Risk Modelling: Why and How Banks Cheat

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Abstract

This paper investigates how and when banks underreport market risk. We study hand-collected data on modelling and disclosure choices and examine how they relate to the level and accuracy of predicted Value-at-Risk (VaR). We find that more elaborate modelling and more transparent reporting *can* correspond to more accurate and/or conservative VaR-predictions. Using longer-than-required historical data and relying on external scaling to approximate required holding periods, however, also enables distressed banks to report lower and/or less accurate VaR. Monte Carlo (MC) simulation methods, instead, which are generally more accurate, seem to be abandoned over time.

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1 Introduction

Risk-sensitive bank capital regulation has been a feature of the Basel Committee on Banking Supervision's (BCBS) global standards since the introduction of "Basel I" in 1988. For credit risk, the regulation has evolved from fixed and discrete risk categories to the internal-ratings based (IRB) approach. This has lead to improved risk-sensitivity and thus efficiency, but also raised concerns about "strategic risk-modelling", i.e. incentives for banks to reduce regulatory capital charges through biased modelling (e.g., Mariathasan & Merrouche, 2014; Plosser & Santos, 2018).

At least since 1996, when the BCBS formally adopted Value-at-Risk (VaR) as a factor in the calculation of capital requirements for market risk, it is plausible that these incentives also affect the reporting of risk for the trading book (BCBS, 1996); especially since the current regulatory framework is comparable to that for the banking book, with banks choosing between (i) a standardized approach that primarily relies on supervisory assumptions, and (ii) an internal model-based approach, which draws on banks' own information and models.[1] Despite these similarities, however, the evidence on strategic modelling for market risk is scarce, with Begley et al. (2017) providing a recent exception.

As recently as March 03, 2019 the secretary general of the BCBS has reportedly called for stronger external auditing of banks' risk-weights (Jenkins, 2019), suggesting that risk-weight manipulation remains a concern for regulators and indicating that additional analysis − in particular into the specific ways in which banks misreport risk − are called for. We contribute to the literature on risk-weight manipulation in general − and to that on strategic market risk-modelling in particular − by analyzing how and when banks underreport market risk. To this end, we hand-collect data, not only on VaR and threshold violations, but also on modelling and disclosure choices from banks' annual reports. Analyzing the 19 largest banks from the US, Canada, and Europe over the period from 2002 to 2016, we find that more elaborate modelling *can* contribute to more accurate and/or conservative VaR-predictions, but that it also enables banks to underreport risk. The use of longer-than-required historical data, for instance, corresponds to more accurate and conservative VaR-predictions during normal times, but to lower and less accurate predictions when markets are volatile and when banks are more leveraged. Banks that exclusively report VaR-predictions for 1-day holding periods, instead, and that therefore rely on external scaling to obtain the required 10-day values, model risk more

[1] Although the BCBS has recently moved towards Expected Shortfall (ES) as the basis for regulatory capital charges (BCBS, 2016), to better capture tail risk exposures, banks and supervisors will − necessarily − continue to rely on VaR for backtesting and model validation. At the same time, it has also been shown that ES is even more sensitive than Value-at-Risk to certain modelling choices, such as, for example, the length of the observation period (Yamai & Yoshiba, 2005).

accurately during normal times, but less accurately during stress periods. Simplicity − and the transparency that it entails − can thus help to improve model accuracy during normal times, while more internal information leads to more model accuracy (but not to higher capital requirements) in volatile markets. Finally, we find the use of Monte Carlo (MC) simulation methods to produce superior VaR-predictions in normal times and when market volatility and systemic stress are high. At the same time, however, it seems that banks move away from MC simulations and increasingly adopt non-MC methods, such as historical simulations (HS), which generally seem to produce less conservative VaR-predictions.

Our results add nuance to the literature on risk-weight manipulation, in that they identify discretionary risk-modelling with banks' internal models as a potentially double-edged sword: while more elaborate modelling with more internal − and thus opaque − information can lead to more accurate and sometimes even more conservative VaR-predictions, the added degrees of freedom also provide opportunities for banks to escape regulatory capital charges by tweaking intransparent assumptions in their favour or by abandoning methodologies that appear to produce more conservative estimates.

2 Related literature

Our paper contributes to the broader literature on regulatory arbitrage, which has been found to be particularly pervasive among distressed and capital-constrained banks (e.g., Acharya et al., 2013; Boyson et al., 2016). Part of this literature has focused on investigating banks' strategic use of internal risk models, and −in the context of credit risk− has produced a considerable amount of evidence of "risk-weight manipulation" (e.g., Mariathasan & Merrouche, 2014; Behn et al., 2016; Benetton et al., 2017). Most recently, Plosser & Santos (2018) have shown that highly leveraged banks tend to lower their capital requirements via internally computed risk estimates which turn out to contain little information on loan prices. Niepmann & Stebunovs (2018), instead, identify strategic behavior of EU banks who have seemingly lowered their projected loan losses through model changes between the European Banking Authority's (EBA) stress tests in 2014 and 2016. The results of these papers are −by and large− consistent with ex-ante expectations and the underlying theory: most importantly, Blum (2008) and Colliard (2018) both predict incentives for the underreporting of risk to be particularly strong for banks with less equity.

Contrary to the literature on credit risk, there is less evidence on how banks' internal models are used in the context of market risk regulation. One notable exception is recent work by Begley et al. (2017), who demonstrate that weakly capitalized banks also understate market risk strategically. Like them, we study underreporting in the context of models for market risk using a sample of hand-collected data on VaR and VaR exceptions. Our focus, however, is on identifying modelling choices that are particularly prone to such underreporting and to assess the performance and usage of these models across banks and over time. We thus contribute to the debate by beginning to open the "black box" of strategic risk-reporting, and by providing evidence on the systematic use of some model characteristics.

With our focus on risk-model characteristics, our paper then also connects to the corresponding technical literature, which elaborates on the formal characteristics of different modelling choices.

As far as methodologies for internal risk-models are concerned, the BCBS imposes few requirements, except that the models need to pass the regulatory backtest. In practice, banks primarily rely on either Historical (HS) or Monte Carlo (MC) simulations to estimate the potential loss distribution. According to recent evidence, and consistent with our evidence in Figure 6, the majority of banks seem to move away from MC and towards HS (e.g., Pérignon & Smith, 2010; Mehta et al., 2012; O'Brien & Szerszen, 2014). HS is a simpler methodology than MC and imposes no assumption on the shape of a bank's return distribution. It instead relies on historically observed patterns and assumes that these are a valid indicator for the future, which crucially assumes a constant portfolio composition. More importantly for our purposes, however, it has also been shown that risk measures based on HS can become inaccurate when they are performed on finite samples. Pérignon & Smith (2010), for instance, argue that historical VaR do not predict future volatility, while Pritsker (2006) discusses necessary refinements when correlations in the trading book are time-varying. In addition, Danielsson & Zhou (2017) point out that HS perfom poorly in the context of structural breaks. MC simulations, instead, are developed from a variety of assumptions about asset classes, risk types, prices, and implied volatilities. They take into the non-linearity of options and other derivatives into account and cover more potential scenarios than HS. Like HS, MC also draws on historic data, but uses it indirectly to compute sensitivities of and correlations between different market factors. MC simulations are thus more elaborate and generally superior to HS, but also more difficult to implement. They have higher computational requirements and may be more difficult to interprete for both internal and external risk management.

