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Working Paper

The Strategic Under-Reporting of Bank Risk

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Ross School of Business Working Paper
Working Paper No. 1260
March 2016

The Strategic Under-Reporting of Bank Risk*

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First Draft: November 18, 2014
This Draft: March 19, 2016

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.

*We are grateful to Sean Campbell, Jean Colliard, Rainer Haselmann, Mauricio Larrain, Gregor Matvos, Uday Rajan, Philipp Schnabl, Sergio Vicente and seminar participants at the Bank of England, Banque de France, Dutch Central Bank, Federal Reserve Bank of New York, London Business School, Notre Dame, University of Houston, University of Michigan, Michigan State University, Purdue University, Surrey, Washington University at St. Louis, and Wharton and conference participants at AFA (San Francisco), Baffi-Carefin (Bocconi), Barcelona GSE Summer Forum, NBER Summer Institute, Texas Finance Festival, Tel-Aviv Finance Conference, and the WFA (Seattle) for helpful comments on the paper.

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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, however, 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, in turn, heavily influence the regulatory treatment of banks such as their capital requirements and deposit insurance premium. These consequences can potentially distort the banks' incentive to truthfully report their risk. Do banks engage in such behavior by under-reporting their true risk? What are the implications of this behavior on the usefulness of risk measures 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, we focus on the trading book because it allows us to cleanly tease out the under-reporting incentives. Specifically, we are able to detect the incidence of under-reporting by comparing the level of risk reported by the bank ex-ante with the realized losses on the same portfolio ex-post. Further, 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, making it an economically attractive setting as well.[1] According to Basel rules, banks 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 to determine capital requirements for market risk. Thus banks can have a strong incentive

[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 under-report their risk when they approach binding capital requirements. Further, the use of an internal risk model leaves a great deal of discretion with the reporting banks. VaR modeling assumptions such as the level of asset volatilities and correlation structure between asset classes can significantly affect the output of their models (BIS, 2013). This discretion gives banks a significant ability to under-report their trading risks. 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 poor models. 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.[2] If a bank has too many 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 requirement is increased for the subsequent periods.[3] However, there is also some probability that the under-reporting does not get detected depending on future asset price movements. In such a scenario, the under-reporting of the bank goes undetected and penalties are altogether avoided while enjoying a lower current capital requirement. 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

[2]See Jorion (2007) for a comprehensive treatment of VaR models, and Kupiec (1995) for further details on backtesting and statistical methods for assessing the accuracy of VaR models.

[3]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. However, if a bank breaches its self-reported VaR level too often, it faces higher capital requirement in future periods. 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.

for the potential for a higher capital charge in the future.[4] All else equal, raising capital is more costly when a bank has a very low capital base – for such banks, 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. The underlying economic trade-off behind our work maps nicely to the literature on crime and punishment such as Becker (1968) and Kaplow and Shavell (1994), in which offending agents trade off the benefit of crime against the cost of punishment in the event of detection.

We assemble a novel data set of self-reported trading book VaR and number of VaR exceptions (i.e., number of times trading losses exceed the reported VaR) for a sample of some of the largest financial institutions from the U.S., Europe, and Canada from 2002-2013 to analyze these incentive effects. In addition to our main tests, our paper makes a contribution to the literature by providing the first systematic descriptive statistics on VaR and its exceptions. On main sample consists of 497 bank-quarter observations of VaR and related exceptions based on 99% confidence level. The 99% VaR model, assuming 63 trading days in a quarter, should yield 0.63 exceptions per quarter in expectation. Our sample shows 0.54 average exceptions per quarter, which is very close to this statistical benchmark. However, the average hides significant time-series variation. The average exception per quarter is below the statistical benchmark during 2002-2006 (0.09 per bank-quarter), increases to almost 2.5 times the statistical benchmark during 2007-2009 (1.52 per bank-quarter), and then again falls to a lower level during 2010-2013 (0.15 per quarter). Was the VaR exception during the crisis period solely an artifact of large changes in asset prices, or was it also related to capital-saving incentives? Our empirical tests are designed to tease out these effects.

In our main test, we estimate the effect of a bank's equity capital at the beginning of the quarter on the frequency of its exceptions during the quarter using a regression model

[4] 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.

with bank and year-quarter fixed effects. We find that one standard deviation decrease in a bank's equity capital at the beginning of the quarter results in an increase of 1.17 exceptions in the following quarter, which is roughly twice the sample average of 0.54. Put differently, banks' future losses exceed their own risk assessment significantly more frequently in periods immediately following a decline in their equity capital. 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, the inclusion of bank and year-quarter fixed effects ensures that our results are not driven by differences in bank-specific risk-modeling skills or market-wide shocks.

The number of exceptions can also be influenced by the quality of the 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 following those with lower equity capital. 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. For example, if some banks were relatively less prepared for the financial crisis, then their risk models is likely to fail at a disproportionately higher rate during 2007-2009. If these banks also experience negative shocks to equity capital during this same period, then it can potentially result in a negative correlation between equity capital and future VaR exceptions.

Given that our sample comprises some of the largest and most sophisticated financial institutions of the world, it is unlikely that these banks' modeling quality changes precisely *after* a period with lower equity capital. Second, banks frequently update their risk models to reflect the changes in volatilities of asset returns and correlations across asset classes. These factors ameliorate concerns regarding the bad model problem. 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. Following the guidelines, bank regulators classify banks into three categories or zones based on the number of exceptions experienced by a bank in the past year: Green (0-4 exceptions), Yellow (5-9), and Red (≥ 10). Banks falling in different categories face different levels of regulatory scrutiny and capital charge. 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 many 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. At the same time, it is unlikely that the quality of a bank's risk model changes sharply at this threshold as well. Under this identifying assumption, we are able to separate the effect of differences in model quality from capital-saving incentives by comparing the under-reporting behavior around this threshold. 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, the relationship between equity capital and future exceptions is stronger and more negative for bank-quarter observations that are just above the Green-Yellow threshold, compared to observations that fall just below.

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 book represents a relatively larger portion of the bank's business (i.e., when the economic benefits of under-reporting are more meaningful). We next show that the relationship between equity capital and VaR exceptions becomes even stronger when the bank has poor stock returns in the prior quarter. Raising external equity capital is more difficult in such situations, and thus the incentives to under-report risk even stronger.

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.

In robustness tests, we show that our results remain strong after controlling for a bank's exposure to market and mortgage-backed-securities risk, and the asset-class composition of the bank's trading book. In addition, we conduct several sub-sample tests and exploit the dynamics of exceptions to further rule out the "bad model" alternative discussed earlier.

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 should be 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 work is closely related to the literature on regulatory arbitrage and failure of model-based regulations (e.g., see Acharya, Schnabl, and Suarez (2013), Behn, Haselmann, and Vig (2014), Plosser and Santos (2016), Boyson, Fahlenbrach, and Stulz (2016)). Behn et al. (2014) find that banks' internal model-based risk estimates systematically underestimated the level of credit risk in banks' loan portfolios. 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 addition, we focus on the trading book risk, which allows us to sharply compare the ex-ante risk assessment with its immediate ex-post realization.

Second, our work is connected to the literature on risk-management practice in banking (e.g., see Ellul and Yerramilli, 2013) and the informativeness of VaR models such as Jorion (2002) and Berkowitz and O'Brien (2002). Our study also has implications for ongoing policy discussions on capital regulations (e.g., see Admati, DeMarzo, Hellwig, and Pfleiderer (2011), Brunnermeier and Pedersen (2009), Kashyap, Rajan, and Stein (2008), and Thakor (2014)). Our findings show that in addition to determining the optimal level of capital requirements for banks, the regulators face an important related challenge in terms of eliciting truthful disclosure of risk. At a broader level, our work is related to the literature on the economics of self-reporting behavior and probabilistic punishment mechanisms. 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 (2016)).

2 Hypothesis Development and Research Design

The theoretical foundation of our research is rooted in two strands of literature: one on the economics of crime and punishment, and the other on the incentives of privately informed financial institutions. The first strand of literature emphasizes the interactions between the benefits of committing crime to the offending party, the negative externality it imposes on the rest of the society, and then the costs of crime detection and punishment. Becker (1968) emphasizes the idea that socially desirable enforcement policy need not be to detect all the crimes all the time. Rather a probabilistic detection strategy with adequately modified sanctions on the detected offender might be the optimal policy. Kaplow and Shavell (1994) extend this idea by adding self-reporting behavior in a model of probabilistic enforcement. The key insight from their work is that in many settings the offender may find it optimal to truthfully self-report the crime and obtain a certain punishment, instead of hiding the crime and receiving higher sanctions in case they are caught. The ideas from this literature map well to the underlying mechanism of VaR reporting: a bank can truthfully report its level of risk and meet its capital requirement today, or face the probability of higher capital charge and regulatory sanctions tomorrow.

Closer to the banking research, papers by Chan, Greenbaum, and Thakor (1992) and Colliard (2014) provide the theoretical bases for our work. In the first paper the authors study the impact of a financial institution's private information on regulatory policies. While they focus on deposit insurance policies, their idea is fairly general: uninformed regulators need to take into consideration the incentives of regulated informed parties in setting policies. Colliard (2014) studies the trade-offs inherent in regulations linking a bank's capital requirements to its risk levels generated by internal models. One of the key features of his model is the possibility of strategic under-reporting when a bank's capital requirement depends on risk levels.

Similar to these theoretical models, in our setting 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 making raising external capital relatively less costly; 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. 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.

Value-at-Risk 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. Absent any incentive conflict, we would expect to see one exception (i.e., losses exceeding the reported VaR level) every 100 trading days for the 99% VaR models. 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 fundamental distinction highlights a key strength of our empirical setting: we relate capital-saving incentives to deviations from self-reported VaR numbers, which is independent of the scale of risk-taking.

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 parameter used by the bank in computing 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.[5] Further 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:[6]

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

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.[7] The distribution

[5]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."

[6]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.

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

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:

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

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

Since $ModelQuality_{it}$ is not perfectly observable, 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, incentive structure and the importance of internal 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)). If these persistent unobserved modeling 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:

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

Our main measure of $Incentives_{it}$ is the bank's equity capital ratio ($Equity_{it}$).

