given by the Federal Reserve System to BHCs. *TA* is the value of BHCs total assets at the end of the year. *Crisis Indicator* is a binary variable that assumes the value of one if the US is deemed to be in recession for at least one month in the year according to the NBER. P-values are presented in parentheses.

Panel A: OLS regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Yearly Loss	0.58**						
	(0.03)						
Count > \$100K (*1,000)		1,628**			1,781**		
		(0.03)			(0.04)		
Severity > \$100K			6.00		-16.42		
			(0.65)		(0.46)		
Individual Bootstrap 95^{th}				0.05			
				(0.17)			
Yearly Loss \$0-\$1Mln						4.56**	
						(0.02)	
Yearly Loss > \$1Mln						0.15	
						(0.11)	
Count \$100K-\$1Mln (*1,000)							2,270**
							(0.04)
Count > \$1Mln (*1,000)							-5,088
							(0.81)
Equity	-0.011***	-0.009**	-0.012***	-0.008**	-0.009**	-0.005**	-0.007**
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.05)
Liabilities	0.003**	0.000	0.001	0.001	0.000	0.002***	-0.001
	(0.02)	(0.92)	(0.70)	(0.38)	(0.89)	(0.00)	(0.78)
Risk (*1,000)	8,381	-70,091	-95,235	-37,534	-55,552	59,481***	-52,881
	(0.74)	(0.62)	(0.56)	(0.41)	(0.54)	(0.01)	(0.70)
Risk*TA	-0.0007	0.0007	0.0007	0.0003	0.0006	-0.0006	0.0007
	(0.22)	(0.76)	(0.69)	(0.57)	(0.60)	(0.02)	(0.72)
Crisis (*1,000)	-110,527***	-25,049	-99,847*	-116,213***	-5,578	-74,990**	-34,150
	(0.01)	(0.48)	(0.10)	(0.01)	(0.75)	(0.02)	(0.50)
Crisis*TA	0.0007**	0.0004	0.0008*	0.0011**	0.0003	0.0010***	0.0005
	(0.03)	(0.21)	(0.05)	(0.01)	(0.33)	(0.00)	(0.19)
Bank Fixed Effects	No	No	No	No	No	No	No
N	220	220	220	220	220	220	220

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Panel B: 95^{th} quantile regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Yearly Loss	1.24						
	(0.42)						
Count > $100K (*1,000)		4,363*			3,661**		
		(0.08)			(0.06)		
Severity > $100K			22.68		-35.01		
			(0.69)		(0.42)		
Individual Bootstrap 95^{th}				-0.05			
				(0.76)			
Yearly Loss $0-$1Mln						11.15**	
						(0.03)	
Yearly Loss > $1Mln						-0.58	
						(0.51)	
Count $100K-$1Mln (*1,000)							5,178***
							(0.00)
Count > $1Mln (*1,000)							-143,162
							(0.12)
Equity	-0.033***	-0.030***	-0.035***	-0.040***	-0.025***	-0.022***	-0.026***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Liabilities	0.006**	0.002	0.007***	0.007***	0.002	0.003*	0.002
	(0.02)	(0.15)	(0.01)	(0.00)	(0.19)	(0.09)	(0.20)
Risk (*1,000)	-22,028	-57,027	-11,490	-64,697	-41,735	31,975	-89,145
	(0.73)	(0.70)	(0.88)	(0.90)	(0.73)	(0.73)	(0.35)
Risk*TA	0.0000	0.0006	-0.0001	0.0000	0.0007	0.0000	0.0011
	(0.96)	(0.65)	(0.84)	(0.94)	(0.55)	(0.76)	(0.22)
Crisis (*1,000)	-244,882**	-283,308**	-182,819*	-278,105*	-276,795*	-211,391***	-168,923*
	(0.03)	(0.03)	(0.08)	(0.07)	(0.08)	(0.00)	(0.10)
Crisis*TA	0.0013	0.0023**	0.0005	0.0014	0.0023*	0.0017**	0.0016*
	(0.16)	(0.04)	(0.29)	(0.21)	(0.06)	(0.03)	(0.07)
Bank Fixed Effects	No	No	No	No	No	No	No
N	220	220	220	220	220	220	220

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 11: **Loss metrics plus control variables - 10^{th} and 90^{th} quantiles used as range for weighting**

