Banks' Next Top Model

Elizaveta Sizova*

August 17, 2022
Latest version here

Abstract

I study the design of regulation using banks' internal risk models. Specifically, I explore the optimal combination of capital requirements and penalties to ensure truthful reporting. I first characterize optimal regulatory capital and penalties when banks have private information about their risk. I find that penalties in practice could be rationalized provided sufficient variation in banks' preferences. I then use hand-collected data on risk model revisions to show that actual penalties provide only weak incentives for model improvements and fail to deter misreporting. In addition, my model suggests that recent changes in regulation may further impair truthful disclosure.

Key Words: Basel Regulation, Internal Risk Models, Capital Requirements, Market Risk

JEL Classification Codes: D82, D86, G01, G21, G28

*Norwegian School of Economics (NHH), elizaveta.sizova@nhh.no

I am deeply grateful to Mike Mariathasan and Charles Kahn for their invaluable guidance and advice at each stage of this project. I also thank Heitor Almeida, Taylor Begley, Diana Bonfim, João Cocco, Filipe Correia, Hans Degryse, Ralph De Haas, Olivier De Jonghe (discussant), Irem Demirci, Florian Hoffmann, Rustom Irani, Elena Istomina, Mahyar Kargar, Peter Kondor, Agnese Leonello, Daniël Linders, Aakriti Mathur, Ouarda Merrouche, Camelia Minoiu, Steven Ongena, Neil Pearson, George Pennacchi, Joshua Pollet, Haresh Sapra, Dejanir Silva, Javier Suarez, seminar participants at the Bank of Canada, Bank of England, Bank of Lithuania, City University of Hong Kong, Durham University, ESCP Business School, Higher School of Economics, Johns Hopkins SAIS, KU Leuven, New Economic School, NHH, Nova SBE, Queen Mary University of London, University of Bristol, University of Illinois at Urbana-Champaign, and participants at the AFA 2022 PhD Student Poster Session, Day-Ahead Workshop on Financial Regulation, DGF 2021 Doctoral Workshop, Rare Voices in Economics Conference, 23rd INFER Annual Conference, 7th International Young Finance Scholars' Conference, 14th Annual Meeting of the Portuguese Economic Journal and Nova SBE Finance PhD Pitch Perfect for their helpful suggestions and comments. All errors are my own.

1 Introduction

This paper examines the design of bank regulation using banks' internal risk models. In particular, I investigate whether the existing rules are effective at revealing true risk of banks.

To understand bank risk, it is essential to grasp the concept of bank capital and its importance. Suppose that there is Bank A that gets $100 (recorded as debt) from one person, gives this $100 to another person and earns money from the difference in rates. If the latter fails, Bank A cannot pay back the former and fails itself. In order to survive, Bank A must have its own funds, i.e., capital, to cover possible losses. The regulator monitors banks to ensure that they have sufficient capital for the risks that they are taking, offering them two ways to link capital to risk: (i) using the "one-size-fits-all" regulatory framework, or potentially more risk-sensitive (ii) using their internal risk models upon the supervisory approval. Under (ii), banks face a trade-off between underreporting of risks to get lower capital requirements ex ante and having higher regulatory penalties ex post for the detected misrepresentation of risks. This in particular applies to market risk that arises from banks' trading activities. Many banks hold large trading portfolios and in particular, those of U.S. banks jointly constitute about $2 trillion and 10% of total assets (as of 2017) relative to 2.5% and 5% in the early 1990s and 2000s (Falato et al., 2019). The failure to correctly manage market risk led to large losses for many banks during the global financial crisis (BCBS, 2019b). Yet there are only few theoretical (Prescott, 2004; Cuoco and Liu, 2006; Colliard, 2019; Leitner and Yilmaz, 2019) and empirical (Begley et al., 2017; Mariathasan et al., 2022) studies concerning the use of internal models for market risk.

I model how the regulator should jointly determine optimal capital requirements and penalties under banks' private information about true risk so that to ensure truthful reporting. Under the trade-off between lower capital ex ante and potentially higher penalties ex post, banks should find it optimal to disclose their risk truthfully in fear of risk-based penalties which depend therefore on banks' risk aversion. In practice, these penalties comprise additionally required capital (up to 1/3 more) and possibly a model revision. To test whether actual penalties are set optimally, I use risk model revisions as more risk-averse banks should revise their models more to better estimate risk that they face and decrease uncertainty about penalties if the current model does not perform well.

To address identification concerns regarding the use of banks' self-reported data, I first employ an instrumental variable approach to recover exogenous variation in the past-year number of risk underreporting incidences. The exclusion restriction rests on the fact that this number is the one and only criterion for a supervisor to disallow the use of a risk model. Moreover, I exploit the change in market risk capital regulation for U.S. banks in 2013 as a plausibly exogenous shock to their market risk reporting requirements (Federal Register, 2012). I also analyze time-varying additional capital requirements using data from the World Bank's *Bank Regulation and Supervision Survey* (BRSS) and data on the global systemically important banks (G-SIBs) published by the Financial Stability Board. Finally, I study the ex post risk model outcomes in the presence of the additional market risk capital requirement and supervisory scrutiny to further inform on the policy side.

I hand-collect information on the reported incidences of risk model revisions and classify them (where possible) into those that ceteris paribus imply higher or lower capital requirements. I use the sample from Mariathasan et al. (2022) for the remaining banks' self-reported data which covers 17 banks from the U.S., Canada and Europe from 2002 to 2019. I complement this self-reported data with supervision data from the BRSS to better examine the role of supervision in market risk capital regulation.

My model illustrates that optimal penalties decrease with banks' risk aversion for all true risk levels. This is different from existing models of capital regulation in which penalties are either fixed (Prescott, 2004) or serve as an unlimited reward to those banks whose losses do not breach a certain threshold (Colliard, 2019). In the data, I find that banks are less likely to report switching to a model that implies higher capital requirements with more underreporting of risk in the past. Moreover, using these risk models corresponds to worse model outcomes ex post. Similarly, the change in regulation intended to better capture market risk of U.S. banks is followed by 50% more underreporting of risk, but also by 35% lower reported risk among these banks and even lower among those with larger trading activities. This result complements Begley et al. (2017) who find that banks with larger trading operations at the beginning of 2006 tend to underreport risk more over the period from 2006 to 2013. Thus, penalties in practice are set suboptimally and built on assuming banks being more risk-averse than they really are as the empirical results demonstrate.

My findings indicate that banks can still use tricks to hide their risk despite many post-crisis reforms. Basel III, however, seems to be more detrimental for truthful reporting: additional market risk capital requirements are halved (BCBS, 2019a, see also Table 1), whereas the estimated impact of Basel III revisions is a 22% increase in the share of market risk in bank capital requirements as of 2022 (BCBS, 2019b). These changes seem to only help banks to look safer than they really are as they did in the global financial crisis. Nevertheless, my analysis suggests that higher quality supervision can reduce the inefficiency.

This paper provides several contributions to the literature. First, I contribute to the existing theoretical work on incentive problems in the market risk capital regulation (Prescott, 2004; Cuoco and Liu, 2006; Colliard, 2019; Leitner and Yilmaz, 2019). Inspired by the design of regulation at place, I consider a simple model setup where the regulator jointly determines the optimal capital requirements and penalties which are set to achieve the truthful reporting of risk and the optimal amount of risk-based capital. Second, using a hand-collected sample which is twice as large as the sample in Begley et al. (2017), I provide evidence on underreporting of bank risk as well as assess regulation with respect to promoting strong incentives among banks to improve their models.

The rest of the paper is organized as follows. Section 2 describes the theoretical model and its numerical application. Section 3 discusses the data and empirical strategy. Section 4 presents the empirical results and Section 5 concludes.

2 Model

Capital regulation using banks' internal models for market risk consists of two major elements: (i) a capital requirement, and (ii) a penalty which includes an additional capital charge that increases with underreporting of risk, and a potential model revision (see Table 1)[1]. Ceteris paribus, the

[1] According to Basel rules, market risk capital requirements (similar to those for credit and operational risk) constitute 8% of market risk-weighted assets. If risk weights are determined internally by banks, their market risk-weighted assets can be represented as $12.5\times(3+\Delta\text{Capital})\times f(\text{Reported Risk})$, where f is an increasing function of risk reported by banks that changes along Basel I, II and III. The corresponding values of ΔCapital are given in Table 1.

lower the risk reported by banks is, the lower is the corresponding capital requirement. This implies that banks would always prefer to report the lowest risk possible when they have private information about their risk. Thus, regulatory penalties for underreporting of risk are key to ensure a correct mapping between bank risk and bank capital. To evaluate the existing regulation, it is therefore necessary to build a model where the regulator jointly determines capital requirements and penalties, and where penalties are used as an incentivizing mechanism to mitigate misreporting of bank risk and thus suboptimal capital requirements ex ante.

To find the optimal combination of regulatory capital and penalties to ensure truthful reporting of bank risk, I consider a simple model setup in the style of Prescott (2004), albeit with a few changes in an attempt to get closer to actual regulation. First, I consider risk-based penalties that are charged to banks when they misreport risk and are equal to zero, otherwise. This is useful because according to the existing capital regulation, banks incur zero penalties when they assess their risks well and their losses do not exceed their own risk estimates. Also, the empirical evidence suggests that banks' misreporting incentives around the threshold when penalties stop being zero are different from those around any other thresholds due to, for example, more close supervision (Begley et al., 2017). The resembling practice design of penalties in this model is different from that in existing models of capital regulation in which penalties are either fixed (Prescott, 2004) or serve as an unlimited reward to those banks whose losses do not exceed a certain threshold (Colliard, 2019). Second, in contrast to Prescott (2004) and Colliard (2019), I consider different attitudes towards risk among banks that will ultimately affect their choice of what risk to report to the regulator given the true risk that they face. This is particularly relevant for actual internal model-based regulation as this design feature allows to have the range of optimal regulatory capital and penalties instead of the "one-size-fits-all" solution. Third, different from Prescott (2004) and similar to Colliard (2019), I include a participation condition for banks that determines the maximum feasible combination of regulatory capital and penalties. Similar to Prescott (2004) and Colliard (2019), I keep the information asymmetry which is highly relevant in practice, letting the regulator observe only a signal about banks' true risk.

