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. Specifically, a decrease in a bank's equity capital results in substantially more violations of its self-reported risk levels in the following quarter. The under-reporting is especially high during the critical periods of high systemic risk and for banks with larger trading operations. We exploit a discontinuity in the expected benefit of under-reporting present in Basel regulations to provide further support for a causal link between capital-saving incentives and under-reporting. Overall, we show that banks' self-reported risk measures become least informative precisely when they matter the most.

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

JEL Classification: G20, G30.

1 Introduction

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 and pay more for deposit insurance. Such banks are also likely to face more risk in the stability of their funding during periods of banking crisis. These consequences have the potential to create an important problem: they give banks incentives to under-report their risk. 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 policy-relevant 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 large financial institutions (banks), we focus on the trading book because it allows us to cleanly tease out the under-reporting incentives. A typical trading portfolio consists of marketable financial instruments linked to interest rates, exchange rates, commodities, and equity prices. The trading desks of large banks have significant risks and have been the subject of many recent policy debates and discussions on risk-management failures within a bank.[1] Basel rules allow banks to measure the risk of their trading portfolios with internal Value-at-Risk (VaR) models. Broadly, VaR 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

[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.

to determine capital requirements for market risk. The use of an internal risk model leaves a great deal of discretion with the reporting bank. For example, banks can vary assumptions about asset volatilities, correlations between asset classes, or alter the length and weighting of the historical period used to estimate these quantities, all of which significantly affect the output of their models (BIS, 2013). This discretion gives banks a significant ability to under-report their trading risks, which directly lowers their current capital requirements. Thus, the incentives to under-report is especially strong when capital is dear (e.g., when they have lower equity capital). The combination of ability and incentive to under-report risk has the potential to compromise the integrity of the risk management system and risk-based regulations.

To mitigate the under-reporting incentive, regulators use a "backtesting" procedure to evaluate banks' self-reported VaR, and impose a penalty on institutions with models that have proven inaccurate. As per the recommendations of Basel committee, a bank's market-risk capital requirement is set at its 99% VaR number over a 10-day horizon multiplied by a capital multiplier k, which is initially set to three.[2] However, if a bank 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.[3] If a bank has more than four exceptions during the trailing four quarters, the regulators assume that the bank is more likely to have under-reported in the past, and its capital multiplier is increased for the subsequent periods for a charge of up to four-times its VaR level.[4] However, there is also some probability that the under-reporting does not

[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]See Kupiec (1995) for further details on backtesting and statistical methods for assessing the accuracy of VaR models.

[4]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). We later exploit the shape of this institutional feature in our empirical tests.

get detected depending on future asset price movements. In such a scenario, the under-reporting bank avoids detection and penalties altogether. Even if the bank does experience VaR exceptions, the potentially significant 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. 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.[5]

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 several quarters 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 in future quarters. 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.

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 (banks) from the U.S., Europe, and Canada from 2002-2012. These cover a significant fraction of the global banking assets, and an even larger fraction of trading assets. A VaR exception occurs when a bank's realized losses exceed its self-reported VaR number. More specifically, VaR numbers are computed and reported at the end of the day for the bank's trading portfolio. Holding fixed that portfolio, gains or losses are measured over the next trading day and compared to the reported number to determine if an exception has occurred.

Our first contribution is descriptive in nature. We provide the first detailed summary

[5]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.

statistics on exceptions across banks and over this time period. Our main tests focus on commercial banks' VaR reporting at the 99% confidence level. We find 0.62 average quarterly exceptions per bank for this sample, which is approximately equal to the statistical benchmark for a 99% VaR model over roughly 63 trading days per quarter. This 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 greater than 2.5-times the statistical benchmark.

In our main empirical test, we show that when banks have lower equity capital at the beginning of a quarter, they have significantly more VaR exceptions in the following quarter. One standard deviation decrease in a bank's equity capital results in an increase of 1.32 exceptions in the following quarter, which is roughly twice the sample average of 0.62. Put differently, banks' future losses exceed their own risk assessment significantly more frequently in periods immediately following a decline in their equity capital (i.e., when they have higher capital-saving incentives). 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 riskiness or equity capital, 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. Further, our model includes both bank and year-quarter fixed effects, which ensures that our results are not driven by differences in bank-specific risk-modeling skills or market-wide shocks. Our design, therefore, relates within-bank variation in the level of equity capital to future VaR exceptions to identify the under-reporting behavior.

The number of exceptions can also be influenced by the quality of risk model used by the reporting bank. If a bank under-reports simply by mistake in a quarter, then it may have more exceptions during that quarter. However, such mistakes should not be systematically concentrated in quarters with lower equity capital. Hence, our results are unlikely to be explained away by unintentional mistakes in risk reporting. A remaining identification concern is as follows: if a bank's VaR-model quality deteriorates precisely following quarters when it has low equity capital, then the negative association between equity capital and VaR exceptions might not reflect under-reporting incentives, but simply a systematic deterioration in model quality right after a negative shock to equity capital.

Given that our sample comprises some of the largest and most sophisticated financial institutions of the world, it is unlikely that the bank's modeling quality changes precisely *after* a period when the bank has lower equity capital. However, we directly address this concern by exploiting a regulation-driven discontinuity in the costs and benefits of under-reporting from the Basel Committee guidelines on market risk. Based on the number of exceptions experienced by a bank in the past year, bank regulators classify banks into three categories or zones: Green (0-4 exceptions), Yellow (5-9), and Red (≥ 10). These classifications, in turn, determine the supervisory pressure and increased scrutiny that the banks face in subsequent quarters. Banks in the Green zone have strong incentives to stay within this zone to avoid both the higher fixed compliance costs that must be incurred by banks in the Yellow zone and higher capital multiplier. In contrast banks in the Yellow zone have already incurred much of these costs, and thus face a lower marginal cost of under-reporting. As a result, banks on differing sides of the Green-Yellow threshold face sharply different under-reporting incentives. While there is a stark change in incentives at this point, it is unlikely that the quality of a bank's risk model changes sharply at this threshold. Under this identifying assumption, we first compare the number of future exceptions around the Green-Yellow threshold, and show that banks just above the threshold have almost 5-times as many exceptions in the following quarter compared to banks just below it. Further, in a difference-in-differences specification, we show that the relationship between equity capital and future exceptions is stronger and more negative for bank-quarter observations that are above the Green-Yellow threshold, compared to observations that fall just below. This difference increases as we limit our sample to observations that are closer to the threshold, providing further confidence in the empirical validity of our research design.

We conduct a series of tests to exploit the cross-sectional and time-series variation in under-reporting incentives to gain a better understanding of the economic channels behind the main findings. First, 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. We next show that the relationship between equity capital and VaR exceptions is stronger when banks have recently experienced a decrease in market equity (low stock returns). Raising external equity capital is even more difficult in such situations, and thus the incentives to under-report risk even stronger.

While it is important to understand the risk reporting dynamics for a given bank over time, from a systemic perspective, it is even more important to understand how banks 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 across all banks. Thus, a bank's private marginal benefit from under-reporting is likely to be higher precisely when the social cost of bank failure is high. Using different measures of systemic stress, we show that the relationship between equity capital and under-reporting is stronger during these periods. These results show that the self-reported risk measures become least informative in periods when understanding financial sector risk is likely to be most important.

We conduct a number of tests to ensure the robustness of our results. First, we exploit the panel data dynamics of exceptions to further rule out the "bad model" alternative discussed earlier. 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. Among other tests, we also show that our results remain strong after controlling for a bank's time-varying exposure to market and mortgage-backed securities risk, and the asset class composition of the bank's trading book.

Finally we 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 dimensions. Properly used discretion 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 future VaR exceptions. We estimate the relationship between past stock market volatility and the reported *level* of VaR. Ceteris paribus, the higher the volatility of a risk factor, the higher the level of VaR. We find that the relationship between past market volatility and reported VaR levels to be weaker when banks have lower equity capital. This is consistent with the notion 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 in the choice of volatility parameters to under-report their risk.

Our paper relates to the literature on bank risk models and a recently growing literature on the implications of risk-management practices in banking (see Ellul and Yerramilli (2013)). Jorion (2002) and Berkowitz and O'Brien (2002) analyze the informativeness and statistical accuracy of VaR models.[6] Recent work by Behn, Haselmann, and Vig (2014) examines the efficacy of model based regulation for the banking book of German banks around the introduction of Basel II. They find that banks' internal model-based risk estimates systematically underestimated the level of credit risk in banks' loan portfolios. Our work is consistent with their evidence highlighting the shortcomings of internal model-based regulations. While they focus on the accuracy of model-based regulation compared to standardized approach, our focus is on the relationship between equity capital and risk under-reporting. In summary, our paper contributes to this growing literature by being the first to directly analyze the effect of capital saving incentives on risk under-reporting.

