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The Strategic Under-Reporting of Bank Risk

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Abstract

We show that banks significantly under-report the risk in their trading book when they have lower equity capital. A decrease in a bank's equity capital results in substantially more frequent violations of its self-reported risk levels in the following quarter. These results are consistent with the view that banks under-report their risks to lower their current regulatory capital requirements at the expense of potentially higher future capital requirements that follow if the under-reporting is detected. The under-reporting is especially high during the critical periods of high systemic risk and for banks with larger trading operations. Our results provide evidence that the current regulations give reporting incentives that make the self-reported risk measures least informative precisely when they matter the most.

Keywords: value-at-risk, risk-based capital requirements, risk measurement, systemic risk.

JEL Classification: G20, G30.

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1 Introduction

Do banks accurately report their risks to outsiders? Accurate and timely measurement of risk is crucial for assessing the soundness of financial institutions and the stability of the financial system and economy as a whole. The complexity of a large bank's business model makes it difficult for regulators and market participants to observe the bank's true risks at a reasonable cost. As a result, outsiders depend on information from the bank itself to judge its riskiness. These self-reported risk levels then heavily influence both regulatory treatment of the banks and market participants' investment decisions. Riskier banks face higher capital charges, pay more for deposit insurance, and are more likely to face regulatory sanctions. Such banks are also likely to face more risk in the stability of their funding during periods of banking crisis. These consequences create an important incentive problem: the under-reporting of risk by the banks. Do banks engage in such behavior? What are the implications of this behavior on the usefulness of risk measurement for the financial system as a whole, particularly in times of systemic stress? We empirically address these important questions by examining the accuracy of self-reported risk measures in banks' trading books.

While accurate risk reporting is important for the entire business of a bank, we focus on the trading book because it allows us to tease out the under-reporting incentives in a clean way. A typical trading portfolio consists of marketable financial instruments linked to interest rates, exchange rates, commodities, and equity prices. The trading desks of large financial institution have significant risks and have been the subject of many recent policy debates and discussions on risk-management failures within a bank.[1] Banks are allowed to measure the risk of their trading portfolio with internal Value-at-Risk (VaR) models. Value-at-Risk is a statistical measure of risk that estimates the dollar amount of potential losses from adverse market moves. Regulators around the world use these numbers to determine

[1]See, for example, the enactment of "Volcker Rule," (under Title VI of the Dodd-Frank Wall Street Reform and Consumer Protection Act) which restricts the trading activity of depository institutions. Recent scandals include "London Whale" Bruno Iksil at J.P. Morgan in 2012 and Kweku Adoboli at UBS in 2011. These events cost their banks about \$6.2 billion and \$2.2 billion in trading losses, respectively.

capital requirements for market risk. Institutions can lower their current capital requirements by under-reporting their risks, and the incentive to do so is especially strong if they have lower equity capital to begin with. The use of an internal risk model leaves a great deal of discretion with the reporting institution. For example, institutions can vary assumptions about correlations between asset classes or the length of the historical period used to estimate asset volatilities to estimate their VaR. This flexibility gives banks a significant ability to under-report their trading risks. The combination of incentive and ability to under-report risk has the potential to compromise the integrity of the risk levels that banks report in their trading portfolios, and this is the focus of our study.

While no prior academic work has empirically investigated this issue, regulators do recognize the possibility of under-reporting. To mitigate this incentive, the regulators use a "backtesting" procedure to evaluate the accuracy of an institution's self-reported VaR, and impose a penalty on institutions with inaccurate models. As per the recommendations of Basel committee, an institution's market-risk capital requirement is set at three times its 99% VaR number over a 10-day horizon.[2] However, if an institution breaches its self-reported VaR level too often, it faces higher capital requirement in future periods. For example, the Office of the Comptroller of the Currency (OCC) examines the number of times a bank breaches its self-reported VaR – which we refer to as *exceptions* or *violations* – every quarter. If an institution has more than four exceptions during the trailing four quarters, its capital requirement for the subsequent periods can increase to up to four-times their VaR level.[3] Thus, regulators impose higher capital charge on institutions that are more likely to have under-reported, but these charges come with significant delay. Depending on the future asset price movements, with some probability the under-reporting does not get detected even

[2]VaR is computed at a certain confidence interval for a fixed horizon of time. A 10-day 99% VaR estimates the dollar amount of loss that the portfolio should not exceed more than 1% of time over the next 10 trading days. See Jorion (2007) for a comprehensive treatment of VaR models.

[3]The multiplier ranges from 3.0 (four or fewer exceptions) to 4.0 (ten or greater exceptions). The purpose of this increasing penalty is in "maintaining the appropriate structure of incentives applicable to the internal models approach" and to "generally support the notion that nine exceptions is a more troubling result than five exceptions" (BIS, 1996).

in the long run, and the under-reporting institution never gets penalized for it. Even if the bank does experience VaR exceptions, the time delay in detection and punishment may be sufficient to allow the offending bank to raise capital at a time when market conditions are more favorable. For example, consider a sharp increase in the true VaR in the fourth quarter of 2008. Truthful reporting and its commensurate necessity to immediately raise capital may have been more costly (from the individual bank's perspective) than under-reporting the risk, potentially experiencing VaR exceptions, and then raising capital in mid 2009. This regulatory structure therefore leads to the fundamental tradeoff we examine in this paper: a bank can under-report its risk to save capital today in exchange for the potential for a higher capital charge in the future. In addition to regulatory forces, the under-reporting incentives can also arise from a desire to understate risk measures to other market participants. For example, a bank that is concerned about large outflows of liabilities can resort to the under-reporting of risk to try to avoid such outflows. Again the basic tradeoff remains the same: benefits from under-reporting risk in the short-run with potential costs in the long-run.

A bank's incentive to under-report its VaR depends on a trade-off between the shadow price of capital today versus the shadow price of capital in the future, which can be more than a year away. All else equal, raising capital is more costly when a bank has a very low capital base. In these cases, the trade-off is more likely to tilt the bank's incentive in favor of saving capital today at the expense of possibly a higher capital charge tomorrow. After all, the bank's capital position may improve in the intervening time, there may be a shift in the supply of bank capital that lowers issuance costs, or prices may move in favorable directions so that outsiders fail to detect the under-reporting. Overall, we argue that the under-reporting incentives are likely to be stronger when the reporting institution has lower equity capital as of the reporting date and also when raising external capital is costly.

We assemble a detailed quarterly data set of self-reported trading book VaR and number of VaR exceptions for a sample of 18 very large financial institutions from the U.S., Europe, and Canada from 2002-2012. These institutions cover a significant fraction of the global banking assets. An exception occurs when a bank's actual trading loss exceeds its self-reported VaR. Our first contribution is descriptive in nature. We provide detailed summary statistics on exceptions across banks and over time. Our main tests focus on commercial banks reporting at the 99% confidence level. We find average quarterly exceptions of 0.62 for the entire sample, which is approximately equal to the statistical benchmark for a 99% VaR model over roughly 63 trading days in a quarter. The average, however, masks an important time-series variation. The average exceptions per quarter is below the statistical benchmark during 2002-2006 at 0.08 per bank-quarter, and increases considerably thereafter. During 2007-2009, we find average exceptions per bank-quarter of 1.64 which is almost three-times higher than the statistical benchmark. We carefully examine the cross-sectional and time-series variations in VaR exceptions in the paper.

In our main empirical test, we show that banks are significantly more likely to violate their self-reported VaR levels (i.e., have more exceptions) when they have lower equity capital. Our estimates show that one standard deviation decrease in a bank's equity capital results in an increase of 1.25 exceptions in the following quarter, which is a roughly twice the sample average of 0.62 exceptions per quarter. Put differently, banks' future losses exceed their own risk assessment significantly more frequently when they have lower levels of capital relative to when they have higher equity capital levels. Our empirical design is powerful because exceptions occur when the losses exceed the bank's self-reported level of VaR, *not* simply when the level of VaR is high. Regardless of a given bank's level of equity capital or riskiness, the expectation of VaR exceptions should be identical: 1 in 100 trading days. Therefore, we do not suffer from any biases due to the endogenous determination of equity capital and the level of risk assumed by the bank. We also include both bank and year-quarter fixed effects in our empirical models. Because VaR models use inputs based on historical volatility of underlying risk factors such as interest rates and equity prices, unexpected increases in these volatilities can result in higher violation frequency for all institutions. The inclusion of year-quarter fixed effects in our model separates out the effect of time-specific changes in violation frequency. The inclusion of bank fixed effects ensure that we separate out the effect of time-invariant differences in banks' risk culture, quality of their VaR model, or level of equity capital. Our design, therefore, relates within-bank variation in the level of its equity capital and VaR exception frequency to identify banks' under-reporting of trading-book risk.

In our next set of tests we exploit variations within the set of low equity capital banks. We show that the relationship between equity capital and VaR exception is stronger when banks have recently experienced lower stock returns. For such banks raising external equity capital is even harder, and thus the incentives to under-report risk even stronger. Second, we show that the effect is stronger when the trading business represents a relatively larger portion of the bank's business. For such banks, under-reporting can be economically more beneficial and our results confirm that. Overall, our results show that banks' response to under-reporting incentives is strong when they stand to benefit more from it.

While it is important to understand the risk reporting dynamics of a given bank over time, from a systemic perspective, it is even more important to understand how institutions report their risk when the entire financial sector is under stress. These are the periods when the shadow cost of capital is likely to be high for all institutions. If many institutions under-report to save capital at such a time, the risk measure becomes least informative during periods when the accuracy of risk measurement is crucial for assessing systemic risks and designing policies to respond the stress on the financial system. Said differently, the individual institution's private marginal benefit of saving capital ex ante is likely to be higher precisely when the social cost of bank failure is high.

We show that the relationship between equity capital and under-reporting is stronger during periods of systemic stress. We use two measures of systemic risk in our main tests. First, we show that the relationship between lower equity capital and subsequent VaR exceptions is significantly amplified just after the failure of Lehman Brothers – a period characterized by significant stress in the market. Second, we consider the Marginal Expected Shortfall

(MES) of the banking sector as a whole, provided by the NYU Stern V-Lab, as a measure of systemic stress in the economy (see Acharya, Pedersen, Philippon, and Richardson (2010)).[4] We show that our results are stronger when MES is higher, and they are particularly concentrated within periods when MES is in it the top quartile for the sample period. Our results, therefore, show that lower equity capital banks are more likely to under-report when the entire banking sector is in stress above and beyond their under-reporting during normal times. This systematic under-reporting when the entire system is under stress renders such risk measures least informative in periods when understanding financial sector risk is likely to be most important.