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. A potential source for such a time-varying changes in model quality could be relative unpreparedness of some banks for the financial crisis of 2007-2009. If the unprepared banks had more frequent and persistent failures of their risk model and if they experienced concomitant negative shocks that gave them lower equity capital during the same period, then our results could be an artifact of relative unpreparedness rather than strategic under-reporting. As mentioned earlier, 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 following quarter only when banks have had low equity capital at the beginning of the quarter and this relationship occured for reasons unrelated to reporting incentives. This explanation is unlikely to be true because banks are required to update their VaR model regularly to better capture the changes in underlying volatilities. Nevertheless, we directly address this concern by exploiting 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 number of exceptions in the past four quarters, banks are categorized into three groups: "Green" (four or less exceptions), "Yellow" (five to ten exceptions), and "Red" (more than ten exceptions). Due to regulatory reasons, the under-reporting incentive increases sharply around the Green-Yellow threshold. The underlying model quality, however, is unlikely to be very different around this threshold – it is unlikely that a bank with four exceptions has a very different model quality than a bank with five exceptions. Under this assumption, by comparing exceptions around this threshold, we are able to separate the incentive effects from the concerns about underlying model quality. For expositional simplicity, we discuss this research design in detail when we present these results in Section 4.1.

3 Data and Sample

Our study provides the first comprehensive analysis of VaR exceptions and its determinants. Therefore, 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 trading risk in banks and the accuracy of their risk models. We discuss the data collection procedure and present some key descriptive statistics of the sample below.

3.1 Data Collection

We start with a list of 50 largest banks of the world and supplement it with the list of 20 largest commercial banks of the U.S. based on asset size as of 2008.[8] We narrow this list down to the subset of 41 banks domiciled in the U.S., Canada, and Europe, and read their 10-Q, 10-K, and 20-F filings from 2002 to 2013 to obtain information on VaR levels and VaR exceptions. Institutions that provide sufficient details about the level of VaR during the quarter, and the number of exceptions over the same period, enter our final sample. Appendix B provides further details on our sample selection criteria and data collection procedure.

Our "base" sample includes 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 three important broker-dealers of the U.S. as well as observations where a commercial bank reports VaR 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. We make use of the expanded sample in our robustness tests.[9]

[8]Since the list of very large financial institutions of the world has remained broadly the same over our sample period, choosing 2008 as the classification year does not pose any serious sample selection concerns for our study.

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

In total, our base sample has 497 bank-quarter observations over 2002-2013 period covering 16 commercial banks. Commercial banks in our sample have over \$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. The expanded sample contains 638 bank-quarter observations over the same time period.

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 St. Louis Federal Reserve Bank, CRSP, and Bloomberg. All data are winsorized at the 1% level to mitigate the effects of any outliers in the regression analysis. 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.

3.2 Descriptive Statistics

Table 1 provides summary statistics for the base sample. The sample banks have an average asset base of \$875 billion. On average, they are profitable during our sample period,

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).

with a mean quarterly net-income-to-assets ratio of 0.16%. On average banks have 6.29% equity as a percentage of their asset base. This ranges from 4.15% for the 25th percentile bank to 8.94% for the 75th percentile. Following prior literature, most of our main tests 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.

3.2.1 Level and Composition of VaR

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. Figure 1 provides the mean, median, 10th and 90th percentiles of the level of VAR over the sample period. The numbers reported in Table 1 and in Figure 1 are 99% VaR for a 1-day holding period. For the regulatory capital requirement calculations, these numbers are scaled up to a 10-day holding period horizon, typically by multiplying them by a factor of $\sqrt{10}$. It is evident that VaR levels increased considerably during the financial crisis, consistent with the idea that as the volatility of underlying assets increase, risk models are updated to reflect this fact. It is also evident that there is a large variation in the importance of trading risk across banks in our sample, a feature we exploit later in our tests.

Figure 2 presents the time-series changes in the breakdown of total VaR across risk-categories, namely interest rate, foreign currency, equities, commodities, and other assets. Interest rate risk forms the largest proportion of the average bank's trading book risk, often representing about 50% of the bank's total trading risk . However, banks have meaningful exposure to foreign exchange, equities, and commodities risk as well.

Table 2 provides some key descriptive statistics for each financial institution that enter our sample. 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. For example, UBS's one-day VaR ranged from $24 million to $447 million during our sample period, corresponding to $79 to $1,414 million for 10-day VaR. Their quarterly exceptions ranged from 0 to 25 over this period. At the same time, we have banks like Bank of Montreal that have relatively relatively fewer quarterly exceptions. These statistics highlight the richness of our data in terms of both within-bank and across-bank variations over time. Overall, the pooled-sample statistics indicate that the sample comprises very large banks with a wide variation in equity capital, trading-book risk exposure, and VaR exceptions.

3.3 Economic significance

How economically meaningful are the market-risk capital charges for trading-book risk? As indicated earlier, we focus on the trading book of a bank because this setting allows us to detect under-reporting in a relatively straightforward and clean way. Our result does not imply that under-reporting in other parts of the business is absent or unimportant. To assess the economic significance of the capital charge from the trading book, we compute the capital charge for two example banks in our sample – one with relatively large and another with relatively small trading-book exposure – and compare the charge to some sensible measures of the capital position of these banks.

The calculation of regulatory capital charge is based on a 10-day holding period VaR, but for reporting purposes banks report 1-day holding period VaR. This effectively means that we need to scale up the one-day VaR (e.g., as listed in Tables 1 and 2) by a factor of $\sqrt{10}$ when computing the regulatory capital charge. As example cases, we examine Bank of America (BoA) and Deutsche Bank (DB) based on their 2008 risk numbers. BoA has relatively smaller trading desk operation as a percentage of its total assets, whereas DB has higher exposure. We provide two sets of calculations: one based on average VaR during the year and the other based on maximum VaR. As shown in the Appendix Table C.1, BoA's capital charge is $1,050 million based on average VaR, and $2,425 million based on maximum VAR. Compared to its Tier-1 equity capital, these numbers represent 0.87% to 2.01% of the bank's capital. For DB, the corresponding numbers are 4.96% to 7.03% (€1.54–€2.23 billion), respectively. These numbers are unlikely to be insignificant for banking institutions that work with very small amount of equity capital as a percentage of their total assets, particularly during times when external capital is more costly. Thus, a single dollar of saving in capital position can support an increase in asset base of $15-20 due to the leverage effect. More importantly, as we show later in the paper our results mainly come from banks that have relatively larger trading portfolio. Thus banks like DB are the ones that exhibit higher tendency to have VaR exceptions when they have lower equity capital compared to banks like BoA. This result (presented in Section 4.2 of the paper) provides further support to our claim that the under-reporting is economically meaningful.

How important is an amount of €1.54–€2.23 billion of capital charge for the trading book of a bank like DB? As we showed above, the number is not insignificant even when compared with the entire equity capital base of the bank. Another meaningful benchmark for evaluating the economic significance of capital charge is not simply a bank's total capital base, but its "marginal" capital base, such as the relevant addition to (or depletion from) the common equity capital of the bank during the year. Dividend payout during the year provides one such benchmark since this amount is directly related to the extent of retained earnings the bank foregoes. As a fraction of dividend payout, the trading book capital charge is significant for our example banks — between 9.11% to 21.04% for BoA and 67%–96% for DB in 2008. Similarly these numbers are high if we compare capital charge to the net income of the bank. In fact, DB had losses in 2008, making the capital charge of €1.54–€2.23 billion even more significant on the marginal basis.

3.3.1 VaR Exceptions Over Time

Table 1 presents summary statistics on VaR exceptions for the sample. On a quarterly basis, we expect to observe an average of about 0.63 exceptions based on roughly 63 trading days per quarter for 99% VaR numbers. Across banks and quarters, the average quarterly exceptions (*Exceptions*) is 0.54 for the base sample which is in line with the statistical expectation. There is substantial variation in the number of exceptions which is present both in the cross-section and the time-series.

Figure 3 presents the aggregate variation in VaR exceptions over time. The average number of VaR exceptions are well below their statistical expectation during 2002-2006 at 0.09 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 1.65 (1.52 after winsorization) exceptions per bank-quarter. From 2010-2013, we once again observe fewer VaR exceptions 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 increase VaR exception frequency during this period solely an artifact of large changes in asset prices, or was it also related to capital-saving incentives? As a prelude to formal statistical tests designed to answer this question, we provide a univariate analysis of the relationship between equity capital and VaR exceptions. We classify banks' observations into four groups based on the level of equity capital at the beginning of a quarter. We first subtract the average level of equity capital of the bank during the entire sample from the quarter's equity capital value. Thus, we are able to classify banks into different groups of equity capital based on the deviation from their average levels. Figure 4 plots the average number of exceptions for each group over the next quarter, and the fraction of banks that have at least one exception over the next quarter. There is a distinct negative association between the two variables: bank-quarter observations in the lower equity capital bucket as of the beginning of the quarter have significantly higher number of VaR exceptions during the quarter as compared to observations in the highest equity capital bucket. The average number of exceptions is 1.17 for the lowest bucket compared to 0.15 for the highest bucket. In terms of the likelihood of getting an exception, the lowest equity capital bucket has a 29% chance of having an exception during the next quarter compared to 11% for the highest bucket.

In sum, the descriptive statistics show that there is a large cross-sectional and time-series variation in VaR exceptions, and number of exceptions increased substantially during the financial crisis of 2007-09. Further, there is a strong negative correlation between VaR exceptions and the reporting bank's equity capital.

4 Results

Our regression model, relating capital-saving incentives to subsequent VaR exceptions, can be expressed in the following general form:

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

Table 3 presents the results of the estimations. We start with a specification that does not include any fixed effects and present the results in Column (1). We find a negative coefficient of -0.30 (p-value< 0.01) on the log of equity capital variable.[10] In column (2), we include

[10]The log-transform of equity ratio follows the literature and assigns more weight on variation in equity

bank fixed-effects and find a coefficient of -0.85 (p-value< 0.01) on the equity capital variable. Column (3) only includes year-quarter fixed effects and finds a negative coefficient of -0.25 (p-value< 0.01). As mentioned earlier, the number of exceptions and all continuous variables are standardized to mean zero and unit standard deviation for ease of interpretation. Thus, these coefficients represent the effect of one standard deviation change in equity capital on the number of standard deviation changes in future exceptions. Comparing the coefficients in columns (1), (2) and (3), it is clear that the effect of equity capital on future exception is much larger when we include bank fixed-effects. Said differently, as banks enter a low equity capital quarter compared to their average levels, they experience significantly more exceptions during the quarter again compared to their average exceptions during the sample. Since the bank fixed effect model controls for the effect of any time-invariant unobserved bank-specific effects, such as risk culture or modeling skills of the bank, this result is of particular relevance for our analysis.

