Strategic Risk-Modelling by Banks: Evidence from Inside the Black Box*

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Abstract

Regulators condition bank capital on risk but struggle to measure risk accurately. Capital requirements thus rely on inputs from banks' internal risk models and banks have discretion on their modelling choices in several ways. Using novel hand-collected data we find systematic differences in reported risk for the chosen simulation method, holding period and historical data size. Hence, modelling choices can be a significant channel of underreporting of risk by banks. Consistent with this presumption we find that banks with low equity capital choose less conservative methods.

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"one element of the Committee's post-crisis reform agenda has yet to be fully finalised: the market risk framework"

- William Coen (former Secretary General of the Basel Committee on Banking Supervision), 25 April 2018 -

1 Introduction

Excessive bank leverage incentivizes risk-taking and reduces banks' capacity to absorb shocks. Insufficient leverage, instead, impairs profitability and might cause aggressive search-for-yield behavior. Regulators attempt to balance these financial stability concerns by conditioning required capital on asset risk but face the challenge of measuring exposures accurately. Risk-sensitive capital requirements thus rely heavily on inputs from banks' internal risk models. These internal models can capture bank-specific risks better than external assessments but using them for regulatory purposes incentivizes strategic modelling. The academic literature has indeed shown that banks underreport risk to alleviate capital constraints (e.g., Mariathasan & Merrouche, 2014; Begley et al., 2017; Plosser & Santos, 2018; Benetton et al., 2021; Behn et al., 2022). Similarly, the ECB's recent "Targeted Review of Internal Models" documents that banks' modelling choices contribute to the underestimation of their capital requirements (ECB, 2021). These findings have implications for policy. The Fed's recent Basel III endgame proposal abandons the use of internal models among U.S. large banks for credit and operational risk (Federal Reserve, 2023). For market risk, banks will continue to rely on internal models. However, little is known about banks' modelling choices for market risk and their effects on capital requirements.

Our paper aims to close this gap in the literature. We use novel data to document the disclosure and adoption of different market risk model characteristics across global banks and over time. We further investigate whether modelling choices at the discretion of banks are a potent channel of underreporting of risk. To this end we analyze how disclosed model characteristics relate to predicted Value-at-Risk (VaR) and the frequency with which predictions are exceeded ex post.

Banks' modelling choices for market risk affect capital requirements in two ways. First, lower VaR translates into lower VaR-based capital charges. Second, if actual losses exceed VaR too often, regulatory scrutiny and capital charges increase via a multiplier. Banks having capital-saving motives may prefer to use models that result in lower capital requirements in terms of VaR without being too inaccurate as frequent violations result in penalties.

We test for the presence of systematic differences in banks' internal model outcomes from using three model characteristics on which banks have discretion. When modelling risk banks can choose the methodology or simulation engines, a lookback period longer than the minimum, and calculate the 10-day VaR directly, or alternatively, obtain a one-day VaR and rescale it using the square root of time approximation.

Similar to Begley et al. (2017), we hand-collect data on banks' internal models from banks' publicly available financial reports covering 17 global banks from the United States, Canada and Europe over the period from 2002 to 2019. These banks consistently report VaR and VaR violations in their quarterly reports throughout our sample period and represent a disproportionately large fraction of trading assets in the world economy. Different from existing work, however, we do not treat internal models as black boxes and extract information on whether banks use Monte Carlo (MC) or other simulation methods, whether they rely on internally determined exposures over a 10-day holding period or on extrapolations from a one-day horizon, as well as their discretionary use of historical data.

Following the theoretical risk management literature, we expect (i) that MC leads to higher and more accurate risk estimates as it incorporates more scenarios via randomization relative to the other simulation methods (like historical simulation); (ii) that 10-day VaR is higher and more precise when extrapolated from a one-day VaR for banks with a dynamic trading portfolio with frequent position changes; (iii) that in normal times using more historical data leads to higher and more precise risk estimates as using more historical information includes more volatility and improves the quality of predictions.

We find that banks' reported risk can be 10 percent to 50 percent lower depending on the simulation method, the horizon, and the length of the historical data used. Precisely, our most conservative results indicate that (i) using MC implies a 10 percent increase in estimated risk; (ii) the external approximations of the 10-day VaR induces a 13 percent increase in estimated risk; and (iii) the use of more-than-required historical data a 50 percent increase in estimated risk. Importantly, we find that outside periods of high volatility, that is most of the time, these reductions in reported risk do not translate into frequent errors and penalties. Therefore since the banks in our sample have large trading portfolios shifting from one modelling approach to another may translate into economically significant variations in aggregate capital ratios.

Having established a significant link between model characteristics and capital requirements we provide direct evidence that (capital) constrained banks choose looser models: low equity banks have a 30 percent lower probability on average of making conservative modelling choices. They are indeed less likely to use a MC simulation method and less likely to calculate the 10-day VaR internally or to use a lookback period longer than the minimum.

Our paper makes three main contributions. First, by providing evidence from inside the black box of banks' internal models, we deepen our understanding of *how* banks underreport risk and manipulate risk assessments in practice. Importantly, our unique focus on banks' internal model characteristics resonates well with initiatives like the ECB's "Targeted Review of Internal Models" and can further inform regulators about the direct mechanisms linking model characteristics to bank capital requirements. We thus make a significant contribution to the literatures on regulatory arbitrage (e.g., Acharya et al., 2013; Boyson et al., 2016; Buchak et al., 2018) and risk-weight manipulation (e.g., Mariathasan & Merrouche, 2014; Begley et al., 2017; Plosser & Santos, 2018; Benetton et al., 2021; Behn et al., 2022) which provide indirect evidence of strategic modelling. Second, our results highlight the importance of studying *banks' use* of different models in addition to their formal properties. This way, we complement the risk management literature that typically analyzes model characteristics theoretically or via simulations, but does not consider the effects of regulation. For instance, assuming independent daily risk events, as one implicitly does when extrapolating from the one-day holding period, should reduce VaR, but as we show corresponds to higher reported predictions in practice. Finally, our data corroborates recent evidence that banks' modelling choices converge to peer benchmarks (Böhnke et al., 2023; Gandhi & Purnanandam, 2023; Rhee & Dogra, 2024). While this may be the reason that strategic risk-modelling is difficult, it runs, in some ways, counter to the original philosophy behind the use of internal models for regulation. When individual banks adopt more similar models over time, this not only implies that the model is less likely to reflect bank-specific risk factors, it also follows that the system as a whole becomes more vulnerable to the model's blind spots.

We conclude that capital requirements based on inputs from banks' internal models can be compromised by strategic modelling, but that the degree of the distortion depends on the model characteristic. Concerns, such as by the former Secretary General of the Basel Committee on Banking Supervision (BCBS) William Coen, who for banks' credit risk-modelling called for "*external audit to play a role in assessing a bank's risk weightings*" (Financial Times, 2019), therefore extend to market risk internal models.[1] Our results suggest that the use of market risk internal models for regulation could be improved if the regulator insists more vigorously on modelling choices that reliably deliver more conservative and precise estimates (such as MC) and that are less prone to be affected by capital-saving incentives (such as the use of more historical data).

The remainder of the paper is organized as follows: Section 2 provides further background on the use of internal models for regulation; Section 3 summarizes the existing literature on regulatory arbitrage and manipulation using internal models and discusses model characteristics in more detail; Section 4 describes our data and empirical strategy. Subsequently, Section 5 discusses our results and Section 6 concludes.

2 Background

Capital requirements reduce banks' risk-taking incentives ex ante and the likelihood of financial distress ex post. Because they also increase financing costs, these benefits need to be weighed against banks' incentives to invest less or to engage in more aggressive rent-seeking (Carletti et al., 2020). As a consequence, when capital requirements are too low, solvency risk increases; when they are too high, funds may not be allocated efficiently. To manage this trade-off for heterogeneous banks, the Basel Committee on Banking Supervision (BCBS) introduced risk-sensitive capital charges within Basel I in 1988. For credit risk, risk weights were initially coarse and determined by the BCBS, but allowed to be based on banks' internal risk models starting from Basel II. The so-called "internal-ratings based approach" (IRB) has improved risk sensitivity, but

[1] It is not always the case that banks use their internal models for both credit and market risk, but it is more likely to happen among larger banks. This is because only banks whose assets exceed a certain threshold have a choice between the internal model approach and the standardized approach for market risk.

also enabled the manipulation of risk weights especially among capital-constrained banks (e.g., Mariathasan & Merrouche, 2014; Plosser & Santos, 2018).

The lowering of capital charges through opportunistic modelling remains a concern for regulators and concerns more than just credit risk, as can be seen from ongoing revisions of Basel rules. For instance, the Basel III finalization package replaced four existing approaches to operational risk by a single standardized approach. Also, the package has set for credit and market risk a so-called "output floor" that limits the reduction in risk weights internally computed by banks to 72.5% of the weights computed using the standardized approach (BCBS, 2017).

Market risk internal models have been less scrutinized despite their longer use for regulation relative to credit risk internal models. The market risk framework has also become more risk-sensitive: first through adopting Stressed VaR in addition to simple VaR and, more recently, Expected Shortfall (ES). Although the BCBS has moved towards ES as the basis for capital requirements (BCBS, 2019), banks and regulators will continue to rely on VaR for model validation and for additional capital charges based on the number of VaR violations. Moreover, more tail risk-focused ES is more sensitive than VaR to some modelling choices, for example, the length of historical data (Yamai & Yoshiba, 2005). Studying the role of banks' modelling choices for market risk is therefore relevant to better understand how banks model and underreport risk in practice and how banks' capital-saving incentives interact with the theoretical properties of modelling choices that we review in the following section.

3 Related Literature

While our paper contributes to the broader literature on regulatory arbitrage (e.g., Acharya et al., 2013; Boyson et al., 2016; Buchak et al., 2018; Gandré et al., 2022), the focus is on the strategic use of internal models for bank capital regulation. In the context of credit risk, Prescott (2004) and Blum (2008) offer early formal analyses of banks' incentives to misreport risk. Both emphasize the importance of complementary policies, such as contingent auditing or an additional leverage requirement, to elicit truthful disclosure. Similarly, Colliard (2019) also considers the trade-off between costly auditing and risk-sensitive capital regulation that relies on truthful reporting by banks. He emphasizes the role of bank supervisors, and adds the insight that national supervisors that do not account for cross-border externalities may be more inclined to permit biased modelling than supranational regulators. Carletti et al. (2021) show that high discrepancy in policies of central and local bank supervisors in turn induces riskier bank portfolios.

Kupiec & O'Brien (1995) and Hendricks & Hirtle (1997) provide early discussions of the internal model approach for market risk introduced by the BCBS in 1996 (BCBS, 1996). They emphasize the advantages of using internal models for improving risk sensitivity, but also point out challenges for model quality and regulatory oversight. Cuoco & Liu (2006) analyze a mechanism that relies on banks' reported VaR and its subsequent validation similar to the internal model approach for market risk in practice. Their model predicts that such mechanism can simultaneously reduce risk-taking and elicit truthful reporting if the threat of higher capital requirements in the future is sufficiently strong.