There are two types of agents in the model: banks and a regulator. Each bank makes a risky investment of size one. The investment may succeed or fail depending on the random failure probability $\omega \in [\underline{\omega}, \overline{\omega}]$ with $0 \leqslant \underline{\omega} < \overline{\omega} \leqslant 1$. This probability is drawn by nature from the cumulative distribution function $F(\omega)$ and density $f(\omega)$. Banks are assumed to perfectly observe ω. The regulator does not observe ω, but $\omega' \in [\underline{\omega}, \overline{\omega}]$ which is reported by banks (and is therefore non-random). When $\omega' < \omega$, true risk ω is underreported by banks, and when $\omega' > \omega$, true risk ω is overstated.

Banks can finance their risky investment with either deposits or capital. $K(\omega') \in [0, 1]$ denotes the amount of capital that is held by banks for a given reported risk ω'. Then, since bank size is normalized to one, the respective amount of deposits is $1 - K(\omega')$. $U(\omega', \omega)$ denotes the banks' payoff if the true risk is ω and risk ω' is reported to the regulator. Banks are assumed to participate in regulation:

Assumption 1. $U(\omega', \omega) \geqslant 0 \;\; \forall\, (\omega', \omega) \in [\underline{\omega}, \overline{\omega}]^2$.

There is a conflict of interest between banks and the regulator. Banks prefer to finance the investment with deposits rather than with capital[2]. The regulator thus sets a *risk-sensitive capital requirement* $K(\omega')$. The less capital K is held by banks, the more deposits the regulator needs to cover ex post in case the investment fails. The corresponding value loss to society is denoted by $V(K) \leqslant 0$ $(V' > 0, V'' < 0)$ which takes value zero when $K = 1$. Figure 2 illustrates the function V. Formally,

Assumption 2. $V\big(K\big) \leqslant 0 \;\; \forall\, K \in [0, 1]$ with $V\big(1\big) = 0$.

Since banks have private information about the true risk ω, they would always prefer to report the lowest possible risk $\underline{\omega}$ and hold the lowest possible amount of capital $K(\underline{\omega})$. Therefore, to incentivize banks to report truthfully, the regulator additionally sets *risk-sensitive penalties* $T(\omega') \in [0, 1]$. They reflect the degree of regulatory scrutiny for a given signal ω'. Penalties T are imposed on banks in case the investment fails which happens with probability ω, while there is probability $1 - \omega$ where there are no penalties. The regulation works as follows:

[2] This preference can stem, for example, from tax treatment and subsidized safety net protections, including deposit insurance and too-big-to-fail subsidies that benefit bank debt more than bank equity (Dagher et al., 2016).

$t = 0$: The regulator specifies formulae linking any reported risk ω' to capital requirement $K(\omega')$ and penalties $T(\omega')$ in case the investment fails.

$t = 1$: Banks observe true risk $\omega \in [\underline{\omega}, \overline{\omega}]$ drawn by nature from $F(\omega)$ and report $\omega' \in [\underline{\omega}, \overline{\omega}]$ to the regulator.

$t = 2$: Banks make their investment financed with $K(\omega')$ capital.

$t = 3$: The investment fails and banks are charged penalties $T(\omega')$ with probability ω, and final payoffs are realized.

The regulator wants to achieve a proper link between bank capital and bank risk, and uses penalties to incentivize truthful reporting among banks. It is therefore not in the regulator's interest to maximize the capital requirement. Instead, consistent with the literature on optimal bank capital (Miles et al., 2013), the regulator's objective is to maximize social welfare balancing between benefits and costs of increasing the capital requirement. On one hand, the benefits appear because a larger buffer of truly-absorbing capital reduces the economic costs in case of failure measured by V. On the other hand, the offset to any such benefits comes in the form of higher costs of bank funding as equity replaces debt, and as a consequence, higher costs of intermediation. These costs are measured by the per unit cost of capital c. Thus, the regulator is searching for capital and penalty schedules which solve the following problem applying the revelation principle:

$$\max_{K(\omega)\in[0,1]} \int_{\underline{\omega}}^{\overline{\omega}} \Big(\omega V\big(K(\omega)\big) - cK(\omega)\Big) dF(\omega)$$

subject to

$$\forall\, (\omega', \omega) \in [\underline{\omega}, \overline{\omega}]^2 \quad U(\omega, \omega) \geqslant U(\omega', \omega), \tag{IC}$$

$$\forall\, \omega \in [\underline{\omega}, \overline{\omega}] \quad U(\omega, \omega) \geqslant 0. \tag{PC}$$

The first term in the regulator's payoff $\omega V\big(K(\omega)\big)$ represents the expected failure loss to society, which the regulator needs to cover for a given capital amount K held by banks. The second term $cK(\omega)$ is the bank cost of issuing capital for a given risk ω. Penalties T do not represent value to society other than from incentivizing truthful reporting, therefore, do not enter the payoff.

The regulator maximizes the payoff to society subject to two constraints: (i) the constraint that the banks' payoff when $\omega' = \omega$, i.e., when risk is reported truthfully, is at least as much as when any other ω' is reported (incentive compatibility (IC) constraint), and (ii) the constraint that for no value of ω is the banks' payoff negative (participation (PC) constraint).

To eliminate possible corner solutions, I make two additional assumptions:

Assumption 3. $\Big(\underline{\omega} V\big(K(\underline{\omega})\big) - cK(\underline{\omega})\Big) dF(\underline{\omega}) > \underline{\omega} V(0) dF(\underline{\omega})$.

Assumption 4. $\Big(\overline{\omega} V\big(K(\overline{\omega})\big) - cK(\overline{\omega})\Big) dF(\overline{\omega}) > -c$.

Assumption 3 ensures that even under the most favorable risk distribution $F(\underline{\omega})$ it should never be optimal for the regulator to set $K = 0$ due to high expected social losses in case of failure $\underline{\omega} V(0) dF(\underline{w})$. Assumption 4 makes sure that setting $K = 1$ is never optimal either due to the high social cost of issuing capital even under the most unfavorable risk distribution $F(\overline{\omega})$.

If the regulator had full information about true risk ω, the first-order condition from solving the regulator's problem combined with Assumption 3 and Assumption 4 would define the interior first-best capital requirement $K^f(\omega)$ as given in Proposition 1:

$$\forall\, \omega \in [\underline{\omega}, \overline{\omega}] \quad \omega V'\big(K(\omega)\big) = c. \tag{1}$$

Here the marginal benefit of capital equates its marginal cost. Since $V' > 0$, $c > 0$, (1) implies that $K(\omega)$ is increasing in ω, i.e., the capital requirement is increasing in the true risk. This positive relationship between risk and capital is consistent with the risk-based capital regulation in practice.

Proposition 1. The first-best regulatory capital $K^f(\omega)$ is defined as:

$$K^f(\omega) = \arg\max_K \int_{\underline{\omega}}^{\overline{\omega}} \Big(\omega V\big(K(\omega)\big) - cK(\omega)\Big) dF(\omega).$$

$K^f(\omega)$ is increasing in ω.

The regulator who observes only a signal about the true risk is looking for the second-best capital

$K^s(\omega)$ and penalties $T^s(\omega)$ that satisfy (IC) and (PC) conditions on banks' payoff U. Therefore, each type of banks' preferences would be associated with a corresponding pair of optimal regulatory capital K and penalties T. Penalties in practice, as depicted in Figure 1, vary with the degree of risk misreporting, supporting the use of different banks' attitude towards risk. In addition, recent empirical evidence suggests that disparities in banks' attitude towards risk matter for how banks value risk given the amount of risk that they face (Camba-Méndez and Mongelli, 2021). This finding is consistent with preceding theoretical work which treats banks as risk-averse agents (see e.g. Ratti, 1980; Sealey, 1980; Ho and Saunders, 1981; Koppenhaver, 1985; Angbazo, 1997). A risk aversion assumption in this literature rests on the traditional explanations for risk-averse behavior including (i) incentive problems such as adverse selection and moral hazard related to regulation (e.g., deposit insurance, bank resolution mechanisms, etc.) requiring banks which enjoy protection to limit risk, (ii) bankruptcy cost from partial or complete default, (iii) management's inability to diversify its human capital, and (iv) insufficient owner diversification. Thus, drawing on actual regulation and the existing studies of banks' risk-related behavior, I assume that banks have different attitudes towards risk and can be either risk-neutral or risk-averse. If banks are risk-neutral (as in e.g. Prescott, 2004; Colliard, 2019), their expected payoff $U^{RN}(\omega', \omega)$ is[3]:

$$U^{RN}(\omega', \omega) = (1 - \omega)\big(1 - K(\omega')\big) + \omega\big(1 - K(\omega') - T(\omega')\big) = 1 - K(\omega') - \omega T(\omega'). \tag{2}$$