This table presents coefficients estimates from regression of operational losses at year t on loss metrics and BHCs characteristics at year $t-1$. Panel A presents OLS estimates while Panel B presents estimates from the 95^{th} quantile regressions. $Yearly\ Loss$ is the sum of the gross amounts of loss events. $Count$ > \$100K is the number of loss events greater than \$100K. *Severity* > \$100K is the average severity of loss events greater than \$100K. *Individual Bootstrap* 95^{th} is the estimate of the 95^{th} quantile of the unconditional distribution using empirical bootstrap. $Yearly\ Loss$ \$0-\$1Mln is the sum of the gross amounts of loss events between \$0 and \$1Mln. $Yearly\ Loss$ > \$1Mln is the sum of the gross amounts of loss events greater than \$1Mln. *Count* \$100K-\$1Mln is the number of loss events between \$100K and \$1Mln. *Count* > \$1Mln is the number of loss events greater than \$1Mln. *Equity* is the value of equity at the end of the year. *Liabilities* is the value of the liabilities at the end of the year. *Risk* is the value of the risk management rating given by the Federal Reserve System to BHCs. TA is the value of BHCs total assets at the end of the year. *Crisis Indicator* is a binary variable that assumes the value of one if the US is deemed to be in recession for at least one month in the year according to the NBER. P-values are presented in parentheses.

Panel A: OLS regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Yearly Loss	0.35^{**}						
	(0.01)						
Count > \$100K (*1,000)		$1,683^{***}$			$1,568^{***}$		
		(0.00)			(0.00)		
Severity > \$100K			9.81		6.29		
			(0.13)		(0.24)		
Individual Bootstrap 95^{th}				0.06			
				(0.34)			
Yearly Loss \$0-\$1Mln						4.44^{***}	
						(0.00)	
Yearly Loss > \$1Mln						0.11	
						(0.41)	
Count \$100K-\$1Mln (*1,000)							$1,966^{***}$
							(0.00)
Count > \$1Mln (*1,000)							-17,991
							(0.43)
Equity	-0.006^{***}	-0.005^{***}	-0.007^{***}	-0.007^{***}	-0.005^{***}	-0.004^{***}	-0.005^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Liabilities	0.002^{***}	0.001^{***}	0.002^{***}	0.002^{***}	0.001^{***}	0.001^{***}	0.001^{*}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.09)
Risk (*1,000)	16,535	$26,324^{*}$	15,153	15,739	26,312	$32,782^{**}$	-6,600
	(0.38)	(0.08)	(0.38)	(0.34)	(0.12)	(0.04)	(0.94)
Risk*TA	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	0.0001
	(0.53)	(0.54)	(0.36)	(0.46)	(0.27)	(0.33)	(0.46)
Crisis (*1,000)	$-67,314^{**}$	$-58,513^{***}$	$-52,711^{**}$	$-61,504^{***}$	$-62,470^{***}$	$-69,067^{***}$	$-74,679^{**}$
	(0.02)	(0.00)	(0.03)	(0.01)	(0.00)	(0.00)	(0.04)
Crisis*TA	0.0007^{***}	0.0009^{***}	0.0005^{*}	0.0006^{**}	0.0010^{***}	0.0010^{***}	0.0009^{***}
	(0.01)	(0.00)	(0.05)	(0.03)	(0.00)	(0.00)	(0.00)
Bank Fixed Effects	No	No	No	No	No	No	No
N	220	220	220	220	220	220	220

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Panel B: 95^{th} quantile regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Yearly Loss	0.47						
	(0.58)						
Count > $100K (*1,000)		4,440**			4,249**		
		(0.02)			(0.02)		
Severity > $100K			8.00		2.87		
			(0.50)		(0.80)		
Individual Bootstrap 95^{th}				0.07			
				(0.77)			
Yearly Loss $0-$1Mln						13.10***	
						(0.00)	
Yearly Loss > $1Mln						-0.02	
						(0.77)	
Count $100K-$1Mln (*1,000)							9,409***
							(0.00)
Count > $1Mln (*1,000)							-205,060
							(0.13)
Equity	-0.028***	-0.021***	-0.028***	-0.031***	-0.018***	-0.021***	-0.031***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Liabilities	0.008***	0.004**	0.007***	0.009***	0.005***	0.004***	0.003**
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)
Risk (*1,000)	80,266	80,584	46,416	92,921	108,501	105,256	-29,008
	(0.42)	(0.22)	(0.39)	(0.32)	(0.24)	(0.17)	(0.86)
Risk*TA	-0.0005	0.0000	-0.0002	-0.0005	-0.0006	-0.0005	0.0006
	(0.43)	(0.42)	(0.28)	(0.38)	(0.35)	(0.35)	(0.86)
Crisis (*1,000)	-204,721	-153,335*	-220,493	-176,731	-195,033*	-234,868**	-242,598
	(0.14)	(0.06)	(0.19)	(0.16)	(0.06)	(0.02)	(0.17)
Crisis*TA	0.0015	0.0018*	0.0017	0.0010	0.0028*	0.0030**	0.0028*
	(0.30)	(0.09)	(0.44)	(0.40)	(0.05)	(0.02)	(0.07)
Bank Fixed Effects	No	No	No	No	No	No	No
N	220	220	220	220	220	220	220