Like the theoretical literature, the recent empirical literature has mostly focused on the strategic use of internal models for credit risk (e.g., Mariathasan & Merrouche, 2014; Plosser & Santos, 2018; Benetton et al., 2021; Behn et al., 2022). Overall, these papers support the "manipulation hypothesis" that is the key insight from existing theoretical work. Plosser & Santos (2018), for example, show that highly leveraged banks tend to lower their capital requirements via internally computed risk estimates that contain little information on loan prices. Niepmann & Stebunovs (2020) also identify strategic behavior by European banks that have lowered their projected loan losses through model changes between the European Banking Authority's stress tests in 2014 and 2016.

Different from the literature on credit risk, however, the evidence on strategic modelling of market risk is scarce. One important exception is Begley et al. (2017), who use hand-collected data to show that banks underreport market risk when their next VaR violation triggers additional regulatory scrutiny. We use hand-collected data on VaR and VaR violations as well, but focus on the role and adoption of different model characteristics. As the first contribution, our results corroborate the hypothesis that banks use internal models for market risk to reduce capital requirements as they do via credit risk internal models. Second, and more importantly, our paper is the first (on credit and market risk) to analyze *how* banks underreport risk in practice. With this focus, our paper bridges the gap to the risk management literature that analyzes the quality of risk predictions based on conventional statistical methods (e.g., Danielsson & Zhou, 2017). Different from our paper, Sizova (2024) does not explore the role of model characteristics and focuses on the effectiveness of model-based regulation.

The regulator sets quantitative and qualitative standards for the internal models for market risk, and requires banks to disclose some model inputs (BCBS, 1995). The BCBS imposes few requirements on methods that are allowed in banks' internal models except that the models must be validated. Banks often rely on either historical (HS) or Monte Carlo (MC) simulation in the internal models. According to recent evidence and our illustration in Figure 1, many banks move away from MC towards HS (e.g., Pérignon & Smith, 2010; Mehta et al., 2012; O'Brien & Szerszen, 2014). HS is simpler than MC and imposes no assumptions on the shape of loss distribution. HS relies on historical patterns and assumes that these are a valid indicator for the future. Importantly, risk measures based on HS can be inaccurate for a given finite sample. Pérignon & Smith (2010), for instance, argue that historical VaR does not predict future volatility well and Pritsker (2006) discusses refinements to HS when correlations in the trading book are time-varying. Lastly, Danielsson & Zhou (2017) show that HS performs poorly in times of structural breaks.

In contrast, MC simulation relies on many assumptions about asset classes, risk types, prices and implied volatilities. MC takes the non-linearity of options and other derivatives into account and produces more diverse scenarios than HS. Similar to HS, MC draws on historical data, but uses it to compute sensitivities of and correlations between different market factors. MC is therefore more elaborate than HS, but more demanding to implement. MC can also be more difficult to interpret for risk management purposes.

Based on the theoretical properties, we therefore expect that MC yields higher and more precise VaR via a wider range of generated scenarios compared to HS. Higher VaR should correspond to higher VaR-based capital charges, but fewer VaR violations reduce the likelihood of the additional capital charge for underreporting risk. Thus, the chosen method can have an effect on bank capital requirements for which we empirically test below.

Another standard set by the BCBS for market risk internal models is the holding period of 10 trading days (BCBS, 1995). The holding period refers to the assumed time during which the positions in the trading book remain unchanged. Fixed trading positions of 10 days, however, are not plausible for banks with dynamic trading portfolios and Sharma (2012) suggests that more frequent position changes cause models to underestimate risk. Banks are allowed to assume a holding period of one day and multiply one-day VaR by $\sqrt{10}$ in order to determine the 10-day VaR required for capital requirements.[2] The "square-root-of-time" scaling assumes independent daily risk events and works well for linear products and under normal market conditions, but then understates exposures (Dacorogna et al., 2001).

Thus, the effect of the holding period on VaR can be different depending on whether we focus on cross-sectional or time-series variation. The one-day holding period can imply lower VaR in specific times as the theory suggests and the 10-day holding period can imply lower VaR for specific banks. This should in turn affect the number of VaR violations and bank capital requirements. Whether the effect of computing VaR over the 10-day holding period internally dominates the effect of extrapolations remains an empirical question that we tackle below.

Also, the BCBS requires banks to use minimum one year of historical data in the internal models (BCBS, 1995). The regulator aims to secure a minimum data amount for accurate forecasts and give banks the flexibility to choose an appropriate observation period. The benefits, however, come with potential costs. First, setting only a lower bound grants banks discretion to affect predictions by strategically selecting the estimation window. Second, evidence (e.g., Jorion, 2002; Sharma, 2012) suggests that the minimum lookback period of one year may be detrimental to the model's ability to forecast volatility. The question of the optimal observation period remains in light of the recent switch to ES for market risk capital requirements (BCBS, 2019). Since ES is further in the tail of loss distribution and more sensitive to the sample size than VaR, a minimum

[2] Basel III requires banks that decide to use a holding period shorter than 10 days to provide a good justification to a supervisor upon request (BCBS, 2010). Basel III also introduced Pillar III Disclosures, i.e., qualitative and quantitative disclosures regarding regulatory capital for credit, market and operational risks. The United States were first to phase in Pillar III Disclosures in 2013 (Federal Reserve, 2012). As part of Pillar III Disclosures, banks must disclose the regulatory 10-day VaR for market risk capital requirements.

of one year of historical data may no longer be sufficient to maintain the same quality standards (Yamai & Yoshiba, 2005).

We therefore expect that using more than one year of historical data should lead to higher and more precise VaR as using more historical information should improve the quality of forecasts. The chosen observation period can hence affect bank capital requirements. To pin down the effect of lookback period, it is important to control for time-series variation to absorb the mechanical effects that the observation window can have on predictions moving along low and high volatility times.

4 Data and Methodology

4.1 Sample

Because the strategic use of internal models is more likely to be concentrated in larger institutions (Gehrig & Iannino, 2021), we restrict attention to 17 of the largest banks from the United States, Canada and Europe. These banks consistently disclose the information we need and represent a disproportionate share of the world trading activity. They also often act as broker-dealers in addition to trading on their own accounts. Begley et al. (2017) use the same sample. Our sample is updated to span the period between 2002Q1 and 2019Q4 and integrates detailed data on the banks' risk model characteristics in addition to the reported VaR and VaR violations. Because banks do not make all information available in all quarters, our sample consists of 928 to 728 bank-quarter observations (depending on the model characteristic).[3]

[3] We do not use data from 2020Q1, to avoid effects related to the COVID-19 pandemic. The additional capital multiplier for underreporting risk, for instance, was frozen at the onset of the pandemic.

We complement our hand-collected data with bank balance sheet data from Fitch, Orbis Bank Focus and S&P Global Market Intelligence (former SNL Financial) and macroeconomic data (foreign exchange, interest rate, market and commodity volatility measures) from the St. Louis Fed, International Financial Statistics, and Eikon. Table 1 presents the definitions of and Table 2 provides summary statistics for all variables used in our analyses including our control variables. The banks in our sample display more difference in reported risk, modelling choices and equity than in size and profitability.

Table 3 reports summary statistics for VaR and VaR exceptions at the bank level. The average number of VaR violations per quarter in our winsorized sample is 0.35 (0.36 if not winsorized); using a 99% VaR model, one expects to have VaR exceeded once in every 100 trading days, or have 0.63 exception per quarter. This implies that banks' internal models in our sample are on average accurate. But this accuracy varies considerably over time: from 2002 to 2006 it is 0.1, from 2007 to 2010 it is approximately 1.1, and from 2011 to 2019 it is around 0.2. The internal models thus overestimate market risk in normal times, but − importantly − underestimate risk during the crisis.

Model characteristics are hand-collected from the banks' publicly available quarterly, annual reports and Pillar III Disclosures. We observe whether banks use MC and/or other methods (HS, or a mix of both methods or the variance-covariance approach, see Figure 1); whether 10-day exposures are approximated from the one-day holding period (see Figure 2); and the amount of used historical data (see Figure 3). The focus on these characteristics is determined by the data availability with sufficient cross-sectional and/or time-series variation. In Figure 1 we see that the simulation method varies across banks but much less over time (banks adopt a method and seldom switch to another method). Figure 2 shows that the horizon varies significantly both across banks and over time while Figure 3 displays variation across banks but almost no within-bank time variation in the amount of data used. These observations are confirmed in Table 4 which reports descriptive statistics of model characteristics by bank.

4.2 Empirical Specification

Our main dependent variables are the natural logarithm of banks' self-reported VaR and the number of VaR exceptions. Figure 4 motivates the use of the logarithm transformation for the VaR. Our explanatory variables are indicators for different model characteristics. MC_{it} is a dummy variable equal to one whenever banks report the use of MC simulation, independent of whether they only use MC or whether they combine it with other simulation methods.[4] $1\text{-}DayHorizon_{it}$ is a dummy variable indicating whether bank i reports only the one-day holding period VaR at quarter t (as opposed to disclosing the 10-day VaR) and $Lookback_{it}$ is equal to one if bank i's observation window at quarter t exceeds the regulatory minimum of one year. The baseline panel regression explaining banks' reported VaR is:

$$\log(VaR_{it}) = \beta ModelCharacteristic_{it} + \gamma X_{it} + \theta V_{it-1} + \alpha_i + \delta_t + \varepsilon_{it}, \tag{1}$$

where $ModelCharacteristic_{it}$ is an indicator capturing one of model characteristics: MC_{it} for the methodology, $1\text{-}DayHorizon_{it}$ for the holding period, $Lookback_{it}$ for the length of historical data. α_i and δ_t are bank and year-quarter fixed effects, X_{it} is a vector of relevant bank-level controls (log(Assets), NI-to-Assets) that control for the size of the trading portfolio and the profitability of the bank or the quality of its assets. V_{it-1} is a vector of lagged country-level measures of market,

[4]Alternatively, we could have contrasted the exclusive use of MC simulation with the exclusive use of HS. While this results in a smaller sample and reduces our ability to perform analyses, we have verified that our main results are more pronounced when the contrast is clearer.

exchange rate, interest rate and commodity volatilities (log(S&P 500 Volatility), log(Interest Rate Volatility), log(Exchange Rate Volatility), log (Commodity Volatility)) to account for time-varying heterogeneity across countries.[5] *Lookback* is time-variant only for one bank in our sample, so we consider the specification without bank fixed effects when including it.[6]

We estimate fixed effects models with clustering of standard errors at the year-quarter level.[7] Bank fixed effects control for unobserved differences, notably in modelling capabilities and risk culture across banks (Fahlenbrach et al., 2012), while year-quarter fixed effects capture the effects of global- and period-specific shocks on the performance of banks' risk models (including the global financial crisis). Fixed effects models are standard for finance panels with relatively low cross-sectional and time-series dimensionality (e.g., Petersen, 2009; Clark & Linzer, 2015), and we draw further confidence in the setup from (unreported) tests of (a) the joint significance of our bank FEs, (b) a comparison with the first difference estimator, and (c) the robustness of our main results to a random effects specification.