Columns (4)-(6) present the results from full specification that includes both bank and year-quarter fixed effects. The results in column (4) confirm the negative effect of equity capital on VaR exceptions even after controlling for both of the fixed effects. In terms of economic magnitude, one standard deviation (s.d.) decrease in equity capital results in approximately 0.69 s.d., or 1.28, more exceptions in the following quarter. With a sample average of 0.54 exceptions, this is an economically significant increase to over three times the average VaR exception frequency. In column (5), we include controls for bank size and profitability, and explicitly include measures of the volatility of underlying risk factors during the quarter in the regression model. 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

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 these results later in the paper.

not perfectly collinear with the calendar time year-quarter fixed effects. Our main result are virtually unaffected, both statistically and economically. This full specification yields a point estimate on equity capital of -0.63 (p-value$<$0.01), which corresponds to 1.15 more exceptions the following quarter. Also, the additional control variables explain very little of the variation in exceptions, as the R^2 only increases from 0.43 to 0.46. We cluster the standard errors in our main specifications at the year-quarter level. In column (6), we compute standard errors clustered at the bank level and find that the results are statistically significant at the 3% level. Since we need a large number of clusters to ensure consistent estimates and bank clustering yields only 16 clusters, we focus on the estimates with year-quarter clustering in the rest of the paper. Overall, Table 3 documents a strong relationship between equity capital on the accuracy of self-reported VaR measures.

In Appendix Table C.2, we estimate the model with various other measures of equity capital ratio. We find a coefficient of -0.22 (p-value=0.07) for the model that uses equity-to-assets (*Eq/A*) as the key explanatory variable. We find stronger results when the parameterization captures the nonlinearity of the relationship between equity and incentives, with the effect being greatest at the lower levels of equity capital as is emphasized in our baseline specification using the *log(Eq/A)*. For example, we estimate a specification with *Eq/A* and its square and find strong results. Building on this idea, we also find a large coefficient for the model that uses square root of *Eq/A* (-0.40 with p-value=0.01) and an even larger coefficient for the model that uses cubic root of *Eq/A* as the explanatory variable (-0.47 with p-value=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.

As discussed earlier, capital charge for trading book can be significant for banks heavily engaged in trading activities. Since we do not directly observe the extent of under-reporting by a bank, but only the incidence of exceptions during a quarter, we are unable to directly compute the economic magnitude of capital savings from under-reporting based on our regression coefficients. However, we can provide a broad sense of this economic magnitude based on some simplifying assumptions. As shown in the Appendix Exhibit C.1, the estimate from our base regression model (Column 5 of Table 3) translates into a VaR under-reporting of approximately 20% by a bank that has one standard deviation lower equity capital than a truthful reporter. This directly results in a saving of one-fifth of regulatory capital requirements for such a bank.

4.1 Identification Using the Shape of the Penalty Function

4.1.1 Institutional Setting and Empirical Motivation

Regulators classify banks into three zones depending on the recent performance of the VaR models. 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.[11] 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 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.

[11] 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."

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 k=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 k=4.0. Figure 5 illustrates these classifications and the associated capital charge for the entire range of exceptions.[12]

Figure 5 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

[12] 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.

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.[13] 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 discontinuous 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.

Of the 445 observations in these tests, 392 are in the Green group, 24 are in the yellow group, and 29 are in the red group. 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. At this threshold, however, the underlying changes in incentives are not as clear. 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 modeling approach of the regulator. Further, we have a

[13] 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.

very few observations in the near the Yellow-Red threshold. Considering these factors, we do not exploit this threshold in our empirical tests.

4.1.2 Results

At the beginning of each quarter, we first compute the number of exceptions reported by the bank in the prior three quarters as discussed above. We call this number "trailing exceptions." 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 6 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 0.28 in the next quarter compared to the average exceptions of 2.38 for banks in the Yellow group. The average difference of 2.10 across the two groups is statistically significant (p-value<0.01). Narrowing the range of examination to [2-7] yields a similar statistically significant difference of 1.98 (2.48 for Yellow observations versus 0.50 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.

As is evident from Figure 6, there is some heterogeneity in the number of exceptions across different buckets in the "Yellow" zone. Most notably, there are relatively fewer exceptions in the bucket with 5 trailing exceptions. There are two key points worth emphasizing here.

First, even with fewer exception in this bucket, it has higher exception than any bucket in the "Green" zone. Second, it is important to note that the outcome variable that we represent in this graph is not the extent of under-reporting itself, but the number of exceptions which is an increasing, but *probabilistic* function of the extent of under-reporting. Hence we expect to see some variance in the realized exceptions on a bucket-by-bucket basis in small samples. Our tests presented below account for such noises in estimating the statistical significance of our results.

We extend the analysis further in a regression framework by including an indicator variable *Yellow* to our base specification (4). Since we require data on trailing three quarters for this analysis, we lose a few observations for this regression. Table 4 presents the results. Column (1) presents the base case analysis relating equity capital to future VaR exceptions for this sample. The estimated coefficient of -0.68 on *log(Eq/A)* is similar 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 negative and significant coefficient of -0.49 (p-value=0.02) on *log(Eq/A)* and 0.62 (p-value=0.01) 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 0.62 s.d., or 1.15, more exception in the following quarter. Economically, the estimates of column (2) suggests that a one s.d. decrease in equity capital and falling on the right 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 negative and significant coefficient on the interaction term *log(Eq/A)* $\times$ *Yellow* of -0.81 (p-value= 0.06): 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 *log(Eq/A)*. 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 size of the coefficient estimate on the interaction *Yellow* $\times$ *log(Eq/A)* increases from about -0.81 to -1.56 as we narrow estimation window.[14] Overall, these results provide strong support for the main hypothesis that capital-saving incentives drive banks' under-reporting behavior.

[14]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 1.38 (p-value$<$0.01) on the interaction term. In sum, our results are not sensitive to the choice of window we consider for the test.

4.2 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 low stock returns.

For the first test, we 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 2006-2013 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. These are the banks that are likely to have the most sophistication in their trading activities. The key idea behind this 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:[15]

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

Column (1) confirms our base result on this smaller subsample. 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 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 (-1.63 with p-value$<$0.01) is

[15] 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.

more than 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 divide all observations into two groups based on their prior quarter's stock returns. *LowRet* equals one for firms 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 0.23. This result also alleviates concerns that our main finding relating equity capital to exception is simply driven by banks that were surprised by changes in market conditions during the financial crisis. Since such banks are likely to experience lower returns too, if our main result was simply driven by these banks, the effect of equity capital on future exception should become insignificant after controlling for prior stock returns. We do not find that.

Column (4) includes the interaction effect of equity capital and stock returns, 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 -0.40 (p-value=0.02) on *log(Eq/A)*, and -0.37 (p-value=0.03) on the interaction term. Thus, the effect of equity capital remains strong for both groups of banks, but it is almost twice as large for banks in the lower return group. We interpret these findings as supportive of the idea that the under-reporting is higher when the shadow cost of raising external equity is higher.

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

Our results so far shed light on an 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 primary 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.

Table 7 presents the results. Column (2) shows that the effect of equity capital on VaR exceptions increases more than 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 4.35 more exceptions during 2008q4.[16] 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).[17] The effect of equity capital on VaR exceptions is primarily concentrated in these quarters. In sum, these results show that the reported risk measures are least informative when accurate risk measurement is likely most important for regulators and policy-makers.

[16] This is computed as the sum of the coefficients ($\hat{\phi} + \hat{\rho}$) times the standard deviation of exceptions: (0.53+1.81)*1.86=4.35.

[17] In robustness tests presented in Table C.3 in the appendix, 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.

4.4 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 this issue.

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 at the level of p-value$= 0.08$. This suggests that when banks have relatively lower equity capital, the sensitivity of reported VaR to past market volatility is significantly lower. We repeat the test using the past 2-year S&P 500 volatility in column (6) and find similar and slightly stronger results. 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.

4.5 Alternative Explanations & Robustness Tests

4.5.1 Stale Model

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. VaR models based on historical data are more likely to be inaccurate when the economy transitions from a relatively stable state to a stressful one. However, as banks learn about the risks and correlations over time, they update their models according to the new levels of risk.[18] 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. To mitigate the effect from the possible initial inaccuracy caused by the crisis in 2007, we exclude the entire year of 2007 from our sample and re-estimate the base model. If some banks simply have poor-quality models, this gives them time to correct those models. After reproducing the baseline results in column (1) for reference, 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

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

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.

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

If some firms are just better than the others in modeling 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 modeling skill seems unlikely, 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 modeling 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 approach 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. While the point estimates on lagged exceptions is indeed positive and significant, the coefficient of interest on equity ratio remains negative and both economically and statistically significant for these specifications. We find a coefficient of -0.46 (p-value= 0.02) on *log(Eq/A)* in the model with one lag and -0.46 (p-value= 0.04) 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.

Risk Management Expertise

Were violations happening simply because some banks were unprepared for it? We now provide a more direct test to rule out this alternative. While it is hard, if not impossible, to directly measure how prepared the banks were for the crisis, we can obtain some useful information on indicators of preparedness such as the importance of risk-management function within the bank, or the importance of the Chief Risk Officer (CRO) within the organization. Ellul and Yerramilli (2013) construct such a measure of risk-management preparedness, called the risk-management index (RMI), using variables such as the presence of CRO, whether the CRO is an executive officer of the bank, the ratio of CRO's compensation to the CEO's compensation, board's risk-management expertise, and the frequency with which the risk-committee of the bank meets. The RMI is computed using the first principal component of these variables, and in essence it captures the risk-management preparedness of the bank. We obtain the value of this index from Ellul and Yerramilli's database for the sample of our banks as of 2006.[19] We choose 2006 as the year to measure this variable to directly address the concern that our results are driven by banks that were relatively more unprepared just before the crisis. With this data, we estimate our baseline regression model without the inclusion of bank fixed effects (since RMI is a bank-specific constant number). As shown in Appendix Table C.4, our main results remain practically unchanged to the inclusion of this variable.

Penalty Function Placebo Tests

Our analysis on the Green-Yellow discontinuity is based on a threshold of four trailing exceptions over the prior three quarters. As a placebo test, we artificially move the threshold

[19]We thank Andrew Ellul and Vijay Yerramilli for graciously sharing their data with us.

to other points on the "trailing-exceptions" axis, and report the results in Appendix Table C.5. For each placebo, we report both the full sample test, and the tests which restrict the window from 2-7 trailing exceptions. Specifically, we move the threshold to 3 (columns 1-2), 5 (columns 5-6), and 6 (columns 7-8) trailing exceptions and repeat our analysis. These results can be compared to those from our main tests with the threshold at 4 trailing exceptions, which we reproduce in columns 3-4. We do not find positive and significant coefficients on the interaction of *log(Eq/A)* $\times$ *Yellow* for the placebo thresholds. 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.