Overall our results establish a link between equity capital and the accuracy of risk measures reported by banks. An alternative explanation is that the documented under-reporting is simply due to poor-quality risk models of the bank. To be precise, as the economy transitions from a relatively quiet to a high volatility period, there may be more VaR exceptions due to an increase in realized volatilities as compared to predicted volatilities. Some banks may be slow in updating their models – though regulations require periodic updating and constant monitoring of VaR models – and hence they have more exceptions because of a "stale model." Note that in all our estimations, we separate out the effects of aggregate changes in volatilities using the year-quarter fixed effects. For the "stale model" explanation to hold, it must be the case that VaR models are more outdated only when bank enters a low-capital quarter. Since we use bank fixed effects in all our estimations, any difference in bank-specific modelling skill is unlikely to drive our results. Thus, it is unlikely that our results are driven by this alternative. As a robustness test, we exclude year 2007 from our sample and re-estimate the model. The key idea behind the test is to leave out the transition period from a low volatility to high volatility regime in our sample. Even after excluding this year, we find that VaR exceptions are significantly driven by low equity capital banks. In an additional test, we exploit the dynamics of exceptions to further rule out this alterna-

[4]See http://vlab.stern.nyu.edu/ for further details and documentation.

tive. We consider the previous quarter's exceptions as a proxy for the quality of the bank's VaR model, and re-estimate our main specification including the lagged exceptions as an explanatory variable. Our results continue to hold. These pieces of evidence point towards decisions that are motivated by capital saving concerns and not an outdated model.

We next shed some light on a possible mechanism through which banks could be under-reporting their risk. Banks have a great deal of discretion in their modeling choices on a variety of dimension. Discretion, when properly used, should improve the quality of the reported levels of risk exposures. On the other hand, if discretion is used to under-estimate risk exposure, then this should lead to a greater number of VaR exceptions. We estimate the relationship between past stock market volatility and the reported level of VaR. Ceteris paribus, the higher the volatility of the risk factor, the higher the level of VaR. We find that the relationship between past market volatility and reported VaR to be weaker when banks have lower equity capital, suggesting that banks use more discretion when they have low equity capital. Combined with the main results above, this suggests that firms may be using their discretion on volatility parameters to under-report their risk.

Our paper contributes to several strands of literature. First, we connect to research work in VaR models. Jorion (2002) analyzes the informativeness of VaR disclosures, and shows that VaR numbers predict future trading losses at a bank. Basak and Shapiro (2001) and Cuoco and Liu (2006) analyze VaR-based constraints and capital requirements, and theoretically analyze the optimality of this mechanism. Berkowitz and OBrien (2002) analyze the accuracy of VaR model as compared to various statistical benchmarks using a sample of six banks from 1998-2000. Our paper is the first one to empirically examine the incentive effect of VaR-based capital requirements. Second, our work is also related to a growing literature on how risk-based capital requirements can alter the risk-taking behavior of banks (e.g., see Acharya, Schnabl, and Suarez, 2013). Unlike this literature, our focus is on the incentive to under-report risk rather than on the level or composition of risk assumed by banks. Third, our work is related to the literature on the economics of self-reporting behavior and probabilistic punishment mechanisms (e.g., Becker, 1968). Kaplow and Shavell (1994) show that self-reporting followed by a probabilistic audit and punishment for violation can be an optimal mechanism in several settings. Such mechanisms saves on costly monitoring, while maintaining the incentive to report truthfully. Our results highlight a potential shortcoming of such a rule in the context of risk-based capital requirement. There is a fundamental difference between these models and our setting. These models do not consider the differences in the shadow price of capital at the time the reporting compared to the time of (potential) punishment. Our work shows that in such settings, the probabilistic punishment mechanism based on the violations of self-reported risk may not work effectively if they ignore state prices, and may have systemic consequences. Finally, our work is related to ongoing policy discussions and research work on capital regulations and risk-taking behavior in the financial sector (e.g., see Admati, DeMarzo, Hellwig, and Pfleiderer (2011), Brunnermeier and Pedersen (2009), and Kashyap, Rajan, and Stein (2008)). Recent work by Behn, Haselmann, and Vig (2014) examines German banks around the introduction of Basel II, and provides evidence that suggests that model-based regulations were not effective in tying capital charges to the true level of loan credit risk in the banking book. They find that banks' internal model-based risk estimates systematically underestimated the level of credit risk in banks' loan portfolios. Their evidence on the banking book is consistent with this paper's evidence on the trading book that the effectiveness of any new policy proposal on capital requirements or risk measurement crucially depends on the quality of risk disclosure by the banks.

The rest of the paper is as follows. In Section 2 we present our hypothesis and research design, Section 3 describes the data, Section 4 presents the results, and Section 5 concludes.

2 Hypothesis and Research Design

VaR is a statistical measure of risk that estimates the dollar amount of potential loss from adverse market moves (see Jorion (2007) for a comprehensive treatment of VaR models).

These losses are measured over a fixed time-horizon of typically one or ten trading days and at a given confidence interval. For example, a 99% confidence interval VaR of $100 million for a 10-day holding period for a portfolio means that over the next 10 days, this portfolio's loss is expected to stay below $100 million with 99% probability. Due to pure statistical chance, we would expect to see one exception (i.e., losses exceeding $100 million) every 100 trading days. Absent any incentive conflicts, we should find no correlation between the frequency of VaR exceptions and the institution's incentive to save capital. As the riskiness of the underlying assets increase (e.g., increases in exchange rate volatility), the *level* of VaR should rise, but *not* the frequency of exceptions.[5] This key distinction highlights the strength of our empirical setting. Alternatively, if incentives play an important role in a bank's reported level of VaR, then a bank's incentive to save capital should positively predict its VaR exceptions over and above the random statistical benchmark. Additionally, the strength of this relationship should rise with increases in incentives to save capital such as, for example, during periods of significant frictions in raising capital by the bank or scarcity of capital in the economy as a whole.

VaR estimates depend heavily on the underlying assumptions about the volatilities and covariances of the underlying assets. To develop the intuition behind our empirical test, consider the VaR of a unit of risky asset. $Reported_{it}$ is the reported VaR of this asset by bank i at the beginning of period t, whereas the true VaR of the asset is $Actual_{it}$. Assume that $\sigma_{predicted}$ is the volatility estimate used by the financial institution in estimating its reported VaR. Financial institutions typically use the underlying asset's historical volatility estimated with past one to three years of data to estimate these numbers.[6] Further assume

[5] Financial institutions develop their own internal model for VaR based on one of these three approaches: (a) variance-covariance method, (b) historical simulation, or (c) Monte Carlo simulation. Although these approaches differ in their implementation approach, they all rely on historical volatility of the assets, and covariances across asset class to estimate the potential loss of the portfolio.

[6] For example, Bank of America state in their 2008 10-K, "Our VaR model uses a historical simulation approach based on three years of historical data and assumes a 99 percent confidence level. Statistically, this means that the losses will exceed VaR, on average, one out of 100 trading days, or two to three times each year."

that the realized volatility of the asset is denoted by $\sigma_{realized}$. We can express the reported VaR as a function G of risk ($\sigma_{predicted}$) at a confidence interval (α) and residual (η_{it}) as follows:

$$\begin{aligned} Reported_{it} &= G(\alpha, \sigma_{predicted}) - \eta_{it} \\ \eta_{it} &= \phi(Incentives_{it}) + u_{it} \end{aligned}$$

For example, for a normally distributed asset, $G(\alpha, \sigma_{predicted}) = \alpha \times \sigma_{predicted}$. However, we do not rely on normality assumption for developing our empirical model. The key term in the equation is the residual term η_{it}. In our model, this measure of under-reporting is driven by incentive effects and the other a pure noise (u_{it}). Our goal is to identify the incentive effects in VaR reporting. The difference between the actual and reported VaR can be represented as:

$$Actual_{it} - Reported_{it} = \{G(\alpha, \sigma_{true}) - G(\alpha, \sigma_{predicted})\} + \phi(Incentives_{it}) + u_{it}$$

This difference is decomposed into three parts: (a) a part that is driven by the difference in realized and actual volatility estimates and the confidence interval of VaR, (b) a part driven by the incentive effects, and (c) a pure noise term. Absent incentive effects, the difference should be driven by factors that affect $\{G(\alpha, \sigma_{realized}) - G(\alpha, \sigma_{predicted})\}$ and pure statistical chance u_{it}. Since we consider VaR reported at 99% confidence interval for all banks in our sample, the first part is essentially driven by the difference in $\{G(\sigma_{realized}) - G(\sigma_{predicted})\}$ which is determined by the changes in volatility of the underlying assets. For our empirical work, we observe the frequency of VaR exceptions as a proxy for $Actual_{it} - Reported_{it}$ and we include year-quarter fixed effects in the empirical model to isolate the effect the economy-wide risk factors which drive $\{G(\sigma_{realized}) - G(\sigma_{predicted})\}$. Thus, our empirical model can be represented as below:

$$Exceptions_{i,t+1} = \beta(Equity_{it}) + \lambda_i + \delta_t + \Gamma X_{it} + \epsilon_{it} \tag{1}$$

$Exceptions_{i,t+1}$ measures bank i's VaR exception frequency at the 99% confidence interval during quarter t to $t+1$. $Equity_{it}$ is the bank's book equity capital ratio at the beginning of the quarter and is a measure of the incentive to save capital during the quarter, thus $\hat{\beta}$ is the key estimate of interest in this model. Bank fixed effects (λ_i) control for the time-invariant unobserved difference between banks. Differences in risk-management skills, organizational structure and the importance of risk controls within the firm can have significant influence on the level of risk-taking by banks (see Ellul and Yerramilli (2013)). Kashyap et al. (2008) discuss the effects of internal controls and traders' incentives on risk-taking behavior. These differences can potentially impact the accuracy of the risk models themselves. The use of bank fixed-effects allow us to separate out the effect of any time-invariant bank-specific skills in modeling VaR (for example, G in our equation above) or the overall risk culture. X_{it} is a vector of control variables including the size and profitability of the institution. In sum, this model allows us to cleanly relate within-bank variation in equity capital ratios to VaR exception frequency.

In the base case, we estimate the above model using OLS. This framework allows us to consistently estimate the fixed-effect specifications. Since $Exceptions_{i,t+1}$ is a count variable, bounded below by zero, in alternative specifications we also estimate our model using poisson and negative binomial regression. As we show later in the paper, our results do not vary with these modelling choices.