For the number of VaR exceptions that is a count variable, we have the choice between a Poisson and a negative binomial (NB) regression model. Given that VaR violations are non-negative integers and Figure 5 suggests that their distribution is highly skewed to the right, we cannot rely on a linear regression model. Together with a variance of VaR exceptions that is more than four times as large as its mean (1.53 vs. 0.35 as given in Table 2), Figure 5 also indicates overdispersion, leading us to use a NB model. We nevertheless run the Poisson regression and check its goodness-of-fit using a χ^2-test. The χ^2-test rejects the use of the Poisson regression consistent with the affirmative result of a likelihood ratio test for the NB regression. Since we have lots of

[5] Volatility measures are one-period lagged, since VaR should reflect past realized volatility (Begley et al., 2017).

[6] Morgan Stanley uses four years of historical data till 2019Q2 and then starts to use one year.

[7] We follow the practitioner's guide by Cameron et al. (2015) to decide at what level we cluster the standard errors. Since we have only 17 banks, an unbalanced panel clustering at the bank level would cause small sample bias.

zero observations in the VaR exceptions' distribution, we use a zero-inflated (ZI) model instead of a standard model. The ZI estimation exploits a specified set of variables to distinguish between two latent groups of observations which can be "always zero" by definition, or reflect the realization of the Poisson or NB distribution, which can be equal to zero or positive counts. The Akaike and Bayesian information criteria take the lowest values and identify a superior fit for the ZINB model relative to the other candidate models. We estimate the following ZINB model with bank and/or year-quarter fixed effects explaining banks' reported number of VaR exceptions:

$$Exceptions_{it} = \beta ModelCharacteristic_{it} + \gamma X_{it} + \theta V_{it-1} + \alpha_i + \delta_t + \varepsilon_{it}. \tag{2}$$

5 Are model characteristics potent channels of underreporting of bank risk?

To answer this question positively two conditions must be fulfilled. First, certain modelling choices must allow banks to significantly save on capital through a reduction in reported risk, as measured by the VaR. Second, the reduction in reported risk must not be counterproductive. This would be the case if it leads to frequent inaccuracies that trigger penalties in the form of higher capital charges. Hence we explore the effects of various model characteristics on VaR, VaR violations and penalties.

5.1 Value-at-Risk

Table 5 reports the results from studying the relationship between banks' self-reported VaR and risk model characteristics (equation 1). The estimates in columns (1) to (11) of Table 5 feature each model characteristic separately with different combinations of fixed effects. The result for *MC* in column (1) with time fixed effects and in column (2) with bank fixed effects imply that using a *MC* simulation method rather than a method solely based on historical data increases reported risk by 19 percent to 30 percent. When we include both time and bank fixed effects in column (3) the estimated effect falls to a 10 percent reduction in VaR but remains economically significant, albeit at the 10 percent level. Owing to the limited within bank time variation in *MC* it is not surprising that the effect is less precisely estimated if we include both bank and time fixed effects. The preferred specification is therefore the speciciation that controls for time fixed effects and exploits cross-sectional variations in *MC*.

The positive relationship between MC and VaR is aligned with the risk management literature. MC produces a wider range of scenarios via randomization compared to the other methods such as historical simulation.

We check whether the results are altered when we exclude the years 2008 and 2009 characterized by a very high market volatility from the sample. The results, reported in the Appendix Table A0, can be interpreted as evidence that the differences in reported risk between MC and other simulation methods are more pronounced during crisis. This may translate into a better accuracy of risk measures using MC compared to other methods during periods of financial instability.

In columns (4) and (5) of Table 5 we report the results for *1-Day Horizon* using the same specification. As expected we find that a bank that shifts from measuring the 10-day VaR directly to deriving it from the 1-day VaR obtains more conservative VaR estimates: banks with a dynamic trading protfolio that use directly a 10-day holding period to calculate the VaR underestimate risk. The most conservative of the two estimates implies a 13 percent increase in VaR for banks that report a 1-day VaR. In columns (6) and (7) the results remain stable when we control simultaneously for the chosen simulation method and horizon. We next explore the effect of using a longer observation period in columns (8)-(9). Here we do not include bank fixed effect since the variable *Lookback* barely displays any variation over time. Instead, we consider a specification with no fixed effects and a specification with time fixed effects. We find that using a longer observation period is associated with a higher VaR in both specifications. These results are stable if we include or not time fixed effects and if we simultaneously control for the chosen simulation method in columns (10) and (11).

All in all, our results indicate that banks can significantly alter the level of reported risk and save on capital through changing their methods and data. Even our most conservative estimates are economically significant. Indeed, a 10 percent drop in reported risk translates into a significant drop in capital requirements for a group of banks whose trading portfolio represents a significant share of their total assets. The next question is whether they can do so most of the time without undermining too significantly the accuracy of their models and triggerring sanctions.

5.2 Exceptions and Penalties

Table 6 reports the results from examining the relationship between banks' self-reported VaR exceptions and internal model characteristics (2). It is organized like the VaR table: columns (1) to (11) give specifications with different combinations of fixed effects: bank fixed effects only, both bank and year-quarter fixed effects, no fixed effects and year-quarter fixed effect.

We consider the ZINB regressions for the count of VaR violations. We report incidence rate ratios (IRRs), where an IRR of x means that banks using a certain model characteristic have x times the number of exceptions of the other banks. The IRR lower than one therefore indicates a negative relationship between the model characteristic and the number of VaR violations, and the IRR higher than one implies a positive relationship between them.

First, we show that banks using MC simulation report significantly fewer VaR exceptions. According to the specification with bank fixed effects in column (2), banks that rely on MC simulation have 57% fewer VaR violations relative to banks that rely on the other methods. The effect remains statistically significant when we add year-quarter fixed effects in column (3). But this effect is likely not large enough to imply more frequent penalties among banks that use alternative methods: the quarterly mean number of VaR exceptions is 0.35 (see Table 2) and banks are sanctionned for underreporting risk only when they record at least 1.25 VaR exceptions per quarter (5 VaR exceptions per year). Indeed, for a 99% confidence level models, an accurate model produces an acceptable 0.63 violations per quarter (63 trading days).

The negative relationship between MC and VaR violations is aligned with the positive effect of MC on VaR. For MC, the findings for VaR and VaR exceptions are therefore consistent with the theory of risk management: MC is associated with higher VaR and fewer VaR violations at the same time.

Next, in columns (4) and (5), we find that banks assuming a one-day holding period for their portfolios report significantly fewer VaR exceptions. According to the specification with bank and year-quarter fixed effects in column (5), banks that use a one-day horizon report 70% fewer VaR violations compared to banks that internally compute 10-day estimates. The results are stable if we control simultaneously for the simulation period and the horizon in columns (6) and (7). But again, these increases in VaR violations relative to the mean of 0.35 violations appear insufficient to trigger (frequent) penalties.

The results for *Lookback* are reported in columns (8) through (11) for different sets of fixed effects and control variables. According to the specification with no fixed effects in column (8), banks that use more data than required report around 38% *more* VaR violations. This is not counterintuitive. Since in this specifications we are only able to exploit cross-sectional variations it is possible that banks using more data on average report higher risk but have also on average less accurate models. And this is mainly driven by data from the crisis period. If we exclude years 2008 and 2009 from the sample this increase in the frequency of VaR violations is smaller in magnitude and insignificant statistically (see the Appendix Table A1). The explanation is simple: inside the storm of a crisis including more data from the pre-crisis period leads to more frequent underestimations of risk.

To confirm that the effects of model characteristics on VaR violations are not sufficiently important to trigger penalties we estimate the effect of model characteristics on the probability of a bank receiving a penalty whereby it is sanctioned with a higher capital charge. The results are reported in Table 7. We estimate a linear probability model and replicate the previous specifications in columns (1) through (11). We find indeed that changes in the chosen simulation methods, holding period, or data have no economically significant effect on the probability of a bank receiving a penalty. The results are robust if we use a logit model instead of a linear probability model (see the Appendix Table A2)

All in all, our results show that most of the time banks can significantly save on capital by opting to use laxer risk models while keeping models that remain sufficiently accurate to escape penalties outside periods of severe economic stress. We will see that during stress times and under tigher supervision banks tend to converge toward tighter models.

The next question we ask is whether banks with low equity effectiviely exploit this opportunity to save on capital.

5.3 Capital-saving incentives and modelling choices: Do banks with low equity capital make less conservative modelling choices?

In Table 8 columns (1) through (6) we report estimates of the relationship between bank equity and the disclosed model characteristics as dependent variables. Banks with low equity have a stronger capital-saving incentive so we expect them to lean toward looser models. For each characteristic we report results from two specifications: one with time and country fixed effects and another with time and bank fixed effects. All columns confirm that banks with low equity choose looser models. On average across the different specifications low equity banks are 30 percent less likely to use a MC simulation method, to extrapolate from a 1-day VaR, and to use more data than required.

To further strengthen our interpretation that these results are indicative of strategic underreporting we analyse what happens when banks' preferences are constrainted by tighter regulatory scrutiny or require approval from the regulator.

In their quarterly reports banks routinely disclose whether they make broader changes to their models that required and received approval from their supervisors. In most cases they also indicate whether the new model is tighter or looser. We have collected this information which gives 252 model changes during 2002-2019, with roughly 60 percent of the new models delivering lower capital requirements.[8]

We hypothesize that low equity banks seek approval more often for looser models and less often for tighter models. However, if supervisors reject looser models for low equity banks the probability of these banks switching to looser models is reduced compared to the case when they have full discretion.

In Table 9 we report estimates of the effect of bank equity on the probability of a model change, a change to a tighter model, and a change to a looser model. In columns (1) and (2) we find no difference between low and high equity banks on the probability of seeking and obtaining approval for a new model (tighter or looser) using different sets of fixed effects. The differences appear when we distinguish between changes toward tighter models and changes toward looser models. In columns (3) and (4) we find that low equity banks have a 12 to 14 percent *lower* probability of seeking and obtaining approval for tighter models. And in columns (5) and (6) we find no significant difference between low equity banks and high equity banks in the probability to have a looser model approved. If we assume that low equity banks seek approval more often for looser models this result confirms that when banks have no discretion on their modelling choices their ability to adopt looser models in order to underreport risk is limited.

To further explore the constraints facing banks in their ability to adopt looser models opportunistically we estimate interaction effects between bank leverage, the number of supervisors per bank (World Bank, 2019), and market volatility. The results are reported in Table 10. In columns (1) to (3) we see that under tighter regulatory scrutiny (measured by the number of supervisors per bank) low and high leverage banks converge toward similar models. As shown in Figures 1 to 3

[8] More information on identifying model changes and their plausible effects on capital requirements can be found in Sizova (2024).

the convergence is toward tigher models, especially in times of heightened market stress.

In columns (4) to (6) we consider the interaction between bank equity and a dummy for periods characterized by a high market volatility (High VIX). In periods of financial instability supervisors may exercise more scrutiny which discourages banks from favoring looser modelling approaches. But at the same time banks face a higher cost of capital during crises which heightens their incentives to save on capital. We find that as a result on average higher market volatility does not systematically translate into a weaker tendency of low equity banks to adopt looser models: the estimated effect of the interaction between bank equity and the High VIX dummy is negative and significant only for *Lookback*.