Non-crisis period results:

It is clear that much of our effects come from the financial crisis period. As a robustness exercise, we exclude the entire crisis period, starting from 2007Q3 and ending in 2009Q4, from our sample, and re-estimate our model only with the non-crisis data. Given the sparse nature of violations during this period (only about 10% of bank-quarters have nonzero exceptions during this non-crisis period), we proceed with our analysis in steps. Results are provided in Appendix Table C.6. In the column (1), we estimate the base specification with neither bank nor year-quarter fixed effects in the model. We find a negative and significant coefficient of -0.03 on equity capital. As expected, the coefficient is economically much smaller and significant only at 5% (compared to 1% for the entire sample) for this specification. In column (2) we include year-quarter fixed effects, and the results remain similar. In column (3), we estimate the full specification including bank fixed effects. The coefficient of interest remains negative, but it is indistinguishable from zero. The results are similar when the dependent variable is simply an indicator of nonzero number of exceptions in a quarter rather than the sum of total exceptions in a quarter. Overall these results show that even though our main results come from the crisis period, the broad pattern remains qualitatively similar outside of this period too.

Bank-by-bank estimates:

To gain further insight into our results, we estimate the regression model on a bank-by-bank basis. In these models, we regress quarterly exceptions on beginning of the quarter equity capital, without any fixed effects. The estimated coefficients provide a bank-specific slope of interest. Since these results are based on much smaller sample sizes, the analysis suffers from usual criticism of small sample biases and concerns about imprecision of the estimates. We find that 70% of the banks in the sample have negative coefficients, showing that our results come from a broad range of banks with a variety of characteristics.

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 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

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

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.

In the base analyses, 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. Considering that the number of exceptions is a count variable, we re-estimate our main regressions using a poisson count data model. This modeling 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.

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 638 observations.

We first estimate a regression with the dependent variable as a dummy variable equal to one if there are any exceptions, and zero otherwise. We also control for whether the reporting is at the 99% or 95% level (*Conf95*), as there is a level difference in exception likelihood between those two groups. In column (6), we find that one s.d. lower equity capital is associated with 34 percentage points (p-value$<$0.01) higher probability of experiencing an exception. Alternatively, we use a measure called *Excess* as the dependent variable, 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 for 95% VaR. Column (7) 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 Discussion & 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 banks' 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 stress because the success of a number of policy responses depends crucially on a clear understanding of the level and nature of the risk undertaken by poorly capitalized financial institutions in the economy. Our findings highlight some important shortcomings of the current regulation. We show that the integrity of self-reported measures becomes most questionable precisely when accurate risk measurement in the financial system is most important.

Our results raise an immediate question: what should be the alternative mechanism of risk-reporting that mitigates the under-reporting incentives? The intuition from our work suggests several possible paths for future policy design. It is clear that under the current mechanism, the penalty function (i.e., k multiplier) ignores the state of the world in which under-reporting occurs. It may be useful to tie down the penalty function to the shadow price of capital for the bank, for example, by differentiating the under-reporting penalty based on the bank's own capital position as well as the capital shortfall of the entire banking sector. Similarly, we conjecture that the policy design can be improved by using relative benchmarking of VaR models. At the very core of this regulation, the regulators need to separate strategic under-reporting from bad model or unlucky ex-post outcomes. Average levels of exceptions across all banks during a quarter can be used as a starting point for gauging the extent of bad-model problems experienced by all banks in the economy. Banks that experience significantly more deviations from the averages are more likely to be under-reporting their true risks. Recent theoretical work by Colliard (2014) considers several policy proposals, such as penalizing banks with large losses or rewarding banks for truthful reporting, to alleviate the concerns about strategic under-reporting. Earlier work by Chan et al. (1992), who highlight the difficulty in estimating risk-sensitive deposit insurance premium for depository institutions that are privately informed about their true risk, also provides theoretical insights into policy alternatives designed to elicit truthful reporting from privately informed banks. Our empirical findings emphasize the need for more theoretical work along these lines to understand the costs and benefits of different mechanisms aimed at extracting accurate information from regulated banks.

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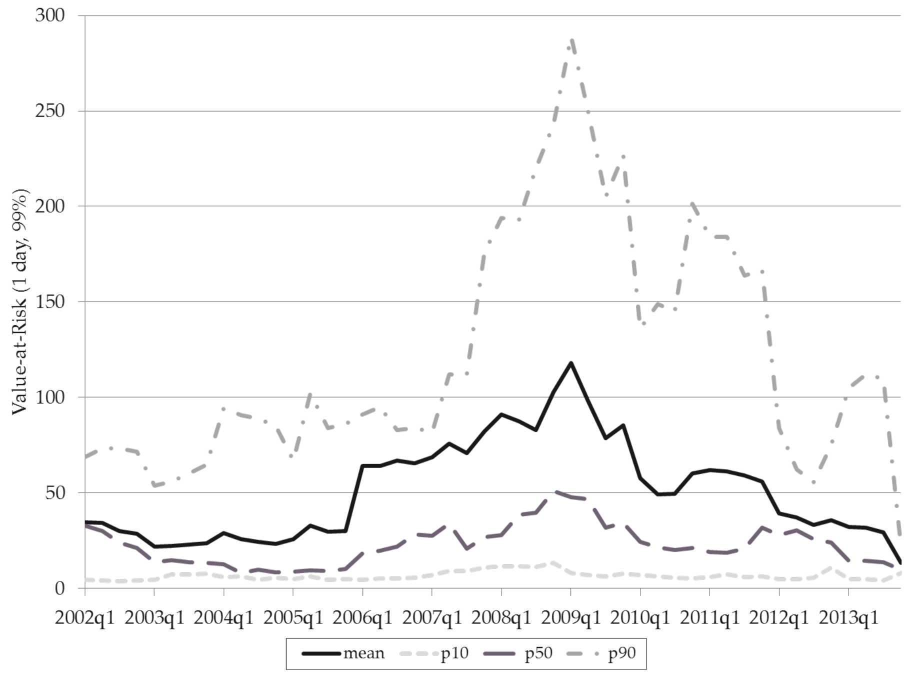


Figure 1: Value-at-Risk Levels Over Time
This figure presents the mean, median, 10th percentile, and 90th percentile of the level of Value-at-Risk across the sample distribution over the sample period based on one-day VaR at the 99% level.

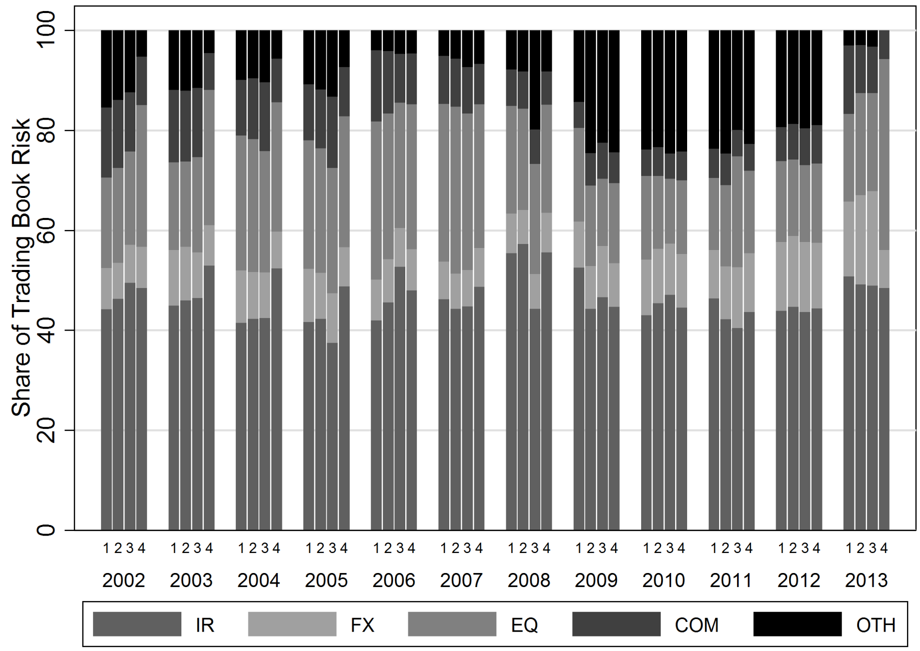


Figure 2: The Composition of Trading-Book Risk
This figure presents the mean composition of trading-book risk across various risk categories over the sample period based on one-day Value-at-Risk at the 99% level. The total trading-book VaR is composed of interest rate risk (IR), foreign exchange risk (FX), equities risk (EQ), commodities risk (COM), and other risk (OTH).

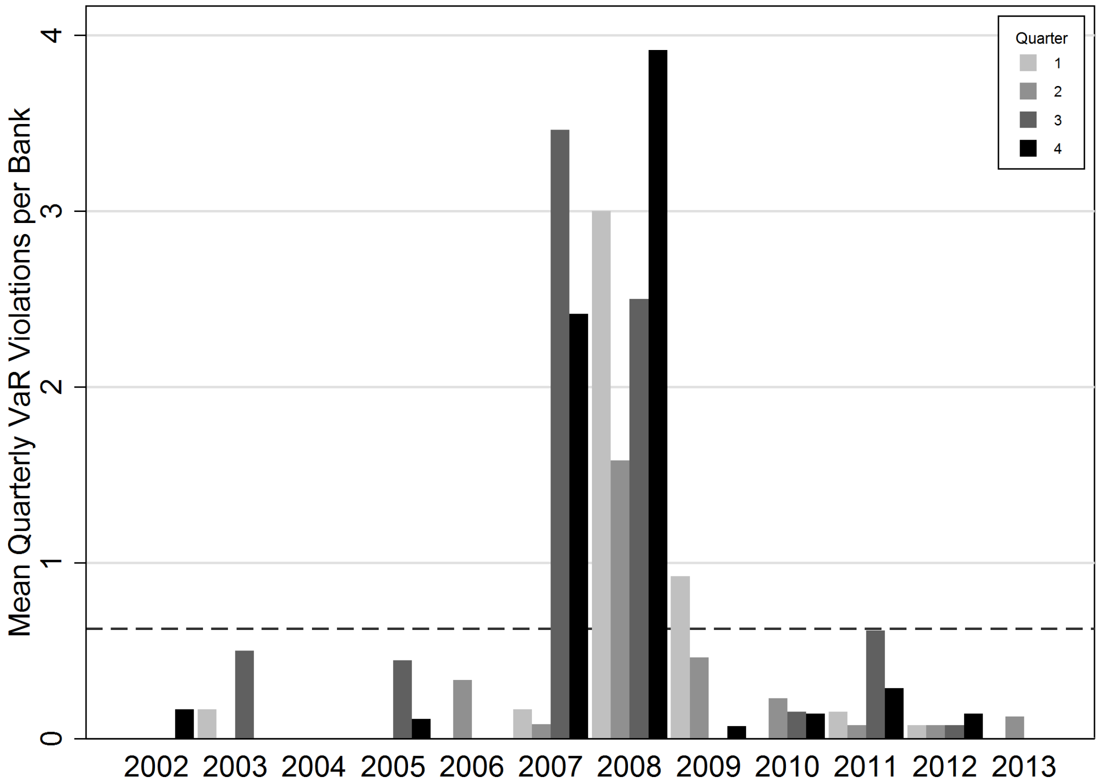


Figure 3: Average Value-at-Risk Exceptions
This figure presents the average frequency of Value-at-Risk (VaR) exceptions for banks each quarter during the 2002-2013 sample period. The dashed line at 0.63 represents the expected exception frequency based on 99% VaR confidence interval and approximately 63 trading days per quarter.