Another quantitative standard under Basel rules is the minimum holding period of 10 trading days for computing VaR (BCBS, 1996). The holding period refers to the assumed time for which the positions in the trading book remain unchanged. Fixed trading positions of 10 days, however, are not particularly plausible for banks with dynamic trading portfolios and Sharma (2012) suggests that more frequent position changes cause models to underestimate true market risk. In practice, banks are often allowed to assume shorter holding periods (e.g., one day) and to apply the “square-root-of-time rule”, i.e., to multiply the 1-day prediction by $\sqrt{10}$ to determine the required 10-day values.[2] This scaling works reasonably well for linear products and under normal market conditions, but fails to capture the non-linearity of derivatives; especially in times of high volatility.

3 Data and methodology

3.1 Sample

We explore hand-collected data on banks’ self-reported VaR levels, as well as on “exceptions”, i.e. violations of the predicted VaR threshold (see below), and on different risk-model characteristics; specifically on the use of (i) MC or non-MC simulations, (ii) internal calculations for 10-day holding periods or external scaling, and (iii) the use of more-than-required historical data. Our sample covers the 19 largest banks from the U.S., Canada and Europe and the period between 2002 and 2016. For our benchmark analysis, this implies 813 bank-quarter observations on VaR and the corresponding VaR exceptions. An *exception* (also a *violation*, *breach*, or *exceedance*) refers to the case when a bank’s daily loss within a given quarter is higher than the corresponding VaR . Similar to Begley et al. (2017), the self-reported VaR numbers and risk model properties are hand-collected from banks’ quarterly and annual reports as well as from Pillar III Disclosures. Balance sheet information is collected from Fitch, Orbis and SNL. Foreign exchange, interest rate, market and commodity volatility measures are computed based on the data obtained from St. Louis Federal Reserve Bank, International Financial Statistics and Thomson Reuters Eikon.

Table 1 below provides summary statistics on VaR and VaR exceptions for the underlying sample. VaR exceedances are winsorized at the 1% level and the raw numbers are reported in brackets. The average number of VaR violations in our winsorized sample is 0.40 (0.44 if not winsorized); using a 99% VaR model, one would expect to have VaR exceeded once in every 100 trading days, or having 0.63 exception during a quarter. This implies that the risk models in our sample are on average rather conservative. At the same time, there is considerable variation in the number of VaR breaches across time: From 2002 to 2006 it

[2] US banks have been obliged to explicitly calculate VaR for 10-day holding periods since 2013, while this remains only a recommendation for all other banks. Option exposures, however, can typically not be approximated with the “square-root-of-time rule”.

is 0.09, from 2007 to 2010 it is approximately 1.05, and from 2011 to 2016 it is 0.19. The internal models thus overestimate market risk in normal times, band − importantly − underestimate risk during the crisis. Table 2 presents summary statistics of selected control variables, illustrating further that quarterly balance sheet data is only available for a subset of 676 bank-quarter observations.

3.2 Models

3.2.1 Benchmark setup

Throughout the analysis, we estimate fixed effects models with multi-dimensional clustering of standard errors at the bank and year-quarter levels. 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, especially the crisis). Fixed effects models are standard for finance panels with relatively low cross-sectional and time-series dimensionality (e.g., Petersen, 2009; Clark & Linzer, 2013), and we draw further confidence in the setup from additional (unreported) tests of (a) the joint significance of our bank FE's, (b) a comparison with the first difference estimator, and (c) the robustness of our main results to a random effects specification.

Our first dependent variable of interest is the natural logarithm of banks' self-reported VaR. Our main explanatory variables are dummies for different risk model characteristics, i.e. for a particular methodology, holding period, and/or the length of the historical period: $Lookback_{it}$ is equal to one if bank i's observation window at period t exceeds the regulatory minimum of four quarters, $MonteCarlo_{it}$ is a dummy for the reported use of MC simulation, and $1\text{-}Day_{it}$ is a dummy variable indicating whether bank i reports only a 1-day horizon VaR at date t (as opposed to separately disclosing a VaR for a 10-day horizon). The corresponding baseline regression explaining the level of banks' VaR is the following:

$$\begin{aligned}\log(VaR_{it}) = &\beta_1 Lookback_{it} + \beta_2 MonteCarlo_{it} + \beta_3 1\text{-}Day_{it} + \\ &+ \gamma X_{it} + \theta V_{it-1} + \alpha_i + \delta_t + \varepsilon_{it},\end{aligned} \tag{1}$$

where α_i and δ_t are bank and year-quarter fixed effects, X_{it} is a vector of bank-level controls (bank size, leverage, profitability), and V_{it-1} is a vector of country-level measures of market, exchange rate, interest rate and commodity volatilities to account for time-varying heterogeneity across countries. All volatility measures are one-period lagged, since VaR predicts future volatility.

To assess model quality, we also analyze a second dependent variable, namely the number of VaR violations ("Exceptions"). Since this is a count variable, the model choice is between a Poisson regression model and a negative binomial (NB) regression model. Since VaR breaches are also non-negative integers and Figure 2 suggests that their distribution is highly skewed to the right, we can also not rely on a simple linear regression model. Together with a variance of VaR exceptions that is more than three times as large as its mean (1.38 vs. 0.4 as given in Table 1), Figure 2 also indicates overdispersion, leading us to use a NB model. We nevertheless run the Poisson regression and check its goodness-of-fit (GOF) using a χ^2-test. Consistent with the affirmative results of a likelihood ratio test for the NB regression, the χ^2-test rejects the use of the Poisson. Since we have lots of zero observations in the VaR exceptions' distribution, we further use a zero-inflated (ZI) instead of a standard model. 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. In our setup, the Vuong test identifies a superior fit for the ZINB model (p-value$<$0.01), and we therefore estimate the following ZINB model with bank and year-quarter fixed effects:

$$\begin{aligned} Exceptions_{it} = & \beta_1 Lookback_{it} + \beta_2 MonteCarlo_{it} + \beta_3 1\text{-}Day_{it} + \\ & + \gamma X_{it} + \theta V_{it-1} + \alpha_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{2}$$

4 Results

4.1 Benchmark

4.1.1 Value-at-Risk

Table 3 displays our results for Model 1, i.e. for the regression of $\log(VaR)$ on different risk model characteristics. Estimates in columns (1) to (3) feature each model characteristic separately, and no bank or volatility controls; in columns (4) to (6), we add bank and volatility controls; in columns (7) to (9), we control for all possible two-way combinations of risk-model choices and the model in column (10) simultaneously includes all three risk-model dummies.

Throughout, we find that taking more-than-necessary information into account corresponds to significantly more conservative (i.e., higher) VaR numbers. Since these translate into higher capital requirements, the choice of the lookback period – on average – seems not to be motivated by capital savings incentives.