6 Conclusion

Banks' risk-modelling is affected by capital-saving incentives. Banks appear to take advantage of modelling discretion to favorably influence capital requirements through lower reported exposures without incurring penalties most of the time. We document systematic differences in reported risk for three model characteristics. Our results show that MC improves the precision of predictions and leads to higher predicted VaR. The fact that banks do not frequently use MC and adopt other methods, especially when capital is expensive and supervisory scrutiny is weak, suggests regulatory arbitrage. Furthermore, reporting VaR for the one-day holding period and relying on scaling to arrive at the 10-day exposures required for capital requirements is associated with higher risk estimates but in the post crisis periods banks tend to move away from adopting this approach. This too suggests that banks strategically use the opacity of internal modelling to their advantage.

Overall, our findings are consistent with the hypothesis that banks underreport market risk by making certain modelling choices. They also indicate that strategic modelling is concentrated among banks that are particularly exposed and emphasize that regulators are well-advised to consider robustness to capital-saving incentives along with the theoretical properties of different modelling choices. For operational risk, the BCBS has phased out the use of internal models and returned to the standardized approach (BCBS, 2017). Also, the Fed's recent Basel III endgame proposal to abandon internal models for credit and operational risk suggests that regulators are concerned about banks' use of internal models. Our results indicate that model-based regulation for market risk can be significantly improved. For example, the regulators may consider to set additional standards for achieving higher accuracy (for instance, impose the use of MC) or setting output floors for alternative modelling choices.

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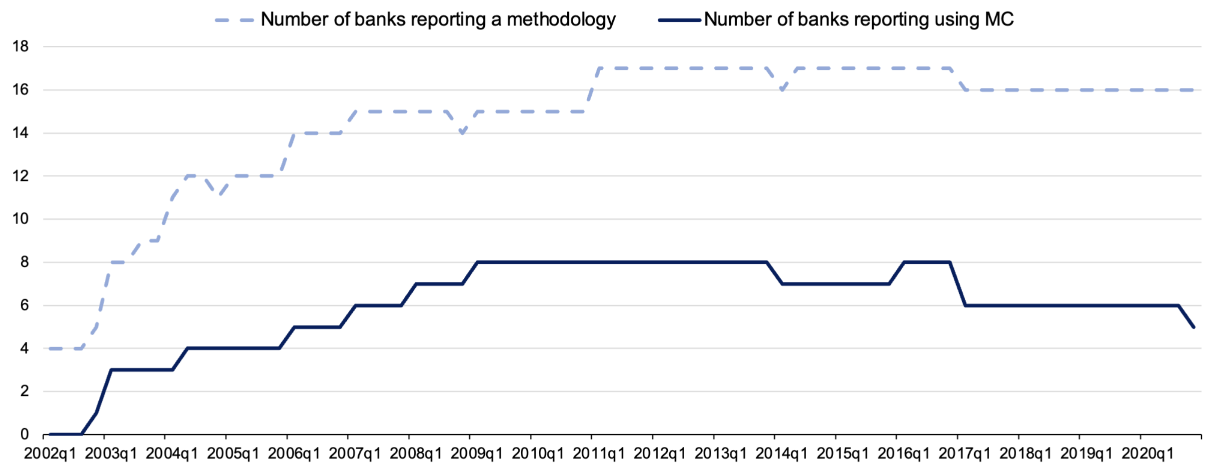
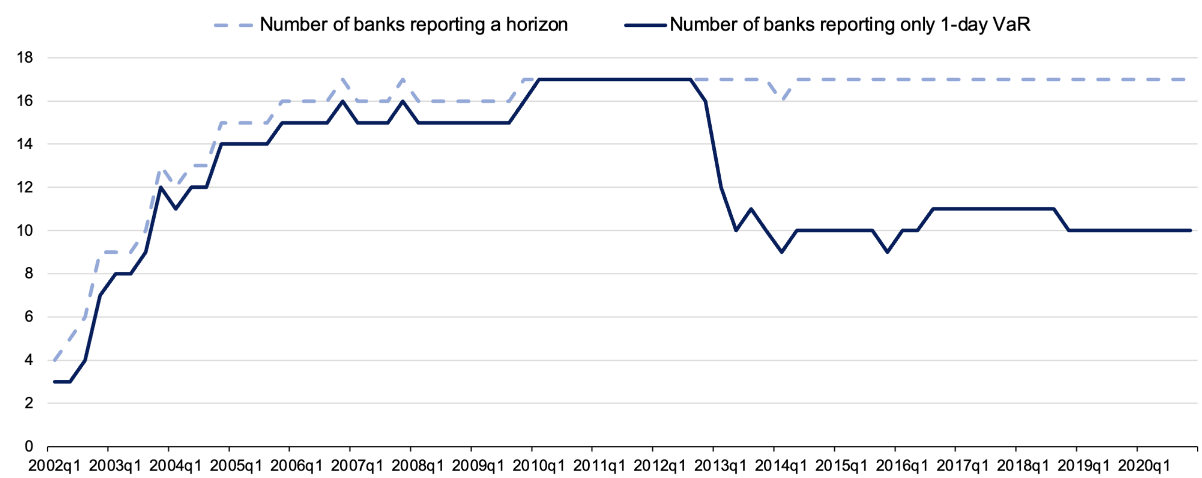
Figures

Figure 1: Number of Banks Reporting the Use of Monte Carlo Simulation



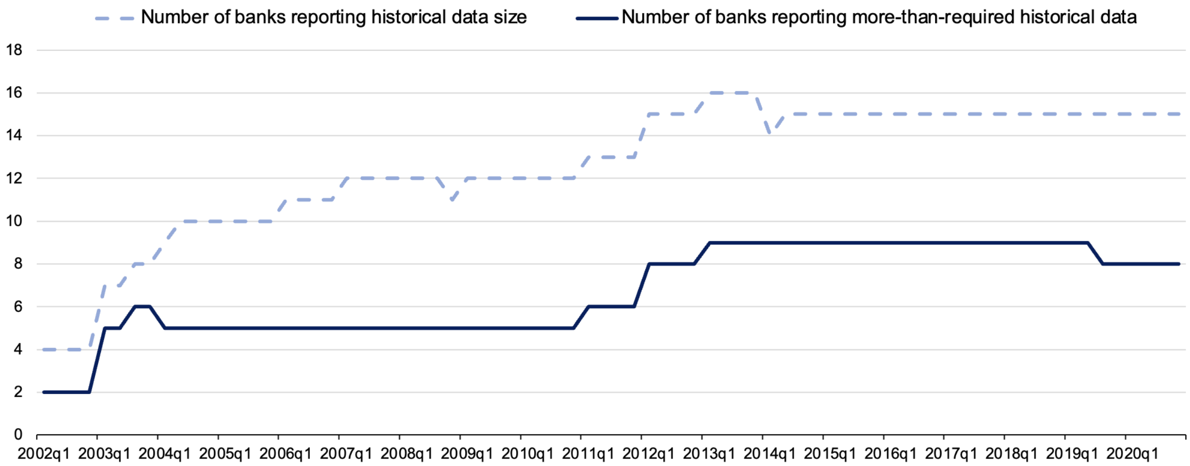
This figure illustrates the quarterly number of sample banks who report the use of Monte Carlo (MC) simulation over the period from 2002 to 2020. The sample covers 17 banks from the United States, Canada and Europe. 2020 data is excluded from the sample for our empirical analysis due to extreme market volatility caused by COVID-19 and the related freeze of the additional capital multiplier for underreporting risk. Only four banks in our sample disclosed the methodology during 2002Q1-2002Q3 and none reported the use of MC. More banks start to disclose their methodology from 2003, including MC. Less than half of our sample banks use MC after the global financial crisis and less than third recently over the COVID-19 period.

Figure 2: Number of Banks Only Disclosing One-Day Value-at-Risk



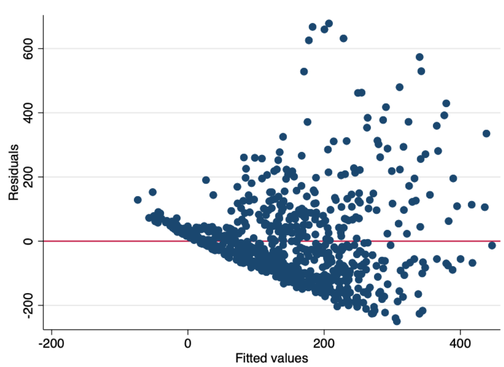
This figure illustrates the quarterly number of sample banks who report 1- but not 10-day VaR over the period from 2002 to 2020. The sample covers 17 banks from the United States, Canada and Europe. 2020 data is excluded from the sample for our empirical analysis due to extreme market volatility caused by COVID-19 and the related freeze of the additional capital multiplier for underreporting risk. The number of banks in our sample who disclose only one-day VaR was increasing till 2010 reaching maximum at 17 banks. Starting from 2013, the number of banks who report only one-day VaR has declined, partially due to the regulatory intervention for U.S. banks (around 35% of our sample) that have been obliged to explicitly calculate 10-day VaR since 2013.

Figure 3: Number of Banks Using More Than One Year of Historical Data

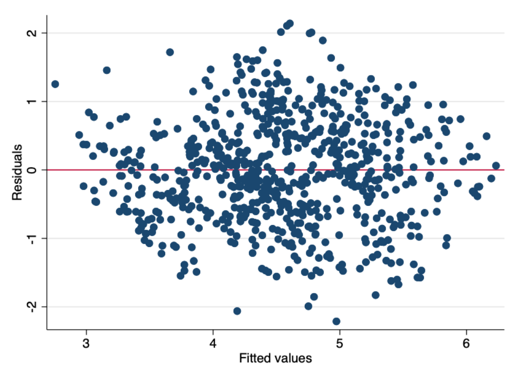


This figure illustrates the quarterly number of of sample banks who use more than one year (regulatory minimium) of historical data in VaR calculations over the period from 2002 to 2020. The sample covers 17 banks from the United States, Canada and Europe. 2020 data is excluded from the sample for our empirical analysis due to extreme market volatility caused by COVID-19 and the related freeze of the additional capital multiplier for underreporting risk. Only one out of sample banks (Bank of Montreal) has never disclosed the length of historical data.