Our baseline tests shed light on a bank's incentive in isolation. It is important to understand the informativeness of a bank's risk measures because its failure can have severe negative consequences for the real economy (e.g., see Khwaja and Mian (2008), Chava and Purnanandam (2011), Schnabl (2012)). These costs are likely to be greater when the entire banking system in under stress. During these periods, the stability of the entire system depends crucially on a proper assessment of the banks' risk exposure. Policy responses such as requiring additional capital to be raised or increased monitoring of institutions by the regulators, in turn, depend on the accuracy of risk measures. These are also times when capital is likely to be most scarce and thus costly to raise. As a result, the incentive to under-report and save on capital requirements is likely to be high during these periods. With this in mind, we design our next test to investigate whether banks' under-reporting behavior is stronger during periods of financial sector stress. We estimate the following empirical model to estimate this effect:

$$\begin{aligned} Exceptions_{i,t+1} = {} & \phi(Equity_{it}) + \theta(System\ Stress_t) + \rho(Equity_{it} \times System\ Stress_t) \\ & + lambda_i + \delta_t + \Gamma X_{it} + \epsilon_{it} \end{aligned} \tag{2}$$

System Stress is a measure of systemic stress in the economy. We interact this variable with *Equity* to estimate the effect of equity capital on under-reporting behavior during such periods. The parameter estimate $\hat{\rho}$ represents the effect of *Equity* during periods of financial system stress beyond its effect in normal times ($\hat{\phi}$), and beyond the level effect on VaR exceptions for all banks during that time period ($\hat{\theta}$). To empirically implement (2), we use two measures of $System\ Stress_t$: an indicator variable for the quarter immediately after the collapse of Lehman Brothers (2008q4) and the total marginal expected shortfall (MES) for the banking sector. Marginal Expected Shortfall measures expected capital shortfall faced by a firm in a potential future financial crisis (Acharya et al., 2010). We use the MES for the aggregate banking sector in our empirical tests which provides a good proxy for economic construct we have in mind for our study.

3 Data and Sample

We construct a sample of large financial institutions from U.S., Canada, and Europe that provide sufficient details in their quarterly filings about the extent of VaR during the quarter, and the number of exceptions over the same period. We collect quarterly data on aggregate VaR of the bank as well as the corresponding number across risk categories such as interest rates, and foreign exchange. Banks typically break down their overall VaR across these categories: interest rate, foreign exchange, equity, commodities, and others. In addition, often they provide the diversification benefit claimed across the asset classes. The total VaR is the sum of VaRs across all categories net of the diversification benefit. As mentioned earlier, banks are required to report their back-testing results to the regulators based on a quarterly basis. When losses exceed the self-reported VaR, an exception occurs. We collect all exceptions during the quarter for each bank, and use it as the key measure of reporting accuracy.

We create two samples for our analysis. Our "base" sample includes only the top commercial banks of these countries that report their VaR at the 99% confidence level, and these observations are the subject of the bulk of our analysis. Our "expanded" sample adds broker-dealers and observations where VaR is reported at 95%. We do not include these observations in our base sample because it is not generally meaningful to compare the frequency of VaR exceptions across different confidence intervals. In addition to the consistency in reporting, commercial banks are also homogenous in terms of their capital requirements. However, we conduct our main tests on the expanded sample that includes VaR exceptions at the 95% level as well as VaR exceptions from broker-dealers. Broker-dealers also face capital requirements for market risks based on similar Basel Committee formula.[7] Our key results are not sensitive to this sampling choice. Finally, we miss some large financial in-

[7]Broker-dealer's net capital requirement is regulated by the Securities and Exchange Commission (SEC). SEC's formula for computing capital requirement for market risk is identical to the formula used by other banking regulators for commercial banks (SEC, 2004).

stitutions altogether from our sample because they do not disclose their VaR exceptions in their quarterly filings at the 95% or 99% level. Our sample period begins in 2002 since the required data on VaR is not available for most banks before this year and concludes in 2012 and it contains 15 commercial banks and 3 broker-dealers.

In total, we cover 18 of the largest financial institutions of the world and thus covers a large portion of assets in the global banking system. Even more important, these institutions cover a disproportionately large fraction of trading assets of the economy. Commercial banks in our sample have about $14 trillion in assets. This compares well with the aggregate asset base of about $13-14 trillion for U.S. commercial banks, and about €30 trillion for banks covered by the ECB as of 2013.

We also collect data on some measures of systemic stress. Our key measure of systemic stress is the Marginal Expected Shortfall (MES) of the banking sector, provided by the New York University's Volatility Lab (see Acharya et al. (2010)). We obtain this measure for all systemically important financial institutions of the world on a quarterly basis, and aggregate them to construct the systemic MES measure. The MES measure varies considerably over time, providing us with reasonable time-series variation in the extent of capital shortfall in the economy. We also use the Financial Stress Index (FSI) developed by the Federal Reserve Banks of Cleveland, Kansas City, and St. Louis as additional measures of systemic stress in the banking sector.[8]

Finally, we collect balance sheet data on bank's equity capital, profitability, and asset base on a quarterly basis from the bank's quarterly filings and Bankscope. We also obtain their stock returns from CRSP and Datastream. Data on interest rate, foreign currency, equity, and commodity volatility come from the Federal Reserve Bank, CRSP, and Bloomberg. Our base sample of commercial banks provides of 424 bank-quarter observations over 2002-2012 for our main tests. The expanded sample contains 545 bank-quarter observations that we

[8]These data are available from the Federal Reserve Bank of St. Louis's FRED Economic Database under the data series names CFSI, KCFSI, and STLFSI.

examine in robustness tests.

Table 1 provides summary statistics for the base sample. The sample banks have an average asset base of $901 billion. On average, they are profitable during our sample period, with a mean quarterly net-income-to-assets ratio of 0.17%. On average banks have 6.32% equity as a percentage of their asset base. This ranges from 4.06% for the 25th percentile bank to 9.01% for the 75th percentile. Most of our main tests will focus on the log of this ratio, which emphasizes the idea that the strength of incentives increase at an increasing rate as capital levels get lower. We use the book equity capital ratio instead of the regulatory capital ratio as the key variable for our tests to avoid measurement error problems. Regulatory capital ratios, such as the risk-weighted Tier-1 capital ratio, use the computed risk-weighted assets of the bank in the denominator. The VaR of the trading book is an important variable in the computation of the ratio, which introduces measurement issues. The use of book equity capital ratio avoids such a problem.

Turning to the VaR data, we find that there is wide variation in VaR exceptions, the level of VaR, and the composition of VaR. On average, a large proportion of trading asset risk is related to interest rate risk, as VaR linked to interest rate represents about 57% of the total VaR of the median bank. They also have considerable exposure to foreign exchange, equities, and commodities risk. Overall, the pooled-sample statistics indicate that the sample comprises very large banks with a wide variation in equity capital, trading desk risk exposure, and VaR exceptions.

Table 2 provides a list of the financial institutions that enter our sample along with some key descriptive statistics for each. It is clear that there is a large cross-sectional variation in the level of VaR as well as exceptions across banks. Table 2 also highlights the substantial within-bank variation of VaR levels and exceptions which we exploit in our main tests.

4 Results

We first present some descriptive statistics on aggregate VaR and overall exceptions in our sample. Following the research design discussed in Section 2, we next use regression analysis to examine the relationship between equity capital and VaR exception in the base sample. We then focus on periods when the financial system is under stress and where the incentives to save capital are particularly strong.

4.1 Value-at-Risk Exceptions Over Time

Table 1 presents summary statistics on VaR exception for the sample. Since the VaR numbers that we consider in the base sample are based on 99% confidence interval, we expect to see 1 exception in every 100 days purely by chance. Hence on a quarterly basis, we expect to observe an average of about 0.63 exceptions assuming 63 trading days in a quarter. Across banks and quarters, the average quarterly exceptions (*Exceptions*) is 0.62 for the base sample which is in line with the statistical expectation. Ranging from 0 to 13, there is substantial variation in the number of exceptions which is present both in the cross-section and the time-series.

Table 2 shows the variation in exception frequency across banks, while Figure 1 presents this variation over time by plotting the average number of exceptions during each quarter in the sample. Average VaR exceptions are well below their statistical expectation during 2002-2006 at 0.08 per bank-quarter, but starting in 2007 the exceptions increase by a considerable amount. The spike in these exceptions coincide with a period of increased systemic risk in the economy of 2007-2009, where there are 1.64 per bank-quarter. From 2010-2012, we once again observe fewer VaR exceptions with an average of 0.18 per bank-quarter. This figure provides a clear insight: on average, the VaR models failed during periods of high systemic risk when timely and accurate risk measurement in the financial sector is most important.

During these periods, the exceptions are far greater than what reliable risk-measurement reporting would predict. While this point has been argued by various market observers, our paper provides first systematic assessment of this issue.

Figure 2 presents the actual distribution of quarterly VaR exceptions along with the expected VaR exception frequency as computed using a binomial distribution. The figure shows that there are far more quarters with zero observations than the binomial distribution would predict, which could be an indication of conservatism in reporting during the early portion of the sample period mentioned above. The figure also illustrates the "fat tail" of the realized distribution – there are considerably more bank-quarter observations with a high number of VaR exceptions than predicted by the binomial distribution.

4.2 Value-at-Risk Exceptions and Equity Capital

We begin the regression analysis by estimating our base Model (1) relating equity capital levels to VaR exceptions. Table 3 presents the results along with several alternative specifications of the model that differ in terms of control variables used and estimation approach. Column (1) reports the effect of equity capital as measured by log(Equity/Assets) on exceptions without any control variables other than bank and year-quarter fixed effects. The log-transform of equity ratio assigns more weight on variation in equity capital at lower values. This is consistent with our key economic argument that incentives to under-report is higher when banks have lower levels of equity.[9]

We find a negative and statistically significant coefficient on the equity capital ratio: when banks have lower equity capital, they have more exceptions. In terms of economic magnitude, one standard deviation decrease in equity capital results in approximately 1.25 more violations in the following quarter. With a sample average of 0.60, this is an economically significant increase to roughly three times the average VaR exception frequency. In columns

[9]We estimate our model with equity-to-asset ratio as well as other natural concave transformations of the ratio such as the square root and cubic root of equity ratio. We discuss them later in the paper.

(2) and (3), we include controls for the effect of bank size and profitability, respectively. Our main result are virtually unaffected, both statistically and economically. In column (4), we explicitly include measures of the volatility of underlying risk factors during the quarter in the regression model and drop year-quarter fixed effect in the model. As expected, we find higher exceptions during quarter with high volatility in market returns, interest rates, and commodity prices. Our main result relating equity capital to exceptions remains unchanged.