We further observe that the use of MC simulation also seems to correspond to higher VaR numbers. Since they are able to account for a wider range of scenarios – including, in particular, extreme events – these more conservative estimates are not necessarily unexpected; because banks have also tended to move from MC to HS (e.g., Mehta et al.,2012), however, they may be indicative of a " strategic modelling" choice.[3]

Finally, we find no evidence that only reporting figures for a 1-day horizon – as opposed to also reporting those for a 10-day horizon – has any significant impact on average VaR reporting. For banks that do not disclose their internal calculations for the 10-day horizon, regulators typically extrapolate using the “square root of 10" rule. This rule, however, only works reasonably well if daily returns are iid (i.e., in the absence of volatility clustering and/or autocorrelation), and tend otherwise to underestimate the exposure. One can therefore interpret the explicit choice to not disclose internal 10-day estimates as a choice against transparency, and might have therefore expected lower internally computed 10-day VaR values.

4.1.2 Exceptions

Higher or lower VaR numbers are informative with respect to banks' capital charges and thus the cost of different modelling choices, but not necessarily with respect to model accuracy. We therefore proceed to investigate the relationship between different model characteristics and the number of threshold violations in a given quarter. Table 4 reports the estimation results for VaR breaches. In column (1) to (3), we run individual OLS regressions for each model characteristic with bank and volatility controls, column (4) jointly includes all model characteristics. In columns (5) and (6), instead, we show the results for our baseline ZINB model, with coefficients reported in column (5) and incidence rate ratios (IRRs) reported in column (6).

We find no significant link between exceptions and the use of MC simulation, while disclosing only daily VaRs and longer-than-necessary lookback periods appears to correspond to significantly fewer VaR exceedances. For the 1-day horizon dummy, the IRR of 0.12 in column (6) can be interpreted as having 0.12 times the violations of those banks that explicitly report 10-day market risk estimates. This is consistent with a systematic underestimation of actual risk by banks that provide the regulator with the 10-day measures

[3]Our point estimates are no longer significant when we simultaneously control for a longer-than-necessary lookback period (columns 7 and 10), which we attribute to our limited sample size and to the dominant effect of the lookback period; they do, however, remain positive throughout, and they are robust to controlling for whether or not banks exclusively report VaR numbers for a 1-day horizon (column 9).

compared to banks that allow for external scaling and are thus more transparent.

As for the historical period, those banks that select a longer-than-necessary period tend to have 96% fewer VaR breaches than those that do not (IRR = 0.04). Combining this finding with the result of the VaR level estimation, one might conclude that a lookback period that exceeds four quarters is not only associated with more conservative VaRs, but also correspond to a higher quality model.

Our findings that certain model choices lead to more conservative and/or more accurate risk estimates are not necessarily unexpected. Some banks could simply have worse risk modelling skills and/or use faulty model assumptions; i.e. they might simply underestimate market risk due to poor risk-models. To the extent that risk-modelling capabilities (or the bank's willingness to invest in them) are time-invariant, the inclusion of bank fixed effects already eliminates some of these differences across banks, but further analysis is required.

Next, we therefore exploit the cross-sectional and time series heterogeneity in our sample and analyse circumstances under which it would be particularly beneficial, or particularly feasible, for banks tounderreport market risk.

4.2 Distress Scenarios

Our benchmark analysis confirms that bank risk models perform – by and large – as theory predicts they should. Consistent with the "manipulation view", however, not all models perform equally well in all circumstances and banks seem to be aware of this. In this section, we therefore proceed to analyse the performance of our three modelling/reporting choices in different distress scenarios.

4.2.1 Longer-Than-Required Historical Data

In Table 5, we analyse the perfomance of risk models for banks that choose to consider longer-than-required historical data, i.e. historical data for more than the past four quarters. Building on the benchmark results from Tables 3 and 4, we specifically assess situations in which banks either have an incentive or the opportunity to underreport their VaR. These situations include periods in which markets are particularly volatile, i.e., in which the VIX exceeds 40, (columns 1 to 4), cases of banks with particularly low levels of pre-crisis equity (columns 5 to 8), and instances in which banks report risk-model changes (columns 9 to 12).[4] We

[4] *High Pre-Crisis Leverage* is equal to 1 if the the ratio of book equity to total assets exceeds the threshold of 4% in 2007Q2, i.e. preceding the global interbank market collapse. *Model Change* identifies quarters during which banks self-report changes to their market risk models. See Figure 4 for the frequency with which this occurs over time.

observe, in all three situations, that risk models become less accurate, i.e. that the number of exceptions increases. At the same time, we also observe that using longer-than-required historical data does not translate into particularly strong increases in VaR, suggesting that the use of more information does not help to capture the *de facto* increase in risk better. For banks that have operated with (excessively) high leverage ratios in the past, the use of a longer lookback period even translates into lower VaR and thus lower capital requirements. The same is true when banks announce risk-model changes in their annual reports: while these changes − on average − correspond to more conservative VaR, the same benefit does not arise when lookback periods are longer than required. Importantly, it is unlikely that banks select a longer-than-necessary lookback window by mistake since under normal market conditions it induces more conservative and more accurate risk estimation (see Tables 3 and 4). We therefore interpret the results in Table 5 as evidence that banks use the added degrees of freedom that they are afforded by current regulatory standards to reduce the precision of their risk forecasts in ways that are consistent with capital savings incentives.

4.2.2 Simulation Method

Concerning the choice of simulation methodology, our analysis provides no statistically significant evidence that the use of MC simulations affects banks' VaR beyond our benchmark results in Table 3. This non-result is potentially surprising, as we do find − in Table 6 − that the use MC simulations corresponds to more accurate risk reporting in periods of high market volatility (columns 1 to 3), during the crisis (columns 4 to 9), and for banks that revealed themselves as risk-takers before the crisis (columns 10 to 12).[5] Rather than providing evidence of manipulation, this set of results indicates that banks seem to use MC simulations to predict risk accurately, precisely when it is essential to do so. What is notable in this context, however, is that banks are increasingly abandoning MC methods (see Figure 6). As with the lookback period, it seems unlikely that banks opt for the inferior non-MC models by accident; the choice, for example, of HS methods is instead often motivated by their relative simplicity. In this context, our results suggest, however, that abandoning MC also reduces risk-model accuracy precisely in those instances when precision is particularly valuable.

[5] *Crisis* is a dummy variable equal to 1 for the period between 2007Q3 and 2010Q4. Our results are robust to considering alternative crisis definitions. To investigate the building-up of market risk in banks' trading books preceding the Lehman Brothers' collapse, we also consider the indicator *Prior to the Lehman's failure*, which takes a value of one during 2007Q3 – 2008Q3.

4.2.3 Holding Period

Finally, we also analyze banks' disclosure choice in the context of the assumed holding period in Table 7. Our findings are best understood in two parts: On one hand, the square-root-of-time rule does not appear to perform well during times of systemic distress, such as the crisis (columns 1 to 4), for which we observe a reduction in accuracy. On the other hand, we do detect some evidence of manipulation in columns 5 to 10, where we consider systemic and bank-specific tail risk exposures.[6] In the absence of strategic modelling, one would expect to observe more precise risk estimates in these cases, if banks use internal information to calculate VaR for a 10-day holding period. What we observe instead is the opposite: banks that rely on the more transparent, but less precise external scaling of their 1-day predictions exhibit (weakly) higher VaR and fewer exceptions, precisely when internal information should be particularly valuable. This is consistent with banks with high tail risk exposure strategically choosing to internally calculate VaR for the required 10-day horizon, precisely when capital savings incentives are particularly high.