Figure 4: Residual Plots for the Value-at-Risk Regression



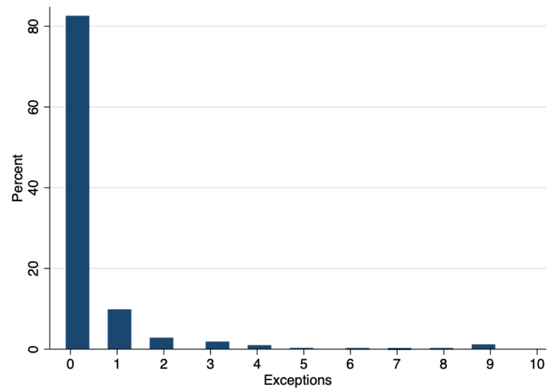
(a) VaR



(b) log(VaR)

These two figures depict the residuals on the vertical axis and the fitted values of the dependent variable on the horizontal axis. The sample covers 17 banks from the United States, Canada and Europe over the period from 2002 to 2019. The plots are based on the following linear regression model (1): $Y_{it} = \beta ModelCharacteristic_{it} + \gamma X_{it} + \theta V_{it-1} + \varepsilon_{it}$. The dependent variable Y_{it} in Figure 1a is VaR, i.e., the 99% 10-day Value-at-Risk (VaR), either self-reported by banks or one-day reported VaR multiplied by the square root of 10. The dependent variable Y_{it} in Figure 1b is log(VaR), i.e., the natural logarithm of the 99% 10-day VaR. $ModelCharacteristic_{it}$ is a vector of our three main explanatory variables which are indicators for the use of Monte Carlo simulation, for reporting only a one-day VaR and for the use of more-than-required historical data, respectively. X_{it} is a vector of bank-level controls (the log of total assets and net income scaled by total assets) and V_{it-1} is a vector of lagged country-level volatility measures (lagged logarithms of S&P 500, interest rate, exchange rate and commodity volatilities). Figure 1b supports the use of the log-transformed VaR for a linear regression model to be appropriate, because the points in Figure 1b (i) are more randomly dispersed around the horizontal axis relative to those in Figure 1a, (ii) more convincingly suggest that the variances of the error terms are equal and (iii) do not include any visible outliers.

Figure 5: Value-at-Risk Exceptions



This figure illustrates the distribution of Value-at-Risk (VaR) exceptions, i.e., the number of days when the actual daily loss of a bank is beyond daily VaR during a given quarter. Exceptions are winsorized at 1% and 99% level. The sample covers 17 banks from the United States, Canada and Europe over the period from 2002 to 2019. The vertical axis represents the percentage of different quantities of exceptions in our sample. Observations are highly dispersed and more than 80% of them are zero, supporting (in addition to the formal tests) the use of the zero-inflated negative binomial regression model for VaR exceptions.

Tables

Table 1: Variable Definitions

Variable Name	Definition
log(VaR)	Quarterly average 99% 10-day Value-at-Risk (VaR) reported by banks in the market risk management-related section of quarterly, annual or Pillar III reports. If unavailable, we use the quarterly average 99% one-day VaR reported by banks in the same reports and multiply it by the square root of 10. The 99% 10-day VaR represents the worst potential loss over a 10-day horizon that should not be exceeded in 99% cases, and is a basis for market risk capital requirements. Figure 4 supports the use of the log-transformed VaR.
Exceptions	Quarterly number of days when the actual daily loss exceeds daily VaR as reported by banks in the market risk management-related section of quarterly, annual or Pillar III reports. Exceptions are winsorized at 1% and 99% level.
Penalty	Dummy equal to 1 when banks are in amber or red zones of the Basel market risk framework and face a penalty in the next quarter. The framework has three zones based on the yearly number of VaR exceptions: green (0-4), amber (5-9) and red (10 or more). When banks are in amber or red zones, they face an additional capital requirement and more supervisory scrutiny.
MC	Dummy equal to 1 when banks report the use of MC simulation, independent of whether they only use MC or whether they combine it with other methods.
1-Day Horizon	Dummy equal to 1 when banks report only the one-day holding period VaR and do not report the 10-day VaR.
Lookback	Dummy equal to 1 when banks report the use of an observation period longer than the regulatory minimum of one year.
log(Equity/Assets)	The natural logarithm of the book value of equity scaled by total book assets.
Model Change	Dummy equal to 1 when banks declare changing their market risk model.
Tight Model Change	Dummy equal to 1 when banks declare changing their market risk models in a way that should result in higher capital requirements.
Loose Model Change	Dummy equal to 1 when banks declare changing their market risk models in a way that should result in lower capital requirements.
Number of Supervisors per Bank	The number of supervisors scaled by the number of banks in a given country according to the World Bank's Bank Regulation and Supervision Survey.
High VIX	Dummy equal to 1 in quarters when VIX excceds 40.
log(Assets)	The natural logarithm of the book value of total assets (control for bank size).
NI-to-Assets	Net income scaled by total book assets (control for bank profitability).
log(S&P 500 Volatility)	The natural logarithm of S&P 500 daily returns' standard deviation over a quarter.
log(Interest Rate Volatility)	The natural logarithm of country-level government bond monthly rates' standard deviation over a quarter.
log(Exchange Rate Volatility)	The natural logarithm of country-level real effective exchange monthly rates' standard deviation over a quarter.
log(Commodity Volatility)	The natural logarithm of Commodity Research Bureau (CRB) index daily returns' standard deviation over a quarter.

Table 2: Summary Statistics

	Mean	SD	Min	Median	Max	N
Main Variables:						
VaR (mln $)	150.19	177.72	8.40	73.00	1078.34	928
log(VaR)	4.42	1.07	2.13	4.29	6.98	928
Exceptions	0.35	1.10	0	0	9	842
Exceptions [raw data]	0.36	1.21	0	0	25	842
Penalty	0.08	0.27	0.00	0.00	1.00	801
MC	0.42	0.49	0.00	0.00	1.00	868
1-Day Horizon	0.75	0.43	0.00	1.00	1.00	928
Lookback	0.52	0.50	0.00	1.00	1.00	728
Equity/Assets (%)	6.06	2.55	1.02	5.38	15.74	928
log(Equity/Assets)	1.72	0.42	0.02	1.68	2.76	928
Model Change	0.23	0.42	0.00	0.00	1.00	928
Tight Model Change	0.09	0.28	0.00	0.00	1.00	928
Loose Model Change	0.14	0.34	0.00	0.00	1.00	928
Number of Supervisors per Bank	0.91	0.67	0.31	1.04	3.00	928
High VIX	0.03	0.17	0.00	0.00	1.00	928
Control Variables:						
Assets (bln $)	1104.67	663.15	77.74	930.96	2764.66	928
log(Assets)	13.70	0.72	11.26	13.74	14.83	928
NI-to-Assets (%)	0.63	0.58	-4.74	0.74	6.36	928
log(S&P 500 Volatility)	-4.75	0.47	-5.65	-4.83	-3.16	928
log(Interest Rate Volatility)	-2.94	1.03	-6.02	-3.00	3.99	928
log(Exchange Rate Volatility)	-4.84	0.72	-8.28	-4.80	-2.72	928
log(Commodity Volatility)	-4.67	0.37	-5.51	-4.63	-3.47	928

This table presents summary statistics for our variables. The sample comprises year-quarter observations for 17 banks from the United States, Canada and Europe over the period from 2002 to 2019. Table 1 presents variable definitions. VaR is the quarterly average 99% 10-day Value-at-Risk (VaR), either self-reported by banks or one-day reported VaR multiplied by the square root of 10. The 99% 10-day VaR represents the worst potential loss over a 10-day horizon that should not be exceeded in 99% cases. VaR is expressed in million U.S. dollars for statistics. Figure 4 supports the use of the log-transformed VaR as a dependent variable. Exceptions is the number of days when the actual daily loss of a bank is beyond daily VaR during a given quarter. Exceptions are winsorized at 1% and 99% level for our analysis (we report raw statistics in a separate row). Penalty is the probability of a bank to be in amber or red zone of the Basel framework in the next quarter. MC is a dummy variable that takes value 1 for the quarter when a bank declares the use of Monte Carlo simulation. 1-Day Horizon is a dummy variable equal to 1 for the quarter when a bank discloses only a one-day VaR and does not report a 10-day VaR. Lookback is a dummy variable that is equal to 1 for the quarter when a bank reports an observation period longer than one year. Model Change is a dummy variable equal to 1 when banks declare changing their market risk model. Tight Model Change and Loose Model Change indicate (when possible) model changes that should result in higher or lower capital requirements, respectively. Data to build internal model-related variables is hand-collected from banks' quarterly, annual reports and Pillar III Disclosures. Equity/Assets is the ratio of total equity to total assets and our measure of bank leverage. Number of Supervisors per Bank is the number of supervisors scaled by the number of banks in a given country according to the World Bank's Bank Regulation and Supervision Survey (World Bank, 2019). High VIX is a a dummy variable that takes value 1 in quarters when VIX excceds 40. Assets represent the book value of total assets and is our control variable for bank size. NI-to-Assets is our measure of bank profitability and is equal to net income scaled by total assets. Log(S&P 500 volatility) is the natural logarithm of S&P 500 daily returns' standard deviation over a quarter. Log(Interest Rate Volatility) is the natural logarithm of country-level government bond monthly rates' standard deviation over a quarter. Log(Exchange Rate Volatility) is the natural logarithm of country-level real effective exchange monthly rates' standard deviation over a quarter. Log(Commodity Volatility) is the natural logarithm of Commodity Research Bureau (CRB) index daily returns' standard deviation over a quarter. In the calculation of volatility measures, we define quarters for Canada in accordance with the accounting scheme used there in order to be compatible with VaR and balance sheet data. Bank control variables are from Fitch, Orbis Bank Focus and S&P Global Market Intelligence (former SNL Financial). Data to compute volatility controls is obtained from Eikon (S&P 500 and CRB data), the IMF International Financial Statistics (interest rate data) and the Federal Reserve Bank of St. Louis (exchange rate data).

Table 3: Value-at-Risk and Value-at-Risk Exceptions Descriptive Statistics

	VaR (mln $)			Exceptions			
Bank	Mean	Min	Max	Mean	Min	Max	N
Bank of America	220.40	44.00	872.16	0.47	0	9 [10]	72
Bank of Montreal	51.02	12.70	125.70	0.38	0	4	63
Bank of NY Mellon	21.45	8.40	42.37	0.13	0	2	69
Canadian IBC	20.27	8.59	59.66	0.11	0	3	46
Citi Group	299.65	73.00	708.35	0.13	0	1	48
Crédit Agricole	48.08	17.77	144.42	0.63	0	5	24
Credit Suisse Group	235.70	58.93	665.28	0.70	0	9 [10]	56
Deutsche Bank	225.74	96.29	506.77	0.62	0	9 [12]	42
Goldman Sachs	279.61	185.00	385.00	0.29	0	3	28
ING Group	59.64	17.58	221.50	0.22	0	3	46
JPMorgan Chase	304.22	129.00	913.90	0.23	0	5	60
Morgan Stanley	327.60	147.00	885.44	0.25	0	6	60
Royal Bank of Canada	70.43	26.19	167.08	0.37	0	4	62
Société Générale	115.19	58.28	293.39	0.88	0	9 [11]	48
Bank of Nova Scotia	35.56	15.24	68.14	0.06	0	1	71
TD Bank	57.19	20.22	171.57	0.07	0	2	68
UBS Group	217.45	19.20	626.09	1.23	0	9 [25]	57

This table presents summary statistics for VaR and VaR exceptions at the bank level based on banks' quarterly, annual reports and Pillar III Disclosures. The sample comprises year-quarter observations for 17 banks from the United States, Canada and Europe over the period from 2002 to 2019. VaR is the quarterly average 99% 10-day Value-at-Risk (VaR), either self-reported by banks or one-day reported VaR multiplied by the square root of 10. The 99% 10-day VaR represents the worst potential loss over a 10-day horizon that should not be exceeded in 99% cases. All VaRs are expressed in million U.S. dollars. Exceptions is the number of days when the actual daily loss of a bank is beyond daily VaR during a given quarter. Exceptions are winsorized at 1% and 99% level with raw figures given in brackets.