The reporting quarter for all banks in our sample are not exactly the same. For example, some banks end their quarter in March, while others in April. Therefore, the volatility measure computed during the quarter is not perfectly collinear with year-quarter fixed effects, and we can include year-quarter fixed effects in the model along with the volatility measures. Column (5) presents results based on this full specification. We cluster our standard errors in our main specifications at the year-quarter level. In column (6), we compute standard errors clustered at the bank level and find that the results are statistically significant at the 3%. Since we need a large number of clusters to ensure consistent estimates and bank clustering yields only 15 clusters, we focus on the estimates with year-quarter clustering. Overall, Table 3 documents a strong effect of equity capital on the accuracy of self-reported VaR measures.

In unreported tests, we estimate the model with various other measures of equity capital ratio. We find a coefficient of -0.14 (p-value of 0.13) for the model that uses Eq/TA as the key explanatory variable. The coefficient is larger for the model that uses square root of Eq/TA (-1.34 with p-value of 0.01) and even larger for the model that uses cubic root of Eq/TA as the explanatory variable (-3.25 with p-value of 0.01). Overall, these results paint a clear picture. Banks with lower equity capital are more likely to under-report their risks, and the under-reporting mainly comes when banks have very low equity capital.

4.3 Further Variation in the Economics Benefits of Under-Reporting

Is the effect of equity capital on under-reporting higher when banks are likely to obtain larger benefits from doing so? We turn to this question in our next set of tests. We exploit variations along two important dimensions: (a) when the firm has recently experienced poor stock returns, and (b) when trading represents a larger fraction of the bank's business. First, we consider the effect of a bank's recent stock market return on the exception frequency. Our tests so far are based on book equity capital. The incentive to save equity capital by under-reporting is likely to be high after a decline in stock prices (i.e., market equity). In these quarters, banks are likely to have relatively higher reluctance and reduced ability to raise external equity capital. Based on this idea, we include the bank's equity capital, prior quarter's stock return, and the interaction of these terms in the regression model. Table 4 presents the results, with the baseline full specification reproduced in column (1). For easier economic interpretation, we divided all observations into two groups based on their prior quarter's stock returns. *LowRet* equals one for firms that fall in the bottom quartile on this dimension(less than -6%). Column (2) shows that banks with lower equity return have more frequent exceptions. Without the interaction effect, we find that banks with lower equity capital as well as banks with poor stock returns have more exceptions, though the estimate on *LowRet* is statistically insignificant with p-value of 0.11. However, column (4) includes the interactive effect and reveals that when banks have lower equity capital, they have significantly higher violations (a coefficient estimate of -1.59 on *log(Eq/AT)*), but the effect is considerably stronger when the banks also have experienced lower stock returns (a coefficient estimate of -1.48 on the interaction term). In economic terms, a low-equity-capital bank with lower recent stock returns has twice as many VaR exceptions as a low-equity-capital bank with higher recent stock returns.

Next, we exploit the cross-sectional variation in the importance of trading business to a bank's overall value. For this test, we first compute the ratio of self-reported VaR to equity capital ratio as of 2006Q1 (called *VE_2006*). We take this ratio as a proxy for the importance of trading business for the bank. We compute this measure based on exposure in the beginning of 2006 to ensure that our measure is not affected by post-crisis changes in risk-taking behavior or equity capital. Using this variable, we estimate our model with data from 2006-2012 period. The key idea behind our test is to examine whether the effect of under-reporting during and in the aftermath of the crisis is larger for banks with larger trading business just before the crisis. We include the bank's equity capital, and its interaction with the trading exposure (i.e., *VE_2006*) in the main regression model.[10] Table 5 presents the results. We find that our main effects are concentrated within banks with larger trading exposure: the coefficient on *VE_2006* × *log(Eq/AT)* is approximately 50% larger than the corresponding coefficient for the entire sample. In an alternative specification, we use an indicator variable *High(VE_2006)* that equals one for banks that have above-median trading exposure (*VE_2006*), and zero otherwise. As shown in Columns (4) and (5) the effect of equity capital on exceptions for high trading exposure banks is almost twice as large as the base case. In other words, the effect of equity capital on under-reporting is higher when banks have more to gain in economic terms. Overall, these results are consistent with the idea that banks are more likely to under-report when they have stronger incentives to save on equity capital.

4.4 Systemic Stress

The next tests examine the effect of equity capital on exceptions during periods of systemic stress. These periods are important for at least two reasons. First, they provide us a source of time-series variation in the banks' incentive to save capital. In such periods, banks face tremendous costs in raising external capital. In extreme cases, the sources of external equity capital can completely dry up during these periods. Second, these are the periods

[10] In this specification, we are unable to estimate the independent effect of the level of trading exposure on under-reporting since it is subsumed by the bank fixed effects.

when an accurate assessment of risk is vital for designing policies aimed at systemic stability. We estimate model (2) using two different proxies of systemic stress: (a) an indicator variable based on the quarter of Lehman's failure, and (b) a variable based on Marginal Expected Shortfall (MES) in the capital of entire banking sector. Lehman Brothers failed on September 15, 2008. Subsequently, the entire world economy experienced a significant increase in systemic risk due to concerns about counterparty and other risk factors in the banking sector. We create an indicator variable that equals one for the fourth quarter of 2008, and zero otherwise, to capture the effect of this systemic shock to banking sector after the collapse of Lehman Brothers. Column (2) of Table 6 presents the results. The effect of equity capital on VaR exceptions increases by almost three-fold for this quarter above the base effect. While a standard deviation decrease in equity capital is associated with more than one additional future exception outside of this period, the total effect is approximately 4.5 more exceptions during 2008q4. Note that we are estimating the marginal effect of equity capital on VaR exceptions during this quarter. Thus, any unconditional increase in volatilities of the underlying risk factors during the quarter is absorbed in the year-quarter fixed effect. The result shows that the low-equity-capital banks breached their self-reported VaR levels considerably more often during this quarter than their high-equity-capital counterparts.

While the Lehman Brother failure provides a clearly identifiable period of stress in the market, a limitation of this measure is that it is based on just one quarter. To exploit time-varying changes in the level of systemic risks, we obtain the MES for the banking sector as a whole and divide all quarters into four groups based on this measure. Using the quarters that fall in top quartile of the MES measure as systemically stressful quarters, we re-estimate our model and present results in Columns (3) and (4).[11] The effect of equity capital on VaR exceptions is primarily concentrated in these quarters.

These results paint a clear picture: in addition to banks breaching their self-reported

[11] In robustness tests shown later, we use a continuous measure of MES along with alternative proxies of financial stress in the economy and find similar results.

VaR limits at a higher rate during periods when their level of capital is low, these effects are most pronounced in periods of systemic stress in the economy. Thus, the reported risk measures are least informative when accurate risk measurement is likely most important for regulators and policy-makers to respond to severe financial shocks.

4.5 Bank Discretion and the Level of Reported Value-at-Risk

Banks have a lot of discretion in implementing their VaR model. The choice of overall modeling technique (e.g., historical versus Monte Carlo simulation), the length of data period for model calibration, risk factor volatilities and correlations are just a few assumptions that can have substantial effects on banks' estimate of their risk for reporting purposes (BIS, 2013). Without the knowledge of precise modeling assumptions and inputs used in the model, we are limited in our ability to pin down the channels through which banks under-report their risk. However, we provide some suggestive evidence in this section to shed light on the channels of under-reporting.

Two crucial inputs for a bank's VaR estimate are the level of exposure to a risk factor undertaken by the bank and assumptions about the risk factor's volatility. The assumption on volatility is typically based on past one or two years' historical data. Consider two banks: one bank uses discretion in making assumptions about volatility parameters versus another bank that follows a strict rule based on past realized volatility. All else equal, the discretionary bank's reported level of VaR should be less sensitive than the rule-based bank's VaR to publicly observed realized volatility measures. Further, if the discretionary bank is using its discretion to get better estimate of its risk, then their VaR exceptions should be lower than the rule-based bank. Based on these ideas, we estimate the sensitivity of reported VaR to past macro-economic volatility measures across high and low capital banks. Using past one year's volatility in the returns to S&P 500 index (Vol) as a measure of aggregate macro-economic volatility, we estimate the following model:

$$VaR_{i,t} = \phi(Equity_{it}) + \theta(Vol_t) + \rho(Equity_{it} \times Vol_t) + \alpha_i + \Gamma X_{it} + \epsilon_{it} \quad (3)$$

The dependent variable is the reported level of VaR at the beginning of quarter t. Vol_t measures market volatility over the past year. We expect to find a positive coefficient on Vol_t (i.e., higher volatility leads to higher value-at-risk). However, if banks use more discretion in their VaR computation when they have low equity capital, we expect this the sensitivity of VaR to volatility to be weaker for such banks. In such a case, $\hat{\rho}$ should be positive and significant.

We estimate the regression model and report its results in Table 7. As shown in column (1), the past year's market volatility significantly affects the reported VaR numbers. However, the full specification in column (3) shows that this relationship is significantly different across banks with varying degree of equity capital. The coefficient of interest ($\hat{\rho}$) is positive and significant. This suggests that when banks have relatively lower equity capital, the sensitivity of reported VaR to past market volatility is significantly lower. This finding, along with our earlier results that such banks have higher exceptions in future quarters, lends support to the hypothesis that banks are under-reporting their VaR by relying on their discretion in choosing volatility measures. We repeat this exercise with the past two years' volatility measures in columns (4)-(6) and find similar results.

4.6 Alternative Explanations & Robustness Tests

4.6.1 Stale Model

Our dependent variable is the number of exceptions with respect to self-reported VaR number. An alternative interpretation of our results is that the under-reporting is not due to incentive to save capital, but due to a poor-quality model that has not been updated. For example, during periods of high volatility in the market, the level of reported VaR is more likely to be exceeded. In such quarters, historical risk measures used to estimate VaR is no longer a good proxy for the realized volatility and correlations across asset classes during the quarter. As a result, there are more exceptions. This effect, however, is likely to be present for all banks, not only the ones with low equity capital. Thus, the year-quarter fixed effects in our estimations alleviate this concern to a large extent. For the alternative explanation to hold, it must be the case that models become relatively more inaccurate (for reasons unrelated to incentives) only for the low-equity-capital banks during stressful periods such as 2007-2008, and these inaccuracies persist over time. While this is unlikely, we perform two additional tests to alleviate this concern.