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Appendix D

Table 12: **Loss metrics plus control variables - Block bootstrap**
This table presents coefficients estimates from regression of operational losses at year t on loss metrics and BHCs characteristics at year $t-1$. Panel A presents OLS estimates while Panel B presents estimates from the 95^{th} quantile regressions. $Yearly\ Loss$ is the sum of the gross amounts of loss events. $Count$ > \$100K is the number of loss events greater than \$100K. *Severity* > \$100K is the average severity of loss events greater than \$100K. *Individual Bootstrap* 95^{th} is the estimate of the 95^{th} quantile of the unconditional distribution using empirical bootstrap. $Yearly\ Loss$ \$0-\$1Mln is the sum of the gross amounts of loss events between \$0 and \$1Mln. $Yearly\ Loss$ > \$1Mln is the sum of the gross amounts of loss events greater than \$1Mln. *Count* \$100K-\$1Mln is the number of loss events between \$100K and \$1Mln. *Count* > \$1Mln is the number of loss events greater than \$1Mln. *Equity* is the value of equity at the end of the year. *Liabilities* is the value of the liabilities at the end of the year. *Risk* is the value of the risk management rating given by the Federal Reserve System to BHCs. TA is the value of BHCs total assets at the end of the year. *Crisis* $Indicator$ is a binary variable that assumes the value of one if the US is deemed to be in recession for at least one month in the year according to the NBER. P-values are presented in parentheses.

Panel A: OLS regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Yearly Loss	0.36*						
	(0.08)						
Count > \$100K (*1,000)		1,856***			1,722		
		(0.00)			(0.24)		
Severity > \$100K			-5.36		-4.56		
			(0.75)		(0.81)		
Individual Bootstrap 95^{th}				0.04			
				(0.20)			
Yearly Loss \$0-\$1Mln						2.87*	
						(0.06)	
Yearly Loss > \$1Mln						0.25	
						(0.25)	
Count \$100K-\$1Mln (*1,000)							1,520
							(0.51)
Count > \$1Mln (*1,000)							-10,269
							(0.90)
Equity	-0.008*	-0.007**	-0.008**	-0.007**	-0.007**	-0.004*	-0.007**
	(0.04)	(0.01)	(0.03)	(0.03)	(0.02)	(0.08)	(0.02)
Liabilities	0.002**	-0.000	0.002***	0.001*	0.000	0.001**	-0.001
	(0.04)	(0.99)	(0.01)	(0.09)	(0.36)	(0.01)	(0.79)
1,000*Risk	11,516	-50,333	-9,610	-19,592	-20,873	33,247**	-137,056
	(0.90)	(0.74)	(0.56)	(0.71)	(0.80)	(0.04)	(0.72)
Risk*TA	-0.0001	0.0005	0.0001	0.0002	0.0002	-0.0001	0.0008
	(0.66)	(0.74)	(0.70)	(0.99)	(0.89)	(0.13)	(0.70)
1,000*Crisis	-62,431*	-95,007*	-41,881	-50,343*	-82,155	-52,720	-55,401
	(0.08)	(0.10)	(0.28)	(0.09)	(0.17)	(0.26)	(0.41)
Crisis*TA	0.0006**	0.0011***	0.0005	0.0005**	0.0010**	0.0009*	0.0006
	(0.02)	(0.01)	(0.10)	(0.01)	(0.03)	(0.06)	(0.26)
Bank Fixed Effects	No	No	No	No	No	No	No
N	220	220	220	220	220	220	220