4.3 Model Changes

In Table 9, we further analyze how banks' self-reported model changes relate to their risk-reporting. Model changes are instances in banks annual reports that suggest adjustments to banks' risk-modelling. For example, the Canadian Imperial Bank of Commerce states in its 2007 annual report: "Starting in the fourth quarter of 2007, we began including in VaR a measure of debt specific risk (DSR)."; we record this case as *Model Change*=1 in 2007Q4. Consistent with our main hypothesis, we find that model changes correspond to lower predicted VaR and thus to regulatory capital charges. The relationship is stronger when banks are more capital-constrained and when market volatility is high.

While our previous analysis indicates channels through which banks might strategically underreport risk, e.g., by moving away from MC simulations or by reporting less transparent internal 10-day predictions, the results in Table 9 indicates that risk-model adjustments, also beyond these broad categories, seem to be motivated by capital savings incentives.

[6]Marginal Expected Shortfall (MES) is based on Acharya et al. (2017), and calculated using daily returns for all 19 banks from our base sample. For convenience, we build a new dummy variable *High MES* which indicates quarters that are in the top-quartile with the highest MES. MES serves as a tail risk measure of the financial system as a whole. Instead, according to Knaup and Wagner (2012), high exposure to derivatives can be used as a tail risk measure at the bank level. We therefore use derivative holdings scaled by trading assets as a proxy for tail risk exposure and call it *Derivatives*. Our results are not driven by changes in the denominator of the constructed ratio.

4.4 Robustness

To exclude potential identification concerns, Table 8 provides a series of additional robustness tests. First, to make sure that our findings do not depend on potential reporting differences during the fourth quarter, we have included a *Q4* dummy in columns 1 and 2. Next, to show that our findings are not driven by the recent financial crisis, we have excluded the observations for 2007 and 2008 in columns 3 and 4.[7] To also consider the effect of unobserved country characteristics, we further added country fixed effects in columns (5) and (6). Finally, we also scaled VaR by total assets in columns 7 and 8 and considered only the Management VaR in column 9; columns 10 to 12 ensure that our results are robust to the different forms of clustering.

5 Conclusion

In summary, we find that banks' risk-modelling for market risk is more likely to be driven by capital-saving incentives when circumstances are exceptional and opportunities arise. Banks then appear to take advantage of their modelling discretion to favourably influence their capital requirements through reduced model accuracy and lower reported VaR. We specifically explore three disclosed model characteristics: the length of the historical period used in VaR calculation, the simulation methodology, and the assumed holding period. Our results show that using a longer-than-required lookback period generally implies more conservative and more accurate risk modelling; when banks are likely to be capital-constrained, however, the added degrees of freedom seem to allow them to underreport risk and to reduce their regulatory capital requirements. Monte Carlo simulations methods, instead, seem to improve model accuracy and – if anything – lead to higher predicted VaR. While this is encouraging from a regulatory perspective, the fact that banks seem to move towards non-MC methods suggests another dimension of regulatory arbitrage and should be a point of concern. Finally, it turns out that exclusively reporting VaR for a 1-day horizon, and relying on external scaling to arrive at the required 10-day assumption, is associated with more precise market risk forecasting, especially when it is supposed to be inaccurate, i.e. under high tail risk exposure. This too suggests that banks strategically use the opacity that is associated with more complex modelling choices to their advantage. Overall, our results are consistent with the hypothesis that banks underreport market risk strategically. At the same time, however, they also indicate that strategic modelling is concentrated in periods and/or among banks that are particularly exposed, and that the same model characteristics that

[7] Results are equally robust to excluding 2007 to 2009 or 2007 to 2010.

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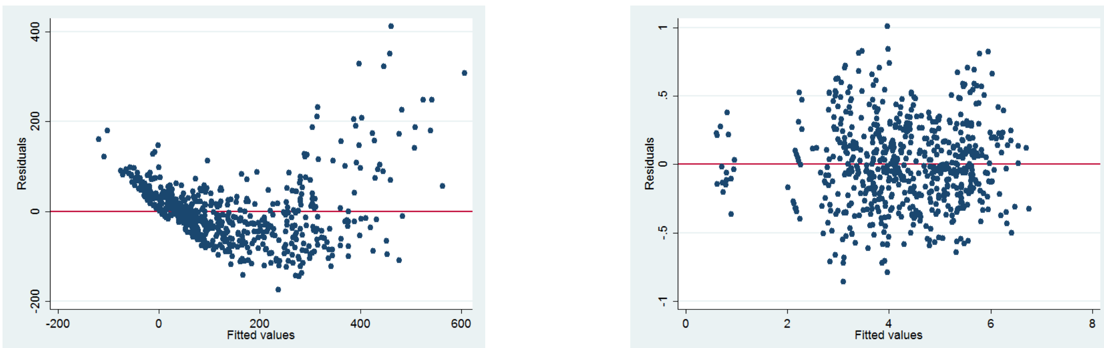
Appendix

Figures

Figure 1: Residual vs. fitted plots.



(A) VaR (B) log(VaR)

Figure 2: VaR exceptions' density plot.

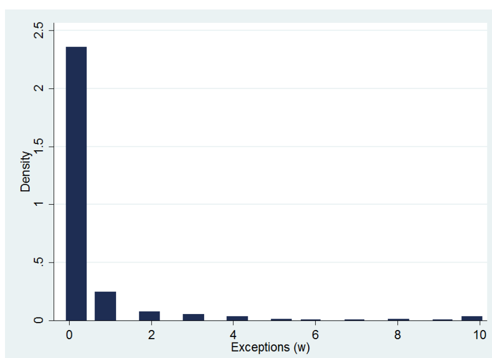


Figure 3: Summary of Results.

	Benchmark	Cases	Tail Risk
Lookback	+ VaR ↑ , Exceptions ↓	– VaR ↓ , Exceptions ↑	·
Monte Carlo	+ VaR ↑	+ Exceptions ↓	·
1-Day Horizon	+ Exceptions ↓	– Exceptions ↑	+ Exceptions ↓

Notes: “+” indicates a positive effect, i.e. higher VaR and/or fewer exceptions, “−” indicates a negative effect, i.e. lower VaR and/or more exceptions; , “.” indicates no systematic effect