With probability $1 - \omega$, the investment succeeds and banks derive utility from the deposit amount $1 - K(\omega')$. With probability ω, the investment fails and banks are additionally charged penalties $T(\omega')$. To define the expected payoff for the rest of bank population which is not risk-neutral, I use CRRA preferences with a risk aversion parameter $\gamma \in (0, 1)$. In choosing CRRA preferences, I follow Cuoco and Liu (2006) who use this type of preferences in their model of market risk capital regulation. Similar to the expected payoff of risk-neutral banks $U^{RN}(\omega', \omega)$, the expected payoff

[3] I follow Prescott (2004) in modelling banks' preferences over capital by $1 - K$ rather than formally including the cost of capital because it has no impact on the model results (banks would still prefer less capital to more) and simplifies the analysis. Also, under this functional form, K may be interpretable as capital net of potentially required penalties.

of risk-averse banks $U^{RA}(\omega', \omega)$ is[4]:

$$\begin{aligned} U^{RA}(\omega', \omega) &= (1-\omega)\frac{\big(1-K(\omega')\big)^{1-\gamma}}{1-\gamma} + \omega\left(\frac{\big(1-K(\omega')\big)^{1-\gamma}}{1-\gamma} - \frac{\big(T(\omega')\big)^{1-\gamma}}{1-\gamma}\right) = \\ &= \frac{\big(1-K(\omega')\big)^{1-\gamma} - \omega\big(T(\omega')\big)^{1-\gamma}}{1-\gamma}, \end{aligned} \tag{3}$$

with $U^{RA}(\omega', \omega) = 1 - K(\omega') - \omega T(\omega') = U^{RN}(\omega', \omega)$ when $\gamma = 0$.

Banks' payoffs as defined in (2) and (3) are decreasing in K and T ($U_K^{RN'} < 0, U_T^{RN'} < 0, U_K^{RA'} < 0, U_T^{RA'} < 0$), meaning that banks are better off from facing lower capital requirements and lower penalties independent of banks' preferences over risk. Moreover, $U_T^{RA''} > 0$ ($U_K^{RA''} < 0$) which implies that an increase in penalties (capital requirements) when they are relatively low is more (less) costly for risk-averse banks than when they are relatively high. The observation about penalties is consistent with the result in Begley et al. (2017) that banks tend to strategically underreport risk near the threshold at which penalties stop being zero, but not when penalties are relatively high.

(IC) condition requires that reporting true risk ω is the solution of banks' maximization problem:

$$\frac{\partial U^{RN}(\omega', \omega)}{\partial \omega'} = -K'(\omega') - \omega T'(\omega'),$$

$$K'(\omega) = -\omega T'(\omega); \tag{4}$$

$$\frac{\partial U^{RA}(\omega', \omega)}{\partial \omega'} = -\big(1-K(\omega')\big)^{-\gamma} K'(\omega') - \omega\big(T(\omega')\big)^{-\gamma} T'(\omega'),$$

$$\big(1-K(\omega)\big)^{-\gamma} K'(\omega) = -\omega\big(T(\omega)\big)^{-\gamma} T'(\omega). \tag{5}$$

(4) and (5) are the first-order conditions that must hold for $\omega' = \omega$ for risk-neutral and risk-averse banks, respectively. According to (4) $\big((5)\big)$, the marginal change in capital requirements (for a given amount of deposits) should be set equal to the expected marginal change in penalties (for a given level of penalties) for risk-neutral (risk-averse) banks. Also, since from (1) $K' > 0$, (4)

[4] Different timing of banks' financing decision and penalties allows me to consider banks' disutility from penalties separately from their deposit-driven utility. This modelling decision does not significantly alter the findings, but simplifies the algebra. More detailed discussion of the effects of this modelling choice and possible alternatives is in Appendix A.

and (5) imply that $T(\omega)$ decreases in ω, i.e, penalties decrease in the true risk. This negative relationship between the true risk and penalties reflects the fact that misreporting of risk is more undesirable from the social perspective when true risk ω is low together with the corresponding capital requirement $K(\omega)$ and the investment fails.

(4) and (5) are the differential equations that pin down capital requirements and penalties such that it is in the interest of banks to report risk truthfully. To ensure that these values are feasible for the regulator, they must satisfy (PC) condition which requires that banks' payoff never goes below zero:

$$\forall\, \omega \in [\underline{\omega}, \overline{\omega}], \quad \forall\, \gamma \in [0, 1) \quad U(\omega, \omega) = \frac{\big(1 - K(\omega)\big)^{1-\gamma} - \omega\big(T(\omega)\big)^{1-\gamma}}{1-\gamma} \geqslant 0.$$

This constraint puts a limit on the maximum feasible regulatory capital $K(\omega)$ and penalties $T(\omega)$:

$$\forall\, \omega \in [\underline{\omega}, \overline{\omega}], \quad \forall\, \gamma \in [0, 1) \qquad K(\omega) \leqslant 1 - \omega^{\frac{1}{1-\gamma}} T(\omega), \tag{6}$$

i.e., the maximum amount of capital that the regulator can ask banks to hold is equal to the amount of banks' assets net of the expected penalties.

The conditions (1), (4), (5) and (6) jointly describe the second-best solution for regulatory capital $K^s(\omega)$ and penalties $T^s(\omega)$. Particularly, the regulator's first-order condition (1) reflects the trade-off between implementing the first-best capital requirements $K^f(\omega)$ and saving on costs of issuing capital c. Under full information, the regulator would perfectly observe ω and could assign banks a unique risk-based capital amount $K(\omega)$ according to (1). Under incomplete information instead, the regulator would bear the social cost of failure only with an unobserved probability ω. This implies that in the presence of information asymmetry the regulator could be better off saving on the cost of issuing capital by marginally reducing K for very high values of ω. Therefore, the capital requirement for the highest possible failure risk $\overline{K} = K(\overline{\omega})$ may not be unique in the second-best and there would exist an interval in the upper tail of risk distribution such that over this interval the capital requirement stays constant at $\overline{K}$ (see Figure 3)[5].

[5] Prescott (2004) and Colliard (2019) also find that regulatory capital remains constant at the upper tail of risk

Thus, there exists a threshold $\widehat{\omega}$ such that banks with any $\omega \in [\widehat{\omega}, \overline{\omega}]$ get the same capital requirement $\overline{K}$. As a consequence, these banks would have incentives to report the highest possible risk $\overline{\omega}$ to get the lowest possible penalties $\overline{T} = T(\overline{\omega})$, because $T' < 0$ and because banks' payoff decreases in penalties ($U_T^{RN'} < 0, U_T^{RA'} < 0$). To be incentive-compatible, penalties should therefore be fixed at $\overline{T}$ for any $\omega \in [\widehat{\omega}, \overline{\omega}]$ similar to the capital requirement over the same interval $\overline{K}$.

Proposition 2 formally describes regulatory capital and penalties which are optimal under banks' private information about the true risk:

Proposition 2. The second-best regulatory capital $K^s(\omega)$ and penalties $T^s(\omega)$ are:

$$K^s(\omega) = \begin{cases} K(\omega) & \text{if } \omega \leqslant \widehat{\omega}, \\ \overline{K} & \text{if } \omega > \widehat{\omega}, \end{cases} \qquad T^s(\omega) = \begin{cases} T(\omega) & \text{if } \omega \leqslant \widehat{\omega}, \\ \overline{T} & \text{if } \omega > \widehat{\omega}, \end{cases}$$

with $K(\omega)$, $T(\omega)$, $\overline{K}$, $\overline{T}$ and $\widehat{\omega}$ characterized by:

$$\forall\, \omega \in [\underline{\omega}, \widehat{\omega}] \qquad \omega V'\big(K(\omega)\big) = c, \qquad \forall\, \gamma \in [0,1) \qquad \big(1 - K(\omega)\big)^{-\gamma} K'(\omega) = -\omega\big(T(\omega)\big)^{-\gamma} T'(\omega);$$

$$T(\omega) \leqslant \frac{1 - K(\omega)}{\omega^{\frac{1}{1-\gamma}}} \qquad \overline{K} = K(\widehat{\omega}) \leqslant 1 - \omega^{\frac{1}{1-\gamma}} T(\omega) \qquad \overline{T} = T(\widehat{\omega}).$$

Regulatory capital $K^s(\omega)$ is increasing in ω for all $\omega \leqslant \widehat{\omega}$ and is constant for all $\omega > \widehat{\omega}$, penalties $T^s(\omega)$ are decreasing in ω for all $\omega \leqslant \widehat{\omega}$ and are constant for all $\omega > \widehat{\omega}$.

In the second-best contract, when true risk ω is relatively high ($\omega > \widehat{\omega}$), there is no risk variation in either capital requirement K or penalties T. In this case, banks are required to hold the highest possible capital amount $\overline{K}$. On the other hand, when true risk ω is relatively low ($\omega \leqslant \widehat{\omega}$), capital requirement K as well as penalties T are risk-sensitive and defined by the first-order conditions (1), (4) and (5). Because different banks' payoffs U^{RN} and U^{RA} decrease in both K and T, whereas $K' > 0$ and $T' < 0$, banks deciding on what risk to report face a trade-off between lower capital requirement K and potentially higher penalties T.

distribution. In their models of credit risk capital regulation, the regulator faces a similar trade-off between saving on auditing costs and implementing capital requirements close to the first-best due to the slightly altered payoff in the second-best compared to the first-best.