Omitting Transition Periods:

VaR models are estimated on a daily basis at large financial institutions. They calibrate their model to historical data and therefore use inputs on volatilities and correlations across asset classes based on frequently updated historical data. When the economy transitions from a relatively stable state to a stressful one, VaR models based on historical data are likely to be inaccurate. However, as banks learn about the risks and correlations over time, they update their models according to the new levels of risk.[12] For example, in its 10-K form Bank of America states, "As such, from time to time, we update the assumptions and historical data underlying our VaR model. During the first quarter of 2008, we increased the frequency with which we updated the historical data to a weekly basis. Previously, this was updated on a quarterly basis." Hence, the initial inaccuracy of the model after a shock should have a short half-life.

In our sample, there is a large increase in the volatilities of the underlying risk measures in 2007 as compared to historical averages. Based on the idea that banks can update their model to reflect risk measures, we exclude the entire year of 2007 from our sample and re-estimate the base model. If some banks simply have poor-quality models, this gives them

[12]BIS standards require that banks update their model at a minimum of once per quarter BIS (2005).

an year to correct those models. We report the result from this test in Column (2) of Table 8. Our results remain similar in both qualitative and quantitative sense: banks have more exceptions after low-equity quarters even after leaving out the transition year from a stable to volatile period. In Column (3) of the Table, we leave out the quarter following the collapse of Lehman Brothers (2008q4) and re-estimate the model. Again, our results are robust. These results show that our findings are not completely driven by periods following extreme changes in the market conditions.

Lagged Exceptions as a Proxy for a Poor-Quality, Stale Model:

In our next test, we include the lagged exceptions as an explanatory variable in the model. The key idea is that if a bank experiences a number of exception during a quarter, it has a relatively more inaccurate model for that quarter. Lagged exceptions is taken as a crude proxy of the "stale model" for the next quarter. If some firms are just better than the others in modelling their risk, then the inclusion of firm fixed effects in our base model separates out such differences. However, if the quality of risk-model is time varying, then the firm fixed effects might not be adequate to remove such effects. Specifically, if the quality of risk models deteriorates precisely when a bank enters a low-capital quarter and the poor quality of the bank's model is persistent (i.e., not updated), then our inference can be problematic. While such a time-varying difference in modelling skill seems unlikely, we exploit the dynamics of panel data to further alleviate this concern.

If the modelling skill is time-varying and correlated with lower equity capital quarters for a given bank, then our model takes the following form:

$$Exceptions_{i,t+1} = \beta(Equity_{it}) + \alpha_i + \delta_t + \Gamma X_{it} + \epsilon_{it} \tag{4}$$

where

$$\epsilon_{it} = ModelQuality_{it} + \eta_{it} \tag{5}$$

and

$$cov(Equity_{it}, \epsilon_{it}) \quad = \quad cov(Equity_{it}, ModelQuality_{it}) \neq 0 \tag{6}$$

If we can control for the time-varying nature of model quality in the above model and if η_{it} are serially uncorrelated, we can consistently estimate the coefficient of interest ($\hat{\beta}$). As argued above, a natural candidate for the time-varying model quality is the number of exceptions in the past quarter. Hence we can rewrite our model as follows:

$$Exceptions_{i,t+1} = \beta(Equity_{it}) + \alpha_i + \delta_t + \Gamma X_{it} + \theta Exceptions_{i,t} + \eta_{it} \tag{7}$$

The inclusion of lagged dependent variable in a fixed effect model, however, results in inconsistent estimates (Arellano and Bond (1991)). Hence, we estimate our model using the GMM approach suggested by Arellano and Bond (1991). This estimator first transforms the equation using first-differences, and then uses lagged values of the dependent variable as instruments to consistently estimate the model parameters.

We estimate the model with both first and second lag of quarterly exceptions as instruments for lagged differences and present the results in columns (4) and (5) of Table (8). The coefficient on equity ratio remains negative and both economically and statistically significant for these specifications. We find a coefficient of -2.12 (p-value of 0.08) on *log(Eq/AT)* in the model with one lag and -2.41 (p-value of 0.08) in the model with two lags as instruments. The Table also reports the p-values for Sargan test and a test for second order autocorrelations in the residual term. Sargan test fails to reject the null hypothesis that the over-identifying restrictions are valid. Similarly, we fail to reject the null hypothesis of zero second-order correlation in the residual term, thus supporting the necessary assumptions for this estimation method.

The use of lagged exception as a proxy for the model quality is a strict specification for our empirical exercise. To the extent that lagged violations are also driven by incentives to save capital, we are underestimating the true effect of capital in the model. Despite this limitation, we find strong results. It is, therefore, unlikely that our results are driven by time varying skills of the bank or the stale model problem.

4.6.2 Other Measures of Systemic Stress

In addition to Marginal Expected Shortfall, we use the Financial Stress Index (FSI) developed by the Federal Reserve Banks of Cleveland, Kansas City, and St. Louis as measures of stress in the banking sector. We estimate the effect of equity capital on VaR exceptions across periods of varying levels of FSI. The results, along with estimates using a continuous measure of MES, are provided in Table 9. Again, we find our main effect to be larger during periods of high systemic stress.

4.6.3 Count Data Model

The number of exceptions is a count variable. We use fixed-effect linear regression models in the base case analyses since this specification allows us to consistently and efficiently estimate the coefficients of interest. As a robustness exercise, we re-estimate our main regressions using a count data model. These modelling approaches explicitly recognize the fact that VaR exceptions only take non-negative integer values. Hence the dependent variable in our regression model is discrete, and also skewed. However, the use of fixed effects in a non-linear model suffers from the incidental parameter problem, which can result in inconsistent estimates. With these caveats in mind, we re-estimate our models using two nonlinear specifications: a Poisson model and a negative Binomial model. Table 10 presents the results, and shows that our main results do not change under the count model specifications.

4.6.4 Business Mix of the Bank

Could our results be driven by different business mix of the banks? Some banks, for example, engage more in risks related to interest rates or mortgages. To account for this possibility, we create a measure of the bank's trading risk based on the level of VaR reported under different risk categories. We compute the fraction of trading VaR that comes from different risk buckets as the ratio of VaR under the given category scaled by total VaR for the quarter. Thus we have the fraction of trading VaR across interest rate, foreign exchange, commodities, equity, and other. We include these variables in the base model as a control for the business mix. Our results remain practically unchanged (unreported).

4.6.5 Expanded Sample

In our paper so far, we report our results based on 99% VaR measures of commercial banks. As mentioned earlier, this allows us to be consistent across all observations. As a robustness exercise, we repeat our main results by including VaR exceptions for the 95% level. This allows us to expand our sample since some institutions, mainly broker-dealers, only report VaR at 95% level in their quarterly disclosures. To be precise, the expanded sample augments the base sample by including broker-dealers as well as commercial bank-quarters that only have reports on 95% VaR. We have 545 observations for this sample.

For this regression analysis, we construct two measures of dependent variable. In the first measure, called *excess*, we compare the actual exception to the statistical benchmark based on the confidence level of VaR. If the exception exceeds the statistical benchmark, *Excess* is set to one, otherwise zero. Thus *Excess* takes a value of one if the reported exception in a quarter is greater than 0.6 for 99% VaR and greater than 3 for 95% VaR. The other measure, *1(Exception)*, is simply an indicator variable that takes a value of one if there is at least one exception during the quarter. In the regressions, we include an indicator variable *95pc CI* that equals one for bank-quarter observations that are based on 95% VaR. Results are provided in Table 11. We find negative and significant coefficient on the equity capital variable. Despite the limitations of mixing 95% and 99% VaR measures, our results remain robust on the larger sample.

5 Conclusions

We show that banks are more likely to under-report their market risks when they have lower equity capital. Regulators and investors rely on the bank's self-reported risk measures for a number of regulatory and investment decisions. Hence, the accuracy of these numbers assume special importance, particularly when banks have lower levels of equity capital. Our results show that when the incentive to save capital is strong, the self-reported risk measures become inaccurate. Even more important, this behavior is strongest during periods of high systemic stress. As a result, the integrity of these self-reported measures becomes most questionable precisely when accurate risk measurement in the financial system is most important.

References

Acharya, Viral V, Lasse Heje Pedersen, Thomas Philippon, and Matthew P Richardson, 2010, Measuring systemic risk, *FRB of Cleveland Working Paper* .

Acharya, Viral V, Philipp Schnabl, and Gustavo Suarez, 2013, Securitization without risk transfer, *Journal of Financial Economics* 107, 515–536.

Admati, Anat R, Peter M DeMarzo, Martin F Hellwig, and Paul C Pfleiderer, 2011, Fallacies, irrelevant facts, and myths in the discussion of capital regulation: Why bank equity is not expensive, *MPI Collective Goods Preprint* .

Arellano, Manuel, and Stephen Bond, 1991, Some tests of specification for panel data: Monte carlo evidence and an application to employment equations, *The review of economic studies* 58, 277–297.

Basak, Suleyman, and Alexander Shapiro, 2001, Value-at-risk-based risk management: optimal policies and asset prices, *Review of Financial Studies* 14, 371–405.

Becker, Gary S., 1968, Crime and punishment: An economic approach, *Journal of Political Economy* 76, pp. 169–217.

Behn, Markus, Rainer FH Haselmann, and Vikrant Vig, 2014, The limits of model-based regulation .

Berkowitz, Jeremy, and James OBrien, 2002, How accurate are value-at-risk models at commercial banks?, *The Journal of Finance* 57, 1093–1111.

BIS, 1996, Supervisory framework for the use of backtesting in conjunction with the internal models approach to market risk capital requirements .

BIS, 2005, Ammendment to the capital accord to incorporate market risks .

BIS, 2013, Regulatory Consistency Assessment Programme (RCAP) – Analysis of Risk-Weighted Assets for Market Risk .

Brunnermeier, Markus K, and Lasse Heje Pedersen, 2009, Market liquidity and funding liquidity, *Review of Financial studies* 22, 2201–2238.

Chava, Sudheer, and Amiyatosh Purnanandam, 2011, The effect of banking crisis on bank-dependent borrowers, *Journal of Financial Economics* 99, 116–135.

Cuoco, Domenico, and Hong Liu, 2006, An analysis of var-based capital requirements, *Journal of Financial Intermediation* 15, 362–394.

Ellul, Andrew, and Vijay Yerramilli, 2013, Stronger risk controls, lower risk: Evidence from us bank holding companies, *The Journal of Finance* 68, 1757–1803.

Jorion, Philippe, 2002, How informative are value-at-risk disclosures?, *The Accounting Review* 77, 911–931.

Jorion, Philippe, 2007, *Value at Risk: The New Benchmark for Managing Financial Risk*, volume 2 (McGraw-Hill New York).