Figure 4: Number of Banks reporting Model Changes

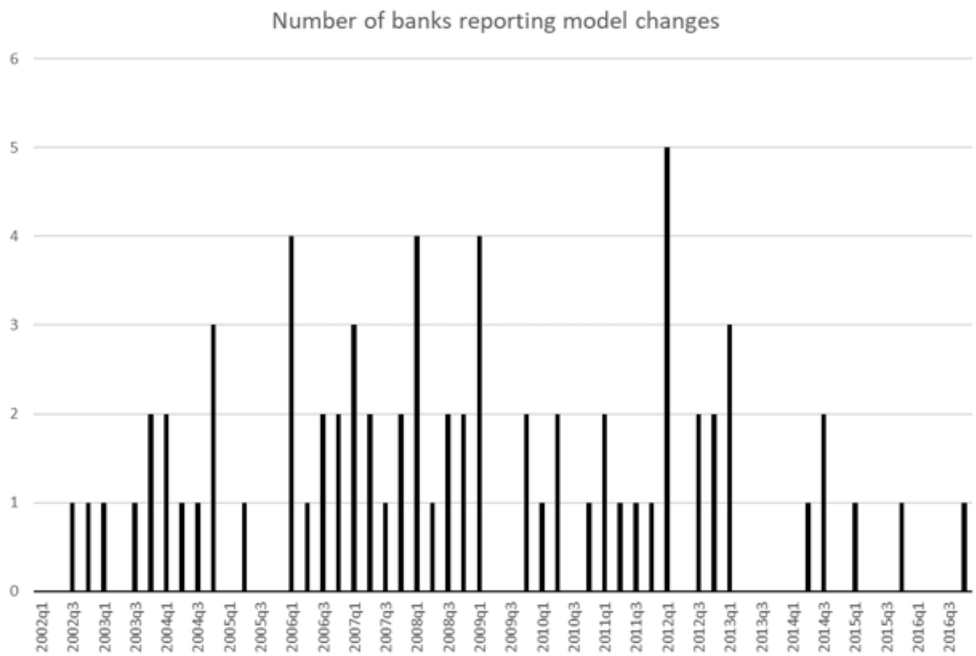


Figure 5: Average Length of the Lookback Period

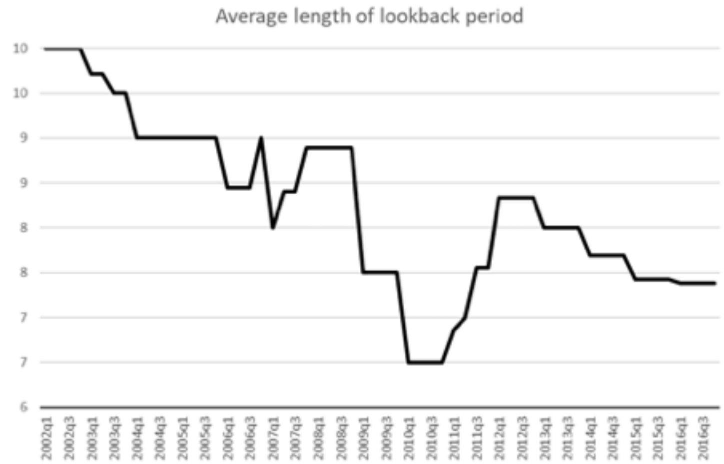


Figure 6: Percentage of Banks using Monte Carlo Simulation

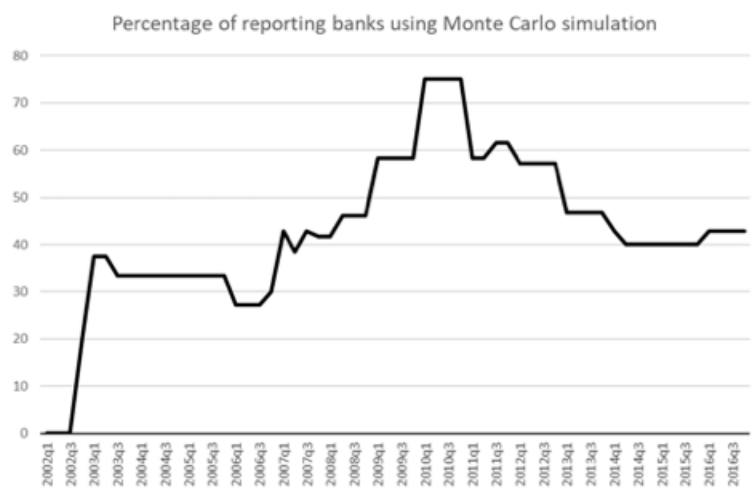
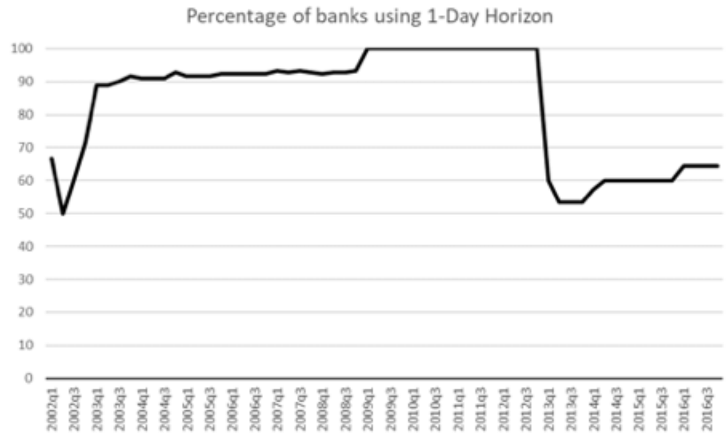


Figure 7: Percentage of Banks only disclosing 1-Day Holding Periods



Tables

Table 1: Base sample descriptive statistics.

	VaR			Exceptions			
Bank	Mean	Min	Max	Mean	Min	Max	N
Bank of America	251.26	67.00	872.16	0.52	0	10	60
Bank of Montreal	58.70	22.05	125.70	0.47	0	4	51
Bank of New York Mellon	23.00	8.40	42.37	0.14	0	2	57
Canadian IBC	20.70	8.59	59.66	0.12	0	3	42
Citi Group	359.89	118.00	708.35	0.14	0	1	36
Credit Agricole	70.90	32.06	144.42	0.33	0	3	12
Credit Suisse Group	262.39	72.14	665.28	0.81	0	10	48
Deutsche Bank	263.55	109.15	506.77	0.75	0	10 [12]	32
Goldman Sachs	321.75	242.00	385.00	0.31	0	3	16
ING Group	71.16	23.88	221.50	0.03	0	1	34
JPMorgan Chase	332.47	129.00	913.90	0.27	0	5	48
Morgan Stanley	366.38	147.00	885.44	0.29	0	6	48
PNC Financial Services	15.20	1.60	37.00	0.26	0	5	46
Royal Bank of Canada	89.58	26.19	167.08	0.46	0	4	50
Societe Generale	127.81	66.49	293.39	1.14	0	10 [11]	36
SunTrust Bank	28.51	6.32	90.76	0.05	0	1	37
Bank of Nova Scotia	36.81	15.24	68.14	0.07	0	1	59
Toronto-Dominion Bank	57.99	20.22	171.57	0.09	0	2	56
UBS Group	245.61	25.16	580.22	1.51	0	10 [25]	45
Total	151.91	1.60	913.90	0.40	0	10 [25]	813

This table presents summary statistics for our base sample. The sample comprises year-quarter observations for 19 banks from the U.S., Canada and Europe over the period from 2002 to 2016. VaR is the self-disclosed 99% confidence interval Value-at-Risk number which stands for 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 amount of times banks' actual losses are beyond self-reported VaR level in a particular quarter. Exceptions are winsorized at 1% and 99% level with raw figures given in brackets. VaR and its exceptions data is hand-collected from banks' quarterly and annual reports, and Pillar III disclosures.

Table 2: Descriptive statistics of selected control variables.