2.1 Numerical Analysis of Optimal Regulatory Capital and Penalties

I illustrate the model solution as defined in Proposition 2 with a numerical example. I assume a simple quadratic loss function V: $V(K) = -(1-K)^2$ with $V(1) = 0$, $V' > 0$ and $V'' < 0$ (see Figure 2). Assuming this form for regulatory function V allows to define the first-best regulatory capital K^f using (1):

$$K^f(\omega) = 1 - \frac{c}{2\omega}, \tag{7}$$

where $K' = \frac{c}{2\omega^2} > 0$, i.e., K^f is increasing in ω as in the model.

The regulator aims at implementing the full-information capital requirement K^f for any $\omega \leqslant \widehat{\omega}$ which is feasible only if there exists T such that (4) $\big((5)\big)$ and (6) hold for risk-neutral (risk-averse) banks. When banks are risk-neutral, optimal penalties T^{RN} can be found from the differential equation (4):

$$T^{RN}(\omega) = \frac{c}{4\omega^2} + c_1, \tag{8}$$

where $T^{RN'}_{\omega} = -\frac{c}{2\omega^3} < 0$, i.e., T is decreasing in ω as in the model.

The range of optimal penalties for risk-averse banks T^{RA} can be obtained by solving the differential equation (5) for different values of γ:

$$\forall\, \gamma \in (0,1) \quad T^{RA}(\omega) = c\left(\frac{1-\gamma}{8\omega^2}\right)^{\frac{1}{1-\gamma}} + c_2, \tag{9}$$

where $T^{RA'}_{\omega} = -\big((1-\gamma)^{\gamma} 2^{-2-\gamma} c^{1-\gamma} \omega^{-3+\gamma}\big)^{\frac{1}{1-\gamma}} < 0$.

Importantly, knowing regulatory function V and the corresponding capital requirement K allows to infer the relation between penalties $T^{RA'}_{\omega}$ and banks' attitude towards risk captured by γ. $T^{RA'}_{\gamma} = \frac{c}{8\omega^2}(1-\gamma)^{\frac{1}{1-\gamma}-2}\big(\log(1-\gamma) - 1\big) < 0$ for any $\gamma \in (0,1)$, i.e., penalties T are decreasing in banks' risk aversion parameter γ.

Table 2 demonstrates the numerical solution with risk-neutral ($\gamma = 0$) and risk-averse ($\gamma = 0.25$) cases depicted in Figure 3. I consider two scenarios for the lower bound of T denoted by $\overline{T} = T(\overline{\omega})$ following penalties in practice (see Figure 1 and Table 1): $\overline{T} = 0.4$ and $\overline{T} = 0.2$. (6), (7), (8) and (9) define the feasible sets of parameters given both values of $\overline{T}$. Accordingly, the following two sets of parameters are chosen: $\underline{\omega} = 0.25$, $\overline{\omega} = 0.5$, $c = 0.19$ if $\overline{T} = 0.4$ and $\underline{\omega} = 0.25$, $\overline{\omega} = 0.7$, $c = 0.19$ if $\overline{T} = 0.2$. For these sets of parameters, Table 2 reports the selection of results and provides further details on how the regulator should optimally choose capital requirement K^s and penalties T^s, including on how to determine the threshold $\widehat{\omega}$.

Figure 3 illustrates several crucial implications of the model. First, the lower is ω, the lower is the corresponding capital requirement $K(\omega)$, but the higher are penalties $T(\omega)$. This is consistent with the trade-off that banks face in practice when deciding on what risk to report. Second, comparing the results for two values of $\overline{T}$, if penalties become lower, the regulator must also optimally adjust capital requirements, making them higher. In the light of recent changes in regulation that make one of penalty components two times smaller (an additional capital charge for the detected misrepresentation of risk), this implies that such changes should be accompanied by an increase in capital requirements, or alternatively by tightening the other penalty component (supervisory scrutiny). Finally, penalties T are lower for more risk-averse banks. Because penalties in practice are heterogeneous and depend on how banks report risk, I test whether actual penalties successfully implement such dependencies and are therefore effective in the sections to follow.

3 Empirical Framework

3.1 Data

To study the effect of market risk capital regulation on banks' reporting behavior, I combine banks' self-reported information with accounting, national supervision and global volatility data as well as data on the global systemically important banks (G-SIBs). I use hand-collected data from publicly available quarterly, annual and Pillar III reports. I extract information on the disclosed incidences of risk model revisions (*New Model*) and classify them (where possible) into those that ceteris paribus imply higher (*Tight Model*) or lower (*Loose Model*) capital requirements. The classification is primarily done based on the information from the market risk management section of a particular filing. Also, starting from 2013Q4 in the light of the Basel III regime implementation, some banks begin to report quarterly changes in market risk-weighted assets and its drivers including model revisions. These values, being either positive or negative, allow to detect additional cases of model revisions and to more explicitly classify those as either *Tight* or *Loose*[6]. Both the number and the distribution of risk model revisions vary significantly across banks and over time (see Figure 4). There are on average more model revisions that imply lower capital requirements, especially right before and after the global financial crisis. However, banks seem to switch more actively to more stringent risk models during economic turmoil, i.e., during 2007-2008 as well as in 2020. Thus, banks tend to adopt more lenient standards for their market risk exposures during normal times and use stricter standards during crisis times. This observation is in line with the literature on credit risk, arguing that lenders choose lax lending standards during booms and switch to tight lending standards during busts (see e.g. Mariathasan and Zhuk, 2018; Farboodi and Kondor, 2021).

For the remaining self-disclosed bank data to study model outcomes, I use the sample from Mariathasan et al. (2022). The sample selection updates and extends Begley et al. (2017) and the final sample covers 17 banks[7] from the U.S., Canada and Europe who provide sufficient quarterly information on market risk models, estimated risk exposures and the number of days when the realized daily loss of a bank exceeds its risk estimate from 2002Q1 to 2019Q4[8]. The final sample comprises 920 bank-quarter observations and, when bank balance sheet information is taken into account, 842 bank-quarter observations[9].

Table 3 shows summary statistics on self-reported model revisions, reported risk exposures[10], its underreporting cases and corresponding additional capital charges. All 17 banks change their model at least once during the sample period. There are 252 risk model revisions in total, with

[6]Market risk capital requirements are proportional to market risk-weighted assets, constituting 8% of the latter.

[7]In contrast to Begley et al. (2017), I exclude PNC and SunTrust Bank from the final sample because they follow the standardized approach for market risk and hence do not use their internal models to self-determine their capital requirements.

[8]2020 data is excluded from the sample because of extreme market volatility caused by COVID-19 and the respective actions of national supervisors including Fed, ECB and FINMA that disregard underreporting of risk during 2020Q1 for the computation of capital requirements during 2020.

[9]Accounting data is obtained from S&P Global Market Intelligence (former SNL Financial), Orbis Bank Focus and Fitch, whereas data to measure exchange rate, interest rate, market and commodity volatilities is from the St. Louis Fed, International Financial Statistics and Eikon (Mariathasan et al., 2022).

[10]Regulatory 10-day 99% Value-at-Risk is considered as banks' self-reported risk exposure which represents the maximum potential loss over a 10-day horizon that should not be exceeded in 99% cases. In case it is unavailable, a one-day 99% Value-at-Risk scaled by a square root of 10 is used.

the vast majority constituting model revisions that imply lower capital requirements (146 out of 252)[11]. Non-U.S. banks tend to change their models more frequently with Credit Suisse doing so most often (36 times). Only three banks out of 17 (Deutsche Bank, Société Générale and Toronto-Dominion Bank) opted for a stricter model more often than for a more optimistic one during 2002-2019. All other banks, especially U.S. banks, seem to do more frequently model revisions that imply lower capital requirements.

The average number of risk underreporting incidences in the sample is 0.38. To further interpret this statistic note that using a risk model of a 99% confidence level, daily risk estimates may be exceeded by realized daily losses once in every 100 trading days on average, or around 0.63 times per quarter. Therefore, risk models in the sample seem to be on average rather conservative. That being said, there is substantial variation in the number of risk underreporting cases over time: between 2002 and 2006 it is around 0.1, between 2007 and 2010 it is approximately 1.1, and between 2011 and 2019 it is nearly 0.2. Thus, risk tends to be overreported during normal times, whereas underreporing of risk is concentrated in crisis times, i.e., when truthful risk reporting matters the most.

Based on risk underreporting data, I determine the additionally required capital multiplier $\Delta Capital$ as outlined in the Basel framework (see Table 1). Moreover, the product of $\Delta Capital$ and self-reported risk exposures represents the minimum quarterly monetary cost of penalties[12]. The average $\Delta Capital$ in the sample is 0.08, the average self-reported risk exposure is just below \$150 million which results in at least \$11 million monetary cost of penalties on average per quarter. The estimated lower bound for pecuniary penalties varies a lot across banks from zero for five banks who face no additional market risk capital requirement over the sample period[13] to nearly \$50 million on average per quarter for Morgan Stanley.

[11] 40 model revisions more occur in 2020 as depicted in Figure 4 (not included in the final sample).

[12] Under Basel I, market risk capital requirements are determined as the product of the quarterly average 10-day Value-at-Risk (unless the quarter-end Value-at-Risk exceeds the quarterly average) and the multiplier that includes $\Delta Capital$ given in Table 1. Basel II and III use a more complex measure for market risk capital requirements which is still based on the 10-day Value-at-Risk and if anything takes a value further in the tail of risk distribution. These changes in the Basel approach to market risk unfortunately make it impossible to accurately estimate the penalties, but its lower bound can be reasonably determined.

[13] These five banks include Bank of New York Mellon, Canadian Imperial Bank of Commerce, Citi, Bank of Nova Scotia and Toronto-Dominion Bank.