[6]Basak and Shapiro (2001) and Cuoco and Liu (2006) analyze VaR-based constraints and capital requirements, and theoretically analyze the optimality of this mechanism. Colliard (2014) examines a theoretical model of optimal regulation in the face of the banks' strategic use of internal risk models.

This work is also related to the literature on the effect of risk-based capital requirements on the lending and risk-taking behavior of banks (e.g., see Acharya, Schnabl, and Suarez (2013) and Thakor (1996)), and the 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), Kashyap, Rajan, and Stein (2008), and Thakor (2014)). At a broad level, 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. These models, however, do not consider the differences in the shadow price of capital at the time of reporting compared to the time of (potential) punishment. Our work shows that in such settings, the probabilistic punishment mechanism that ignores state prices may have negative systemic consequences. Finally our work is related to the literature on mis-reporting incentives in financial markets in a broader setting (see Piskorski, Seru, and Witkin (2015), and Griffin and Maturana (2015)).

2 Hypothesis Development and Research Design

VaR is a statistical measure of risk that estimates a dollar amount of potential loss from adverse market moves over a fixed time-horizon and at a given confidence interval. For example, a 99% confidence interval, 10-day holding period VaR of $100 million for a portfolio means that over the next 10 days, this portfolio will lose less than $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 conflict, the number of exceptions should be unrelated to the bank's prior equity capital. Alternatively, we should observe more frequent exceptions for banks following quarters with lower equity capital if banks strategically under-report their risk to save capital. Note that a bank may change its risk-taking behavior in response to changes in its equity capital position, but these changes should only affect the *level* of VaR, *not* the frequency of exceptions. This distinction highlights a key strength of our empirical setting: we relate capital-saving incentives to deviation from self-reported VaR numbers, which is independent of the scale of risk-taking.

As mentioned earlier, banks are likely to trade-off the marginal cost of equity capital at the time of reporting with the marginal cost at the time of detection. When a bank enters a low equity capital state, the trade-off is likely to tilt its decision in favor of under-reporting to get immediate capital relief. Such a bank may experience an improvement in its equity capital position in future quarters; the aggregate market conditions might improve in the meantime; or the under-reporting might never get detected. All these forces provide incentives to under-report. Conversely, if managers know that the bank's equity capital shocks are likely to be extremely persistent over time or the probability of detection is very high, then the under-reporting incentives are unlikely to be as strong. Under this scenario, we should not expect to see a negative association between equity capital and under-reporting. In the end, the relationship between equity capital and under-reporting incentives remains an empirical question that we tackle in the rest of the paper.

To develop the intuition behind our empirical test, consider the VaR of a single unit of a risky asset i at time t. Denote this portfolio's reported and actual VaR by $Reported_{it}$ and $Actual_{it}$, respectively. Assume that $\sigma_{predicted}$ is the volatility estimate used by the bank in estimating its reported VaR. Banks typically develop their own internal model for VaR based on one of three approaches: (a) variance-covariance method, (b) historical simulation, or (c) Monte Carlo simulation. Although these approaches differ in their implementation approach, they all require the modeler to take a stand on the volatility of the assets, and covariances between securities and asset classes to estimate the potential loss of the portfolio.[7] Further

[7] Banks typically use the past one to three years of data as an estimate of the underlying asset's historical volatility. 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."

assume 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) with residual (η_{it}) as follows:[8]

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

The key term in the equation is the residual term η_{it}. In our model, this captures the extent of under-reporting and is driven by incentive effects and pure noise (u_{it}). The actual VaR, if the analyst had a perfect foresight of future volatility, can be expressed as $G(\alpha, \sigma_{realized})$. Our goal is to identify the incentive effects in VaR reporting using the following framework:

$$Actual_{it} - Reported_{it} = \{G(\alpha, \sigma_{realized}) - G(\alpha, \sigma_{predicted})\} + \phi(Incentives_{it}) + u_{it} \quad (1)$$

We use the frequency of VaR exceptions for bank i in a given quarter t ($Exceptions_{i,t+1}$) as an empirical proxy for the difference between actual (or realized) and reported risk numbers ($Actual_{it} - Reported_{it}$) in (1). To ensure comparability across observations, we focus on VaR reported at a 99% confidence interval in all of our main specifications.[9] The distribution of $\{G(\alpha, \sigma_{realized}) - G(\alpha, \sigma_{predicted})\}$ measures the quality of risk model – for a good model, this difference should be close to zero and uncorrelated with the incentive variable. We refer to this difference as the "model quality" in the rest of the paper. Thus, our model can be rewritten as follows:

$$Exceptions_{i,t+1} = ModelQuality_{it} + \phi(Incentives_{it}) + u_{it} \quad (2)$$

[8]For example, $G(\alpha, \sigma_{predicted}) = 2.33 \times \sigma_{predicted}$ for a normally distributed asset at a 99% confidence level. For a normally distributed changes in asset value, $VaR = \mathcal{N}^{-1}(\alpha) \times \sigma$, where $\mathcal{N}^{-1}()$ is the inverse normal CDF. -2.33 is the point at which 1% of the mass of the distribution lies below (to the left). The corresponding number for a 95% confidence level is -1.65. Note, however, that we do not rely on normality assumptions for developing our empirical model.

[9]In a robustness test, we expand the sample and reconstruct the test to include observations where VaR is reported at 95% confidence level.

where $Exceptions_{i,t+1}$ measures the number of VaR exceptions over the next period.

If $ModelQuality_{it}$ were perfectly observable, we could identify the effect of under-reporting incentives on the frequency of exceptions by directly controlling for it in the regressions. In the absence of a precise measure of model quality, we confront three primary challenges in identifying the incentive effects on under-reporting. First, banks may have different modelling skills. Differences in risk-management skills, organizational structure, risk culture, and the importance of risk controls within the firm can have significant influence on the level of risk-taking by banks (see Fahlenbrach, Prilmeier, and Stulz (2012); Ellul and Yerramilli (2013)). Kashyap et al. (2008) discuss the effects of internal controls and traders' incentives on risk-taking behavior. If these persistent unobserved modelling skills correlate with equity capital, then our estimates will be inconsistent. We include bank fixed-effect in the empirical specification to address this concern. Second, during periods of large fluctuations in market prices, the realized volatility may be significantly higher than the predicted volatility used in the VaR model, leading to general failures in VaR models across banks during these times. We include year-quarter fixed effect in the empirical specification to address this concern. Thus, our baseline model that addresses these two concerns can be expressed as below, where λ_i and δ_t are bank and year-quarter fixed effects, and X_{it} is a vector of further control variables including the size and profitability of the bank:

$$Exceptions_{i,t+1} = \beta(Incentives_{it}) + \lambda_i + \delta_t + \Gamma X_{it} + \epsilon_{it} \tag{3}$$

Our main measure of $Incentives_{it}$ is the bank's equity capital ratio ($Equity_{it}$). This measure directly maps to our economic argument that banks with stronger incentives to save equity capital are more likely to engage in under-reporting behavior.

The third primary identification challenge is related to concerns about potentially time-varying, bank-specific changes in model quality that correlates with their level of equity. The tests relate equity capital at the beginning of the quarter to the number of VaR exceptions during the next quarter. For the alternative explanation to hold, it must be the case that the VaR model becomes relatively more inaccurate during the quarter, for reasons unrelated to reporting incentives, only when banks have had low equity capital at the beginning of the quarter. Since banks are expected to update their VaR model regularly to better capture the changes in underlying volatilities, this explanation is unlikely to be true. It is also worth emphasizing that the inclusion of year-quarter fixed effects in the model removes the effect of economy-wide deterioration in model quality. However, to directly address this concern we exploit an institutional feature of the market risk capital regulation formulated by Basel Committee on Bank Supervision (BIS, 1996).

As mentioned earlier, bank regulators use a back-testing procedure to check the quality of a bank's risk model. Based on the bank's number of exceptions in the past four quarters, regulators categorize them into one of three zones: "Green," "Yellow," or "Red." Banks with four or fewer exceptions during the past year are categorized into the "Green" zone; those between five and nine are categorized into the "Yellow" zone; and those with ten or more exceptions are categorized into the "Red" zone. These zones, in turn, dictate both the level of regulatory scrutiny and capital charges that the bank faces in subsequent quarters. Banks in the Green zone do not face any special regulatory scrutiny of their risk model, as the lack of exceptions indicate a model that is likely to be more accurate or sufficiently conservative. As per the BIS (1996) policy document, "the green zone needs little explanation. Since a model that truly provides 99% coverage would be quite likely to produce as many as four exceptions in a sample of 250 outcomes, there is little reason for concern raised by backtesting results that fall in this range."