Variable	Mean	Sd	Min	Max	N
Bank Controls					
Assets (bln $)	919.34	644.49	79.72	2,577.15	676
NI-to-Assets (%)	0.67	0.52	-4.74	2.73	676
Equity/Assets (%)	6.63	2.95	1.42	14.88	676
Volatility Controls					
Log(S&P 500 volatility)	-4.71	0.44	-5.39	-3.17	676
Log(Interest rate volatility)	-3.05	0.87	-6.02	1.36	676
Log(Exchange rate volatility)	-4.79	0.69	-7.16	-2.72	676
Log(Commodity volatility)	-4.62	0.38	-5.51	-3.47	676

This table presents summary statistics for our base sample. The sample comprises year-quarter observations for 19 banks from the U.S., Canada and Europe over the period from 2002 to 2016. Assets stands for 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. Equity/Assets is the ratio of total equity to 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. Data to compute volatility controls is obtained from the Thomson Reuters 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: Benchmark - Value-at-Risk.

	(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)
Lookback	0.51***			0.57***			0.49***	0.65***		0.53***
	(0.106)			(0.105)			(0.135)	(0.143)		(0.164)
Monte Carlo (MC)		0.48***			0.39**		0.24		0.39**	0.23
		(0.137)			(0.160)		(0.162)		(0.165)	(0.168)
1-Day Horizon			0.25			0.42		0.48	0.11	0.17
			(0.336)			(0.322)		(0.312)	(0.166)	(0.161)
Bank Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Volatility Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	YQ & Bank	YQ & Bank	YQ & Bank	YQ & Bank	YQ & Bank	YQ & Bank	YQ & Bank	YQ & Bank	YQ & Bank	YQ & Bank
Observations	813	750	813	676	627	676	627	676	627	627
R^2	0.881	0.906	0.879	0.895	0.930	0.896	0.934	0.903	0.930	0.934

This table presents OLS estimates from a fixed effects panel regression of VaR level on market risk modelling choices and control variables. The sample covers 19 banks from the U.S., Canada and Europe over the period from 2002 to 2016. The dependent variable is log(VaR), i.e. the natural logarithm of the 99% 10-day Value-at-Risk, either self-reported by banks or scaled by square root of 10 ourselves using self-disclosed daily VaRs. Lookback is a dummy variable that is equal to 1 for the quarter when a bank reports exploiting observation period longer than a year and zero otherwise. Monte Carlo is a dummy variable that takes value 1 for the quarter when a bank claims 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. Bank controls include the log of total assets, net income scaled by total assets and the log of the book equity-to-assets ratio. These variables are standardized to have a zero mean and unit variance. A vector of volatility measures comprises lagged logarithms of S&P 500, interest rate, exchange rate and commodity volatilities. Standard errors are clustered at both bank and year-quarter levels and reported in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4: Model choices and VaR exceptions.

	(1) Exceptions	(2) Exceptions	(3) Exceptions	(4) Exceptions	Coefficients (5) Exceptions	IRRs (6) Exceptions
Lookback	-0.21			-0.38*	-3.22**	0.04**
	(0.150)			(0.201)	(1.391)	(0.056)
Monte Carlo (MC)		-0.04		0.08	0.03	1.03
		(0.134)		(0.161)	(0.467)	(0.482)
1-Day Horizon			-0.36**	-0.55**	-2.11**	0.12**
			(0.154)	(0.244)	(0.842)	(0.102)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Volatility Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	YQ	YQ	YQ	YQ	YQ	YQ
Model	OLS	OLS	OLS	OLS	ZINB	ZINB
Observations	676	627	676	627	627	627
R^2	0.364	0.366	0.368	0.375		

This table presents OLS and zero-inflated negative binomial (ZINB) estimates from a fixed effects panel regression of VaR exceptions on market risk modelling choices and control variables. The sample covers 19 banks from the U.S., Canada and Europe over the period from 2002 to 2016. The dependent variable is Exceptions, i.e. the amount of times banks' actual losses are beyond self-reported VaR level in a particular quarter. Exceptions are winsorized at 1% and 99% level. We provide ZINB coefficients' estimates in column (5) and the corresponding incidence rate ratios (IRRs) in column (6). Lookback is a dummy variable that is equal to 1 for the quarter when a bank reports exploiting observation period longer than a year and zero otherwise. Monte Carlo is a dummy variable that takes value 1 for the quarter when a bank claims 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. Bank controls include the log of total assets, net income scaled by total assets and the log of the book equity-to-assets ratio. These variables are standardized to have a zero mean and unit variance. A vector of volatility measures comprises lagged logarithms of S&P 500, interest rate, exchange rate and commodity volatilities. Standard errors are clustered at the year-quarter level and reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Longer-than-required Lookback Period (>4Q)

	(1) log(VaR)	(2) Exceptions	(3) log(VaR)	(4) Exceptions	(5) log(VaR)	(6) Exceptions	(7) log(VaR)	(8) Exceptions	(9) log(VaR)	(10) Exceptions	(11) log(VaR)	(12) Exceptions
Lookback	0.56***	-0.23	0.53***	-0.39*	0.57***	-0.59**	0.66***	-1.45**	0.59***	-0.24	0.56***	-0.41**
	(0.107)	(0.151)	(0.165)	(0.202)	(0.179)	(0.268)	(0.217)	(0.583)	(0.108)	(0.151)	(0.171)	(0.194)
Monte Carlo (MC)			0.23	0.06			0.15	0.60			0.22	0.07
			(0.168)	(0.158)			(0.164)	(0.452)			(0.168)	(0.161)
1-Day Horizon			0.17	-0.57**			0.29	-0.70*			0.19	-0.57**
			(0.161)	(0.252)			(0.179)	(0.358)			(0.163)	(0.247)
High Volatility x Lookback	0.08	0.45***	0.06	0.58***								
	(0.086)	(0.146)	(0.082)	(0.146)								
High Pre-Crisis Leverage x Lookback					-0.65*	0.68**	-0.89***	1.67***				
					(0.358)	(0.302)	(0.306)	(0.565)				
Model Change									0.21***	-0.19	0.25***	-0.18
									(0.051)	(0.174)	(0.075)	(0.172)
Model Change x Lookback									-0.25***	0.46*	-0.27***	0.52*
									(0.093)	(0.260)	(0.080)	(0.302)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Volatility Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	YQ & Bank	YQ	YQ & Bank	YQ	YQ & Bank	YQ	YQ & Bank	YQ	YQ & Bank	YQ	YQ & Bank	YQ
Period	Full Sample	Full Sample	Full Sample	Full Sample	Post-2007Q2	Post-2007Q2	Post-2007Q2	Post-2007Q2	Full Sample	Full Sample	Full Sample	Full Sample
Observations	676	676	627	627	537	537	516	516	676	676	627	627
R^2	0.895	0.361	0.934	0.372	0.917	0.371	0.942	0.391	0.896	0.367	0.935	0.379