As mentioned above, data on changes in capital requirements due to model revisions becomes available for some banks starting from 2013Q4. *Tight* (*Loose*) (\$M) in Table 3 represents the average quarterly positive (negative) change in capital requirements attributed to model revisions. Drawing on the available data, banks tend to lower their capital requirements when relaxing their risk models significantly more than to increase them when switching to a more stringent model. The average quarterly reduction in market risk capital requirements due to model revisions exceeds \$125 million whereas the average quarterly increase in those is just above \$50 million. Only two banks out of 11 for which the data is available experience a larger change in their capital requirements when switching to a more conservative model than to a more optimistic one, but do so at a lower frequency[14]. Moreover, comparing how much capital banks tend to save from relaxing a model *Loose* (\$M) to how much addditional capital they are required to hold in case of detected misrepresentation of risk $\Delta Capital$ (\$M), I conclude that the monetary cost of penalties seems to be negligibly small (if not zero) for most banks. This suggests that the non-pecuniary component of penalties, which manifests itself in a supervisory action, is crucial in ensuring truthful reporting of bank risk.

3.2 Empirical Strategy

In the model, it is optimal to penalize more risk-averse banks less for all true risk levels (see Figure 3). To test whether penalties in practice are set optimally, we need a measure for banks' risk aversion. However, according to the recent literature, the existing direct proxies for banks' risk aversion are weak. In the context of credit risk, Camba-Méndez and Mongelli (2021) handle this by using an implicit approach to study how much of the observed heterogeneity in bank loan pricing is explained by disparities in banks' attitude towards risk. The authors' approach is based on disentangling the amount of risk faced by banks and the price they charge for holding that risk. Similarly but for market risk, one would ideally want to observe how banks differently assess their market risk when producing their own risk estimates which eventually means to observe their market risk internal models. As these models are proprietary, banks disclose publicly a limited amount

[14] These are two Canadian banks: Canadian Imperial Bank of Commerce and Royal Bank of Canada.

of related information, but they do disclose when they make some model adjustments. Using this information, I am able to test whether banks are more likely to revise their models if the current model does not predict risk well, in order to assess risks better. Critically, this pattern is expected to be more prevalent among more risk-averse banks. To understand whether the heterogeneity in penalties proposed by the Basel Committee effectively aligns with disparities in banks' preferences, I proceed in two steps. First, I examine whether banks indeed revise their models if the current model does not perform well. To do that, I use the number of risk underreporting cases in the preceding year which is the main model performance criterion according to the Basel framework. Second, I investigate whether risk prediction improves when banks revise their models.

A key identification challenge stems from the fact that underreporting of risk, albeit over the past year, is self-reported by banks and is hence potentially endogenous to model revisions. To alleviate this concern, I use an instrumental variable (IV) approach where I exploit the product of a supervisory enforcement index and the past-year S&P 500 index volatility as an instrument. The supervisory enforcement index is based on the number of enforcement powers available to the supervisory agency according to the World Bank's *Bank Regulation and Supervision Survey* (BRSS) (World Bank, 2019). The magnitude of the supervisory enforcement index depends on the answer to the following question: *11.1 Please indicate whether the following enforcement powers are available to the supervisory agency*[15]. I ensure that the coefficient for the instrument is statistically significant in the first-stage regressions (t-statistic = 4.35 and F-statistic = 18.94 in the first-stage

[15] These include the supervisory powers to "(a) cease and desist-type orders for imprudent bank practices, (b) forbearance (i.e. to waive regulatory and supervisory requirements), (c) require a bank to meet supervisory requirements (e.g. capital, liquidity etc.) that are stricter than the legal or regulatory minimum, (d) require bank to enhance governance, internal controls and risk management systems, (e) require bank to apply specific provisioning and/or write-off policies, (f) require banks to constitute provisions to cover actual or potential losses, (g) restrict or place conditions on the types of business conducted by bank, (h) withdraw the bank's license, (i) require banks to reduce/restructure their operations (e.g. via asset sales and branch closures) and adjust their risk profile, (j) require banks to reduce or suspend dividends to shareholders, (k) require banks to reduce or suspend bonuses and other remuneration to bank directors and managers, (l) suspend or remove bank directors, (m) suspend or remove managers, (n) require commitment/action from controlling shareholder(s) to support the bank with new equity (e.g. capital restoration plan)" (World Bank, 2019). Using other supervision strength proxies for the instrument based on the 2019 BRSS, e.g., disclosure power of supervisors (*"10.10 Do supervisors require banks to publicly disclose . . . "*), supervisory frequency (*"12.23.2 How frequently are onsite inspections conducted in a year in the 10 largest banks by asset size?"*), supervisory training hours (*"12.43 How many hours of training (at the supervisory agency or elsewhere) on average have supervisors had in the last year?"*), number of supervisors per bank (*"12.39 How many professional bank supervisors are there in total (excluding all support functions and management)?"*), yield qualitatively similar estimates.

regressions in columns (5) and (7) of Table 4), hence indicating that the chosen instrument is relevant. Moreover, I select the instrument based on the economic argument (exclusion restriction) that the number of past-year risk underreporting incidences is the one and only criterion for the supervisor to disallow the use of a model (see Table 1), and the supervisory decision to enforce a model revision critically depends on the supervision strength combined with the origin of observed underreporting of risk given market volatility[16].

By exploiting exogenous variation in the number of risk underreporting cases in the preceding year, I examine whether worse risk model performance makes model revisions more likely and what is the nature of these model revisions. As a dependent variable, I consider two indicators: one for a model revision by bank i at quarter t ($NewModel_{it}$) and another for a switch by bank i at quarter t to a model that ceteris paribus implies higher capital requirements ($TightModel_{it}$). The endogenous regressor is $\sum_{s=1}^{s=4} \#Underreport_{it-s}$ which is the number of days from quarter $t-4$ to quarter $t-1$ on which the actual daily loss of bank i exceeds its risk estimate. Thus, $\sum_{s=1}^{s=4} \#Underreport_{it-s}$ captures the total number of risk underreporting cases in the past year which is a key model performance criterion for a supervisor according to the Basel framework. Given a binary outcome variable and a discrete endogenous regressor, the model choice is between the IV 2SLS estimator and the maximum likelihood estimator (probit). The former allows an endogenous regressor to take any form, however, the predicted values below zero and above one can be encountered which is not the case for probit. Also, the IV 2SLS estimator produces constant marginal effects. Instead, the probit model with an endogenous regressor can be used to compute marginal effects at certain values of the regressor, but generally requires that the regressor is continuous. Therefore, I consider both the IV probit and IV 2SLS regressions of the following form:

$$Y_{it} = \beta \sum_{s=1}^{s=4} \#Underreport_{it-s} + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \varepsilon_{it}. \tag{10}$$

Here the outcome variable Y_{it} is either $NewModel_{it}$ or $TightModel_{it}$. β is hence the coefficient of interest. X_{it} represents controls for several bank characteristics including bank size (proxied by

[16] The exclusion restriction assumption is further supported by the recent actions taken by national supervisors seeing extreme market volatility due to COVID-19 to disregard underreporting of risk during 2020Q1 for the computation of capital requirements.

total assets), leverage (proxied by the equity ratio) and profitability (proxied by the ratio of the net income to total assets). V_{it-1} represents lagged volatility measures to control for interest rate, exchange rate and commodity volatilities to account for time-varying sources of market risk across countries[17]. α_t represents year-quarter fixed effects that capture the effect of period-specific global shocks on risk model performance (including especially the crisis).

The next step is to analyze risk model outcomes following model changes. Even if banks revise their risk models when it is necessary, it is not clear whether these revisions lead to the improved reporting of bank risk ex post. In order to assess the ex-post model performance, I look at how many times true risk is underreported after a model change. Similar to Begley et al. (2017), I construct a variable $\#Underreport_{it}$ measuring the number of days during quarter t on which the actual daily loss of bank i exceeds its risk estimate. $\#Underreport$ is therefore a variable which represents positive discrete counts. Since OLS assumes normally distributed residuals and cannot rule out having negative and non-integer predicted values for a dependent variable, I choose another model that is more suitable for count data. More specifically, I consider a zero-inflated negative binomial (ZINB) regression model[18]. I use the natural logarithm of VIX to distinguish between two latent groups of $\#Underreport$ observations which can unconditionally take zero values, or reflect the realization of the negative binomial distribution and constitute either zero or positive integers.

Observing underreporting of risk does not necessarily mean that the model is per se bad unless it is associated with systematically lower risk estimates. To study whether such intentional underreporting of risk takes place, I analyze self-reported banks' risk exposures $ReportedRisk$ in addition to $\#Underreport$. $ReportedRisk_{it}$ is the natural logarithm of the 10-day 99% Value-at-Risk self-reported by bank i at quarter t. In case it is unavailable, a one-day 99% Value-at-Risk scaled by a square root of 10 is used instead.

To study model outcomes $\#Underreport$ and $ReportedRisk$, I first exploit the change in market

[17] Volatility variables are one-period lagged because risk model information comes from banks' financial reports as well as the other accounting data and is hence disclosed ex post for the quarter that just passed. Also, I include the S&P 500 index volatility as a market volatility control in the other regressions, but exclude it from volatility controls in (10) because it is used in the instrument.