Banks in the Yellow zone automatically come under additional regulatory scrutiny and face significantly higher compliance costs. As stated by the BCBS guidelines: "the burden of proof in these situations should not be on the supervisor to prove that a problem exists, but rather should be on the bank to prove that their model is fundamentally sound. In such a situation, there are many different types of additional information that might be relevant

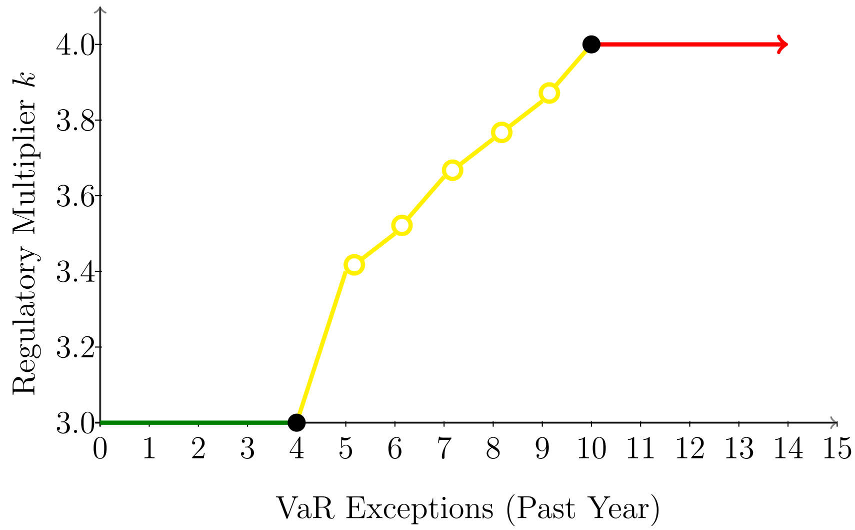

Figure 1: The Shape of Penalties
This figure presents the shape of regulatory capital multiplier k as a function of past exceptions (based on trailing 250 trading days).

to an assessment of the bank's model." As per the guidelines, such banks may be required to provide more granular data on trading risk exposure, intraday trading activities, and a number of other additional pieces of information. Finally, banks with ten or more exceptions fall into the Red zone. Their model is considered inaccurate by the regulators: in extreme cases the regulators can even suspend the bank's internal risk model, and require the bank to use a punitive standardized model for risk assessment.

In addition to the changes in the level of regulatory scrutiny, banks in different zones face different levels of capital charge as well, which is a function of the bank's reported VaR and a regulatory capital charge multiplier (k). Banks in the Green zone face a capital charge multiplier of 3.0; those in Yellow zone face a multiplier between 3.0 and 4.0 depending on the number of past exceptions; and banks in the Red zone face a multiplier of 4.0. Figure 1 illustrates these classifications and the associated capital charge for the entire range of exceptions.[10]

[10]Specifically, the market risk charge C equals the greater of the previous day's reported VaR and the average of the prior 60 days' VaR multiplied by the regulatory multiplier k: $C = \max(VaR_{t-1}, k \times VaR^{ave}_{60-day})$. Table A.1 in the appendix presents mapping from number of exceptions over the last 250 trading days to the corresponding supervisory zone and regulatory multiplier.

Figure 1 makes clear that there are two prominent abrupt changes in the relationship between past exceptions and resulting regulatory scrutiny and capital charges: the Green-Yellow threshold and the Yellow-Red threshold. The quality of banks' VaR model, however, is unlikely to be very different within a given neighborhood along the x-axis. For example, model quality of banks with four exceptions in the past year is likely quite similar to those with three or five exceptions, particularly since the occurrence of an exception is a probabilistic event. We use this similarity in model quality combined with the stark change in economic incentives around the threshold to tease out the causal effect of capital-saving incentives on risk-reporting.

In particular, we focus on the reporting incentive of banks that are around the Green-Yellow threshold. Since the zone assignment is based on the back-testing result of past one year, at the beginning of each quarter we first compute the number of exceptions that a bank had in the trailing three quarters. Absent any under-reporting incentives, banks expect to incur roughly one additional exception every quarter by construction due to the 99% VaR confidence interval. For example, a bank that has two exceptions in the past 3 quarters will, in expectation, have an additional exception in the next quarter for annual total of three exceptions. Thus, banks with three or fewer exceptions in the past 3 quarters are expected to stay within the Green zone at the end of the quarter with a four-quarter total of four or fewer exceptions. We refer to these observations – which in expectation will avoid the additional scrutiny that faces those in the Yellow zone – as the Green group for the remainder of the paper. These observations can be thought of as a control group. Banks with four up to eight exceptions, on the other hand, will in expectation be in the Yellow zone in the next quarter even without any under-reporting. We refer to these observations as the Yellow group, and they can be thought of as a treatment group. Given the significantly higher costs and scrutiny incurred by banks in the Yellow zone relative to the Green zone, banks in the Green zone have incentives to be relatively more conservative in their risk reporting compared to banks in the treatment group. However, such incentives disappear for banks in the Yellow group who expect to face this scrutiny in any case. The remainder of the observations are in the Red group.

In addition to the changes in regulatory pressure around the threshold, the shape of the multiplier function provides further support to our identification strategy. There is a significant change from a flat multiplier charge of 3.0 to a sharp increase in capital charge as a bank moves from the Green to the Yellow zone, which makes Green zone banks face a convex penalty function. However, for banks in the Yellow zone, the multiplier increases broadly at a linear pace until it reaches a level of 4.0, after which it is capped. Therefore, the shape of penalty function is concave for banks in this region. This switch in the shape from a convex penalty function to a concave one further strengthens the relative under-reporting incentive of banks in the Yellow zone.

In summary, banks in the Yellow group are likely to have a stronger under-reporting incentive to save capital in the current quarter as compared to the Green group.[11] Also, the comparability of these two groups is likely to improve as we narrow the window around the threshold, where our assumption of similarity in unobserved model quality is most reasonable. Under the identifying assumption that banks in the neighborhood of the Green-Yellow threshold are likely to have similar model quality, we are able to identify the effect of the incentive to save capital on under-reporting by simply comparing the differences in exceptions around this threshold. Further, using a difference-in-differences research design, we compare the effect of equity capital on under-reporting in the Yellow zone compared to the corresponding difference in the Green zone. The effect of equity capital on under-reporting is expected to be higher for banks in the Yellow zone since the net-benefit from under-reporting increases sharply at the threshold. The identifying assumption here is that any potential correlation between equity capital and unobserved model quality does not change in a dis-

[11] The combination of Green zone banks' desire to avoid additional regulatory scrutiny and the convex cost function may help explain the seemingly excessive conservatism in VaR reporting we see in the early periods. Berkowitz and O'Brien (2002) also find that VaR estimates tended to be conservative relative to the 99% benchmark for six large U.S. banks during 1998-2000.

continuous manner at the Green-Yellow threshold. Hence the incremental effect of equity capital in the Yellow zone is more likely an outcome of stronger under-reporting incentives, and not simply due to poor model quality. For expositional clarity, we defer further details on the empirical implementation to the results sections.

While our tests focus on the threshold between the Green and Yellow zones, there is a second kink as a bank moves from the Yellow to Red zone. However, the underlying changes in incentives are not as clear at this threshold. On one hand, banks face a flat multiplier charge of $k = 4.0$ for any number of exceptions beyond ten, providing them with an incentive to be aggressive in risk reporting. On the other hand, such banks might also have concerns that their permission to use internal models may be revoked by the regulator. In such a situation, they face the risk of a much higher capital charge based on the standardized modelling approach of the regulator. Further, we have a very few observations in the Red group. Considering these factors, we do not exploit this threshold in our empirical tests.

Following our main empirical tests, we examine further cross-sectional and time series variation in the economic incentives to under-report. Cross-sectionally, we exploit variation across banks in the size of their trading books. Banks with larger trading books may have stronger incentive to under-report when capital is costly. We then exploit time series variation in financial system stress to examine the systemic implications of 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.[12] 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 on a given day, an exception occurs. We collect all exceptions during the quarter for each bank, and use it as the key measure of reporting accuracy.

Our "base" sample includes large commercial banks 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 more homogenous in terms of their capital requirements. For robustness tests, 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.[13] Finally, we miss some banks 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 are not available for most banks before this year. Our sample ends in 2012. The total sample comprises 15 commercial banks and 3 broker-dealers, which covers a large portion of assets in the global banking system. 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. Even more important, these institutions cover a disproportionately large fraction of trading assets of the economy. Our base sample of commercial banks provides 424 bank-quarter observations over 2002-2012 for our main tests. The expanded sample contains 545 bank-quarter observations that we

[12]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.

[13]Broker-dealers also face capital requirements for market risks based on similar Basel Committee formula. Their 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).

examine in robustness tests.