$^{*}p$ < 0.10, $^{**}p$ < 0.05, $^{***}p$ <0.01

Panel B: 95^{th} quantile regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Yearly Loss	1.30						
	(0.40)						
Count > \$100K (*1,000)		4,629*			3,610*		
		(0.06)			(0.09)		
Severity > \$100K			-7.42		-31.26		
			(0.89)		(0.62)		
Individual Bootstrap 95^{th}				0.02			
				(0.98)			
Yearly Loss \$0-\$1Mln						13.22***	
						(0.00)	
Yearly Loss > \$1Mln						-0.21	
						(0.56)	
Count \$100K-\$1Mln (*1,000)							6,479***
							(0.00)
Count > \$1Mln (*1,000)							-232,244
							(0.14)
Equity	-0.033**	-0.025**	-0.034**	-0.034**	-0.025**	-0.021***	-0.032**
	(0.04)	(0.02)	(0.04)	(0.02)	(0.02)	(0.00)	(0.02)
Liabilities	0.005**	0.002**	0.008***	0.007***	0.002**	0.004***	0.002**
	(0.01)	(0.04)	(0.01)	(0.00)	(0.04)	(0.01)	(0.05)
1,000*Risk	-32,262	-12,710	5,411	-21,891	-41,984	90,148	-142,737
	(0.81)	(0.86)	(0.93)	(0.60)	(0.78)	(0.31)	(0.53)
Risk*TA	0.0001	0.0005	-0.0002	0.0000	0.0007	-0.0003	0.0013
	(0.92)	(0.68)	(0.84)	(0.70)	(0.70)	(0.64)	(0.40)
1,000*Crisis	-258,807	-256,503*	-293,428*	-273,677**	-278,617**	-149,305**	-132,772
	(0.11)	(0.05)	(0.07)	(0.05)	(0.03)	(0.03)	(0.15)
Crisis*TA	0.0014	0.0023**	0.0022	0.0018*	0.0024**	0.0014**	0.0013
	(0.20)	(0.03)	(0.20)	(0.09)	(0.03)	(0.03)	(0.06)
Bank Fixed Effects	No	No	No	No	No	No	No
N	220	220	220	220	220	220	220

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Appendix E

Table 13: **Loss Metrics alone - 90th and 99th quantile regressions**

This table presents coefficient estimates from the regression of operational losses at year t on loss metrics at year $t-1$. Panel A presents estimates of the 90th quantile regression while Panel B presents estimates from the 99th quantile regressions. *Yearly Loss* is the sum of the gross amounts of loss events. *Count* > \$100K is the number of loss events greater than \$100K. *Severity* > \$100K is the average severity of loss events greater than \$100K. *Individual Bootstrap* 95th is the estimate of the 95th quantile of the unconditional distribution using empirical bootstrap. *Yearly Loss* \$0-\$1Mln is the sum of the gross amounts of loss events between \$0 and \$1Mln. *Yearly Loss* > \$1Mln is the sum of the gross amounts of loss events greater than \$1Mln. *Count* \$100K-\$1Mln is the number of loss events between \$100K and \$1Mln. *Count* > \$1Mln is the number of loss events greater than \$1Mln. P-values are presented in parentheses.

Panel A: 90th quantile regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Yearly Loss	2.65***						
	(0.00)						
Count > \$100K (*1,000)		7,240***			5,895***		
		(0.00)			(0.00)		
Severity > \$100K			926.89***		65.61		
			(0.00)		(0.37)		
Individual Bootstrap 95th				0.88***			
				(0.00)			
Yearly Loss \$0-\$1Mln						10.53	
						(0.17)	
Yearly Loss > \$1Mln						1.40*	
						(0.09)	
Count \$100K-\$1Mln (*1,000)							6,684*
							(0.09)
Count > \$1Mln (*1,000)							29,201
							(0.53)
N	240	240	240	240	240	240	240

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Panel B: 99th quantile regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Yearly Loss	15.48***						
	(0.00)						
Count > \$100K (*1,000)		12,321***			20,522***		
		(0.00)			(0.00)		
Severity > \$100K			3,481.84***		67.58		
			(0.00)		(0.46)		
Individual Bootstrap 95th				2.08***			
				(0.00)			
Yearly Loss \$0-\$1Mln						24.38*	
						(0.09)	
Yearly Loss > \$1Mln						8.30*	
						(0.10)	
Count \$100K-\$1Mln (*1,000)							10,899***
							(0.00)
Count > \$1Mln (*1,000)							501,758
							(0.74)
N	240	240	240	240	240	240	240

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 14: **Loss metrics plus control variables - 90^{th} and 99^{th} quantile regressions**
This table presents coefficients estimates from regression of operational losses at year t on loss metrics and BHCs characteristics at year $t-1$. Panel A presents estimates of the 90^{th} quantile regression while Panel B presents estimates from the 99^{th} quantile regressions. $Yearly\ Loss$ is the sum of the gross amounts of loss events. *Count* > \$100K is the number of loss events greater than \$100K. *Severity* > \$100K is the average severity of loss events greater than \$100K. $Individual\ Bootstrap$ 95^{th} is the estimate of the 95^{th} quantile of the unconditional distribution using empirical bootstrap. $Yearly\ Loss$ \$0-\$1Mln is the sum of the gross amounts of loss events between \$0 and \$1Mln. $Yearly\ Loss$ > \$1Mln is the sum of the gross amounts of loss events greater than \$1Mln. *Count* \$100K-\$1Mln is the number of loss events between \$100K and \$1Mln. *Count* > \$1Mln is the number of loss events greater than \$1Mln. *Equity* is the value of equity at the end of the year. *Liabilities* is the value of the liabilities at the end of the year. *Risk* is the value of the risk management rating given by the Federal Reserve System to BHCs. TA is the value of BHCs total assets at the end of the year. $Crisis\ Indicator$ is a binary variable that assumes the value of one if the US is deemed to be in recession for at least one month in the year according to the NBER. P-values are presented in parentheses.