[18] χ^2-test rejects the use of the Poisson model, an alternative popular model for count data. Vuong test supports the use of the zero-inflated model over the regular model.

risk capital regulation in the U.S. as a plausibly exogenous shock to banks' risk reporting requirements. In particular, I look at the introduction of the Market Risk Capital Rule (MRCR) enforced by Fed in 2013[19]. Starting from January 2013, 30 U.S. banks have been required to report more detailed market risk information to Fed (Federal Register, 2012). All six U.S. banks in the sample have been affected by the MRCR. I construct a variable $MRCR_{it}$ which is an indicator for bank i being affected by the MRCR at quarter t from 2013Q1 onwards. I estimate the regression:

$$Y_{it} = \beta MRCR_{it} + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \alpha_i + \varepsilon_{it}. \tag{11}$$

Here the outcome variable Y_{it} is either $\#Underreport$ or $ReportedRisk_{it}$ and α_i represents bank fixed effects. If the new regulation is effective, banks should enhance their reporting standards and have less incentives to underreport risk. This in particular applies to banks with significant trading activities that the MRCR targets. Hence, to better understand how related bank characteristics affect the MRCR implementation, I also include bank-specific interaction variables I_i, capturing banks' trading exposure pre-MRCR and the additional capital requirements set out for the G-SIBs by the Financial Stability Board in November 2012[20]. In these cases, the model therefore becomes:

$$Y_{it} = \beta_1 MRCR_{it} + \beta_2 MRCR_{it} \times I_i + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \alpha_i + \varepsilon_{it}. \tag{12}$$

I consider three variables for I_i: (i) $TA_{i2012\text{Q1}}$ which is the ratio of trading assets to total assets of bank i freezed at 2012Q1 level, i.e., one year before the MRCR comes into force; (ii) $HighTA_{i2012\text{Q1}} = 1$ if the ratio of trading assets to total assets of bank i as of 2012Q1 is above the sample mean and (iii) $G\text{-}SIBBucket_{i2012}$ which is the additional capital requirement (in %) according to the G-SIB list disclosed by the Financial Stability Board in November 2012.

The key identification assumption is that all changes observed in outcome variables for U.S. banks post-MRCR attribute to the change in regulation. In an attempt to capture some of cross-sectional variation, I include interaction variables I_i constructed as pre-MRCR intensity measures. Never-

[19]The press release by Fed can be consulted here.

[20]The G-SIB list published by the Financial Stability Board in November 2012 was the first G-SIB list where bank-specific additional capital requirements ("buckets") ranging from 1% to 3.5% were announced.

theless, to improve further upon the identification when studying risk model outcomes, I further exploit additional capital charges imposed on different banks at different moments of time. More specifically, I consider time-varying interaction variables I_{it}, capturing the introduction of supervisory tools to oversee more closely additional capital requirements in general, and of the additional capital requirements for the G-SIBs. First, I construct an indicator $SupervisoryOversight_{it}$ based on the answer to the question 12.34.1 in the 2019 BRSS where additional capital requirements are selected and the respective date of introduction is specified (*12.34.1 Does the banking supervisor have any tools to oversee more closely and/or limit the activities of large/interconnected institutions?*). Second, I further explore data on the G-SIBs and their additional capital requirements published by the Financial Stability Board using two variables: (i) $GSIB_{it} = 1$ if bank i is in a G-SIB list disclosed by the Financial Stability Board at quarter t, and (ii) *G-SIBBucket*$_{it}$ which is the additional capital requirement (in %) according to G-SIB lists published during 2014-2017[21]. To examine the effect of the additional capital burden on risk model outcomes also in times when banks revise their models $NewModel$, I consider the following model:

$$Y_{it} = \beta_1 NewModel_{it} + \beta_2 I_{it} + \beta_3 NewModel_{it} \times I_{it} + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \alpha_i + \varepsilon_{it}. \quad (13)$$

In the last part of the empirical analysis, I zoom in at the additional capital burden and supervisory attention directly related to market risk. To understand how a model revision relates to underreporting of risk in the presence of the additional capital requirement for market risk ΔCapital, I consider the interaction with an indicator variable $\mathbb{1}^{\Delta\text{Capital}}_{it-1}$ for ΔCapital of bank i taking non-zero values at quarter $t-1$. I run the regression:

$$\#Underreport_{it} = \beta_1 Model_{it} + [\beta_2 \mathbb{1}^{\Delta\text{Capital}}_{it-1} + \beta_3 Model_{it} \times \mathbb{1}^{\Delta\text{Capital}}_{it-1}] + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \alpha_i + \varepsilon_{it}, \quad (14)$$

where $Model_{it}$ is either $NewModel_{it}$ or $TightModel_{it}$. In the first set of regressions (14), I include only one of $Model$ indicators and β_1 is the coefficient of interest. If model revisions lead to a better reporting of bank risk, they should be associated with lower number of risk underreporting

[21] I choose this time period because there is a 14-month gap between the G-SIB list publication date and the actual implementation date, and G-SIB buckets have been implemented since 2016.

cases, especially those model revisions that imply higher capital requirements ($TightModel$). In the second set of regressions (14), I additionally include the interaction between one of $Model$ indicators and $\mathbb{1}^{\Delta\text{Capital}}_{it-1}$. β_3 thus captures the effect on $\#Underreport$ of those model revisions that occur in line with the recommendations from the Basel Committee.

Finally, to understand how a model revision affects model outcomes in the presence of the additional capital requirement for market risk given supervisory scrutiny, I also include interaction variables I_i, capturing the number of supervisors per bank and the number of hours of supervisory training obtained from the 2019 BRSS (*12.39 How many professional bank supervisors are there in total (excluding all support functions and management)?; 12.43 How many hours of training (at the supervisory agency or elsewhere) on average have supervisors had in the last year (2016)?*). In these cases, the model becomes:

$$Y_{it} = \beta_1 NewModel_{it} + \beta_2 \mathbb{1}^{\Delta\text{Capital}}_{it-1} + \beta_3 NewModel_{it} \times \mathbb{1}^{\Delta\text{Capital}}_{it-1} + \beta_4 NewModel_{it} \times I_i + \beta_5 \mathbb{1}^{\Delta\text{Capital}}_{it-1} + \\ + \beta_6 NewModel_{it} \times \mathbb{1}^{\Delta\text{Capital}}_{it-1} \times I_i + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \alpha_i + \varepsilon_{it}, \quad (15)$$

where I_i is either $\#Supervisors\ per\ Bank_i$ or $\#Hours\ of\ Supervisory\ Training_i$.

4 Results

Table 4 reports the findings from examining the relation between the past-year performance of banks' risk model and their willingness to revise it. Columns (1)-(4) present results for the IV probit estimation and columns (5)-(8) present results for the IV 2SLS estimation. I find that both the coefficient on $NewModel$ and the coefficient on $TightModel$ are significantly negative. This indicates that banks are less likely to revise their risk models and in particular switch to more stringent risk models as the past-year number of risk underreporting cases increases. More specifically, the average marginal effects of having one more incidence of risk underreporting in the past year on the probability of switching to a new or more stringent risk model are -10% and -4%, respectively (columns 5 and 7). Provided that the additional market risk capital requirement is imposed in approximately 10% cases in the sample, the results suggest that, on one hand, national supervisors seem to be more lenient towards banks than the Basel Committee proposes with regard to banks' internal models, and on the other hand, banks' own incentives to revise their risk models when it is probably necessary seem to be rather weak.

Table 5 reports the results from examining the effect of a plausibly exogenous shock to bank risk estimation and reporting requirements on risk model outcomes. In particular, I look at the new regulation (MRCR) enforced by Fed in 2013 (Federal Register, 2012). The MRCR targets U.S. banks with significant trading activities to adjust their capital requirements to better capture market risk of those activities as well as to enhance their risk computation and disclosures. The effect of the MRCR is expected to be negative on the number of risk underreporting incidences *#Underreport* and positive on the reported risk *ReportedRisk* provided banks should better account for different sources of market risk after the change in regulation. Instead, I find that the coefficient on *#Underreport* is significantly positive (columns 1-4), whereas the coefficient on *ReportedRisk* is significantly negative (columns 5-8). More specifically, U.S. banks tend to have 1.5 times more risk underreporting incidences after the shock (incidence-rate ratio for column 1). Moreover, following the implementation of the MRCR, U.S. banks tend to report approximately 35% lower risk exposure than non-U.S. banks (column 5). These results indicate that the Fed enforcement of Basel post-crisis rules is inefficient, suggesting that additional complexity from the MRCR allows for more misreporting by banks.

To study the heterogeneity of U.S. banks' response to the change in regulation, I additionally investigate the range of relevant cross-sectional characteristics in Table 5. In particular, I take into account banks' relative trading exposure pre-MRCR (columns 2-3 and 6-7) and the global systemic importance of banks captured by the additional capital requirements initially set out by the Financial Stability Board in November 2012 (columns 4 and 8). If the MRCR is effective, those banks who have larger trading operations should respond more to it by having lower *#Underreport* and higher *ReportedRisk*. Also, the G-SIB regulation is supposed to address the systemic and moral hazard risks associated with the selected institutions: the higher the G-SIB bucket is, the more such risks are present in the G-SIB itself. According to columns (2)-(3) and (6)-(7), banks with larger trading operations tend to have less underreporting of risk, but also lower risk estimates, resulting in lower capital requirements for these banks post-MRCR. On the other hand, the effect of the G-SIB bucket is significantly positive (column 8), suggesting that those banks who have relatively more complex portfolios in general[22] tend to report higher risk arising from their trading activities as well. If banks with higher trading exposure indeed became less risky post-MRCR as columns (6)-(7) suggest, this effect would translate into the G-SIB result as well. Thus, observing lower reported risk among U.S. banks with larger trading operations raises concerns about the effectiveness of MRCR.