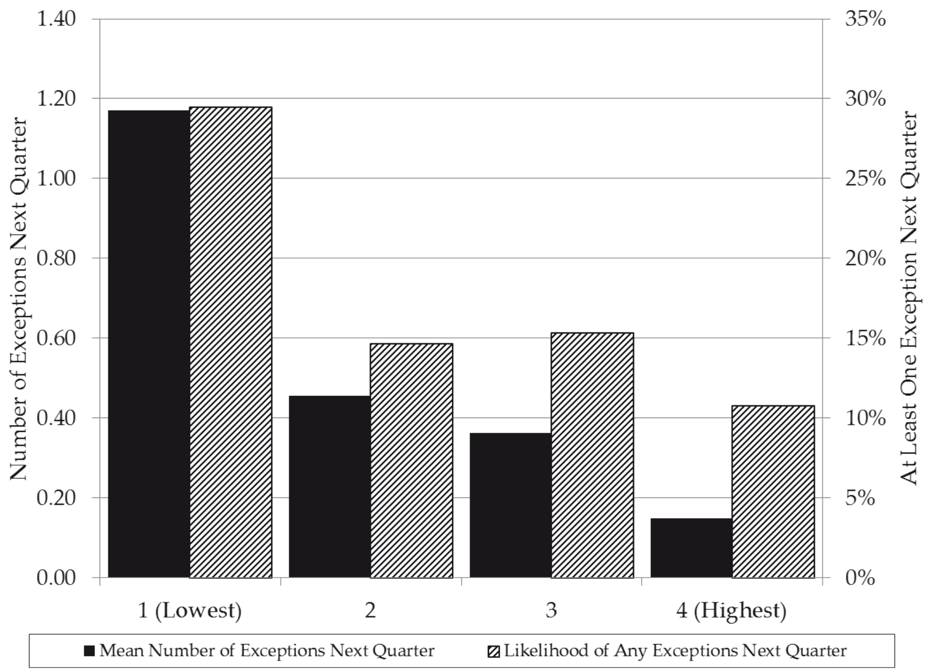


Figure 4: Equity Capital and Future Exceptions
This figure presents the average number of Value-at-Risk exceptions (left axis) and the portion of observations with at least one exception (right axis) for different levels of equity capital. We divide the observations within each bank into four groups based on the bank's equity capital position at the beginning of the quarter from lowest equity capitalization to highest.

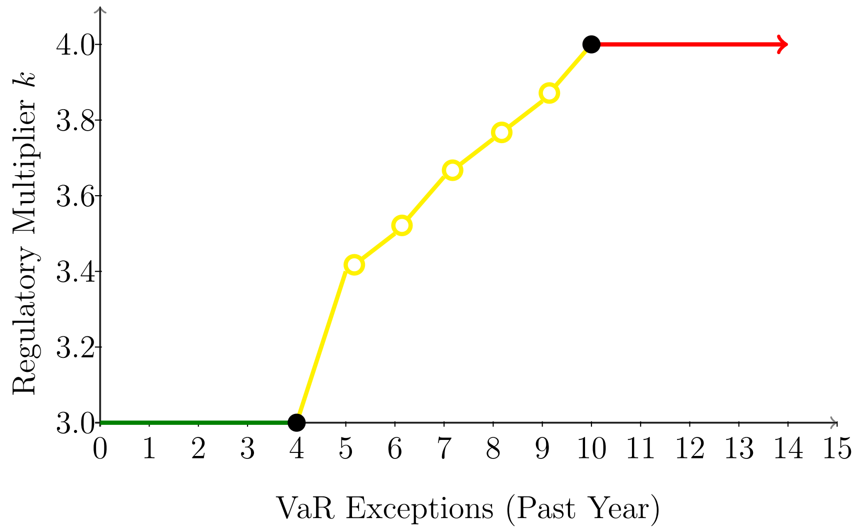


Figure 5: The Shape of Penalties
This figure presents the shape of regulatory capital multiplier k as a function of past exceptions (based on trailing 250 trading days).

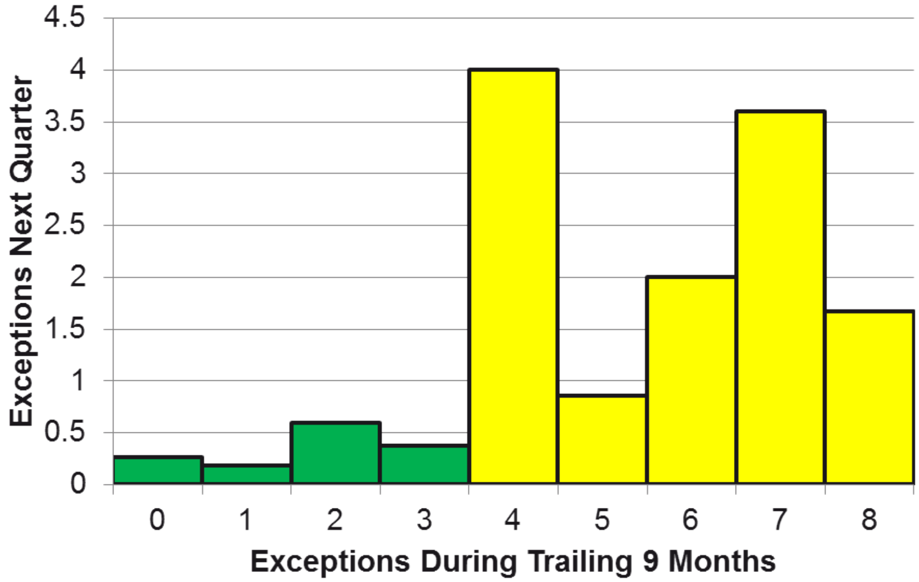


Figure 6: Distribution of Value-at-Risk Exceptions
This figure presents the average number of Var exceptions reported by a bank in quarter t across different groups of "trailing exceptions." "Trailing exceptions" measures the total number of VaR exceptions reported by the bank in trailing three quarters ($Exceptions_{t-1} + Exceptions_{t-2} + Exceptions_{t-3}$).

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 2002-2013. 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)	875.24	741.04	73.14	302.21	571.54	1393.60	3643.58	497
NI-to-Assets (%,Q)	0.16	0.15	-0.52	0.09	0.19	0.24	0.49	497
BookEq/A (%)	6.29	3.01	1.66	4.15	5.24	8.94	13.84	497
log(Eq/A)	-2.88	0.49	-4.10	-3.18	-2.95	-2.41	-1.98	497
Value-at-Risk ($MM):								
Exceptions [Raw Data]	0.58	2.19	0.00	0.00	0.00	0.00	25.00	497
Exceptions [Winsorized 99%]	0.54	1.86	0.00	0.00	0.00	0.00	13.00	497
Total Value-at-Risk	56.74	81.82	4.00	9.60	21.50	69.00	447.00	491
VaR-Interest Rate	41.65	69.07	0.00	4.76	12.83	51.01	430.58	491
VaR-Foreign Exchange	8.33	11.94	0.00	0.90	2.43	12.00	62.82	491
VaR-Equities	18.74	29.48	0.00	3.16	6.38	23.90	204.60	491
VaR-Commodities	6.68	10.31	0.00	0.32	1.46	8.43	52.31	491
VaR-Other	15.76	46.17	0.00	0.00	0.00	9.12	322.88	491
VaR-Diversification Benefit	37.53	51.33	0.00	5.01	10.76	54.82	241.67	491

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 2002-2013. 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%). Where there are differences, we report both the winsorized figures and the raw figures [in brackets] for exceptions data.

Panel A: Base Sample

	Exceptions (99% CI)			Value-at-Risk			
Bank	Mean	Min	Max	Mean	Min	Max	N
Bank of America Corporation	0.42	0.00	10.00	92.08	32.50	275.80	48
Bank of Montreal	0.68	0.00	5.00	23.32	7.60	46.00	37
Bank of New York Mellon	0.06	0.00	2.00	7.74	4.00	13.40	48
Canadian Imperial Bank of Commerce	0.13	0.00	3.00	8.44	4.00	18.70	48
Citi Group	0.15	0.00	1.00	152.67	105.00	224.00	13
Credit Suisse Group	1.39	0.00	11.00	119.18	44.00	243.00	28
Deutsche Bank	1.38	0.00	13 [16]	88.63	55.10	142.90	32
ING Group	0.00	0.00	0.00	17.85	7.30	39.00	17
JPMorgan Chase	0.38	0.00	5.00	113.34	53.70	289.00	32
PNC Financial Service Group	0.44	0.00	5.00	7.39	4.70	11.70	27
Royal Bank of Canada	0.66	0.00	4.00	34.31	18.00	60.00	32
Scotia Bank	0.09	0.00	1.00	13.40	6.80	29.30	46
SunTrust Bank	0.00	0.00	0.00	11.57	4.00	28.00	17
TD Bank	0.12	0.00	2.00	21.12	8.20	60.00	41
UBS	2.39	0.00	13 [25]	247.18	24.00	447.00	28
UniCredit Group	0.00	0.00	0.00	33.43	28.80	39.80	3

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	0.73	6.00	115.48	44
JPMorgan Chase	–	–	–	0	0.50	3.00	66.63	16
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	1.17	9 [13]	97.57	30
PNC	–	–	–	0	0.25	1.00	3.53	12
UBS	–	–	–	0	0.00	0.00	15.75	4

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)	(2)	(3)	(4)	(5)	(6)
(z)log(Eq/A)	-0.30***	-0.85***	-0.25***	-0.69***	-0.63***	-0.63**
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(0.03)
(z)log(Total Assets)					0.54	0.54**
					(0.12)	(0.05)
(z)NI-to-Assets					-0.03	-0.03
					(0.65)	(0.70)
(z)Vol-Commodities					0.05	0.05
					(0.57)	(0.16)
(z)Vol-S&P 500					0.35**	0.35**
					(0.03)	(0.03)
(z)Vol-Foreign Exchange					0.07	0.07
					(0.40)	(0.18)
(z)Vol-Interest Rate					0.03	0.03
					(0.88)	(0.71)
Bank FE	No	Yes	No	Yes	Yes	Yes
Year-Quarter FE	No	No	Yes	Yes	Yes	Yes
Observations	497	497	497	497	497	497
R^2	0.09	0.20	0.35	0.43	0.46	0.46
Clustered by	Y-Q	Y-Q	Y-Q	Y-Q	Y-Q	Bank

p-values in parentheses

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

Table 4: 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, *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.