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, Pedersen, Philippon, and Richardson (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 collect balance sheet data on banks' 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. All data are winsorized at the 1% level to mitigate the effects of any outliers. Continuous variables and the number of exceptions are standardized to have zero mean and unit standard deviation prior to the regression analysis for easier interpretation.

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. Following prior literature, 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 then leads to a mechanical correlation between under-reporting and regulatory capital ratio. The use of book equity capital ratio avoids such a problem.

Turning to the VaR data, we find a wide variation in VaR exceptions, the level of VaR, and the composition of VaR in our sample. On average, interest rate risk forms the largest proportion of banks' trading book risk. 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 that we exploit in our main tests.

4 Results

In addition to our main exercise that examines the under-reporting incentives, our paper makes an important contribution to the literature by documenting some key empirical facts about VaR and its exceptions. Therefore, 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 incentives to save equity and VaR exceptions. We then examine further cross-sectional and time series variation in the banks' economic incentives to under-report by looking at banks with larger trading exposures, and periods when the financial system is under stress.

4.1 Value-at-Risk Exceptions Over Time

Table 1 presents summary statistics on VaR exceptions for the sample. Since the VaR numbers that we consider in the base sample are based on 99% confidence interval, we expect to see one exception in every 100 days purely by chance. Hence on a quarterly basis, we expect to observe an average of about 0.63 exceptions based on roughly 63 trading days per 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 3 presents this variation over time by plotting the average number of exceptions per bank during each quarter in the sample. The average number of 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 exceptions 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 likely 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. Was the VaR exception during this period simply an artifact of large changes in asset prices, or was it also related to capital-saving incentives? The following empirical analysis teases out these alternatives.

4.2 Value-at-Risk Exceptions and Equity Capital

We begin the regression analysis by estimating our base regression model relating capital-saving incentives to subsequent VaR exceptions. As mentioned earlier, the number of exceptions and all continuous variables are standardized to mean zero and unit standard deviation for ease of interpretation. Table 3 presents the baseline results along with several alternative specifications of the following model that differ in terms of control variables used and estimation approach:

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

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.[14] We find a negative and statistically significant coefficient on the equity capital ratio: when banks have lower equity capital, they have more VaR exceptions in the following period. In terms of economic magnitude, one standard deviation (s.d.) decrease in equity capital results in approximately 0.70 s.d., or 1.40, more exceptions in the following quarter. With a sample average of 0.62 exceptions and s.d. of 2.00, this is an economically significant increase to over three times the average VaR exception frequency. In column (2), we include controls for bank size and profitability. Our main result are virtually unaffected, both statistically and economically. Also, including bank-specific controls explains little if any of the variation in exceptions, as the R^2 across the first three columns remains at 0.45. In column (3), we explicitly include measures of the volatility of underlying risk factors during the quarter in the regression model and drop year-quarter fixed effects. As expected, we find higher exceptions during quarter with high volatility in market returns, interest rates, and commodity

[14] The log-transform of equity ratio follows the literature and 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. 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 and discuss those later in the paper.

prices. Our main result relating equity capital to exceptions remains similar.

The quarterly timing of reporting is not exactly the same for all banks in our sample. For example, some banks end their quarter in March, while others end in April. Therefore, the volatility measures during the bank's reporting quarter is not perfectly collinear with the calendar time year-quarter fixed effects. Thus we can include year-quarter fixed effects in the model along with the volatility measures computed during the bank's reporting quarter. Column (4) shows that our results are similar based on this full specification with a point estimate of 0.66 (p-value<0.01), which corresponds to 1.32 more exceptions the following quarter. We cluster the standard errors in our main specifications at the year-quarter level. In column (5), we compute standard errors clustered at the bank level and find that the results are statistically significant at the 3% level. 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 in the rest of the paper. Overall, Table 3 documents a strong effect of equity capital on the accuracy of self-reported VaR measures.

In untabulated tests, we estimate the model with various other (standardized) measures of equity capital ratio. We find a coefficient of -0.21 (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* (-0.41 with p-value of 0.01) and even larger for the model that uses cubic root of *Eq/TA* as the explanatory variable (-0.50 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 Identification Using the Shape of the Penalty Function

We now present the results of empirical tests based on the discontinuity in incentives around the Green-Yellow threshold highlighted earlier in Figure 1. At the beginning of each quarter, we first compute the number of exceptions reported by the bank in the prior three quarters. We call this number as “trailing exceptions.” As discussed in Section 2, banks in the Yellow group are likely to have higher under-reporting incentives compared to similar banks in the Green group that fall just below this threshold.

In our first test, we compute the average exceptions in the next quarter for observations currently in the neighborhood of the Green-Yellow threshold. Figure 2 presents a plot of these averages for each trailing-exceptions bin from 0 to 8. Banks in the Yellow group have significantly higher exceptions than the banks in the Green group. In fact, each trailing-exception bin in the Yellow group has higher exception than any bin in the Green group. Overall, banks in the Green group have an average exceptions of 0.32 in the next quarter compared to the average exceptions of 2.38 for banks in the Yellow group. The average difference of 2.06 across the two groups is statistically significant at 1%. Narrowing the range of examination to [2-7] yields a similar difference of 1.96 (2.47 for Yellow observations versus 0.51 for Green). Table A.2 in the appendix presents this statistic along with other bank characteristics which shows the comparability of the two groups on observable dimensions. This finding is consistent with our key assertion in the paper: when the under-reporting incentive increases discontinuously around the Green-Yellow threshold, we observe significantly higher VaR exceptions the following quarter. Note that our identification strategy remains valid even if there is some smooth, continuous change in the model quality around the threshold, as long as such a change is not discontinuous at the same point. Since it is unlikely that the model quality changes discontinuously at this point, our empirical results are likely to be causal in nature.

We extend this analysis further in a regression framework by including an indicator *Yellow* to our base regression specification (4). Since we require data on trailing three quarters for this analysis, we lose a few observations for this regression. For easier interpretation of estimates that include interaction effect, we use the negative of $\log(Eq/A)$, called *NegativeEquity*, as the measure of equity capital in this portion of the analysis. Table 4 presents the results.

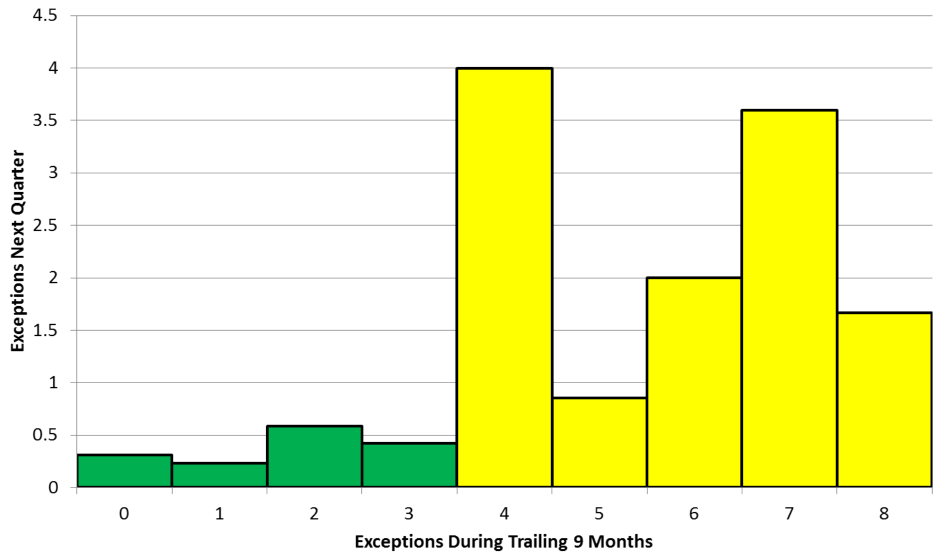

Figure 2: Distribution of Value-at-Risk Exceptions
This figure presents the average number of Var exceptions reported by a bank in quarter t across different groups of "trailing exceptions." "Trailing exceptions" measures the total number of VaR exceptions reported by the bank in trailing three quarters ($Exceptions_{t-1} + Exceptions_{t-2} + Exceptions_{t-3}$).

Column (1) presents the base case analysis relating equity capital to future VaR exceptions for this sample. The estimated coefficient of 0.75 on *NegativeEquity* is almost identical to our full sample result. We next estimate the effect of *Yellow* for the full sample, and then progressively narrow down the sample by decreasing the window around the Green-Yellow threshold. In addition, we include an indicator variable *Red* for banks with ten or more trailing exceptions. Thus, the omitted category is the Green group that have three or fewer trailing exceptions. In column (2), we find a positive and significant coefficient of 0.59 (p-value=0.02) on *NegativeEquity* and 0.54 (p-value=0.02) for the Yellow group. This indicates that after controlling for bank characteristics, bank fixed effects, and year-quarter fixed effects, banks in the Yellow group have 0.54 s.d., or 1.08, more exception in the following quarter. Economically, column (2) suggests that when included independently, a one s.d. decrease in equity capital and being on the right-hand side of the Green-Yellow threshold have quantitatively similar incentive effects.