Panel A: 90^{th} quantile regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Yearly Loss	0.65						
	(0.35)						
Count > \$100K (*1,000)		2,509*			2,123**		
		(0.06)			(0.05)		
Severity > \$100K			11.38		-13.57		
			(0.96)		(0.66)		
Individual Bootstrap 95^{th}				0.01			
				(0.89)			
Yearly Loss \$0-\$1Mln						11.39***	
						(0.00)	
Yearly Loss > \$1Mln						-0.33	
						(0.57)	
Count \$100K-\$1Mln (*1,000)							2,884***
							(0.01)
Count > \$1Mln (*1,000)							-76,711
							(0.18)
Equity	-0.018***	-0.017***	-0.020***	-0.020***	-0.017***	-0.013***	-0.017***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Liabilities	0.003**	0.002	0.004**	0.004**	0.003	0.002**	0.001
	(0.03)	(0.38)	(0.01)	(0.04)	(0.19)	(0.04)	(0.45)
Risk (*1,000)	-3,413	7,121	-9,581	-15,379	15,657	69,239	-83,061
	(0.84)	(0.79)	(0.70)	(0.45)	(0.87)	(0.28)	(0.39)
Risk*TA	0.0000	0.0004	0.0002	0.0001	0.0001	-0.0001	0.0010
	(0.99)	(0.54)	(0.62)	(0.55)	(0.59)	(0.88)	(0.27)
Crisis (*1,000)	-180,571**	-166,939***	-155,941**	-157,535***	-206,062***	-122,660***	-73,358
	(0.01)	(0.01)	(0.02)	(0.01)	(0.00)	(0.01)	(0.16)
Crisis*TA	0.0015**	0.0017**	0.0010*	0.0011**	0.0018***	0.0016***	0.0009*
	(0.04)	(0.01)	(0.08)	(0.03)	(0.00)	(0.01)	(0.06)
Bank Fixed Effects	No	No	No	No	No	No	No
N	220	220	220	220	220	220	220

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Panel B: 99^{th} quantile regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Yearly Loss	-0.90						
	(0.50)						
Count > \$100K (*1,000)		7,248***			6,653***		
		(0.01)			(0.01)		
Severity > \$100K			-22.88		50.39		
			(0.47)		(0.80)		
Individual Bootstrap 95^{th}				-0.09			
				(0.88)			
Yearly Loss \$0-\$1Mln						27.62***	
						(0.00)	
Yearly Loss > \$1Mln						-0.29	
						(0.53)	
Count \$100K-\$1Mln (*1,000)							16,544***
							(0.00)
Count > \$1Mln (*1,000)							-344,656*
							(0.07)
Equity	-0.057***	-0.046***	-0.057***	-0.053***	-0.048***	-0.041***	-0.044***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Liabilities	0.018***	0.007***	0.017***	0.015***	0.010**	0.007**	0.004***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.02)	(0.01)	(0.01)
Risk (*1,000)	190,798	36,887	182,760	122,695	89,304	176,611	-5,794
	(0.74)	(0.43)	(0.54)	(0.77)	(0.52)	(0.30)	(0.89)
Risk*TA	-0.0015	0.0000	-0.0012	-0.0013	-0.0013	-0.0006	0.0008
	(0.64)	(0.52)	(0.60)	(0.56)	(0.59)	(0.69)	(0.73)
Crisis (*1,000)	-232,772	-380,097	-317,377	-287,505	-384,861*	-245,710*	-246,858
	(0.13)	(0.12)	(0.20)	(0.13)	(0.08)	(0.09)	(0.25)
Crisis*TA	0.0009	0.0025	0.0018	0.0017	0.0025	0.0023	0.0025
	(0.55)	(0.18)	(0.68)	(0.46)	(0.14)	(0.12)	(0.25)
Bank Fixed Effects	No	No	No	No	No	No	No
N	220	220	220	220	220	220	220

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$