This table presents OLS and zero-inflated negative binomial (ZINB) estimates from a fixed effects panel regression of VaR level and VaR exceptions on market risk modelling choices and control variables. The sample covers 19 banks from the U.S., Canada and Europe over the period from 2002 to 2016. In columns (1), (3), (5), (7), (9) and (11), the dependent variable is log(VaR), i.e. the natural logarithm of the 99% 10-day Value-at-Risk, either self-reported by banks or scaled by square root of 10 ourselves using self-disclosed daily VaRs. In columns (2), (4), (6), (8), (10) and (12), the dependent variable is Exceptions, i.e. the amount of times banks' actual losses are beyond self-reported VaR level in a particular quarter. Exceptions are winsorized at 1% and 99% level. Lookback is a dummy variable that is equal to 1 for the quarter when a bank reports exploiting observation period longer than a year and zero otherwise. Monte Carlo is a dummy variable that takes value 1 for the quarter when a bank claims 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. In columns (1)-(4), High Volatility is a dummy variable that takes value 1 for the quarter when the previous-period VIX value exceeds 40. In columns (5)-(8), High Pre-Crisis Leverage is a dummy variable equal to 1 if the bank's equity ratio as of 2007Q2 is below 4%. In coulmns (9)-(12), Model Change is a dummy variable that takes value 1 for the quarter when a bank announces having a major model adjustment. We consider the full sample in columns (1)-(4) and (9)-(12) and the subsample starting from 2007Q3 in columns (5)-(8). Bank controls include the log of total assets, net income scaled by total assets and the log of the book equity-to-assets ratio. These variables are standardized to have a zero mean and unit variance. A vector of volatility measures comprises lagged logarithms of S&P 500, interest rate, exchange rate and commodity volatilities. Standard errors are clustered at both bank and year-quarter level in a VaR level regression and at the year-quarter level in a regression of VaR exceptions, and reported in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6: Monte Carlo Simulations

	(1) Exceptions	(2) Exceptions	(3) Exceptions	(4) Exceptions	(5) Exceptions	(6) Exceptions	(7) Exceptions	(8) Exceptions	(9) Exceptions	(10) Exceptions	(11) Exceptions	(12) Exceptions
Monte Carlo (MC)	0.34	0.68	1.21**	0.14	0.29*	0.65	0.03	0.16	0.23	0.06	0.26	0.20
	(0.341)	(0.698)	(0.526)	(0.113)	(0.150)	(0.433)	(0.147)	(0.170)	(0.488)	(0.130)	(0.184)	(0.461)
Lookback		-0.52	-16.11***		-0.39*	-3.14**		-0.39**	-3.30**		-0.51**	-3.37**
		(0.464)	(0.935)		(0.205)	(1.484)		(0.196)	(1.376)		(0.250)	(1.470)
1-Day Horizon		-0.40**	-3.51***		-0.63**	-2.50***		-0.58**	-2.45***		-0.60**	-2.12**
		(0.184)	(1.051)		(0.275)	(0.754)		(0.236)	(0.588)		(0.253)	(0.854)
High Volatility x MC	-0.25***	-0.21***	-0.82									
	(0.060)	(0.055)	(0.532)									
Crisis x MC				-0.51	-0.60	-1.41***						
				(0.358)	(0.386)	(0.484)						
Prior to the Lehman's failure x MC							-0.60***	-0.67***	-1.00**			
							(0.217)	(0.215)	(0.421)			
High Pre-Crisis Leverage x MC										-0.66*	-0.95**	-16.74***
										(0.368)	(0.445)	(1.278)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Volatility Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	YQ	YQ	YQ	YQ	YQ	YQ	YQ	YQ	YQ	YQ	YQ	YQ
Model	OLS	OLS	ZINB	OLS	OLS	ZINB	OLS	OLS	ZINB	OLS	OLS	ZINB
Period	Post-Crisis	Post-Crisis	Post-Crisis	Full Sample	Full Sample	Full Sample	Full Sample	Full Sample	Full Sample	Full Sample	Full Sample	Full Sample
Observations	365	365	365	627	627	627	627	627	627	627	627	627
R^2	0.299	0.320		0.373	0.384		0.370	0.380		0.368	0.380	

This table presents OLS and zero-inflated negative binomial (ZINB) estimates from a fixed effects panel regression of VaR level and VaR exceptions on market risk modelling choices and control variables. The sample covers 19 banks from the U.S., Canada and Europe over the period from 2002 to 2016. The dependent variable is Exceptions, i.e. the amount of times banks' actual losses are beyond self-reported VaR level in a particular quarter. Exceptions are winsorized at 1% and 99% level. Monte Carlo is a dummy variable that takes value 1 for the quarter when a bank claims the use of Monte Carlo simulation. Lookback is a dummy variable that is equal to 1 for the quarter when a bank reports exploiting observation period longer than a year and zero otherwise. 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. In columns (1)-(3), High Volatility is a dummy variable that takes value 1 for the quarter when the previous-period VIX value exceeds 40. In columns (4)-(6), Crisis is a dummy variable that is equal to 1 over the period from 2007Q3 to 2010Q4. In columns (7)-(9), Prior to the Lehman's failure is a dummy variable that takes value 1 over the period between 2007Q3 and 2008Q3. In columns (10)-(12), High Pre-Crisis Leverage is a dummy variable equal to 1 if the bank's equity ratio as of 2007Q2 is below 4%. We consider the subsample starting from 2011Q1 in columns (1)-(3) and the full sample in columns (4)-(12). Bank controls include the log of total assets, net income scaled by total assets and the log of the book equity-to-assets ratio. These variables are standardized to have a zero mean and unit variance. A vector of volatility measures comprises lagged logarithms of S&P 500, interest rate, exchange rate and commodity volatilities. Standard errors are clustered at the year-quarter level and reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Holding Period

	(1) Exceptions	(2) Exceptions	(3) Exceptions	(4) Exceptions	(5) log(VaR)	(6) Exceptions	(7) log(VaR)	(8) Exceptions	(9) log(VaR)	(10) Exceptions	(11) log(VaR)	(12) Exceptions
1-Day Horizon	-1.67***	-2.11**	-0.36**	-0.55**	0.38	-0.30*	0.13	-0.50**	0.00	-0.08	0.10	-0.16
	(0.571)	(0.843)	(0.154)	(0.244)	(0.334)	(0.165)	(0.165)	(0.247)	(0.259)	(0.263)	(0.251)	(0.297)
Lookback		-3.22**		-0.38*			0.52***	-0.37*			0.51***	-0.26
		(1.391)		(0.202)			(0.162)	(0.200)			(0.176)	(0.176)
Monte Carlo		0.03		0.08			0.24	0.07			0.23	0.15
		(0.467)		(0.161)			(0.168)	(0.158)			(0.190)	(0.213)
Crisis x 1-Day Horizon	11.85***	13.24***										
	(1.472)	(1.205)										
Prior to the Lehman's failure x 1-Day Horizon			0.94***	0.57*								
			(0.245)	(0.339)								
High MES x 1-Day Horizon					0.25**	-0.33**	0.36***	-0.43***				
					(0.113)	(0.158)	(0.124)	(0.135)				
Derivatives									-1.00*	1.13	-1.21**	1.32*
									(0.580)	(0.746)	(0.569)	(0.763)
Derivatives x 1-Day Horizon									0.63	-1.62*	0.44	-1.89*
									(0.552)	(0.943)	(0.552)	(0.989)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Volatility Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	YQ	YQ	YQ	YQ	YQ & Bank	YQ	YQ & Bank	YQ	YQ & Bank	YQ	YQ & Bank	YQ
Model	ZINB	ZINB	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Observations	676	627	676	627	676	676	627	627	622	622	596	596
R^2			0.368	0.375	0.896	0.369	0.935	0.377	0.925	0.401	0.939	0.404