Table 6 presents the results from examining the effect of time-varying additional capital burden for different banks on their model outcomes. Columns (1) and (4) capture the introduction of supervisory tools to oversee more closely additional capital requirements according to the 2019 BRSS, whereas columns (2)-(3) and columns (5)-(6) focus on the G-SIB designation and the respective additional capital requirements. In accordance with the guidance from the Financial Stability Board, G-SIBs *"are required to meet higher supervisory expectations for risk management functions, data aggregation capabilities, risk governance and internal controls."* Therefore, the expected effect of additional supervisory oversight and G-SIB regulation is negative on underreporting of risk, particularly when a new model is adopted. The results in columns (1) and (2) seem to be consistent with this prediction: banks tend to have around 0.4 times less underreporting incidences when revising their model once their national supervisor starts to more closely oversee their capital requirements or once they are included in the G-SIB list. However, more underreporting and lower reported risk are observed when the model remains unchanged despite the additional regulatory attention. Consistent with the results in Table 4, these findings further illustrate that banks' own incentives for the improvement of their risk models and of risk reporting are very weak.

Table 7 reports the findings from examining the relation between risk model revisions and the number of risk underreporting incidences in the presence of the additional capital requirement for market risk. Here I focus on the effects of revising a model in general $NewModel$ (columns 1-2) and of switching to a more stingent model $TightModel$ (columns 3-4). Both $NewModel$ and $TightModel$ are expected to be associated with lower numbers of risk underreporting cases among

[22]The G-SIB designation is based on 12 indicators including size and the complexity of banks' portfolios (Degryse et al., 2020).

banks, especially after facing the penalty in terms of the additionally required capital. Consistent with this prediction, the coefficients on $NewModel$ and $TightModel$ in columns (1)-(4) are significantly negative (incidence-rate ratios are 0.7 and 0.6, respectively). However, the effects of model revisions turn the opposite once the additional capital requirement is imposed. More specifically, revising a risk model after that is associated with 4 times more risk underreporting incidences on average and switching to a more stringent risk model is associated with 5 times more risk underreporting incidences on average. These results suggest that even though model adjustments tend to correspond to less underreporting of risk on average, misrepresentation of true risk persists when it is most concerning from the regulatory perspective, i.e., after having more than 4 risk underreporting incidences in the preceding year.

To better understand the role of supervision in market risk capital regulation, I consider a specification similar to the one in column (3) of Table 7 but with a triple interaction including supervision strength measures, and present the corresponding findings in Table 8. I employ the data from the 2019 BRSS on the number of supervisors per bank (columns 1 and 3) and on the number of hours of supervisory training (columns 2 and 4). I use these two variables to proxy how strict supervision is in terms of enforcing Basel rules for market risk which cannot be directly observed, but plays a crucial role in how regulation ultimately works (see Table 1). Overall, I conclude that supervision seems to decrease underreporting of risk both on the extensive (the amount of supervision) and intensive margins (the quality of supervision). Importantly, the significantly lower $\#Underreport$ and significantly higher *ReportedRisk* is observed for the interaction *New Model* × *#Supervisors per Bank* without the additionally imposed capital requirement. This prompts some doubts about its relevance for truthful reporting of bank risk given the results in Table 7. Nevertheless, the supervisory training seems to alleviate the inefficiency (column 2), suggesting that the supervisory expertise is a potential avenue for improving existing regulation.

Table 9 presents the results from numerous robustness tests to exclude potential concerns about the identification. First, I show that the main result in Table 7 (column 3) is robust when using OLS (column 1), including country fixed effects (column 2) and clustering the standard errors at the bank level (column 3). In column 4, I drop 2008Q4 data, which follows Lehman Brothers' collapse and find that the results are not solely driven by 2008Q4 events. For the same specification, I run the placebo test with the interaction between having a new model and the additionally required capital five quarters before, which should have no effect in contrast to the additional capital charge imposed a quarter before based on the past-year outcomes (column 5). I also run the placebo test for the introduction of the MRCR and falsely assume that it was enforced in 2005 when actually Basel II pre-crisis rules for market risk were set (BCBS, 2005) (column 6). Finally, the result from examining the relation between the past-year risk model performance and the probability of switching to a less optimistic risk model using OLS seem to be consistent with the results in Table 4 (column 7).

5 Conclusion

This paper investigates the design of bank regulation using banks' internal models for market risk stemming from banks' trading activities. Banks may use their internal models to measure market risk subject to supervisory approval. This creates an asymmetric information problem where the regulator has to rely on banks' declared risk exposures while banks are better off reporting more optimistically because of lower capital requirements. In case of detected misrepresentation of risk, banks may incur penalties during the quarterly supervisory review. The penalties are set by the Basel Committee *"to maintain strong incentives for the continual improvement of banks' internal risk measurement models"* (BCBS, 1996). However, the question whether current penalties are sufficient to ensure truthful reporting by banks and improvement of risk models remains open.

I contribute to the literature by examining the incentive conflicts between banks and the regulator who relies on banks' internal risk models, evaluating the efficiency of existing regulation concerning truthful reporting, and providing empirical evidence on the deteriorating quality of models using hand-collected data on banks' self-reported risk exposures, model revisions and penalties. Drawing on the recent finding in Begley et al. (2017) that the shape of penalties amplifies strategic underreporting of bank risk, I build a theoretical model in the style of Prescott (2004). The theoretical contribution of this paper is to consider a simple model where the regulator jointly determines optimal capital requirements and penalties given the risk reported by banks and their risk aversion. This allows me to gauge the heterogeneity in regulatory penalties given the degree of risk misreporting.

My empirical findings indicate that the current combination of regulatory capital requirements and penalties is ineffective at eliciting truthful reporting and at improving risk model quality. In turn, Basel III revisions seem to go in the other direction with incentivizing banks to report their risk truthfully and if anything make it only more tempting for banks to mask their risks. While the additional capital requirement for market risk will be halved as of 2022 (BCBS, 2019a), supervision will still play a major role in how regulation works in practice. My results show that the interplay between supervision and additional capital charges can possibly reduce the inefficiency but what probably matters more then is not how much there is supervision, but its quality.

References

Angbazo, L. (1997). Commercial bank net interest margins, default risk, interest-rate risk, and off-balance sheet banking. *The Journal of Banking & Finance*, 21(1):55–87.

Basel Committee on Banking Supervision (1996). Supervisory framework for the use of "back-testing" in conjunction with the internal models approach to market risk capital requirements.

Basel Committee on Banking Supervision (2005). The application of Basel II to trading activities and the treatment of double default effects.

Basel Committee on Banking Supervision (2019a). Minimum capital requirements for market risk.

Basel Committee on Banking Supervision (2019b). The market risk framework. In brief.

Begley, T. A., Purnanandam, A., and Zheng, K. (2017). The strategic underreporting of bank risk. *The Review of Financial Studies*, 30(10):3376–3415.

Camba-Méndez, G. and Mongelli, F. P. (2021). Risk aversion and bank loan pricing. *Economics Letters*, 200:109723.

Colliard, J.-E. (2019). Strategic selection of risk models and bank capital regulation. *Management Science*, 65(6):2591–2606.

Cuoco, D. and Liu, H. (2006). An analysis of VaR-based capital requirements. *The Journal of Financial Intermediation*, 15(3):362–394.

Dagher, J., Dell'Ariccia, M. G., Laeven, M. L., Ratnovski, M. L., and Tong, M. H. (2016). *Benefits and costs of bank capital*. International Monetary Fund.

Degryse, H., Mariathasan, M., and Tang, T. H. (2020). GSIB status and corporate lending: An international analysis. *CEPR Discussion Paper No. 15564*.

Falato, A., Iercosan, D., and Zikes, F. (2019). Banks as regulated traders. *FEDS Working Paper*.

Farboodi, M. and Kondor, P. (2021). Cleansing by tight credit: Rational cycles and endogenous lending standards. *Working Paper*.

Federal Register (2012). Risk-based capital guidelines: market risk. *Federal Register*, 78(169).

Ho, T. S. and Saunders, A. (1981). The determinants of bank interest margins: theory and empirical evidence. *The Journal of Financial and Quantitative Analysis*, pages 581–600.

Koppenhaver, G. D. (1985). Bank funding risks, risk aversion, and the choice of futures hedging instrument. *The Journal of Finance*, 40(1):241–255.

Leitner, Y. and Yilmaz, B. (2019). Regulating a model. *The Journal of Financial Economics*, 131(2):251–268.

Mariathasan, M., Merrouche, O., and Sizova, E. (2022). Strategic risk–modelling by banks: evidence from inside the black box. *Working Paper*.

Mariathasan, M. and Zhuk, S. (2018). Attention allocation and counter-cyclical credit quality. *Available at SSRN*, https://ssrn.com/abstract=2933476.

Miles, D., Yang, J., and Marcheggiano, G. (2013). Optimal bank capital. *The Economic Journal*, 123(567):1–37.

Prescott, E. S. (2004). Auditing and bank capital regulation. *FRB Richmond Economic Quarterly*, 90(4):47–63.

Ratti, R. A. (1980). Bank attitude toward risk, implicit rates of interest, and the behavior of an index of risk aversion for commercial banks. *The Quarterly Journal of Economics*, 95(2):309–331.

Sealey, C. W. (1980). Deposit rate-setting, risk aversion, and the theory of depository financial intermediaries. *The Journal of Finance*, 35(5):1139–1154.

World Bank (2019). Bank Regulation and Supervision Survey. https://www.worldbank.org/en/research/brief/BRSS.