	(z)Exceptions					
	(1) Full	(2) Full	(3) Full	(4) [0-8]	(5) [1-8]	(6) [2-7]
(z)log(Eq/A)	-0.68***	-0.49**	-0.34*	-0.23	-0.09	-1.94*
	(<0.01)	(0.02)	(0.08)	(0.15)	(0.80)	(0.07)
Yellow		0.62**	0.51*	0.62**	0.67**	1.06
		(0.01)	(0.06)	(0.02)	(0.04)	(0.36)
(z)log(Eq/A) * Yellow			-0.81*	-0.79*	-1.48***	-1.56**
			(0.06)	(0.06)	(<0.01)	(0.04)
Red		0.96	0.61			
		(0.21)	(0.31)			
(z)log(Eq/A) * Red			-0.40			
			(0.20)			
(z)log(Total Assets)	0.80*	0.73	0.52	0.38	-0.62	-2.04
	(0.08)	(0.12)	(0.32)	(0.48)	(0.39)	(0.13)
(z)NI-to-Assets	-0.00	0.01	0.00	0.06	0.13	-0.02
	(1.00)	(0.95)	(0.96)	(0.38)	(0.32)	(0.95)
(z)Vol-Commodities	0.04	0.01	0.03	0.09	0.16	0.18
	(0.72)	(0.88)	(0.71)	(0.20)	(0.21)	(0.51)
(z)Vol-S&P 500	0.37**	0.38**	0.37**	0.37**	0.41*	0.61***
	(0.05)	(0.02)	(0.02)	(0.01)	(0.06)	(0.01)
(z)Vol-Foreign Exchange	0.06	0.04	0.05	-0.03	0.07	0.14
	(0.51)	(0.58)	(0.52)	(0.43)	(0.63)	(0.59)
(z)Vol-Interest Rate	0.03	0.13	0.10	0.15	0.08	-0.11
	(0.85)	(0.45)	(0.58)	(0.37)	(0.62)	(0.71)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	445	445	445	416	133	67
R^2	0.49	0.51	0.54	0.56	0.76	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.

	(z)Exceptions		
	(1)	(2)	(3)
(z)log(Eq/A)	-0.82**	-0.45	0.13
	(0.01)	(0.15)	(0.63)
(z)VE_2006 * (z)log(Eq/A)		-0.46**	
		(0.01)	
High(VE_2006) * (z)log(Eq/A)			-1.63***
			(<0.01)
(z)log(Total Assets)	0.41	0.01	0.08
	(0.34)	(0.97)	(0.83)
(z)NI-to-Assets	-0.06	-0.00	-0.02
	(0.56)	(0.95)	(0.80)
(z)Vol-Commodities	0.05	0.06	0.04
	(0.63)	(0.54)	(0.68)
(z)Vol-S&P 500	0.36**	0.35**	0.38**
	(0.05)	(0.03)	(0.02)
(z)Vol-Foreign Exchange	0.08	0.07	0.07
	(0.47)	(0.50)	(0.49)
(z)Vol-Interest Rate	0.03	0.09	0.08
	(0.87)	(0.63)	(0.70)
Bank FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Observations	389	389	389
R^2	0.46	0.49	0.49

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.

	(z)Exceptions			
	(1)	(2)	(3)	(4)
(z)log(Eq/A)	-0.63***		-0.61***	-0.40**
	(<0.01)		(<0.01)	(0.02)
LowRet		0.19	0.16	0.15
		(0.17)	(0.23)	(0.21)
(z)log(Eq/A) * LowRet				-0.37**
				(0.03)
(z)log(Total Assets)	0.54	0.73*	0.53	0.66**
	(0.12)	(0.06)	(0.13)	(0.04)
(z)NI-to-Assets	-0.03	-0.03	-0.03	-0.01
	(0.65)	(0.67)	(0.70)	(0.83)
(z)Vol-Commodities	0.05	0.04	0.05	0.06
	(0.57)	(0.63)	(0.55)	(0.45)
(z)Vol-S&P 500	0.35**	0.31*	0.32*	0.31**
	(0.03)	(0.08)	(0.06)	(0.04)
(z)Vol-Foreign Exchange	0.07	0.07	0.07	0.07
	(0.40)	(0.43)	(0.38)	(0.37)
(z)Vol-Interest Rate	0.03	0.04	0.03	0.02
	(0.88)	(0.82)	(0.88)	(0.92)
Bank FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	497	497	497	497
R^2	0.46	0.44	0.46	0.48

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.

	(z)Exceptions			
	(1)	(2)	(3)	(4)
(z)log(Eq/A)	-0.63***	-0.53***	-0.62***	-0.28*
	(<0.01)	(0.01)	(<0.01)	(0.09)
(z)log(Eq/A) * 2008q4		-1.81***		
		(<0.01)		
HiMES (top 4-tile)			0.09	0.10
			(0.78)	(0.74)
(z)log(Eq/A) * HiMES				-0.38**
				(0.04)
(z)log(Total Assets)	0.54	0.60*	0.54	0.62**
	(0.12)	(0.08)	(0.12)	(0.05)
(z)NI-to-Assets	-0.03	-0.05	-0.03	-0.02
	(0.65)	(0.49)	(0.65)	(0.75)
(z)Vol-Commodities	0.05	0.05	0.05	0.07
	(0.57)	(0.58)	(0.55)	(0.44)
(z)Vol-S&P 500	0.35**	0.34**	0.33*	0.30*
	(0.03)	(0.04)	(0.06)	(0.09)
(z)Vol-Foreign Exchange	0.07	0.07	0.07	0.06
	(0.40)	(0.40)	(0.42)	(0.46)
(z)Vol-Interest Rate	0.03	0.03	0.04	0.03
	(0.88)	(0.85)	(0.84)	(0.87)
Bank FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	497	497	497	497
R^2	0.46	0.54	0.46	0.48

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 (similarly defined for lagged two year volatility), *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.

	log(Value-at-Risk)					
	(1)	(2)	(3)	(4)	(5)	(6)
L.log(1yr S&P vol)	0.12***	0.04*	0.04*			
	(<0.01)	(0.09)	(0.06)			
(z)log(Eq/A)		-0.23***	-0.24***		-0.24***	-0.24***
		(<0.01)	(<0.01)		(<0.01)	(<0.01)
(z)log(Total Assets)		0.44***	0.43***		0.46***	0.44***
		(<0.01)	(<0.01)		(<0.01)	(<0.01)
(z)NI-to-Assets		-0.10***	-0.10***		-0.11***	-0.11***
		(<0.01)	(<0.01)		(<0.01)	(<0.01)
(z)log(Eq/A) × L.log(1yr S&P vol)			0.02*			
			(0.08)			
L.log(2yr S&P vol)				0.07**	0.01	0.01
				(0.03)	(0.67)	(0.52)
(z)log(Eq/A) × L.log(2yr S&P vol)						0.03**
						(0.04)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	452	452	452	452	452	452
R^2	0.85	0.88	0.88	0.84	0.88	0.88

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 estimates of panel regressions using the Arellano and Bond (1991) approach 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.

	(z)Exceptions			
	(1) All	(2) Drop 2007	(3) AB1lag	(4) AB2lags
(z)log(Eq/A)	-0.63***	-0.60**	-0.46**	-0.46**
	(<0.01)	(0.01)	(0.02)	(0.04)
L.(z)Exceptions			0.32***	0.31***
			(<0.01)	(<0.01)
L2.(z)Exceptions				0.01
				(0.95)
(z)log(Total Assets)	0.54	0.36	0.66**	0.68**
	(0.12)	(0.11)	(0.02)	(0.02)
(z)NI-to-Assets	-0.03	-0.05	0.07**	0.07**
	(0.65)	(0.47)	(0.02)	(0.02)
(z)Vol-Commodities	0.05	0.07	0.07	0.06
	(0.57)	(0.44)	(0.11)	(0.38)
(z)Vol-S&P 500	0.35**	0.26**	0.42***	0.42***
	(0.03)	(0.05)	(<0.01)	(<0.01)
(z)Vol-Foreign Exchange	0.07	0.07	0.04	0.03
	(0.40)	(0.40)	(0.38)	(0.48)
(z)Vol-Interest Rate	0.03	-0.09	0.16***	0.17***
	(0.88)	(0.34)	(<0.01)	(<0.01)
Bank FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	497	448	461	445
R^2	0.46	0.45		
2nd Order AR Test			0.98	0.94
Sargan Test			0.54	0.51

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* ≥ 0.6 for 99% CI and *Exceptions* ≥ 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. *Conf95* is an indicator variable equal to one if the VaR confidence level is at the 95% level, and zero if it is at the 99% level. 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.

	(z)Exceptions					Expanded	
	(1) Tier 1	(2) Betas	(3) VaR Mix	(4) Drop 2008q4	(5) Poisson	(6) 1(Exception)	(7) Excess
(z)log(Eq/A)		-0.56***	-0.64***	-0.53***	-1.18***	-0.34***	-0.29**
		(<0.01)	(0.01)	(0.01)	(<0.01)	(<0.01)	(0.03)
(z)log(Tier 1 Ratio)	-0.22*						
	(0.05)						
(z)Market Beta		-0.11					
		(0.36)					
(z)MBS Beta		0.03					
		(0.73)					
d_Conf95						0.42**	0.01
						(0.02)	(0.93)
(z)log(Total Assets)	0.71*	0.55	0.53	0.59*	-0.67	-0.04	-0.08
	(0.06)	(0.11)	(0.12)	(0.09)	(0.21)	(0.85)	(0.68)
(z)NI-to-Assets	-0.04	-0.05	-0.04	-0.04	0.05	-0.01	0.02
	(0.58)	(0.51)	(0.58)	(0.54)	(0.59)	(0.85)	(0.66)
(z)Vol-Commodities	0.03	0.05	0.05	0.08	-0.03	0.06	0.04
	(0.68)	(0.59)	(0.55)	(0.34)	(0.84)	(0.44)	(0.49)
(z)Vol-S&P 500	0.33**	0.34**	0.35**	0.41***	1.15***	0.61***	0.70***
	(0.04)	(0.04)	(0.04)	(0.01)	(<0.01)	(<0.01)	(<0.01)
(z)Vol-Foreign Exchange	0.05	0.06	0.07	0.00	0.08	-0.03	-0.04
	(0.53)	(0.40)	(0.38)	(0.96)	(0.62)	(0.54)	(0.47)
(z)Vol-Interest Rate	0.06	0.03	0.03	0.01	-0.14	-0.03	-0.05
	(0.68)	(0.86)	(0.89)	(0.94)	(0.37)	(0.79)	(0.67)
VaR Mix	No	No	Yes	No	No	No	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	497	497	491	485	460	638	638
R^2	0.44	0.46	0.46	0.45		0.44	0.45