Table 4: Model Characteristics Summary Statistics

		MC						1-Day Horizon						Lookback					
Bank	Country	Mean	SD	Min	Median	Max	N	Mean	SD	Min	Median	Max	N	Mean	SD	Min	Median	Max	N
Bank of America	US	0.00	0.00	0.00	0.00	0.00	67	0.58	0.50	0.00	1.00	1.00	67	1.00	0.00	1.00	1.00	1.00	67
Bank of Montreal	CA	1.00	0.00	1.00	1.00	1.00	40	1.00	0.00	1.00	1.00	1.00	63						
Bank of NY Mellon	US	0.83	0.38	0.00	1.00	1.00	69	0.59	0.49	0.00	1.00	1.00	69	1.00	0.00	1.00	1.00	1.00	28
Canadian IBC	CA	0.00	0.00	0.00	0.00	0.00	62	1.00	0.00	1.00	1.00	1.00	62	0.00	0.00	0.00	0.00	0.00	27
Citi Group	US	1.00	0.00	1.00	1.00	1.00	36	0.56	0.50	0.00	1.00	1.00	63	1.00	0.00	1.00	1.00	1.00	36
Crédit Agricole	FR	0.51	0.51	0.00	1.00	1.00	47	1.00	0.00	1.00	1.00	1.00	47	0.00	0.00	0.00	0.00	0.00	47
Credit Suisse Group	SW	0.00	0.00	0.00	0.00	0.00	51	0.86	0.35	0.00	1.00	1.00	51	1.00	0.00	1.00	1.00	1.00	51
Deutsche Bank	DE	1.00	0.00	1.00	1.00	1.00	54	0.98	0.14	0.00	1.00	1.00	54	0.00	0.00	0.00	0.00	0.00	54
Goldman Sachs	US	0.00	0.00	0.00	0.00	0.00	28	0.00	0.00	0.00	0.00	0.00	28	1.00	0.00	1.00	1.00	1.00	28
ING Group	NL	0.20	0.40	0.00	0.00	1.00	45	0.85	0.36	0.00	1.00	1.00	46	0.00	0.00	0.00	0.00	0.00	45
JPMorgan Chase	US	0.00	0.00	0.00	0.00	0.00	54	0.48	0.50	0.00	0.00	1.00	54	0.00	0.00	0.00	0.00	0.00	54
Morgan Stanley	US	1.00	0.00	1.00	1.00	1.00	39	0.31	0.47	0.00	0.00	1.00	39	0.95	0.22	0.00	1.00	1.00	39
Royal Bank of Canada	CA	0.02	0.13	0.00	0.00	1.00	57	0.92	0.27	0.00	1.00	1.00	63	1.00	0.00	1.00	1.00	1.00	33
Société Générale	FR	0.00	0.00	0.00	0.00	0.00	50	0.86	0.35	0.00	1.00	1.00	50	0.00	0.00	0.00	0.00	0.00	50
Bank of Nova Scotia	CA	0.65	0.48	0.00	1.00	1.00	68	0.96	0.20	0.00	1.00	1.00	71	1.00	0.00	1.00	1.00	1.00	68
TD Bank	CA	0.69	0.47	0.00	1.00	1.00	70	1.00	0.00	1.00	1.00	1.00	70	0.00	0.00	0.00	0.00	0.00	70
UBS Group	SW	0.29	0.46	0.00	0.00	1.00	31	0.00	0.00	0.00	0.00	0.00	31	1.00	0.00	1.00	1.00	1.00	31
Total		0.42	0.49	0.00	0.00	1.00	868	0.75	0.43	0.00	1.00	1.00	928	0.52	0.50	0.00	1.00	1.00	728

This table presents summary statistics for market risk modelling choices at the bank level. The sample comprises year-quarter observations for 17 banks from the United States, Canada and Europe over 2002–2019. MC is a dummy variable that takes value 1 for the quarter when a bank declares the use of Monte Carlo simulation. 1-Day Horizon is a dummy variable equal to 1 for the quarter when a bank discloses only a one-day VaR and does not report a 10-day VaR. Lookback is a dummy variable that is equal to 1 for the quarter when a bank reports an observation period longer than one year. Data is hand-collected from banks' quarterly, annual reports and Pillar III Disclosures.

Table 5: Value-at-Risk and Model Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	log(VaR)	log(VaR)	log(VaR)	log(VaR)	log(VaR)	log(VaR)	log(VaR)	log(VaR)	log(VaR)	log(VaR)	log(VaR)
MC	0.19***	0.30***	0.10*			0.18***	0.08			0.08*	0.15***
	(0.034)	(0.061)	(0.059)			(0.060)	(0.060)			(0.040)	(0.034)
1-Day Horizon				0.56***	0.13***	0.56***	0.16***				
				(0.060)	(0.049)	(0.067)	(0.060)				
Lookback								0.52***	0.56***	0.52***	0.57***
								(0.062)	(0.057)	(0.062)	(0.057)
log(Assets)	1.13***	0.37***	1.03***	0.53***	0.99***	0.54***	1.04***	1.02***	1.16***	1.02***	1.17***
	(0.028)	(0.061)	(0.071)	(0.056)	(0.055)	(0.055)	(0.068)	(0.040)	(0.034)	(0.040)	(0.034)
NI-to-Assets	0.13**	-0.14**	-0.01	-0.13**	-0.02	-0.12**	-0.01	-0.16**	0.02	-0.15**	0.03
	(0.059)	(0.063)	(0.036)	(0.051)	(0.033)	(0.056)	(0.037)	(0.060)	(0.062)	(0.060)	(0.062)
L.log(Exchange Rate Vol)	0.07	0.02	0.00	0.02	-0.00	0.03	0.00	0.02	0.01	0.02	0.01
	(0.050)	(0.031)	(0.022)	(0.027)	(0.021)	(0.027)	(0.022)	(0.041)	(0.043)	(0.040)	(0.042)
L.log(S&P 500 Vol)	-0.09	0.24***	-0.06	0.25***	-0.05	0.22***	-0.05	0.25**	-0.10	0.24**	-0.11
	(0.152)	(0.081)	(0.097)	(0.067)	(0.073)	(0.065)	(0.085)	(0.095)	(0.146)	(0.096)	(0.156)
L.log(Interest Rate Vol)	-0.01	-0.19***	0.04**	-0.16***	0.03	-0.17***	0.03	-0.21***	-0.02	-0.21***	-0.01
	(0.036)	(0.026)	(0.020)	(0.022)	(0.020)	(0.023)	(0.022)	(0.029)	(0.032)	(0.029)	(0.033)
L.log(Commodity Vol)	-0.06	0.40***	-0.09	0.34***	-0.10	0.32***	-0.10	0.39***	-0.12	0.39***	-0.11
	(0.248)	(0.113)	(0.158)	(0.097)	(0.136)	(0.093)	(0.149)	(0.131)	(0.240)	(0.132)	(0.257)
Bank FE	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Year-Quarter FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	868	868	868	928	928	868	868	728	728	728	728
R^2	0.565	0.828	0.918	0.849	0.919	0.849	0.919	0.442	0.555	0.443	0.560

This table presents OLS estimates from a fixed effects panel regression of Value-at-Risk (VaR) on market risk modelling choices. The sample covers 17 banks from the United States, Canada and Europe over the period from 2002 to 2019. The dependent variable is log(VaR), i.e., the natural logarithm of the 99% 10-day VaR, either self-reported by banks or one-day reported VaR multiplied by the square root of 10. MC is a dummy variable that takes value 1 for the quarter when a bank declares the use of Monte Carlo simulation. 1-Day Horizon is a dummy variable equal to 1 for the quarter when a bank discloses only a one-day VaR and does not report a 10-day VaR. Lookback is a dummy variable that is equal to 1 for the quarter when a bank reports exploiting an observation period longer than a year and zero otherwise. Lookback is time-variant only for one bank in our sample (Morgan Stanley uses 16 quarters of historical data till 2019Q2 and then starts to use 4 quarters). Therefore, we consider the specification with only year-quarter fixed effects when including Lookback. We include bank (the log of total assets and net income scaled by total assets) and volatility (lagged logarithms of S&P 500, interest rate, exchange rate and commodity volatilities) controls. Standard errors are clustered at the year-quarter level and reported in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6: Value-at-Risk Exceptions and Model Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Exceptions	Exceptions	Exceptions	Exceptions	Exceptions	Exceptions	Exceptions	Exceptions	Exceptions	Exceptions	Exceptions
MC	1.00	0.43**	0.45**			0.46**	0.54			0.56***	0.82
	(0.175)	(0.158)	(0.179)			(0.179)	(0.220)			(0.110)	(0.192)
1-Day Horizon				0.62	0.30***	0.70	0.36**				
				(0.257)	(0.129)	(0.320)	(0.167)				
Lookback								1.38**	1.45***	1.35*	1.44**
								(0.208)	(0.203)	(0.225)	(0.206)
log(Assets)	1.67***	0.64	0.81	0.55*	0.54	0.55*	0.62	1.71***	1.73***	1.68***	1.70***
	(0.300)	(0.194)	(0.361)	(0.182)	(0.278)	(0.182)	(0.322)	(0.294)	(0.307)	(0.293)	(0.306)
NI-to-Assets	0.76**	0.78	0.97	0.72	0.90	0.77	0.95	0.36***	0.46***	0.37***	0.45***
	(0.100)	(0.155)	(0.187)	(0.159)	(0.209)	(0.160)	(0.221)	(0.075)	(0.089)	(0.070)	(0.085)
L.log(Exchange Rate Vol)	0.74**	1.00	0.74*	0.97	0.71*	0.98	0.70*	0.71*	0.70*	0.73*	0.70*
	(0.105)	(0.172)	(0.134)	(0.170)	(0.130)	(0.167)	(0.129)	(0.132)	(0.133)	(0.127)	(0.131)
L.log(S&P 500 Vol)	0.36	0.70	0.20	0.72	0.19*	0.72	0.18*	0.42*	0.26	0.40*	0.26
	(0.553)	(0.241)	(0.219)	(0.246)	(0.189)	(0.242)	(0.184)	(0.200)	(0.349)	(0.189)	(0.345)
L.log(Interest Rate Vol)	1.34**	0.83*	1.14	0.78**	1.11	0.80**	1.14	0.96	1.39***	0.98	1.39***
	(0.157)	(0.094)	(0.160)	(0.088)	(0.145)	(0.086)	(0.155)	(0.125)	(0.145)	(0.130)	(0.147)
L.log(Commodity Vol)	3.96	1.80	4.49	1.93	6.42	1.84	5.80	3.11**	11.96	3.07**	12.09
	(7.219)	(0.828)	(7.245)	(0.895)	(10.001)	(0.862)	(9.443)	(1.767)	(20.427)	(1.721)	(20.785)
Bank FE	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Year-Quarter FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	805	805	805	842	842	805	805	681	681	681	681