We now present the results of the difference-in-differences specification that compares the effect of equity capital on under-reporting in the Yellow group compared to the corresponding difference in the Green group. Results are provided in Column (3). We find a positive and significant coefficient on the interaction term $NegativeEquity \times Yellow$: banks with lower equity capital in the Yellow group have significantly more future exceptions. As argued earlier, while the benefit of under-reporting increases significantly above the Green-Yellow threshold, it is unlikely that the correlation between equity capital and any unobserved model quality also sharply changes around the same threshold. Hence, this empirical specification allows us to get closer to a causal interpretation of the effect of equity capital on risk under-reporting. The model also includes the indicator variable for *Red* zone and its interaction with *NegativeEquity*. The effect of equity capital on future exceptions is higher for banks in the Red zone as compared to the similar effects for banks in the Green group, however this effect is not statistically significant.

Our specifications so far include all observations for which we have data on trailing exceptions. In columns (4)-(6), we progressively tighten our window of investigation, limiting our sample to narrower bands around the Green-Yellow threshold. Column (4) limits observations to banks that have trailing exceptions in [0,8], column (5) to [1,8], and column (6) to [2,7]. There is a standard trade-off in terms of bias and efficiency as we narrow the band: the unobserved characteristics such as model quality of banks in the treatment and control groups are likely to be more similar as we narrow the band, but the fewer observations results in a loss of statistical precision. Despite the loss in efficiency, we find stronger results as we narrow the band. The coefficient estimate on the interaction $Yellow \times NegativeEquity$ increases from about 0.8 to 1.5 as we narrow estimation window.[15] Overall, these results provide strong support for the main hypothesis that capital-saving incentives drive banks'

[15]The window of [2-7] provides a better balance in terms of the number of observations across Green and Yellow zones. In untabulated tests, we also experiment with windows with symmetric distances from the cut-off point. For example, in one test we limit our sample to observations that have trailing exceptions between 1 and 6. Thus bank-quarters with 1,2, or 3 trailing exceptions belong to the Green group, and those with 4,5, or 6 exceptions to the Yellow group in this sample. Our results remain similar: we find a point estimate of 1.39 (p-value<0.01) on the interaction term. In sum, our results not sensitive to the choice of window we consider for the test.

under-reporting behavior.

4.4 Cross-Sectional Variation in the Benefits of Under-Reporting

In the next set of tests, we focus attention on the effect of equity capital on under-reporting when banks are likely to obtain larger net benefits from doing so. We exploit variation along two important dimensions: (a) when trading represents a larger fraction of the bank's business, and (b) when the firm has recently experienced poor stock returns.

First, 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 as of 2006Q1 (called VE_2006_i) as a proxy for the importance of trading business for the bank. We compute and freeze this measure for each bank based on exposure at 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 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. The key idea behind our test is that under-reporting gives these banks significantly more capital relief as compared to banks with smaller trading operations. Table 5 presents the estimates from the following regression model:[16]

$$Exceptions_{i,t+1} = \beta(Equity_{it}) + \psi(Equity_{it} \times VE\_2006_i) + \lambda_i + \delta_t + \Gamma X_{it} + \epsilon_{it} \qquad (5)$$

Column (1) presents an estimate of the base specification on this smaller subsample (2006-2012), and shows the similar result that low equity capital is strongly related to future exceptions. Column (2) shows that our main effects are concentrated within banks with larger trading exposure: the coefficient on $VE\_2006 \times log(Eq/A)$ is negative and statistically

[16] In this specification, the independent effect of the level of trading exposure on under-reporting cannot be estimated since it is subsumed by the bank fixed effects.

significant. In an alternative specification, we use an indicator variable *High(VE_2006)*$_i$ that equals one for banks that have above-median trading exposure (*VE_2006*), and zero otherwise. Column (3) shows that the effect of equity capital on exceptions for high-trading-exposure banks is about twice as large as the base case. Overall, these results are consistent with the idea that the effect of equity capital on under-reporting is higher when banks have more to gain in economic terms.

Next, we consider the effect of a bank's recent stock market return on subsequent exception frequency. While our tests so far have shown the effects based on book equity capital, the incentive to save equity capital by under-reporting is likely to be even higher after a large 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 6 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 whose stock price has declined by at least 5% (approximately 30% of observations). Without the interaction effect, column (3) shows 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 0.12. Column (4) includes the interactive effect and reveals that when banks have lower equity capital and lower stock returns, they have significantly higher future exceptions: we find a coefficient estimate of -0.41 (p-value=0.02) on *log(Eq/A)*, and -0.35 (p-value=0.03) 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.

4.5 Time Series Variation in the Benefits of Under-Reporting: Systemic Stress

Our results so far shed light on a individual bank's incentive in isolation. The informativeness of a bank's risk measures is important to understand 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 is under stress. During these periods, the stability of the entire system depends crucially on a proper assessment of the banks' risk exposure. The risk measures form a key basis for policy responses such as requiring banks to raise additional capital. These are also times when the supply of capital to banks is likely to be most scarce and thus costly to raise. As a result, the incentive to under-report and save on capital is likely to be higher across all banks during these periods. With this in mind, we design our next test to investigate whether the cross-sectional variation in banks' under-reporting behavior documented in the main tests are stronger during periods of financial sector stress. We estimate the following empirical model to estimate this effect:

$$\begin{aligned} Exceptions_{i,t+1} = \phi(Equity_{it}) + \theta(System\ Stress_t) + \rho(Equity_{it} \times System\ Stress_t) \\ + \lambda_i + \delta_t + \Gamma X_{it} + \epsilon_{it} \end{aligned} \tag{6}$$

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 (6), we use two measures of $System\ Stress_t$: (a) an indicator variable for the quarter immediately after the collapse of Lehman Brothers (2008q4) and (b) 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.

Table 7 presents the results. The effect of equity capital on VaR exceptions increases by about three-fold for the Lehman failure 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 about 4.64 more exceptions during 2008q4.[17] Note that we are estimating the marginal effect of equity capital on VaR exceptions within 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 Brothers 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 (*HiMES*), we re-estimate our model and present results in Columns (3) and (4).[18] 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 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

[17] This is computed as the sum of the coefficients ($\hat{\phi} + \hat{\rho}$) times the standard deviation of exceptions: (0.57+1.75)*2.00=4.64.

[18] In unreported robustness tests, we use a continuous measure of MES, and also examine three additional financial stress indexes which are constructed by the Federal Reserve Banks of Cleveland, Kansas City, and St. Louis, respectively, and find similar results.

measures are least informative when accurate risk measurement is likely most important for regulators and policy-makers.

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

Banks have a great deal of discretion in constructing and implementing their VaR model. The choice of overall modeling technique (e.g., historical simulation versus Monte Carlo simulation), the length and weighting scheme of the 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 a channel 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, where the assumption on volatility is typically based on a trailing historical data period. Consider two banks: one bank uses discretion in making assumptions about volatility parameters versus another that follows a fixed policy 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. Ex ante, the use of discretion can cause the models to be more or less accurate in capturing risk. However, if the discretionary bank is using its discretion to systematically lower their model's estimate relative to the true risk in the trading book, then their VaR exceptions should be higher than the rule-based bank ex post. Based on these ideas, we estimate the sensitivity of reported VaR level to past macro-economic volatility measures across high- and low-capital banks.

We use a simplified model to link these ideas to our empirical tests. For normally distributed changes in portfolio value,

$$VaR = \mathcal{N}^{-1}(\alpha) \times \sigma \tag{7}$$

where $\mathcal{N}^{-1}()$ is the inverse normal CDF, α is the confidence level, and σ is the underlying volatility. Taking logs and assuming a noise term ξ leads to the following linear relationship:

$$\log(VaR) = \log(\mathcal{N}^{-1}[\alpha]) + \log(\sigma) + \xi \tag{8}$$

where $\log(\mathcal{N}^{-1}[\alpha])$ is a constant. Using past one year's volatility in the returns to S&P 500 index as a measure of aggregate macro-economic volatility σ, we estimate the following model where we additionally control for the bank specific covariates X_{it} and bank fixed effects (λ_i):

$$\log(VaR_{i,t}) = \phi(Equity_{it}) + \theta(\log[Vol_t]) + \rho(Equity_{it} \times \log[Vol_t]) + \lambda_i + \Gamma X_{it} + \epsilon_{it} \tag{9}$$

The dependent variable is the log of the reported level of VaR at the beginning of quarter t, and Vol_t is the market volatility over the past year as measured by S&P 500 volatility. We expect to find a positive relationship between past volatility and VaR ($\hat{\theta} > 0$). However, if banks use more discretion in their VaR computation when they have low equity capital, we expect 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 (9) and report the results in Table 8. 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. These findings, along with our earlier results that such banks have higher exceptions in future quarters, lend support to the hypothesis that banks are under-reporting their VaR by relying on their discretion in choosing volatility measures.