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

A Appendix: Regulatory Response to VaR Exceptions

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=46) 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)	1016.07	927.42	-88.66	(0.68)
Net-Income-(MM)	974.88	1116.34	141.46	(0.67)
NI-to-Assets-(%,Q)	0.14	0.15	0.01	(0.74)
BookEq/AT	5.58	5.83	0.25	(0.74)
Exceptions	0.50	2.48	1.98^{***}	**(<0.01)**

B Appendix: Sample Construction

Data Collection

Our sample covers some of the largest commercial banks from U.S., Canada, and Europe who provide sufficient data on VaR exceptions in their quarterly and annual filings. Because most trading book activity is concentrated among the largest banks, this is a natural starting point for our sample construction. It is also worth emphasizing that even though the number of banks covered in our sample is relatively small, these are the banks that cover most of the trading businesses in the market. To create a list of all top global banks, we first pulled top 50 banks as of year 2008 from Bankers Almanac maintained at the website www.accuity.com. This list contains banks from around the world. From this list we narrow our sample to the subset of North American (Canadian and U.S.) and European Banks. We exclude other regions for both data availability issues (Asian banks typically do not provide information on exceptions) and relatively large differences in the timing of the adoption of various provisions of Basel Recommendations in these countries. After this step, we are left with a list of 29 banks in the sample. We supplement this sample with the sample of all banks that are in top 20 banks in the list of U.S. banks. Together, the union of these lists yield 41 banks for which we search the quarterly and annual filings

Data on value-at-risk and exceptions are not available in existing publicly available datasets. We hand-collect these key data items for our analysis directly from banks' financial statements. Specifically, we collect the data from the banks' commentary on their market risk as discussed in the form 10-Q and 10-K for US banks or form 20-F for foreign banks. We go through the annual and quarterly reports of each of the remaining banks and include them in the sample if they report data on VaR exceptions in their quarterly filings. Since some banks only report annual exceptions, we miss them from our sample because our regressions are conducted at a quarterly basis. However, the large majority of banks that do not enter our sample are the ones that do not report this statistics. For example, RBS only mentions the color zone (e.g, green or yellow) that it belongs to without providing any data on the number of exceptions. In Table B.1 we provide the names of banks that enter our sample as well as non-sample banks.

In their discussions of market risk, banks discuss their risk modeling practices and then provide a table with the level of VaR for the quarter, and also the components that make up that total. For example, the report includes the break-down of total VaR of the bank across foreign-exchange VaR, interest-rate VaR, equities VaR, commodities VaR, and the other category. The table also gives information on diversification factor which accounts for the imperfect correlation between these asset classes. Table B.2 provides an example from Credit Suisse in 2007q1. Along with the table, we provide the text that accompanies that disclosure in the financial statement.

In addition to the level and composition of VaR, banks also provide the number of exceptions for the quarter. In some case, especially, for the last quarter of the year, some banks provide the annual number of exceptions. In such cases we back out the quarterly exceptions for the last quarter by subtracting from the annual exception the summed values of the first three quarters of the year. Not all banks report these statistics for the entire sample period. Though they are required to report these figures to regulators, they are not required to report them in their public financial statements. However, as is typical with several disclosure practices, most banks continue to disclosure information on exceptions once they initiate it. A natural question arises: how different are our sample banks from the rest? We provide a comparison of the banks that are and are not included in our sample and show that those that disclose are not significantly different from those that do not in Table B.1A.

As we can see from the Table, the two samples are equally matched on asset size and equity capital ratio. In the figure in Table B.1B we graphically show that they are similar of these dimensions. The most reliable difference between the two group is the amount of trading business they have. Our sample covers banks that engage in relatively higher trading activity. We think this is an advantage of our sample; we are making inference based on a subset that has meaningful trading business.

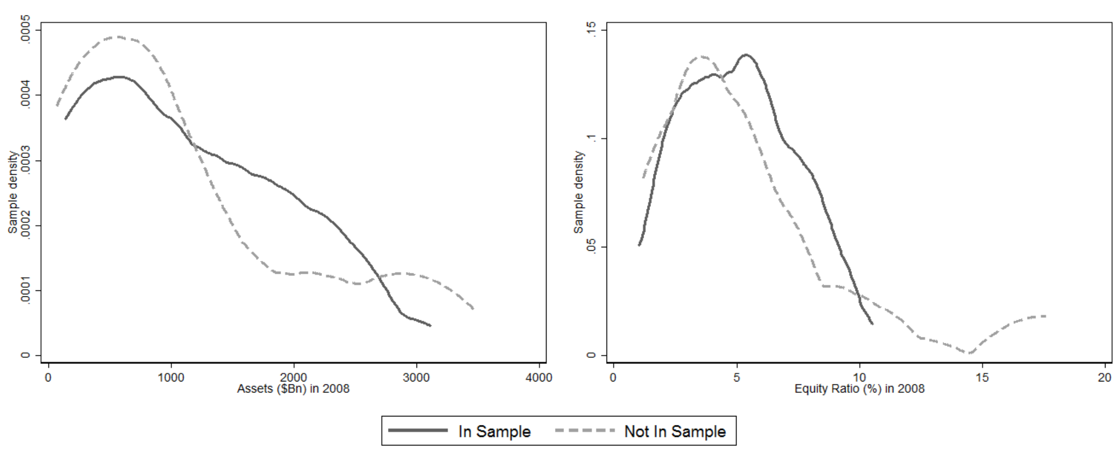
Table B.1: Sample Comparability

Panel A presents a comparison of the size of banks in 2008 that are in the sample with banks that are not in the sample. The table also shows the mean equity-to-assets ratio for each group of banks (not individually listed in the table). Panel B presents kernel densities of the size and capitalization data for each group. The banks chosen for comparison are based on a sample of the largest 50 banks in the world, and then further restricted to those based in North America or Europe.

Panel A: Raw Statistics

In Sample		Not In Sample	
Bank	Assets ($Bn)	Bank	Assets ($Bn)
Deutsche Bank	3107.31	Royal Bank of Scotland	3462.97
JPMorgan Chase	2175.05	Barclays	2960.21
Citi Group	1938.47	BNP Paribas	2928.31
UBS	1909.51	HSBC	2527.47
ING Group	1878.79	Credit Agricole	2516.97
Bank of America Corporation	1817.94	BPCE, France	1613.60
UniCredit Group	1475.21	Societe Generale	1594.28
Credit Suisse Group	1109.18	Banco Santander	1480.88
Goldman Sachs	884.55	Wells Fargo	1309.64
Royal Bank of Canada	696.96	Intesa Sanpaolo	897.49
Morgan Stanley	658.81	Commerzbank	882.10
Scotia Bank	488.76	Rabobank	863.62
Toronto Dominion Bank	462.98	Natixis	784.10
Bank of Montreal	341.99	BBVA	761.68
Canadian Imperial Bank of Commerce	290.93	Nordea Bank	668.85
Bank of New York Mellon	195.16	Lloyds Banking Group	628.72
SunTrust Bank	185.10	Standard Chartered	435.07
PNC	140.78	Westpac Banking Corporation	357.53
		Itau Unibanco	273.36
		Ally Financial	189.48
		American Express	126.07
		Capital One	115.14
		Fifth Third Bank	69.46
Mean Size (listed above)	1097.64		1193.35
Mean Equity-to-Assets (not listed above)	5.01%		5.02%

Panel B: Kernel Densities



Data Example: Credit Suisse 2007q1

The following is from the Credit Suisse 2007q1 financial review. From this report, we collect data on the number of VaR exceptions for the quarter (2 here), and the average total VaR for the quarter along with its components.

> We assume market risk primarily through the trading activities in Investment Banking. The other divisions also engage in some trading activities, but to a much lesser extent.
>
> Trading risks are measured using VaR as one of a range of risk measurement tools. VaR is the potential loss in fair value of trading positions due to adverse market movements over a defined time horizon and for a specified confidence level. In order to show the aggregate market risk in our trading books, the table above shows the trading-related market risk on a consolidated basis, as measured by a 10-day VaR scaled to a one-day holding period and based on a 99% confidence level. This means there is a 1-in-100 chance of incurring a daily mark-to-market trading loss that is at least as large as the reported VaR.
>
> Credit Suisses average one-day, 99% VaR in 1Q07 was CHF 78 million compared to CHF 70 million during 4Q06 and CHF 71 million during 1Q06. The increase was mainly due to the introduction of a new methodology to better capture certain equity risks, as explained below.
>
> Various techniques are used to assess the accuracy of the VaR model, including backtesting. Daily backtesting profit and loss is compared with VaR calculated using a one-day holding period. Backtesting profit and loss is a subset of actual trading revenue and includes only the profit and loss effects from movements in financial market variables such as interest rates, equity prices and foreign exchange rates on the previous nights positions. A backtesting exception occurs when the daily loss exceeds the daily VaR estimate.
>
> We had two backtesting exceptions during the first quarter of 2007 due to market stress events in late February and early March. During this period, market volatility was larger than the volatility reflected in the VaR model.
>
> We regularly review our VaR model to ensure that it remains appropriate given evolving market conditions and the composition of our trading portfolio. Towards the end of 1Q07, we introduced an enhanced approach for modeling certain equity risks. If this methodology had been in place as of the end of 4Q06, the period-end Total VaR would have been CHF 105 million rather than CHF 89 million and the equity VaR would have been CHF 77 million rather than CHF 57 million. In addition, we are now extending the length of the historical data set used in the VaR model beyond two years so that it captures more historical events. Given current positions and market conditions, these changes will tend to make the VaR model more conservative.

Table B.2: Credit Suisse 2007q1 Value-at-Risk
This presents an example of the value-at-risk reporting from the Credit Suisse 2007q1 financial review. As the maximum and minimum occur on different days for different risk types, it is not meaningful to calculate a maximum or minimum portfolio diversification benefit. All figures are in CHF millions.

	Interest Rate/ Credit Spread	Foreign Exchange	Commodities	Equities	Diversification Benefit	**Total**
Average	**53**	**17**	**12**	**64**	**-68**	**78**
Minimum	46	8	8	51	-	56
Maximum	67	31	20	84	-	96
End of period	55	21	10	77	-67	96
Exceptions	-	-	-	-	-	**2**

C Appendix: Additional Tests

Table C.1: Computation of Trading Book Capital Charge

The table below displays calculations of the market risk capital charges for Bank of America and Deutsche Bank based on their respective reported Value-at-Risk figures in 2008.