Kaplow, Louis, and Steven Shavell, 1994, Optimal law enforcement with self-reporting of behavior, *Journal of Political Economy* 583–606.

Kashyap, Anil, Raghuram Rajan, and Jeremy Stein, 2008, Rethinking capital regulation, *Maintaining stability in a changing financial system* 431–471.

Khwaja, Asim Ijaz, and Atif Mian, 2008, Tracing the impact of bank liquidity shocks: Evidence from an emerging market, *The American Economic Review* 1413–1442.

Schnabl, Philipp, 2012, The international transmission of bank liquidity shocks: Evidence from an emerging market, *The Journal of Finance* 67, 897–932.

SEC, 2004, Alternative net capital requirements for broker-dealers that are part of consolidated supervised entities, *17 CFR Parts 200 and 204* .

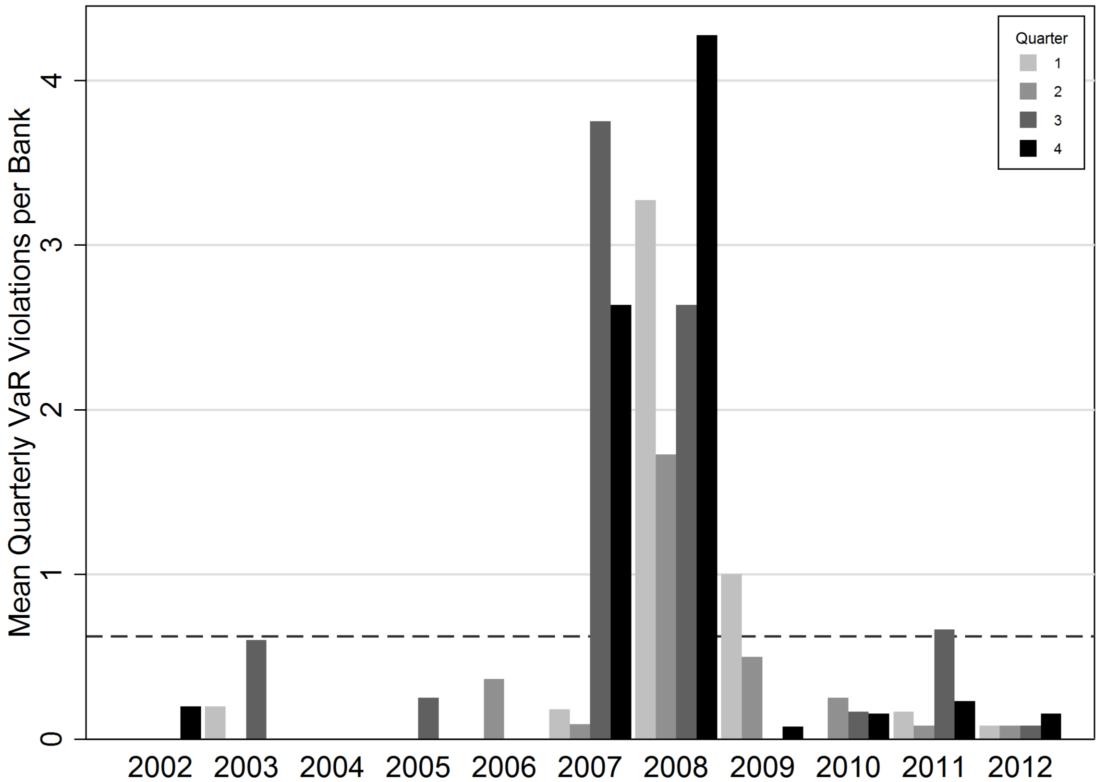

Figure 1: Average Value-at-Risk Exceptions
This figure presents the average frequency of Value-at-Risk (VaR) exceptions for banks each quarter during the 2002-2012 sample period. The dashed line at 0.63 represents the expected exception frequency based on at 99% VaR confidence interval and approximately 63 trading days per quarter.

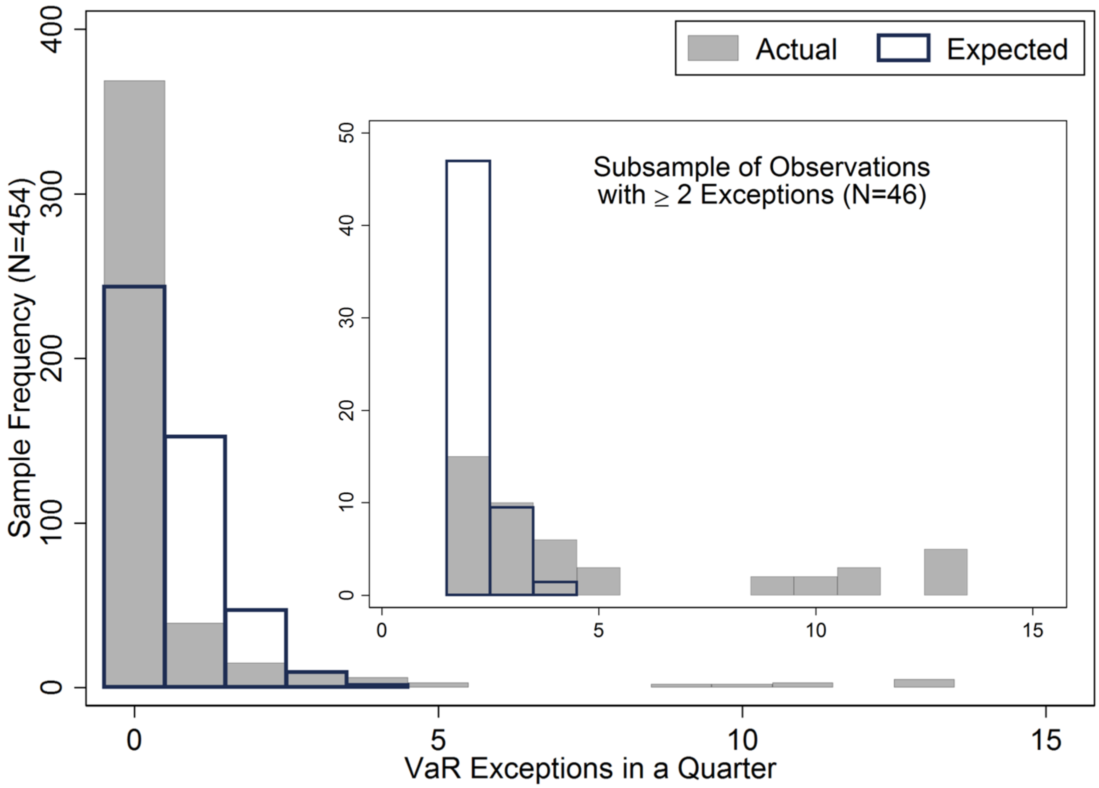

Figure 2: Distribution of Value-at-Risk Exceptions
This figure presents the distribution of observed quarterly VaR exceptions (shaded) along with the corresponding expected distribution based on the binomial nature of VaR Exceptions. The inset figure presents observations with at least two VaR exceptions on a different scale for readability.

Table 1: Base Sample Summary Statistics

This table presents summary statistics for our sample. These sample statistics are for the base sample of commercial banks reporting 99% Value-at-Risk during 2002-2012. Table 2 provides details of the specific banks in the sample. *Exceptions* is the number of times the bank had losses that exceeded their self-reported Value-at-Risk during the next quarter, *Value-at-Risk* is the reported level of future loss that should not be exceeded at the 99% confidence level, and *VaR-[Trading Desk]* variables are the reported value-at-risk for the various trading desks (interest rate, foreign exchange, equities, and commodities) with *Diversification Benefit* representing the claimed reduction in VaR due to less than perfect correlation across trading desks.

	Mean	SD	Min	P25	Median	P75	Max	N
Bank Characteristics:								
Total Assets ($Bn)	901.40	767.93	73.14	291.14	602.46	1428.16	3643.58	424
NI-to-Assets (%,Q)	0.17	0.20	-1.16	0.09	0.18	0.25	1.57	424
BookEq/AT (%)	6.32	3.15	1.69	4.06	5.14	9.01	13.84	424
log(Eq/AT)	-2.89	0.51	-4.08	-3.20	-2.97	-2.41	-1.98	424
Value-at-Risk ($MM):								
Exceptions	0.62	2.00	0.00	0.00	0.00	0.00	13.00	424
Total Value-at-Risk	61.90	85.86	3.60	9.00	26.00	75.00	433.00	422
VaR-Interest Rate	46.42	73.39	0.00	4.40	15.28	60.80	430.58	422
VaR-Foreign Exchange	9.09	12.44	0.00	0.89	2.69	15.70	62.82	422
VaR-Equities	20.87	31.39	0.00	3.14	7.64	27.12	204.60	422
VaR-Commodities	7.49	10.80	0.00	0.29	2.08	10.50	52.31	422
VaR-Other	17.23	49.72	0.00	0.00	0.00	8.65	322.88	422
VaR-Diversification Benefit	40.89	54.01	0.00	4.86	11.70	59.60	241.67	422

Table 2: Sample Composition and Value-at-Risk Statistics

This table presents summary statistics for our sample. Panel A presents statistics for the "Base Sample," which comprises commercial banks reporting 99% Confidence Interval Value-at-Risk (VaR) during 2002-2012. Panel B presents statistics for observations that are added to form the "Expanded Sample," which also includes commercial bank observations reporting 95% VaR and observations from broker/dealers. *Exceptions* is the number of times the bank had losses that exceeded their self-reported Value-at-Risk during the next quarter, *Value-at-Risk* is the reported level of future loss that should not be exceeded at the defined confidence level (99% or 95%).