4.7 Alternative Explanations & Robustness Tests

4.7.1 Stale Model

Our main 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 incentives to save capital, but due to a poor-quality model that has not been updated. Our test based on the Green-Yellow zone threshold minimizes such concerns. We conduct two more tests to provide further evidence to rule out this alternative hypothesis.

Omitting Transition Periods

VaR models are estimated on a daily basis at large banks. 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 more 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.[19] For example, in their 10-K form, Bank of America state, "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-

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

estimate the base model. If some banks simply have poor-quality models, this gives them time to correct those models. We report the result from this test in column (2) of Table 9. 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. These results show that our findings are not completely driven by periods following extreme shocks in the market conditions.

As an additional robustness check, we re-estimate our model by dropping every year from our sample, one at a time. Our results remain similar. Similarly, we estimate our model by dropping one quarter at a time, and find that our results remain the similar. Thus our key findings are not driven by any specific year or quarter in the sample.

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

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 and such concerns are mitigated by our tests that exploit the Green-Yellow threshold, we also exploit the dynamics of the panel data to further alleviate this concern. In our next test, we include the lagged exceptions as an explanatory variable in the model.

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:

$$Exceptions_{i,t+1} = \beta(Equity_{it}) + \lambda_i + \delta_t + \Gamma X_{it} + \epsilon_{it} \tag{10}$$

where

$$\epsilon_{it} = ModelQuality_{it} + \eta_{it} \tag{11}$$

and

$$cov(Equity_{it}, \epsilon_{it}) = cov(Equity_{it}, ModelQuality_{it}) \neq 0 \tag{12}$$

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 ($\hat{\beta}$). A natural candidate for the time-varying model quality is the number of exceptions in the past quarter. The key idea is that if a bank experiences a number of exception during a quarter, that could indicate that it has a relatively more inaccurate model for that quarter. We include lagged exceptions as a proxy for the potentially "stale model" for the next quarter to rewrite our regression model as follows:

$$Exceptions_{i,t+1} = \beta(Equity_{it}) + \alpha_i + \delta_t + \Gamma X_{it} + \theta Exceptions_{i,t} + \eta_{it} \tag{13}$$

The inclusion of lagged dependent variable in a fixed effect model, however, results in inconsistent estimates. To avoid this problem, 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 (3) and (4) of Table 9. The coefficient on equity ratio remains negative and both economically and statistically significant for these specifications. We find a coefficient of -0.45 (p-value of 0.01) on *log(Eq/A)* in the model with one lag and -0.47 (p-value of 0.02) 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 exceptions 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.

Placebo Test

Our analysis on the Green-Yellow discontinuity is based on a threshold of 4 trailing exceptions. As a placebo test, we artificially move the threshold to other points on the trailing exception axis. Specifically, we move the threshold to 3, 5, or 6 trailing exceptions and repeat our analysis. We do not find positive and significant coefficients on the interaction of *NegativeEquity* × *Yellow*. Thus our main results are not simply driven by differences in behavior across bank-quarter observations with higher versus lower trailing exceptions. Instead, the results are driven by changes in under-reporting incentives at a specific threshold where the marginal cost of under-reporting changes in a discontinuous fashion. The result provides further confidence in our identification strategy.

Other Robustness Tests

Table 10 presents results from a battery of additional robustness tests. As discussed earlier, one of the reasons we focus on the book equity-to-assets ratio in our empirical tests is that the reported VaR directly affects the computation of regulatory Tier 1 capital requirements, thus introducing measurement concerns.[20] Nevertheless, column (1) highlights

[20]This regression can also be interpreted as exploiting variation in the within bank relative tightness of

that our results are robust to using Tier 1 capital as our measure of equity capital.

Banks have differing sensitivities to various risk factors depending on their business model. To ensure that our results are not driven by these differences, in a robustness test we control for differences in sensitivities to two major risk factors during our sample period, namely the exposure to the aggregate stock markets and mortgage-backed securities. We first compute the sensitivity of each bank's stock returns to equity market returns (proxied by CRSP value-weighted index) and mortgage-backed securities returns (proxied by PIMCO's mortgage-backed securities index). Next we include the estimated sensitivity as control variables in the regression model. Column (2) shows that these two betas, called *Market Beta* and *MBS Beta*, do not explain our results.

We showed substantial variation in trading book risk composition in the summary statistics in Table 2. Some banks, for example, engage more in risks related to interest rates or equities. In column (3), we directly control for bank's VaR composition by including the fraction of total VaR from each exposure to each asset class, and our results remain virtually unaffected. Column (4) shows that our results remain similar after dropping observations from 2008q4, the quarter when Lehman Brothers collapsed and the most volatile quarter in our sample.

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. We re-estimate our main regressions using a poisson count data model. This modelling approach explicitly recognizes the fact that VaR exceptions only take non-negative integer values. However, the use of fixed effects in a nonlinear model suffers from the incidental parameter problem, which can result in inconsistent estimates. With these caveats in mind, column (5) presents the results from a poisson model regression estimation and shows that our main results do not change under the count model specifications. We find similar results using a negative binomial regression.

capital constraints.

In the tests so far, we report our results based on 99% VaR measures of commercial banks. As mentioned earlier, this allows us to have sensible comparison across all observations. As a robustness exercise, we now repeat our main results by including observations where VaR exceptions are reported for the 95% level. This allows us to expand our sample to 545 observations.

For the empirical test, we use a measure called *Excess*, which compares the actual exceptions to the statistical benchmark based on the reporting confidence level of VaR. If the exceptions exceed the statistical benchmark, *Excess* is set to one and is zero otherwise. Thus, *Excess* takes a value of one if the reported exception in a quarter is greater than 0.63 for 99% VaR and greater than 3.15 for 95% VaR. Column (6) presents the estimation results, and confirms that banks are more likely to have future excess exceptions following quarters when they have low equity capital.

5 Conclusions

We show that banks are more likely to under-report their market risks when they have stronger incentives to save equity capital. Specifically, banks under-report their risk when they have lower equity capital, and during periods of high systemic stress. Regulators and investors rely on the bank's self-reported risk measures for a number of regulatory and investment decisions. The accuracy of these numbers assume special importance particularly when banks have lower levels of equity capital, and thus they are closer to failure. Moreover, accurate risk reporting is extremely valuable during periods of systemic crisis because the success of a number of policy responses depends crucially on a clear understanding of the level of risk undertaken by poorly capitalized financial institutions in the economy. While our empirical results cannot directly speak to the optimality of the current regulatory framework, our findings do highlight some of its important shortcomings. Our results show that the integrity of self-reported measures becomes most questionable precisely when accurate risk measurement in the financial system is most important.

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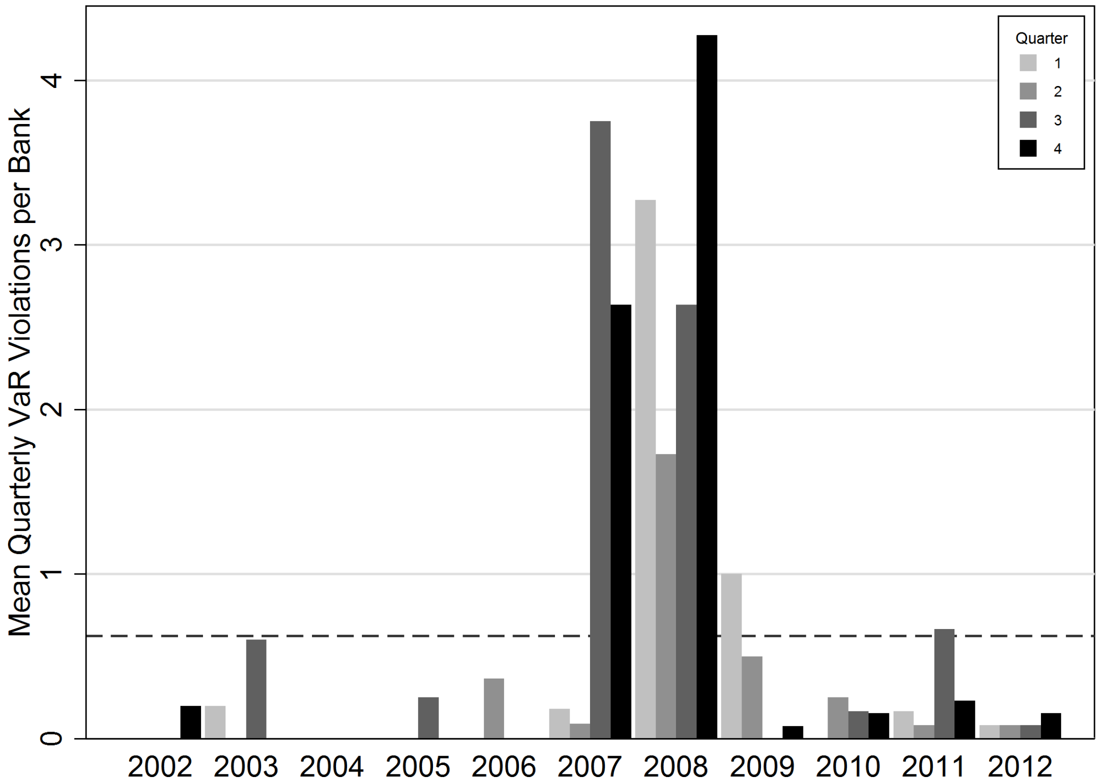

Figure 3: Average Value-at-Risk Exceptions
This figure presents the average frequency of Value-at-Risk (VaR) exceptions for banks each quarter during the 2002-2012 sample period. The dashed line at 0.63 represents the expected exception frequency based on 99% VaR confidence interval and approximately 63 trading days per quarter.