	Bank of America		**Deutsche Bank**	
	(All numbers except ratios in $ ml.)		(All numbers, except ratios, in Euro ml.)	
VaR	Ave VaR	Max VaR	Ave VaR	Max VaR
1-day holding period	110.7	255.7	122	172.9
10-day holding period	350.1	808.6	385.8	546.8
k-multiplier	3	3	4	4
Capital Charge for trading	1050.2	2425.8	1543.2	2187.0
Company Financials				
Tier-1 Capital	120814	120814	31094	31094
Net Income	4008	4008	-3896	-3896
Cash Dividend	11528	11528	2274	2274
Trading Book Capital as a % of				
Tier-1 Capital	0.87%	2.01%	4.96%	7.03%
Net Income	26.20%	60.52%	NA	NA
Cash Dividend	9.11%	21.04%	67.86%	96.18%

Table C.2: Alternative Parameterizations of Equity Capital

This table presents OLS estimates from a regression of the number of VaR exceptions in the next quarter on various parameterizations of banks' equity capital ratio 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, and *(Eq/A)* is the book equity-to-assets ratio. *Bank Controls* include the ratio of quarterly net income-to-assets and the log of total assets. *Volatility Controls* include 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.

	(z)Exceptions				
	(1)	(2)	(3)	(4)	(5)
(z)log(Eq/A)	-0.63***				
	(<0.01)				
(z)(Eq/A)		-0.22*	-1.52**		
		(0.07)	(0.02)		
(z)(Eq/A)^2			1.09**		
			(0.04)		
(z)sqrt(Eq/A)				-0.40***	
				(0.01)	
(z)cube root(Eq/A)					-0.47***
					(0.01)
Bank Controls	Yes	Yes	Yes	Yes	Yes
Volatility Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	497	497	497	497	497
R^2	0.46	0.44	0.45	0.44	0.45

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

Table C.3: Alternative Measures of Financial Stress

This table presents OLS estimates from a regression of the number of VaR exceptions in the next quarter on banks' equity capital ratio *log(Eq/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, *MES* is an the Marginal Expected Shortfall of the financial sector, *Cleveland FSI, Kansas City FSI* and *St. Louis FSI* are financial stress indices (FSI) from the respective federal reserve banks, *Bank Controls* include the ratio of quarterly net income-to-assets and the log of total assets. *Volatility Controls* include 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.

	(z)Exceptions				
	(1)	(2)	(3)	(4)	(5)
(z)log(Eq/A)	-0.63***	5.35***	-0.28*	-0.21	-0.27
	(<0.01)	(<0.01)	(0.09)	(0.23)	(0.19)
log(MES)		1.09			
		(0.15)			
(z)log(Eq/A) × log(MES)		-0.43***			
		(<0.01)			
Cleveland FSI			0.33*		
			(0.07)		
(z)log(Eq/A) × Cleveland FSI			-0.21**		
			(0.01)		
Kansas City FSI				0.32	
				(0.44)	
(z)log(Eq/A) × Kansas City FSI				-0.20**	
				(0.05)	
StLouis FSI					0.80***
					(<0.01)
(z)log(Eq/A) × StLouis FSI					-0.20**
					(0.04)
Bank Controls	Yes	Yes	Yes	Yes	Yes
Volatility Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	497	497	497	497	497
R^2	0.46	0.50	0.51	0.53	0.56

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

Table C.4: Controlling for Risk Management

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, *RMI_2006* is the risk-management index, which is a measure of the importance of risk-management function within the bank, or the importance of the Chief Risk Officer (CRO) within the organization. Ellul and Yerramilli (2013) construct this measure of risk-management preparedness using variables such as the presence of a CRO, whether the CRO is an executive officer of the bank, the ratio of CRO's compensation to the CEO's compensation, board's risk-management expertise, and the frequency with which the risk-committee of the bank meets. The RMI is computed using the first principal component of these variables. *Bank Controls* include the ratio of quarterly net income-to-assets and the log of total assets. *Volatility Controls* include 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.

	(z)Exceptions					
	(1)	(2)	(3)	(4)	(5)	(6)
(z)log(Eq/A)	-0.30***	-0.25***	-0.26***	-0.19**	-0.18**	-0.21**
	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.01)
RMI_2006			-0.49**			-0.35**
			(0.02)			(0.02)
Bank Controls	No	No	No	Yes	Yes	Yes
Volatility Controls	No	No	No	Yes	Yes	Yes
Year-Quarter FE	No	Yes	Yes	No	Yes	Yes
Observations	497	497	431	497	497	431
R^2	0.09	0.35	0.38	0.31	0.38	0.41

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

Table C.5: Shape of Penalties – Placebo Tests

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, *Bank Controls* include the ratio of quarterly net income-to-assets and the log of total assets. *Volatility Controls* include the volatilities of commodity, S&P 500, Foreign Exchange, and Interest Rate indices. *Red* is an indicator variable equal to 1 when the bank has ten or more VaR exceptions in the past 3 quarters. For the base specification (columns 3-4), *Yellow* is an indicator variable equal to 1 when the bank has four to nine VaR exceptions in the past 3 quarters, with those having fewer than that many exceptions classified as the *Green* (omitted) group. Columns (1-2) provide estimates of placebo tests where the Green/Yellow threshold is (incorrectly) placed at three VaR exceptions in the past 3 quarters (rather than four), with column (1) representing the test using the full sample, and column (2) constraining the test to the sample nearest to the threshold (See Table 4 for details on the main test). Columns (3-4) reproduce the base results using the correct threshold of four, and columns (5-6) and columns (7-8) estimate placebo tests with the threshold at five and six trailing exceptions, respectively. 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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Placebo		True Threshold		Placebo		Placebo	
Green/Yellow Threshold	3	3	4	4	5	5	6	6
(z)log(Eq/A)	-0.40*	-1.59	-0.34*	-1.94*	-0.44*	-1.75	-0.44*	-1.50
	(0.08)	(0.34)	(0.08)	(0.07)	(0.10)	(0.35)	(0.10)	(0.33)
Yellow	-0.03	-0.61	0.51*	1.06	0.29	-0.89	0.47	-1.78
	(0.82)	(0.20)	(0.06)	(0.36)	(0.39)	(0.28)	(0.10)	(0.41)
(z)log(Eq/A) * Yellow	-0.48	-0.78	-0.81*	-1.56**	-0.49	0.58	-0.51	1.03
	(0.17)	(0.23)	(0.06)	(0.04)	(0.24)	(0.52)	(0.26)	(0.39)
Red	0.45		0.61		0.49		0.52	
	(0.45)		(0.31)		(0.42)		(0.36)	
(z)log(Eq/A) * Red	-0.39		-0.40		-0.32		-0.33	
	(0.23)		(0.20)		(0.34)		(0.33)	
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Volatility Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	445	67	445	67	445	67	445	67
R^2	0.52	0.77	0.54	0.85	0.51	0.76	0.51	0.76

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

Table C.6: Base Specification Excluding Observations from 2007q3-2009q4

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 for observations outside the financial crisis (2007q3-2009q4). *Exceptions* is the number of times the bank had losses that exceeded their self-reported Value-at-Risk during the next quarter, *1(Exception)* is an indicator variable equal to one if the bank experienced at least one exception 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.

	(z)Exceptions			1(Exception)		
	(1)	(2)	(3)	(4)	(5)	(6)
(z)log(Eq/A)	-0.03**	-0.04**	-0.02	-0.03*	-0.04**	-0.05
	(0.05)	(0.04)	(0.73)	(0.08)	(0.02)	(0.46)
(z)log(Total Assets)	0.03**	0.03*	0.06	0.03**	0.03	-0.05
	(0.02)	(0.06)	(0.55)	(0.04)	(0.17)	(0.57)
(z)NI-to-Assets	0.02	0.04**	0.04*	0.01	0.05**	0.05
	(0.15)	(0.05)	(0.06)	(0.53)	(0.05)	(0.14)
(z)Vol-Commodities	-0.00	0.01	0.01	-0.01	0.01	0.01
	(0.68)	(0.60)	(0.66)	(0.58)	(0.62)	(0.61)
(z)Vol-S&P 500	0.10**	0.23***	0.22***	0.12***	0.29***	0.29***
	(0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
(z)Vol-Foreign Exchange	-0.01	-0.00	-0.00	-0.02	-0.02	-0.02
	(0.76)	(0.96)	(0.92)	(0.26)	(0.34)	(0.45)
(z)Vol-Interest Rate	-0.00	0.02	0.02	-0.01	0.03	0.04
	(0.92)	(0.41)	(0.45)	(0.71)	(0.54)	(0.47)
Bank FE	No	No	Yes	No	No	Yes
Year-Quarter FE	No	Yes	Yes	No	Yes	Yes
Observations	359	359	359	359	359	359
R^2	0.11	0.23	0.27	0.08	0.24	0.30

p-values in parentheses

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

Exhibit C.1: VaR Calculation for Economic Significance.

Our regression estimates are based on the level of VaR exceptions. In order to compute the economic importance of VaR under-reporting, we need to invert the number of exceptions back to the extent of under-reporting. Without the knowledge of the risk-model of the bank, this is an impossible task. However, we can provide some rough estimates based on simplifying assumptions. We do so in this section by assuming a very simple VaR model – one based on normally distributed asset returns. For such a model, the 99% VaR is simply given by: $VaR\_99 = 2.33 \times \sigma$, where σ is the standard deviation of the portfolio. In this model, under-reporting translates into assuming a lower than true σ by the bank. Let's assume that banks under-report their risk by a percentage ur. Then the reported VaR equals $2.33 \times \sigma \times (1 - ur)$. Let $\tilde{X}$ be the return on this portfolio on a given day. Thus the probability of exception with under-reporting on a given day is given by the following:

$$Pr\{\tilde{X} < -2.33 \times \sigma \times (1 - ur)\}$$

Let Z be a standard normal random variable. Then, with $\tilde{X}$ as normally distributed with mean zero and standard deviation of σ, we can easily compute this probability as follows:

$$Pr\{\frac{\tilde{X}}{\sigma} < -2.33 \times (1 - ur)\} \implies Pr\{Z < -2.33 \times (1 - ur)\}$$

We solve this equation for ur such that the probability of exception matches with our empirical estimates. Recall, we find that one standard deviation decrease in equity capital results in an increase of 1.28 exceptions per quarter. Assume 63 trading days in the quarter, which gives 0.63 exceptions per quarter for truthful reporter. Thus, we have 1.28+0.63=1.91 exceptions for banks that have one standard deviation lower equity capital than a truthful reporter. Assuming independence across days in the quarter, this translates into a probability of 1.91/63=0.0303. Put differently, our estimates suggest 3.03% exceptions compared to 1% that is expected for a 99% VaR model. Thus we need to solve for ur such that the following holds:

$$Pr\{Z < -2.33 \times (1 - ur)\} = 0.0303 \tag{14}$$

Using standard normal table, we find that: $-2.33 \times (1 - ur) = -1.88$, which in turn gives $ur = 19.3\%$. Thus our regression estimates translates into an under-reporting of 19.3% under these assumptions.