This table presents OLS and zero-inflated negative binomial (ZINB) estimates from a fixed effects panel regression of VaR level and VaR exceptions on market risk modelling choices and control variables. The sample covers 19 banks from the U.S., Canada and Europe over the period from 2002 to 2016. In columns (1)-(4), (6), (8), (10) and (12), the dependent variable is Exceptions, i.e. the amount of times banks' actual losses are beyond self-reported VaR level in a particular quarter. Exceptions are winsorized at 1% and 99% level. In columns (5), (7), (9) and (11), the dependent variable is log(VaR), i.e. the natural logarithm of the 99% 10-day Value-at-Risk, either self-reported by banks or scaled by square root of 10 ourselves using self-disclosed daily VaRs. 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 observation period longer than a year and zero otherwise. Monte Carlo is a dummy variable that takes value 1 for the quarter when a bank claims the use of Monte Carlo simulation. In columns (1) and (2), Crisis is a dummy variable that is equal to 1 over the period from 2007Q3 to 2010Q4. In columns (3) and (4), Prior to the Lehman's failure is a dummy variable equal to 1 over the period between 2007Q3 and 2008Q3. In columns (5)-(8), High MES is a dummy variable that takes value 1 for the quarters in the top-quartile based on the corresponding Marginal Expected Shortfall (MES) values. In columns (9)-(12), Derivatives is the ratio of derivative assets to trading assets. Bank controls include the log of total assets, net income scaled by total assets and the log of the book equity-to-assets ratio. These variables are standardized to have a zero mean and unit variance. A vector of volatility measures comprises lagged logarithms of S&P 500, interest rate, exchange rate and commodity volatilities. Standard errors are clustered at both bank and year-quarter level in a VaR level regression and at the year-quarter level in a regression of VaR exceptions, and reported in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 8: Robustness.

	(1) log(VaR)	(2) Exceptions	(3) log(VaR)	(4) Exceptions	(5) log(VaR)	(6) Exceptions	(7) VaR/Assets (bps)	(8) log(VaR/Assets)	(9) log(Mngm VaR)	(10) Exceptions	(11) Exceptions	(12) Exceptions
Lookback	0.54***	-3.16**	0.72***	-16.43***	0.53***	-3.22**	0.87***	0.46***	0.29**	-0.38	-0.38	-3.22***
	(0.171)	(1.365)	(0.148)	(1.142)	(0.164)	(1.391)	(0.283)	(0.159)	(0.118)	(0.371)	(0.393)	(0.702)
Monte Carlo (MC)	0.21	0.19	0.03	0.56	0.23	0.03	-0.12	0.10	0.35***	0.08	0.08	0.03
	(0.181)	(0.491)	(0.162)	(0.452)	(0.169)	(0.467)	(0.239)	(0.142)	(0.126)	(0.274)	(0.280)	(0.323)
1-Day Horizon	0.19	-2.10**	0.31**	-3.63***	0.17	-2.11**	0.34*	0.16	-0.08	-0.55**	-0.55*	-2.11***
	(0.159)	(0.834)	(0.150)	(0.668)	(0.162)	(0.842)	(0.195)	(0.131)	(0.131)	(0.232)	(0.283)	(0.701)
Q4 x Lookback	-0.04	-0.18										
	(0.059)	(0.297)										
Q4 x MC	0.03	-0.65										
	(0.095)	(0.533)										
Q4 x 1-Day Horizon	-0.06	-0.15										
	(0.064)	(0.619)										
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Volatility Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	Yes	Yes	No	No	No	No	No	No
Cluster	YQ & Bank	YQ	YQ & Bank	YQ	YQ & Bank	YQ	YQ & Bank	YQ &Bank	YQ & Bank	Bank	YQ & Bank	Bank
Model	OLS	ZINB	OLS	ZINB	OLS	ZINB	OLS	OLS	OLS	OLS	OLS	ZINB
Period	Full Sample	Full Sample	Drop 2007-2008	Drop 2007-2008	Full Sample	Full Sample	Full Sample	Full Sample	Full Sample	Full Sample	Full Sample	Full Sample
Observations	627	627	545	545	627	627	627	627	600	627	627	627
R^2	0.934		0.946		0.934		0.773	0.882	0.918	0.375	0.375	

This table presents OLS and zero-inflated negative binomial (ZINB) estimates from a fixed effects panel regression of VaR level and VaR exceptions on market risk modelling choices and control variables. The sample covers 19 banks from the U.S., Canada and Europe over the period from 2002 to 2016. In columns (1), (3) and (5), the dependent variable is log(VaR), i.e. the natural logarithm of the 99% 10-day Value-at-Risk, either self-reported by banks or scaled by square root of 10 ourselves using self-disclosed daily VaRs. In columns (2), (4), (6) and (10)-(12), the dependent variable is Exceptions, i.e. the amount of times banks' actual losses are beyond self-reported VaR level in a particular quarter. Exceptions are winsorized at 1% and 99% level. In column (7), the dependent variable is the 99% 10-day Value-at-Risk scaled by total assets. In column (8), the dependent variable is the log of the 99% 10-day Value-at-Risk scaled by total assets. In column (9), the dependent variable is the log of the 99% 10-day Value-at-Risk, computed and reported by banks for the internal management purposes. Lookback is a dummy variable that is equal to 1 for the quarter when a bank reports exploiting observation period longer than a year and zero otherwise. Monte Carlo is a dummy variable that takes value 1 for the quarter when a bank claims 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. In columns (1) and (2), Q4 is a dummy variable that takes value 1 for the fourth quarters. In columns (3) and (4), we exclude 2007-2008 data from the sample. In columns (5) and (6), we include the country-fixed effects. Bank controls include the log of total assets, net income scaled by total assets and the log of the book equity-to-assets ratio. These variables are standardized to have a zero mean and unit variance. A vector of volatility measures comprises lagged logarithms of S&P 500, interest rate, exchange rate and commodity volatilities. In columns (1)-(9), standard errors are clustered at both bank and year-quarter level in a VaR level regression and at the year-quarter level in a regression of VaR exceptions. In columns (10) and (12), standard errors are clustered at the bank level and, in column (11), they are clustered at both bank and year-quarter level in a regression of VaR violations. Standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Model changes and variations in reported risk.

	I	II	III	IV	V
				Low Equity	Higl Equi
Model Change	-0.007	-0.344	0.195	0.029	0.0
	(0.089)	(0.170)*	(0.110)*	(0.066)	(0.2
Model Change* Equity/Assets		0.056			
		(0.021)**			
Equity/Assets		-0.024		-0.011	-0.0
		(0.011)*		(0.045)	(0.0
Model Change*Low Equity			-0.279		
			(0.152)*		
Low Equity			0.079		
			(0.016)***		
Model Change*High VIX				-0.327	0.2
				(0.177)*	(0.2
R^2	0.22	0.23	0.23	0.35	0.3
N	497	497	497	228	269

The dependent variable is the within bank quarter-to-quarter variation in the predicted log VaR residual from our benchmark regression. *Model Change* is a dummy for quarters in which banks report significant changes in their VaR model; * p<0.1; ** p<0.05; *** p<0.01