Panel A: Base Sample

	Exceptions (99% CI)			Value-at-Risk			
Bank	Mean	Min	Max	Mean	Min	Max	N
Bank of America Corporation	0.45	0.00	10.00	93.75	32.50	275.80	44
Bank of Montreal	0.73	0.00	5.00	25.00	11.00	46.00	33
Bank of New York Mellon	0.07	0.00	2.00	7.48	3.90	13.40	44
Canadian Imperial Bank of Commerce	0.14	0.00	3.00	8.67	3.60	18.70	44
Citi Group	0.22	0.00	1.00	167.22	109.00	224.00	9
Credit Suisse Group	1.39	0.00	11.00	119.18	44.00	243.00	28
Deutsche Bank	1.50	0.00	13.00	88.63	55.10	142.90	32
ING Group	0.00	0.00	0.00	20.62	11.80	39.00	13
JPMorgan Chase	0.38	0.00	5.00	113.34	53.70	289.00	32
PNC	0.44	0.00	5.00	7.39	4.70	11.70	27
Royal Bank of Canada	0.75	0.00	4.00	36.25	18.00	60.00	28
Scotia Bank	0.10	0.00	1.00	13.12	6.80	29.30	42
SunTrust Bank	0.00	0.00	0.00	11.40	4.00	28.00	17
UniCredit Group	0.00	0.00	0.00	33.43	28.80	39.80	3
UBS	2.61	0.00	13.00	244.68	24.00	433.00	28

Panel B: Additional Observations for Expanded Sample

	99% CI				95% CI			
	Exceptions				Exceptions			
Bank	Mean	Max	VaR	N	Mean	Max	VaR	N
Goldman Sachs	–	–	–	0	0.80	6.00	118.79	40
JPMorgan Chase	–	–	–	0	0.50	3.00	70.75	12
Lehman Brothers	4.50	9.00	126.50	2	0.33	3.00	45.09	15
Morgan Stanley	0.00	0.00	66.50	18	1.38	13.00	102.16	26
PNC	–	–	–	0	0.25	1.00	3.77	8

Table 3: Equity Ratio and Future Value-at-Risk Exceptions

This table presents OLS estimates from a regression of the number of VaR exceptions in the next quarter on banks' equity capital ratio *log(Eq/AT)* and a vector of control variables. *Exceptions* is the number of times the bank had losses that exceeded their self-reported Value-at-Risk during the next quarter, *log(Eq/AT)* is the log of the book equity-to-assets ratio, *Total Assets* is the log of total assets, *NI-to-Assets* is the ratio of quarterly net income-to-assets, and *Vol* variables are the volatilities of commodity, S&P 500, Foreign Exchange, and Interest Rate indices.

	(1) Exceptions	(2) Exceptions	(3) Exceptions	(4) Exceptions	(5) Exceptions	(6) Exceptions
log(Eq/AT)	-2.70***	-2.46***	-2.46***	-3.04***	-2.56***	-2.56**
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)
Total Assets		1.04	1.00	0.69**	1.01	1.01**
		(0.14)	(0.16)	(0.02)	(0.14)	(0.04)
NI-to-Assets			-0.36	-0.23	-0.53	-0.53
			(0.74)	(0.81)	(0.57)	(0.65)
Vol-Commodities				1.09**	0.69	0.69
				(0.03)	(0.45)	(0.11)
Vol-S&P 500				1.00***	1.20**	1.20**
				(0.00)	(0.02)	(0.03)
Vol-Foreign Exchange				0.12	0.90	0.90
				(0.85)	(0.42)	(0.23)
Vol-Interest Rate				0.95**	0.54	0.54
				(0.02)	(0.70)	(0.38)
Year-Quarter (Y-Q) FE	Yes	Yes	Yes	No	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	424	424	424	424	424	424
R^2	0.45	0.45	0.45	0.41	0.47	0.47
SE Clustered by	Y-Q	Y-Q	Y-Q	Y-Q	Y-Q	Bank

p-values in parentheses

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

Table 4: Equity Ratio, Recent Returns, and Future Value-at-Risk Exceptions

This table presents OLS estimates from a regression of the number of VaR exceptions in the next quarter on banks' equity capital ratio *log(Eq/AT)* and a vector of control variables. *Exceptions* is the number of times the bank had losses that exceeded their self-reported Value-at-Risk during the next quarter, *log(Eq/AT)* is the log of the book equity-to-assets ratio, *LowRet* is an indicator variable equal to 1 when the prior quarter's return is in the lower quartile, *Total Assets* is the log of total assets, *NI-to-Assets* is the ratio of quarterly net income-to-assets, and *Vol* variables are the volatilities of commodity, S&P 500, Foreign Exchange, and Interest Rate indices. Standard errors are clustered by year-quarter.

	(1) Exceptions	(2) Exceptions	(3) Exceptions	(4) Exceptions
log(Eq/AT)	-2.56***		-2.52***	-1.59**
	(0.00)		(0.01)	(0.02)
LowRet		0.50	0.47	-3.82**
		(0.10)	(0.11)	(0.04)
log(Eq/AT) * LowRet				-1.48**
				(0.03)
Total Assets	1.01	1.34*	1.00	1.27**
	(0.14)	(0.07)	(0.14)	(0.04)
NI-to-Assets	-0.53	-0.32	-0.33	-0.19
	(0.57)	(0.73)	(0.71)	(0.82)
Vol-Commodities	0.69	0.50	0.70	0.74
	(0.45)	(0.56)	(0.41)	(0.32)
Vol-S&P 500	1.20**	1.11**	1.14**	1.09**
	(0.02)	(0.03)	(0.02)	(0.01)
Vol-Foreign Exchange	0.90	0.79	0.91	0.88
	(0.42)	(0.48)	(0.41)	(0.38)
Vol-Interest Rate	0.54	0.59	0.55	0.47
	(0.70)	(0.69)	(0.71)	(0.74)
Year-Quarter FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Observations	424	424	424	424
R^2	0.47	0.46	0.48	0.51

p-values in parentheses

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

Table 5: Future Exceptions when VaR is a larger portion of Equity Capital
This table presents OLS estimates from a regression of the number of VaR exceptions in the next quarter on banks' equity capital ratio *log(Eq/AT)* and a vector of control variables. *Exceptions* is the number of times the bank had losses that exceeded their self-reported Value-at-Risk during the next quarter, *log(Eq/AT)* is the log of the book equity-to-assets ratio, *VE_2006* is the ratio percentage of Value-at-Risk to Equity ($\frac{VaR}{Equity} * 100$) at the beginning of 2006, *High(VE_2006)* is an indicator equal to 1 for observations where *VE_2006* is above the sample median, *Total Assets* is the log of total assets, *NI-to-Assets* is the ratio of quarterly net income-to-assets, and *Vol* variables are the volatilities of commodity, S&P 500, Foreign Exchange, and Interest Rate indices. With *VE_2006* measured as of 2006, all observations prior to 2006 are dropped from this subsample.

	(1) Exceptions	(2) Exceptions	(3) Exceptions	(4) Exceptions	(5) Exceptions
log(Eq/AT)	-3.58**	-0.86	-0.86	1.35	1.35
	(0.01)	(0.57)	(0.55)	(0.45)	(0.36)
VE_2006 * log(Eq/AT)		-5.54**	-5.54***		
		(0.02)	(0.00)		
High(VE_2006) * log(Eq/AT)				-7.45**	-7.45***
				(0.02)	(0.00)
Total Assets	0.62	-0.20	-0.20	-0.16	-0.16
	(0.46)	(0.80)	(0.81)	(0.85)	(0.83)
NI-to-Assets	-0.65	0.06	0.06	-0.15	-0.15
	(0.58)	(0.95)	(0.96)	(0.90)	(0.90)
Vol-Commodities	0.77	0.86	0.86*	0.48	0.48
	(0.53)	(0.44)	(0.08)	(0.70)	(0.39)
Vol-S&P 500	1.20**	1.15**	1.15**	1.27**	1.27**
	(0.04)	(0.02)	(0.04)	(0.02)	(0.05)
Vol-Foreign Exchange	0.99	0.98	0.98	0.95	0.95
	(0.49)	(0.49)	(0.27)	(0.50)	(0.25)
Vol-Interest Rate	0.59	1.02	1.02	0.86	0.86
	(0.73)	(0.50)	(0.14)	(0.62)	(0.13)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Observations	330	330	330	330	330
R^2	0.47	0.50	0.50	0.51	0.51
SE Clustered by	Y-Q	Y-Q	Bank	Y-Q	Bank

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Equity Ratio and Future Value-at-Risk Exceptions during Stress

This table presents OLS estimates from a regression of the number of VaR exceptions in the next quarter on banks' equity capital ratio *log(Eq/AT)* and a vector of control variables. *Exceptions* is the number of times the bank had losses that exceeded their self-reported Value-at-Risk during the next quarter, *log(Eq/AT)* is the log of the book equity-to-assets ratio, *2008q4* is an indicator variable equal to 1 for the quarter following Lehman Brothers' collapse, *HiMES* is an indicator variable equal to 1 for quarter when the Marginal Expected Shortfall of the financial sector is in the top quartile for the sample, *Total Assets* is the log of total assets, *NI-to-Assets* is the ratio of quarterly net income-to-assets, and *Vol* variables are the volatilities of commodity, S&P 500, Foreign Exchange, and Interest Rate indices. Standard errors are clustered by year-quarter.

	(1) Exceptions	(2) Exceptions	(3) Exceptions	(4) Exceptions
log(Eq/AT)	-2.56***	-2.22**	-2.55***	-1.01
	(0.00)	(0.01)	(0.01)	(0.18)
log(Eq/AT) * 2008q4		-6.78***		
		(0.00)		
HiMES			0.44	-4.33*
			(0.56)	(0.09)
log(Eq/AT) * HiMES				-1.64**
				(0.04)
Total Assets	1.01	1.15*	1.02	1.07*
	(0.14)	(0.09)	(0.14)	(0.09)
NI-to-Assets	-0.53	-0.79	-0.48	-0.30
	(0.57)	(0.40)	(0.60)	(0.73)
Vol-Commodities	0.69	0.62	0.78	0.88
	(0.45)	(0.50)	(0.39)	(0.35)
Vol-S&P 500	1.20**	1.19**	1.04*	0.94*
	(0.02)	(0.02)	(0.07)	(0.09)
Vol-Foreign Exchange	0.90	1.03	0.82	0.78
	(0.42)	(0.40)	(0.47)	(0.50)
Vol-Interest Rate	0.54	0.58	0.76	0.64
	(0.70)	(0.68)	(0.60)	(0.67)
Year-Quarter FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Observations	424	424	424	424
R^2	0.47	0.56	0.48	0.51

p-values in parentheses

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

Table 7: Explaining the Level of Reported VaR

This table presents OLS estimates from a regression of *log(Value-at-Risk)* on banks' equity capital ratio *log(Eq/AT)*, past stock market volatility, and a vector of control variables. *log(Eq/AT)* is the log of the book equity-to-assets ratio, *L.log([t]yr S&P vol)* is the log of the annualized volatility of daily S&P500 returns over the past t years, *Total Assets* is the log of total assets. Standard errors are clustered by year-quarter.