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 ($Bn)	901.40	767.93	73.14	291.14	602.46	1428.16	3643.58	424
NI-to-Assets (%,Q)	0.17	0.20	-1.16	0.09	0.18	0.25	1.57	424
BookEq/AT (%)	6.32	3.15	1.69	4.06	5.14	9.01	13.84	424
log(Eq/A)	-2.89	0.51	-4.08	-3.20	-2.97	-2.41	-1.98	424
Value-at-Risk ($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/A)* 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/A)* is the log of the book equity-to-assets ratio, *log(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. All continuous variables and *Exceptions* are standardized (denoted by "(z)") to have a mean of zero and unit variance.

	(1) (z)Exceptions	(2) (z)Exceptions	(3) (z)Exceptions	(4) (z)Exceptions	(5) (z)Exceptions
(z)log(Eq/A)	-0.70***	-0.63***	-0.78***	-0.66***	-0.66**
	(0.01)	(0.00)	(0.00)	(0.00)	(0.03)
(z)log(Assets)		0.51	0.35**	0.51	0.51**
		(0.16)	(0.02)	(0.14)	(0.04)
(z)NI-to-Assets		-0.03	-0.02	-0.04	-0.04
		(0.74)	(0.81)	(0.57)	(0.65)
(z)Vol-Commodities			0.11**	0.07	0.07
			(0.03)	(0.45)	(0.11)
(z)Vol-S&P 500			0.31***	0.37**	0.37**
			(0.00)	(0.02)	(0.03)
(z)Vol-Foreign Exchange			0.01	0.07	0.07
			(0.85)	(0.42)	(0.23)
(z)Vol-Interest Rate			0.13**	0.07	0.07
			(0.02)	(0.70)	(0.38)
Bank FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	No	Yes	Yes
Observations	424	424	424	424	424
R^2	0.45	0.45	0.41	0.47	0.47
Clustered by	Y-Q	Y-Q	Y-Q	Y-Q	Bank

p-values in parentheses

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

Table 4: The Shape of Penalties, Equity Ratio, and Future Violations

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/A)* 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, *Yellow* is an indicator variable equal to 1 when the bank has four to nine VaR exceptions in the past 3 quarters, *Red* is an indicator variable equal to 1 when the bank has ten or more VaR exceptions in the past 3 quarters, *NegativeEquity* is the negative of log of the book equity-to-assets ratio, *log(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. All continuous variables and *Exceptions* are standardized (denoted by "(z)") to have a mean of zero and unit variance. Standard errors are clustered by year-quarter.

	(1) Full	(2) Full	(3) Full	(4) [0-8]	(5) [1-8]	(6) [2-7]
(z)NegativeEquity	0.75***	0.59**	0.40*	0.26	-0.08	1.68
	(0.00)	(0.02)	(0.09)	(0.20)	(0.83)	(0.13)
Yellow		0.54**	0.45*	0.54**	0.61*	1.01
		(0.02)	(0.08)	(0.03)	(0.05)	(0.38)
(z)NegativeEquity * Yellow			0.79*	0.78*	1.47***	1.54**
			(0.06)	(0.06)	(0.00)	(0.04)
Red		0.83	0.54			
		(0.25)	(0.34)			
(z)NegativeEquity * Red			0.37			
			(0.24)			
(z)log(Assets)	0.80*	0.74	0.50	0.36	-0.57	-1.88
	(0.10)	(0.13)	(0.38)	(0.53)	(0.40)	(0.15)
(z)NI-to-Assets	-0.01	-0.00	0.00	0.07	0.19	-0.00
	(0.95)	(1.00)	(0.99)	(0.34)	(0.17)	(0.99)
(z)Vol-Commodities	0.07	0.04	0.06	0.12	0.17	0.22
	(0.56)	(0.68)	(0.56)	(0.14)	(0.22)	(0.44)
(z)Vol-S&P 500	0.40**	0.41**	0.40**	0.37**	0.42**	0.51*
	(0.03)	(0.02)	(0.01)	(0.02)	(0.04)	(0.06)
(z)Vol-Foreign Exchange	0.06	0.04	0.05	-0.03	0.09	0.18
	(0.58)	(0.64)	(0.57)	(0.59)	(0.57)	(0.58)
(z)Vol-Interest Rate	0.11	0.18	0.16	0.20	0.11	-0.12
	(0.61)	(0.35)	(0.44)	(0.29)	(0.51)	(0.72)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	378	378	378	349	119	64
R^2	0.50	0.52	0.55	0.58	0.77	0.85

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/A)* 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/A)* 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, *log(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. All continuous variables and *Exceptions* are standardized (denoted by "(z)") to have a mean of zero and unit variance. Standard errors are clustered by year-quarter.

	(1) (z)Exceptions	(2) (z)Exceptions	(3) (z)Exceptions
(z)log(Eq/A)	-0.92**	-0.50	0.35
	(0.01)	(0.15)	(0.45)
(z)VE_2006 * (z)log(Eq/A)		-0.48**	
		(0.02)	
High(VE_2006) * (z)log(Eq/A)			-1.92**
			(0.02)
(z)log(Assets)	0.31	-0.10	-0.08
	(0.46)	(0.80)	(0.85)
(z)NI-to-Assets	-0.05	0.00	-0.01
	(0.58)	(0.95)	(0.90)
(z)Vol-Commodities	0.08	0.09	0.05
	(0.53)	(0.44)	(0.70)
(z)Vol-S&P 500	0.37**	0.35**	0.39**
	(0.04)	(0.02)	(0.02)
(z)Vol-Foreign Exchange	0.08	0.08	0.07
	(0.49)	(0.49)	(0.50)
(z)Vol-Interest Rate	0.08	0.13	0.11
	(0.73)	(0.50)	(0.62)
Bank FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Observations	330	330	330
R^2	0.47	0.50	0.51

p-values in parentheses

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

Table 6: 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/A)* 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/A)* 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 less than -5%, *log(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. All continuous variables and *Exceptions* are standardized (denoted by "(z)") to have a mean of zero and unit variance. Standard errors are clustered by year-quarter.

	(1) (z)Exceptions	(2) (z)Exceptions	(3) (z)Exceptions	(4) (z)Exceptions
(z)log(Eq/A)	-0.66***		-0.64***	-0.41**
	(0.00)		(0.01)	(0.02)
LowRet		0.23	0.19	0.18
		(0.12)	(0.19)	(0.16)
(z)log(Eq/A) * LowRet				-0.35**
				(0.03)
(z)log(Assets)	0.51	0.67*	0.50	0.66**
	(0.14)	(0.08)	(0.15)	(0.03)
(z)NI-to-Assets	-0.04	-0.03	-0.03	-0.02
	(0.57)	(0.68)	(0.65)	(0.74)
(z)Vol-Commodities	0.07	0.06	0.08	0.08
	(0.45)	(0.54)	(0.40)	(0.34)
(z)Vol-S&P 500	0.37**	0.32**	0.34**	0.32**
	(0.02)	(0.05)	(0.03)	(0.02)
(z)Vol-Foreign Exchange	0.07	0.07	0.08	0.07
	(0.42)	(0.44)	(0.38)	(0.36)
(z)Vol-Interest Rate	0.07	0.07	0.08	0.06
	(0.70)	(0.66)	(0.69)	(0.76)
Bank FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	424	424	424	424
R^2	0.46	0.48	0.50	0.51

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

Table 7: 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/A)* 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/A)* 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, *log(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. All continuous variables and *Exceptions* are standardized (denoted by "(z)") to have a mean of zero and unit variance. Standard errors are clustered by year-quarter.