This table presents zero-inflated negative binomial (ZINB) incidence rate ratio (IRR) estimates from a fixed effects panel regression of Value-at-Risk (VaR) exceptions on market risk modelling choices. The sample covers 17 banks from the United States, Canada and Europe over the period from 2002 to 2019. The dependent variable is Exceptions, i.e., the number of days when the actual daily loss of a bank is beyond daily VaR during a given quarter. Exceptions are winsorized at 1% and 99% level. The IRR of x associated with the use of a particular model characteristic means that the banks who use it have the number of exceptions x times that of the other banks. Thus, an IRR lower than one indicates a negative relationship, higher than one - a positive relationship. MC is a dummy variable that takes value 1 for the quarter when a bank declares the use of Monte Carlo simulation. 1-Day Horizon is a dummy variable equal to 1 for the quarter when a bank discloses only a one-day VaR and does not report a 10-day VaR. Lookback is a dummy variable that is equal to 1 for the quarter when a bank reports exploiting an observation period longer than a year and zero otherwise. Lookback is time-variant only for one bank in our sample (Morgan Stanley uses 16 quarters of historical data till 2019Q2 and then starts to use 4 quarters). Therefore, we consider the specification with only year-quarter fixed effects when including Lookback. We include bank (the log of total assets and net income scaled by total assets) and volatility (lagged logarithms of S&P 500, interest rate, exchange rate and commodity volatilities) controls. Standard errors are clustered at the year-quarter level and reported in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7: Regulatory Penalties and Model Characteristics

	(1) Penalty	(2) Penalty	(3) Penalty	(4) Penalty	(5) Penalty	(6) Penalty	(7) Penalty	(8) Penalty	(9) Penalty	(10) Penalty	(11) Penalty
MC	-0.02	-0.05	-0.03			-0.05	-0.03			-0.07***	-0.02
	(0.016)	(0.032)	(0.032)			(0.034)	(0.034)			(0.022)	(0.019)
1-Day Horizon				0.00	-0.04	0.01	-0.03				
				(0.037)	(0.033)	(0.041)	(0.039)				
Lookback								0.05**	0.05***	0.05***	0.05***
								(0.018)	(0.018)	(0.018)	(0.018)
log(Assets)	0.05**	0.03	0.10*	0.03	0.08	0.04	0.10*	0.07***	0.07***	0.07***	0.07***
	(0.022)	(0.025)	(0.056)	(0.024)	(0.055)	(0.028)	(0.056)	(0.020)	(0.025)	(0.020)	(0.025)
NI-to-Assets	0.01	-0.01	0.03*	-0.01	0.03*	-0.01	0.03*	-0.04	0.00	-0.05	0.00
	(0.016)	(0.020)	(0.016)	(0.020)	(0.016)	(0.020)	(0.016)	(0.033)	(0.022)	(0.032)	(0.022)
L.log(Exchange Rate Vol)	-0.05***	-0.02	-0.05***	-0.02	-0.05***	-0.02	-0.05***	-0.05**	-0.07***	-0.05**	-0.07***
	(0.019)	(0.020)	(0.019)	(0.019)	(0.018)	(0.020)	(0.019)	(0.021)	(0.022)	(0.020)	(0.022)
L.log(S&P 500 Vol)	0.04	0.11***	0.04	0.11***	0.03	0.11***	0.04	0.08**	0.02	0.08**	0.02
	(0.068)	(0.037)	(0.071)	(0.036)	(0.066)	(0.037)	(0.073)	(0.036)	(0.076)	(0.036)	(0.077)
L.log(Interest Rate Vol)	0.02	-0.03*	0.01	-0.03*	0.01	-0.03*	0.01	-0.01	0.03	-0.01	0.03
	(0.016)	(0.015)	(0.016)	(0.014)	(0.016)	(0.014)	(0.016)	(0.014)	(0.016)	(0.014)	(0.016)
L.log(Commodity Vol)	0.05	0.10**	0.06	0.09**	0.06	0.10**	0.06	0.11***	0.10	0.11***	0.10
	(0.063)	(0.040)	(0.066)	(0.042)	(0.065)	(0.043)	(0.067)	(0.040)	(0.117)	(0.040)	(0.117)
Bank FE	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Year-Quarter FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	772	772	772	801	801	772	772	654	654	654	654
R^2	0.382	0.179	0.428	0.174	0.427	0.179	0.428	0.104	0.402	0.119	0.404

This table presents OLS estimates from a fixed effects panel regression of the likelihood to face regulatory penalties on market risk modelling choices. The sample covers 17 banks from the United States, Canada and Europe over the period from 2002 to 2019. Penalty is a dummy variable equal to 1 when banks are in amber or red zones of the Basel market risk framework and face a penalty in the next quarter. The framework has three zones based on the yearly number of VaR exceptions: green (0-4), amber (5-9) and red (10 or more). When banks are in amber or red zones, they face an additional capital requirement and are also more likely to face more supervisory scrutiny. MC is a dummy variable that takes value 1 for the quarter when a bank declares the use of Monte Carlo simulation. 1-Day Horizon is a dummy variable equal to 1 for the quarter when a bank discloses only a one-day VaR and does not report a 10-day VaR. Lookback is a dummy variable that is equal to 1 for the quarter when a bank reports exploiting an observation period longer than a year and zero otherwise. Lookback is time-variant only for one bank in our sample (Morgan Stanley uses 16 quarters of historical data till 2019Q2 and then starts to use 4 quarters). Therefore, we consider the specification with only year-quarter fixed effects when including Lookback. We include bank (the log of total assets and net income scaled by total assets) and volatility (lagged logarithms of S&P 500, interest rate, exchange rate and commodity volatilities) controls. Standard errors are clustered at the year-quarter level and reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Bank Leverage and Model Characteristics

	(1) MC	(2) MC	(3) 1-Day Horizon	(4) 1-Day Horizon	(5) Lookback	(6) Lookback
log(Equity/Assets)	0.34***	0.25***	0.30***	0.33***	0.32***	0.20**
	(0.070)	(0.087)	(0.053)	(0.091)	(0.054)	(0.079)
log(Assets)	-0.17***	0.35***	0.03***	0.13*	-0.07***	-0.10***
	(0.021)	(0.050)	(0.011)	(0.069)	(0.018)	(0.020)
NI-to-Assets	-0.01	0.03	-0.02	-0.01	0.00	0.01
	(0.027)	(0.020)	(0.026)	(0.025)	(0.026)	(0.035)
Year-Quarter FE	Yes	Yes	Yes	Yes	No	Yes
Country FE	Yes	No	Yes	No	Yes	Yes
Bank FE	No	Yes	No	Yes	No	No
Observations	868	868	928	928	728	728
R^2	0.273	0.735	0.570	0.651	0.509	0.524

This table presents OLS estimates from a fixed effects panel regression of bank leverage on market risk modelling choices. The sample covers 17 banks from the United States, Canada and Europe over the period from 2002 to 2019. log(Equity/Assets) is the natural logarithm of the book value of equity scaled by book assets. MC is a dummy variable that takes value 1 for the quarter when a bank declares the use of Monte Carlo simulation. 1-Day Horizon is a dummy variable equal to 1 for the quarter when a bank discloses only a one-day VaR and does not report a 10-day VaR. Lookback is a dummy variable that is equal to 1 for the quarter when a bank reports exploiting an observation period longer than a year and zero otherwise. Lookback is time-variant only for one bank in our sample (Morgan Stanley uses 16 quarters of historical data till 2019Q2 and then starts to use 4 quarters). Therefore, we consider the specification with only year-quarter fixed effects when including Lookback. We include bank controls (the log of total assets and net income scaled by total assets). Standard errors are clustered at the year-quarter level and reported in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 9: Bank Leverage and Model Changes

	(1) Model Change	(2) Model Change	(3) Tight Model Change	(4) Tight Model Change	(5) Loose Model Change	(6) Loose Model Change
log(Equity/Assets)	0.10	0.07	0.12**	0.14***	-0.00	-0.04
	(0.079)	(0.054)	(0.058)	(0.045)	(0.068)	(0.045)
log(Assets)	0.11	0.13***	0.00	0.04***	0.10	0.09***
	(0.078)	(0.023)	(0.053)	(0.013)	(0.062)	(0.022)
NI-to-Assets	0.02	0.03	0.01	0.00	0.02	0.03
	(0.020)	(0.021)	(0.014)	(0.013)	(0.019)	(0.020)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	Yes	No	Yes
Bank FE	Yes	No	Yes	No	Yes	No
Observations	928	928	928	928	928	928
R^2	0.343	0.257	0.178	0.145	0.243	0.179

This table presents OLS estimates from a fixed effects panel regression of bank leverage on market risk model changes. The sample covers 17 banks from the United States, Canada and Europe over the period from 2002 to 2019. log(Equity/Assets) is the natural logarithm of the book value of equity scaled by book assets. Model Change is a dummy variable equal to 1 when banks declare changing their market risk model. Tight Model Change and Loose Model Change indicate (when possible) model changes that should result in higher or lower capital requirements, respectively. We include bank controls (the log of total assets and net income scaled by total assets). Standard errors are clustered at the year-quarter level and reported in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 10: Regulatory Scrutiny and Model Characteristics

	(1) MC	(2) 1-Day Horizon	(3) Lookback	(4) MC	(5) 1-Day Horizon	(6) Lookback
log(Equity/Assets)	0.79***	0.09	0.41***	0.24***	0.32***	0.22***
	(0.116)	(0.112)	(0.130)	(0.087)	(0.096)	(0.079)
log(Equity/Assets) x Number of Supervisors per Bank	-0.49***	0.24***	-0.19***			
	(0.070)	(0.081)	(0.044)			
log(Equity/Assets) x High VIX				0.05	0.05	-0.16***
				(0.035)	(0.104)	(0.044)
log(Assets)	0.34***	0.15**	-0.10***	0.35***	0.13*	-0.10***
	(0.045)	(0.067)	(0.020)	(0.050)	(0.069)	(0.020)
NI-to-Assets	0.03	-0.00	0.01	0.03*	-0.00	0.01
	(0.018)	(0.024)	(0.035)	(0.020)	(0.025)	(0.035)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	No	No	Yes
Bank FE	Yes	Yes	No	Yes	Yes	No
Observations	781	840	659	868	928	728
R-squared	0.808	0.675	0.475	0.735	0.652	0.526

This table presents OLS estimates from a fixed effects panel regression of bank leverage combined with more supervisory scrutiny and in times of high volatility on modelling choices. The sample covers 17 banks from the United States, Canada and Europe over the period from 2002 to 2019. log(Equity/Assets) is the natural logarithm of the book value of equity scaled by book assets. Number of Supervisors per Bank is the total number of supervisors in a given country scaled by the number of banks in a given country according to the World Bank's Bank Regulation and Supervision Survey (World Bank, 2019). High VIX is a a dummy variable that takes value 1 in quarters when VIX excceds 40. MC is a dummy variable that takes value 1 for the quarter when a bank declares the use of Monte Carlo simulation. 1-Day Horizon is a dummy variable equal to 1 for the quarter when a bank discloses only a one-day VaR and does not report a 10-day VaR. Lookback is a dummy variable that is equal to 1 for the quarter when a bank reports exploiting an observation period longer than a year and zero otherwise. Lookback is time-variant only for one bank in our sample (Morgan Stanley uses 16 quarters of historical data till 2019Q2 and then starts to use 4 quarters). Therefore, we consider the specification with only year-quarter fixed effects when including Lookback. We include bank controls (the log of total assets and net income scaled by total assets). Standard errors are clustered at the year-quarter level and reported in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix

Robustness Tables

Tables A0 and A1: same as Tables 5 and 6 but excluding 2008-2009 observations (the global financial crisis)

Table A0: Value-at-Risk and Model Characteristics (Without 2008-2009)

	(1) log(VaR)	(2) log(VaR)	(3) log(VaR)	(4) log(VaR)	(5) log(VaR)	(6) log(VaR)	(7) log(VaR)	(8) log(VaR)	(9) log(VaR)	(10) log(VaR)	(11) log(VaR)
MC	0.22***	0.29***	0.07			0.14**	0.03			0.09**	0.16***
	(0.036)	(0.059)	(0.065)			(0.058)	(0.065)			(0.043)	(0.038)
1-Day Horizon				0.59***	0.17***	0.60***	0.22***				
				(0.059)	(0.050)	(0.066)	(0.061)				
Lookback								0.52***	0.59***	0.51***	0.58***
								(0.069)	(0.062)	(0.069)	(0.063)
log(Assets)	1.11***	0.28***	0.95***	0.45***	0.90***	0.48***	0.96***	0.97***	1.14***	0.97***	1.15***
	(0.031)	(0.062)	(0.075)	(0.057)	(0.052)	(0.059)	(0.068)	(0.042)	(0.035)	(0.043)	(0.035)
NI-to-Assets	0.13	-0.12	-0.04	-0.12**	-0.05	-0.12**	-0.04	-0.13*	0.00	-0.12*	0.02
	(0.078)	(0.072)	(0.040)	(0.054)	(0.033)	(0.057)	(0.039)	(0.069)	(0.070)	(0.070)	(0.072)
L.log(Exchange Rate Vol)	0.06	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.01	0.01
	(0.054)	(0.033)	(0.022)	(0.027)	(0.021)	(0.026)	(0.021)	(0.045)	(0.044)	(0.045)	(0.044)
L.log(S&P 500 Vol)	-0.04	0.13	-0.04	0.13*	-0.03	0.11	-0.03	0.15	-0.03	0.15	-0.04
	(0.157)	(0.090)	(0.105)	(0.068)	(0.077)	(0.065)	(0.087)	(0.103)	(0.143)	(0.104)	(0.153)
L.log(Interest Rate Vol)	-0.02	-0.16***	0.05**	-0.13***	0.03	-0.13***	0.04	-0.20***	-0.03	-0.20***	-0.02
	(0.040)	(0.026)	(0.022)	(0.023)	(0.022)	(0.023)	(0.024)	(0.030)	(0.035)	(0.030)	(0.036)
L.log(Commodity Vol)	-0.04	0.27**	-0.09	0.19**	-0.11	0.18*	-0.12	0.26**	-0.10	0.27**	-0.08
	(0.263)	(0.114)	(0.171)	(0.093)	(0.143)	(0.090)	(0.158)	(0.130)	(0.251)	(0.131)	(0.271)
Bank FE	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Year-Quarter FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	767	767	767	819	819	767	767	651	651	651	651
R^2	0.506	0.829	0.916	0.851	0.915	0.857	0.919	0.376	0.492	0.378	0.498

Table A1: Value-at-Risk Exceptions and Model Characteristics (Without 2008-2009)

	(1) Exceptions	(2) Exceptions	(3) Exceptions	(4) Exceptions	(5) Exceptions	(6) Exceptions	(7) Exceptions	(8) Exceptions	(9) Exceptions	(10) Exceptions	(11) Exceptions
MC	1.01	0.61	0.51*			0.61	0.56			0.77	1.01
	(0.184)	(0.232)	(0.188)			(0.251)	(0.213)			(0.177)	(0.208)
1-Day Horizon				0.87	0.51*	0.94	0.57				
				(0.325)	(0.191)	(0.393)	(0.232)				
Lookback								1.09	1.35**	1.10	1.35**
								(0.222)	(0.178)	(0.232)	(0.176)
log(Assets)	1.75***	0.57	1.06	0.54*	0.67	0.56	0.93	1.75***	1.77***	1.75***	1.77***
	(0.274)	(0.205)	(0.690)	(0.191)	(0.475)	(0.202)	(0.649)	(0.298)	(0.334)	(0.302)	(0.325)
NI-to-Assets	0.73	1.25	1.25	1.21	1.25	1.24	1.22	0.86	0.53**	0.80	0.54**
	(0.384)	(0.464)	(0.339)	(0.457)	(0.410)	(0.467)	(0.349)	(0.252)	(0.170)	(0.242)	(0.163)
L.log(Exchange Rate Vol)	0.73**	0.82	0.74*	0.80	0.72*	0.82	0.71**	0.70**	0.80	0.71*	0.80
	(0.103)	(0.137)	(0.119)	(0.129)	(0.121)	(0.133)	(0.116)	(0.126)	(0.112)	(0.125)	(0.111)
L.log(S&P 500 Vol)	0.04**	0.44**	0.09*	0.45**	0.11*	0.45**	0.09**	0.34**	0.34	0.34**	0.34
	(0.060)	(0.175)	(0.122)	(0.173)	(0.134)	(0.176)	(0.108)	(0.181)	(0.495)	(0.180)	(0.495)
L.log(Interest Rate Vol)	1.33**	0.94	1.32*	0.93	1.28*	0.93	1.34*	1.08	1.41***	1.07	1.41***
	(0.175)	(0.124)	(0.215)	(0.109)	(0.190)	(0.109)	(0.209)	(0.165)	(0.140)	(0.166)	(0.143)
L.log(Commodity Vol)	37.25	1.72	14.56	1.71	17.73	1.73	16.64	2.28	5.90	2.35	5.91
	(84.694)	(0.813)	(33.616)	(0.822)	(39.132)	(0.828)	(38.483)	(1.241)	(10.127)	(1.257)	(10.131)
Bank FE	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Year-Quarter FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	720	720	720	757	757	720	720	620	620	620	620

Tables A2-A4: same as Tables 7-9 but using logistic regressions. Average marginal effects are reported.

Table A2: Regulatory Penalties and Model Characteristics (Logit)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Penalty	Penalty	Penalty	Penalty	Penalty	Penalty	Penalty	Penalty	Penalty	Penalty	Penalty
MC	-0.04	-0.08	-0.19			-0.08	-0.20			-0.07**	-0.06
	(0.040)	(0.094)	(0.135)			(0.094)	(0.134)			(0.029)	(0.055)
1-Day Horizon				-0.01	-0.13	-0.01	-0.14				
				(0.065)	(0.138)	(0.067)	(0.148)				
Lookback								0.04**	0.13***	0.04**	0.13***
								(0.017)	(0.032)	(0.017)	(0.033)
log(Assets)	0.11**	-0.06	-0.22	-0.05	-0.29	-0.06	-0.26	0.07***	0.17***	0.06***	0.16***
	(0.046)	(0.046)	(0.188)	(0.048)	(0.182)	(0.053)	(0.185)	(0.021)	(0.044)	(0.020)	(0.046)
NI-to-Assets	0.00	-0.01	0.24**	-0.01	0.22**	-0.02	0.23**	-0.02	-0.05	-0.03	-0.05
	(0.039)	(0.044)	(0.112)	(0.043)	(0.109)	(0.044)	(0.113)	(0.019)	(0.045)	(0.018)	(0.044)
L.log(Exchange Rate Vol)	-0.11**	-0.05*	-0.22***	-0.05**	-0.22**	-0.05**	-0.21**	-0.05**	-0.20***	-0.05***	-0.20***
	(0.046)	(0.026)	(0.084)	(0.024)	(0.088)	(0.026)	(0.085)	(0.020)	(0.067)	(0.019)	(0.070)
L.log(S&P 500 Vol)	0.14	0.14***	0.66	0.15***	0.65	0.14***	0.72*	0.06	0.08	0.06*	0.10
	(0.254)	(0.052)	(0.415)	(0.050)	(0.422)	(0.052)	(0.430)	(0.041)	(0.226)	(0.037)	(0.227)
L.log(Interest Rate Vol)	0.06*	-0.04**	0.00	-0.04**	0.00	-0.04**	0.01	-0.01	0.05	-0.01	0.05
	(0.034)	(0.017)	(0.066)	(0.016)	(0.056)	(0.016)	(0.059)	(0.013)	(0.031)	(0.012)	(0.033)
L.log(Commodity Vol)	-0.19	0.14**	-0.44	0.12*	-0.44	0.14*	-0.51	0.09*	-0.02	0.09**	-0.02
	(0.248)	(0.067)	(0.513)	(0.068)	(0.526)	(0.072)	(0.544)	(0.048)	(0.302)	(0.043)	(0.305)
Bank FE	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Year-Quarter FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	298	474	184	497	188	474	184	654	236	654	236

Table A3: Bank Leverage and Model Characteristics (Logit)

	(1)	(2)	(3)	(4)	(5)	(6)
	MC	MC	1-Day Horizon	1-Day Horizon	Lookback	Lookback
log(Equity/Assets)	0.50***	0.60***	0.18***	-1.21	0.61***	0.94***
	(0.098)	(0.230)	(0.068)	(1.032)	(0.038)	(0.162)
log(Assets)	-0.18***	0.45***	-0.03***	-0.20*	-0.16***	-0.36***
	(0.022)	(0.126)	(0.009)	(0.113)	(0.032)	(0.050)
NI-to-Assets	-0.03	0.07*	-0.02	0.08*	-0.03	-0.01
	(0.032)	(0.035)	(0.025)	(0.047)	(0.034)	(0.046)
Year-Quarter FE	Yes	Yes	Yes	Yes	No	Yes
Country FE	Yes	No	Yes	No	Yes	Yes
Bank FE	No	Yes	No	Yes	No	No
Observations	809	386	638	308	728	450

Table A4: Bank Leverage and Model Changes (Logit)

	(1) Model Change	(2) Model Change	(3) Tight Model Change	(4) Tight Model Change	(5) Loose Model Change	(6) Loose Model Change
log(Equity/Assets)	0.13	0.07	0.27**	0.26***	0.06	-0.12
	(0.097)	(0.084)	(0.139)	(0.093)	(0.117)	(0.091)
log(Assets)	0.14	0.18***	-0.02	0.07***	0.22**	0.17***
	(0.100)	(0.030)	(0.088)	(0.028)	(0.094)	(0.036)
NI-to-Assets	0.03	0.02	0.05	0.01	0.01	0.03
	(0.027)	(0.028)	(0.040)	(0.033)	(0.031)	(0.038)
YQ FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	Yes	No	Yes
Bank FE	Yes	No	Yes	No	Yes	No
Cluster	YQ	YQ	YQ	YQ	YQ	YQ
Observations	746	773	520	572	607	634