	(1) log(VaR)	(2) log(VaR)	(3) log(VaR)	(4) log(VaR)	(5) log(VaR)	(6) log(VaR)
L.log(1yr S&P vol)	0.26^{***}	0.12^{**}	0.70^{***}			
	(0.00)	(0.05)	(0.00)			
log(Eq/AT)		-0.84^{***}	-0.53^{**}		-0.87^{***}	-0.48^{**}
		(0.00)	(0.01)		(0.00)	(0.03)
Total Assets		0.62^{***}	0.60^{***}		0.66^{***}	0.62^{***}
		(0.00)	(0.00)		(0.00)	(0.00)
log(Eq/AT) × L.log(1yr S&P vol)			0.20^{**}			
			(0.01)			
L.log(2yr S&P vol)				0.16^{*}	0.07	0.75^{***}
				(0.07)	(0.26)	(0.00)
log(Eq/AT) × L.log(2yr S&P vol)						0.23^{***}
						(0.00)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	405	405	405	405	405	405
R^2	0.86	0.89	0.89	0.85	0.88	0.89

p-values in parentheses

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

Table 8: Stale Model – Omitting Periods and Arellano-Bond Estimates

This table presents OLS estimates from a regression of the number of VaR exceptions in the next quarter on banks' equity capital ratio *log(Eq/AT)* and a vector of control variables. Column (1) is the baseline specification for comparision. Columns (2) and (3) present estimates omitting observations in 2007 and 2008q4, respectively. Columns (4) and (5) present estimates of panel estimates using Arellano-Bond (1991) estimation with one and two lags, respectively. *Exceptions* is the number of times the bank had losses that exceeded their self-reported Value-at-Risk during the next quarter, *log(Eq/AT)* is the log of the book equity-to-assets ratio, *2008q4* is an indicator variable equal to 1 for the quarter following Lehman Brothers' collapse, *HiMES* is an indicator variable equal to 1 for quarter when the Marginal Expected Shortfall of the financial sector is in the top quartile for the sample, *Total Assets* is the log of total assets, *NI-to-Assets* is the ratio of quarterly net income-to-assets, and *Vol* variables are the volatilities of commodity, S&P 500, Foreign Exchange, and Interest Rate indices. Standard errors are clustered by year-quarter.

	(1) All	(2) drop2007	(3) drop2008q4	(4) AB1lag	(5) AB2lags
log(Eq/AT)	-2.56***	-2.52**	-2.27**	-2.12*	-2.41*
	(0.00)	(0.01)	(0.01)	(0.08)	(0.08)
L.Exceptions				0.30***	0.31***
				(0.00)	(0.00)
L2.Exceptions					-0.01
					(0.92)
Total Assets	1.01	0.80	1.16*	1.75**	1.70**
	(0.14)	(0.13)	(0.09)	(0.02)	(0.02)
NI-to-Assets	-0.53	-0.74	-0.67	1.21***	1.29***
	(0.57)	(0.44)	(0.48)	(0.01)	(0.01)
Vol-Commodities	0.69	0.85	0.88	0.97*	1.01
	(0.45)	(0.37)	(0.30)	(0.05)	(0.25)
Vol-S&P 500	1.20**	0.98**	1.33***	1.37***	1.37***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)
Vol-Foreign Exchange	0.90	0.80	0.10	0.53	0.46
	(0.42)	(0.46)	(0.89)	(0.45)	(0.58)
Vol-Interest Rate	0.54	-0.41	0.42	1.74***	1.76***
	(0.70)	(0.63)	(0.76)	(0.00)	(0.00)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Observations	424	379	413	392	378
R^2	0.47	0.48	0.47		
2nd Order AR Test p-val				0.91	0.99
Sargan Test p-val				0.42	0.48

p-values in parentheses

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

Table 9: Alternative Measures of Financial Stress

This table presents OLS estimates from a regression of the number of VaR exceptions in the next quarter on banks' equity capital ratio *log(Eq/AT)* and a vector of control variables. *Exceptions* is the number of times the bank had losses that exceeded their self-reported Value-at-Risk during the next quarter, *log(Eq/AT)* is the log of the book equity-to-assets ratio, *log(MES)* is log of the Marginal Expected Shortfall of the financial sector, *Cleveland FSI* is Financial Stress Index computed by the Federal Reserve Bank of Cleveland, *KansasCity FSI* is Financial Stress Index computed by the Federal Reserve Bank of Kansas City, *StLouis FSI* is Financial Stress Index computed by the Federal Reserve Bank of St. Louis, *Total Assets* is the log of total assets, *NI-to-Assets* is the ratio of quarterly net income-to-assets, and *Vol* variables are the volatilities of commodity, S&P 500, Foreign Exchange, and Interest Rate indices. Standard errors are clustered by year-quarter.

	(1) Exceptions	(2) Exceptions	(3) Exceptions	(4) Exceptions	(5) Exceptions
log(Eq/AT)	-2.56***	20.81***	-1.11	-0.76	-1.01
	(0.00)	(0.01)	(0.13)	(0.35)	(0.28)
log(MES)		-2.58			
		(0.29)			
log(Eq/AT) × log(MES)		-1.68***			
		(0.00)			
Cleveland FSI			-1.90*		
			(0.05)		
log(Eq/AT) × Cleveland FSI			-0.86**		
			(0.01)		
KansasCity FSI				-1.67	
				(0.35)	
log(Eq/AT) × KansasCity FSI				-0.76*	
				(0.06)	
StLouis FSI					-0.80
					(0.48)
log(Eq/AT) × StLouis FSI					-0.76*
					(0.05)
Total Assets	1.01	1.83***	1.67***	1.39**	1.51***
	(0.14)	(0.00)	(0.00)	(0.02)	(0.01)
NI-to-Assets	-0.53	-0.73	-0.45	-0.53	-0.48
	(0.57)	(0.40)	(0.59)	(0.58)	(0.63)
Vol-Commodities	0.69	1.07	0.96	0.77	0.94
	(0.45)	(0.23)	(0.28)	(0.40)	(0.28)
Vol-S&P 500	1.20**	0.66	0.38	0.53	0.20
	(0.02)	(0.27)	(0.53)	(0.42)	(0.65)
Vol-Foreign Exchange	0.90	0.91	0.82	1.18	-0.27
	(0.42)	(0.44)	(0.41)	(0.28)	(0.75)
Vol-Interest Rate	0.54	0.68	0.32	0.51	0.06
	(0.70)	(0.62)	(0.81)	(0.70)	(0.96)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Observations	424	424	424	424	424
R^2	0.47	0.52	0.53	0.55	0.57

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Equity Ratio and Future Violations – Non-linear models

This table presents count model regression of the number of VaR exceptions in the next quarter on banks' equity capital ratio *log(Eq/AT)* and a vector of control variables. Columns (1) and (2) present estimates from a negative binomial regression model, and columns (3) and (4) present estimates from a poisson regression model *Exceptions* is the number of times the bank had losses that exceeded their self-reported Value-at-Risk during the next quarter, *log(Eq/AT)* is the log of the book equity-to-assets ratio, *Total Assets* is the log of total assets, *NI-to-Assets* is the ratio of quarterly net income-to-assets, and *Vol* variables are the volatilities of commodity, S&P 500, Foreign Exchange, and Interest Rate indices.

	(1) Exceptions	(2) Exceptions	(3) Exceptions	(4) Exceptions
log(Eq/AT)	-1.22*	-1.55*	-1.14*	-2.12***
	(0.07)	(0.06)	(0.05)	(0.00)
Total Assets		-0.79		-0.86
		(0.26)		(0.14)
NI-to-Assets		0.16		0.23
		(0.83)		(0.70)
Vol-Commodities		-0.61		-0.59
		(0.56)		(0.48)
Vol-S&P 500		2.41***		2.45***
		(0.00)		(0.00)
Vol-Foreign Exchange		-1.02		-0.63
		(0.49)		(0.62)
Vol-Interest Rate		-0.60		-0.73
		(0.55)		(0.35)
Year-Quarter FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Observations	391	391	391	391
log likelihood	-210.42	-197.84	-223.83	-207.22

p-values in parentheses

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

Table 11: Expanded Sample Tests

This table presents OLS estimates from a regression of measures of VaR exceptions in the next quarter on banks' equity capital ratio *log(Eq/AT)* and a vector of control variables. These test include the base sample observations (commercial banks reporting 99% VaR) and expanded sample observations (broker/dealers and reports of 95% VaR). *Exceptions* is the number of times the bank had losses that exceeded their self-reported Value-at-Risk during the next quarter with *1(Exception)* an indicator equal to 1 if the bank has at least 1 exception, *Excess* is an indicator variable equal to 1 when a bank's number of exceptions exceeds their expected number of exceptions based on the confidence level (i.e., *Exceptions* $\geq$ 0.6 for 99% CI and *Exceptions* $\geq$ 3.0 for 95% CI), *95pc CI* is an indicator variable equal to 1 when a bank reports VaR at the 95% level, *log(Eq/AT)* is the log of the book equity-to-assets ratio, *Total Assets* is the log of total assets, *NI-to-Assets* is the ratio of quarterly net income-to-assets, and *Vol* variables are the volatilities of commodity, S&P 500, Foreign Exchange, and Interest Rate indices.

	(1) Excess	(2) Excess	(3) Excess	(4) 1(Exception)	(5) 1(Exception)	(6) 1(Exception)
log(Eq/AT)	-0.20*	-0.17*	-0.21**	-0.25**	-0.23**	-0.26***
	(0.06)	(0.07)	(0.03)	(0.01)	(0.04)	(0.01)
95pc CI	0.02	0.02	0.02	0.17**	0.17**	0.17**
	(0.72)	(0.67)	(0.64)	(0.04)	(0.02)	(0.04)
Total Assets	-0.07	0.09*	-0.07	-0.07	0.12**	-0.07
	(0.48)	(0.09)	(0.46)	(0.52)	(0.04)	(0.49)
NI-to-Assets	0.14	-0.03	0.07	0.09	-0.09	0.03
	(0.29)	(0.80)	(0.54)	(0.53)	(0.42)	(0.84)
Vol-Commodities		0.24***	0.02		0.24**	0.04
		(0.01)	(0.88)		(0.01)	(0.79)
Vol-S&P 500		0.25***	0.51***		0.27***	0.47***
		(0.00)	(0.00)		(0.00)	(0.00)
Vol-Foreign Exchange		-0.08	-0.23		-0.14	-0.17
		(0.58)	(0.19)		(0.39)	(0.34)
Vol-Interest Rate		0.07	-0.15		0.11	-0.12
		(0.38)	(0.36)		(0.23)	(0.45)
Year-Quarter FE	Yes	No	Yes	Yes	No	Yes
Bank FE	Yes	No	Yes	Yes	No	Yes
Observations	545	545	545	545	545	545
R^2	0.44	0.38	0.49	0.45	0.38	0.49

p-values in parentheses

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