	(1) (z)Exceptions	(2) (z)Exceptions	(3) (z)Exceptions	(4) (z)Exceptions
(z)log(Eq/A)	-0.66***	-0.57**	-0.66***	-0.26
	(0.00)	(0.01)	(0.01)	(0.18)
(z)log(Eq/A) * 2008q4		-1.75***		
		(0.00)		
HiMES			0.22	0.21
			(0.56)	(0.57)
(z)log(Eq/A) * HiMES				-0.42**
				(0.04)
(z)log(Assets)	0.51	0.58*	0.52	0.54*
	(0.14)	(0.09)	(0.14)	(0.09)
(z)NI-to-Assets	-0.04	-0.06	-0.04	-0.02
	(0.57)	(0.40)	(0.60)	(0.73)
(z)Vol-Commodities	0.07	0.06	0.08	0.09
	(0.45)	(0.50)	(0.39)	(0.35)
(z)Vol-S&P 500	0.37**	0.37**	0.32*	0.29*
	(0.02)	(0.02)	(0.07)	(0.09)
(z)Vol-Foreign Exchange	0.07	0.08	0.06	0.06
	(0.42)	(0.40)	(0.47)	(0.50)
(z)Vol-Interest Rate	0.07	0.08	0.10	0.08
	(0.70)	(0.68)	(0.60)	(0.67)
Bank FE	Yes	Yes	Yes	Yes
Year-Quarter 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 8: 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/A)*, past stock market volatility, and a vector of control variables. *log(Eq/A)* is the log of the book equity-to-assets ratio, *L.log(1yr S&P vol)* is the log of the annualized volatility of daily S&P500 returns over the past year, *log(Assets)* is the log of total assets, and *NI-to-Assets* is the ratio of quarterly net income-to-assets. All continuous variables are standardized (denoted by "(z)") to have a mean of zero and unit variance.Standard errors are clustered by year-quarter.

	(1) (z)log(VaR)	(2) (z)log(VaR)	(3) (z)log(VaR)
L.(z)log(1yr S&P vol)	0.09***	0.01	0.02
	(0.00)	(0.66)	(0.54)
(z)log(Total Assets)		0.43***	0.41***
		(0.00)	(0.00)
(z)NI-to-Assets		-0.12***	-0.12***
		(0.00)	(0.00)
(z)log(Eq/A)		-0.30***	-0.31***
		(0.00)	(0.00)
(z)log(Eq/A) × L.log(1yr S&P vol)			0.03**
			(0.04)
Bank FE	Yes	Yes	Yes
Observations	405	405	405
R^2	0.86	0.89	0.89

p-values in parentheses

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

Table 9: 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/A)* and a vector of control variables. Column (1) is the baseline specification for comparison. Column (2) presents estimates omitting observations in 2007. Columns (3) and (4) 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/A)* is the log of the book equity-to-assets ratio, *log(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. All continuous variables and *Exceptions* are standardized (denoted by "(z)") to have a mean of zero and unit variance. Standard errors are clustered by year-quarter.

	(1) All	(2) drop2007	(3) AB1lag	(4) AB2lags
(z)log(Eq/A)	-0.66***	-0.65**	-0.45**	-0.47**
	(0.00)	(0.01)	(0.01)	(0.02)
L.(z)Exceptions			0.30***	0.31***
			(0.00)	(0.00)
L2.(z)Exceptions				-0.01
				(0.96)
(z)log(Assets)	0.51	0.40	0.75***	0.75**
	(0.14)	(0.13)	(0.01)	(0.01)
(z)NI-to-Assets	-0.04	-0.06	0.07**	0.07**
	(0.57)	(0.44)	(0.04)	(0.02)
(z)Vol-Commodities	0.07	0.09	0.09*	0.09
	(0.45)	(0.37)	(0.08)	(0.30)
(z)Vol-S&P 500	0.37**	0.30**	0.42***	0.43***
	(0.02)	(0.01)	(0.00)	(0.00)
(z)Vol-Foreign Exchange	0.07	0.06	0.05	0.04
	(0.42)	(0.46)	(0.37)	(0.46)
(z)Vol-Interest Rate	0.07	-0.05	0.21***	0.22***
	(0.70)	(0.63)	(0.00)	(0.00)
Bank FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	424	379	392	378
R^2	0.47	0.48		
2nd Order AR test p-value			0.94	1.00
Sargan Test p-value			0.49	0.52

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

Table 10: Robustness Tests

This table presents OLS estimates from a regression of the number of VaR exceptions in the next quarter on banks' equity capital ratio and a vector of control variables. Columns (1)-(4) present OLS estimates of the base specification along with various control variables. Column (5) presents estimates from a poisson regression. Column (6) OLS regression estimates of a measure of excess future VaR exceptions in the next quarter on banks' equity capital ratio and a vector of control variables. *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). *Exceptions* is the number of times the bank had losses that exceeded their self-reported Value-at-Risk during the next quarter, *log(Tier 1 Ratio)* is the log of the Tier 1 capital ratio, *log(Eq/A)* is the log of the book equity-to-assets ratio, *Market Beta* is the bank's regression market beta estimated using the banks' prior two years' stock returns against the CRSP value-weighted market portfolio, *Market Beta* is the bank's regression MBS beta estimated using the banks' prior two years' stock returns against the PIMCO mortgage-backed securities index, *log(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. All continuous variables and *Exceptions* are standardized (denoted by "(z)") to have a mean of zero and unit variance. Standard errors are clustered by year-quarter.

	(1) Tier 1	(2) Betas	(3) VaR Mix	(4) Drop 2008q4	(5) Poisson	(6) Excess
(z)log(Eq/A)		-0.59***	-0.67***	-0.59**	-1.08***	-0.30**
		(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
(z)log(Tier 1 Ratio)	-0.28**					
	(0.04)					
(z)Market Beta		-0.12				
		(0.34)				
(z)MBS Beta		0.04				
		(0.71)				
(z)log(Assets)	0.68*	0.55	0.53	0.59*	-0.86	-0.18
	(0.07)	(0.11)	(0.19)	(0.09)	(0.14)	(0.45)
(z)NI-to-Assets	-0.04	-0.06	-0.05	-0.05	0.04	0.01
	(0.62)	(0.44)	(0.62)	(0.48)	(0.70)	(0.81)
(z)Vol-Commodities	0.06	0.07	0.09	0.09	-0.12	0.02
	(0.51)	(0.43)	(0.38)	(0.30)	(0.48)	(0.78)
(z)Vol-S&P 500	0.34**	0.37**	0.39**	0.41***	1.50***	0.70***
	(0.02)	(0.03)	(0.03)	(0.01)	(0.00)	(0.00)
(z)Vol-Foreign Exchange	0.06	0.07	0.08	0.01	-0.10	-0.07
	(0.49)	(0.42)	(0.37)	(0.89)	(0.62)	(0.34)
(z)Vol-Interest Rate	0.10	0.07	0.09	0.06	-0.19	-0.07
	(0.52)	(0.69)	(0.68)	(0.76)	(0.35)	(0.48)
VaR Mix	No	No	Yes	No	No	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	420	424	422	413	391	545
R^2	0.46	0.48	0.49	0.47		0.48

p-values in parentheses

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

Table A.1: VaR Exceptions and the Regulatory Multiplier
This table is reproduced from BIS (1996) and presents the Green, Yellow, and Red zones that supervisors use to assess VaR model backtesting results. This provides the relationship between VaR exceptions and the regulatory multiplier k that is used for the market-risk capital charge. The number of exceptions is based on results from the last 250 trading days (one year).

Zone	Number of Exceptions	Regulatory Multiplier
Green Zone	0	3.00
	1	3.00
	2	3.00
	3	3.00
	4	3.00
Yellow Zone	5	3.40
	6	3.50
	7	3.65
	8	3.75
	9	3.85
Red Zone	10 or more	4.00

Table A.2: Comparability Around the Green-Yellow Threshold

This table presents sample means for observations in the neighborhood of the Green-Yellow threshold in the regulatory multiplier function. This includes bank-quarter observations where the trailing three quarters' exceptions are in the range [2-7], where observations with 2-3 exceptions (N=43) are in the Green group, and observations with 4-8 exceptions (N=21) are in the Yellow Group. The last two columns present the difference in the two means, and the p-value of that difference.

Variable	Green	Yellow	Difference	p-value
Total Assets (Bn)	1060.96	927.42	-133.54	(0.55)
Net Income (MM)	974.88	1116.34	141.46	(0.67)
NI-to-Assets (%,Q)	0.13	0.15	0.02	(0.51)
BookEq/Assets (%)	5.66	5.83	0.17	(0.83)
Exceptions next Quarter	0.51	2.47	1.96^{***}	(0.00)