A Model

1. **The form of banks' payoff when the investment fails.**

   Banks' utility $U(\omega', \omega)$ can be represented as:

$$U(\omega', \omega) = (1-\omega) \times U(\omega', \omega \,|\, \text{investment does not fail}) + \omega \times U(\omega', \omega \,|\, \text{investment fails}),$$

   where ω is the probability of failure. Penalties T are imposed when the investment fails and depending on their interpretation one can choose between different forms of banks' payoff:

   (*) the current version - because of different timing, penalties can be separated from the rest and the specific (same as for deposits) utility function is assumed for them:

$$U(\omega', \omega \,|\, \text{investment fails}) = \frac{\big(1-K(\omega')\big)^{1-\gamma}}{1-\gamma} - \frac{\big(T(\omega')\big)^{1-\gamma}}{1-\gamma}.$$

   (i) alternative 1 - penalties are in the same units as capital and cannot be separated:

$$U(\omega', \omega \,|\, \text{investment fails}) = \frac{\big(1-K(\omega')-T(\omega')\big)^{1-\gamma}}{1-\gamma}.$$

   (ii) alternative 2 - penalties are future costs of foregone opportunites, e.g. due to stricter supervision; no specific utility function is assumed, so this form can be seen as the generalization of the current version and potentially less controversial:

$$U(\omega', \omega \,|\, \text{investment fails}) = \frac{\big(1-K(\omega')\big)^{1-\gamma}}{1-\gamma} - T(\omega').$$

   The choice of either (i) or (ii) implies slightly different incentive compatibility constraints compared to (*). The participation/limited liability condition change as well, the discussion of this is below - for now, let us focus on the incentive compatibility constraint. In the current version:

$$U(\omega', \omega) = (1-\omega)\frac{\big(1-K(\omega')\big)^{1-\gamma}}{1-\gamma} + \omega\left(\frac{\big(1-K(\omega')\big)^{1-\gamma}}{1-\gamma} - \frac{\big(T(\omega')\big)^{1-\gamma}}{1-\gamma}\right) =$$
$$= \frac{\big(1-K(\omega')\big)^{1-\gamma} - \omega\big(T(\omega')\big)^{1-\gamma}}{1-\gamma},$$

$$\frac{\partial U(\omega', \omega)}{\partial \omega'} = -\big(1-K(\omega')\big)^{-\gamma} K'(\omega') - \omega\big(T(\omega')\big)^{-\gamma} T'(\omega').$$

   The first order condition is: :

$$\left.\frac{\partial U(\omega', \omega)}{\partial \omega'}\right|_{\omega'=\omega} = 0.$$

   This translates to:

$$\big(1-K(\omega)\big)^{-\gamma} K'(\omega) = -\omega\big(T(\omega)\big)^{-\gamma} T'(\omega). \tag{16}$$

Considering (i) results in a slightly different FOC:

$$U_1(\omega',\omega) = (1-\omega)\frac{\big(1-K(\omega')\big)^{1-\gamma}}{1-\gamma} + \omega\frac{\big(1-K(\omega')-T(\omega')\big)^{1-\gamma}}{1-\gamma},$$

$$\frac{\partial U_1(\omega',\omega)}{\partial\omega'} = -(1-\omega)\big(1-K(\omega')\big)^{-\gamma}K'(\omega') - \omega\big(1-K(\omega')-T(\omega')\big)^{-\gamma}\big(K'(\omega')+T'(\omega')\big),$$

$$\text{FOC:}\quad \big(1-K(\omega)\big)^{-\gamma}K'(\omega) = -\frac{\omega}{1-\omega}\big(1-K(\omega)-T(\omega)\big)^{-\gamma}\big(K'(\omega)+T'(\omega)\big). \tag{17}$$

Similar to (16), (17) implies that $T' < 0$. For different values of γ, the difference between (16) and (17) is determined by the difference in the order of functions $K(\omega)$ and $T(\omega)$ with respect to ω. For instance, when $\gamma = 0$ for (16) and (17) to yield similar solutions for K and T it is sufficient that $K'(\omega)/T'(\omega)$ is linear in ω - as it is in the current numerical example where $K(\omega) = 1 - \frac{c}{2\omega}$, $K' = \frac{c}{2\omega^2}$, $T(\omega) = \frac{c}{4\omega^2}$, $T' = -\frac{c}{2\omega^3}$.

Now considering (ii) we get:

$$U_2(\omega',\omega) = (1-\omega)\frac{\big(1-K(\omega')\big)^{1-\gamma}}{1-\gamma} + \omega\left(\frac{\big(1-K(\omega')\big)^{1-\gamma}}{1-\gamma} - T(\omega')\right) =$$

$$= \frac{\big(1-K(\omega')\big)^{1-\gamma}}{1-\gamma} - \omega T(\omega'),$$

$$\frac{\partial U_2(\omega',\omega)}{\partial\omega'} = -\big(1-K(\omega')\big)^{-\gamma}K'(\omega') - \omega T'(\omega'),$$

$$\text{FOC:}\quad \big(1-K(\omega)\big)^{-\gamma}K'(\omega) = -\omega T'(\omega). \tag{18}$$

From (18), we get $T' < 0$ and the same solution for $\gamma = 0$ as from (16). (18) is also easier to solve than (16) for different values of γ. As $T \to 1$, the closer (18) gets to (16).

2. **Limited liability constraint vs. participation constraint.**

   In the current version, I have the participation constraint ensuring that banks' utility in $\omega' = \omega$ is non-negative:

$$U(\omega,\omega) = \frac{\big(1-K(\omega)\big)^{1-\gamma} - \omega\big(T(\omega)\big)^{1-\gamma}}{1-\gamma} \geqslant 0.$$

   Rearranging terms, we get:

$$T(\omega) \leqslant \frac{1-K(\omega)}{\omega^{\frac{1}{1-\gamma}}} \tag{19}$$

   (19) is the constraint introduced in the current version of the model (see Proposition 2). The potential concern here is that (19) is not restrictive enough and in certain cases banks may have not enough money to pay penalties. Assuming limited liability on banks' side, penalties could not take values higher than what banks have when the investment fails such that banks have money to pay penalties. This implies that banks' payoff when penalties are

imposed (i.e., when the investment fails) should be non-negative. From (*) for $\omega' = \omega$, we get:

$$U(\omega, \omega \,|\, \text{investment fails}) = \frac{\big(1 - K(\omega)\big)^{1-\gamma}}{1-\gamma} - \frac{\big(T(\omega)\big)^{1-\gamma}}{1-\gamma} \geqslant 0.$$

Rearranging terms, we get:

$$T(\omega) \leqslant 1 - K(\omega). \tag{20}$$

Note that one arrives at the same inequality as (20) if chooses (i) instead of (*) for banks' payoff when the investment fails. Instead, if one interprets penalties as the costs of foregone opprotunities and opts for (ii), he should include the participation constraint and not limited liability:

$$U_2(\omega, \omega) = \frac{\big(1 - K(\omega)\big)^{1-\gamma}}{1-\gamma} - \omega T(\omega) \geqslant 0,$$

Rearranging terms, we get:

$$T(\omega) \leqslant \frac{\big(1 - K(\omega)\big)^{1-\gamma}}{\omega(1-\gamma)} \tag{21}$$

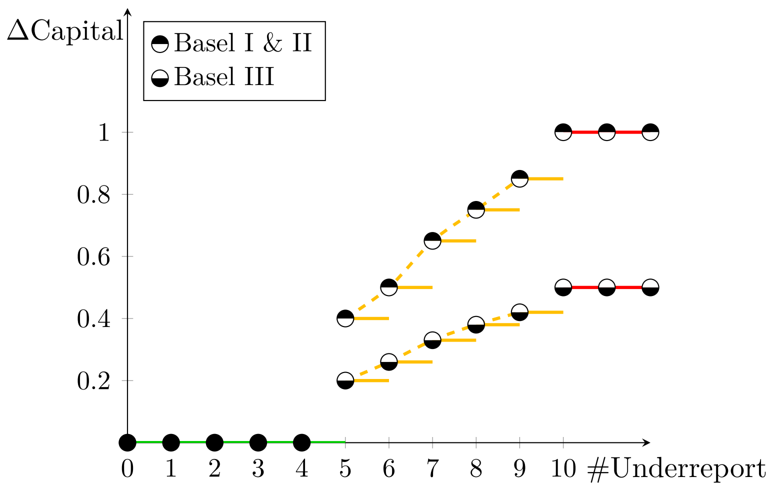
Thus, the only change that the choice of either (20) or (21) over (19) would imply is the change of maximum feasible capital requirement compared to the current version of the model:

$$\begin{aligned} \overline{K}_* &\leqslant 1 - \omega^{\frac{1}{1-\gamma}} T(\omega) \\ \overline{K}_{1 \text{ or LL for } *} &\leqslant 1 - T(\omega) \\ \overline{K}_2 &\leqslant 1 - \omega^{\frac{1}{1-\gamma}} (1-\gamma)^{\frac{1}{1-\gamma}} T(\omega)^{\frac{1}{1-\gamma}} \end{aligned}$$

For the model solution, this implies that the only thing that is affected is $\widehat{\omega}$, i.e., the point where there is a kink in both K and T functions when it is no longer possible to implement the risk-sensitive capital requirement under the second best. The optimal regulatory capital and penalty functions remain the same for all $[\underline{\omega}, \overline{\omega}]$ when K and T are monotonically increasing and decreasing, respectively. The numerical solution and its more detailed description under Table 2 further demonstrate that functional forms of non-constant K and T are independent on $\overline{K}$ and $\widehat{\omega}$. The feasible set of exogenous parameters $\{\underline{\omega}, \overline{\omega}, c, \overline{T}\}$ may get adjusted correspondingly.

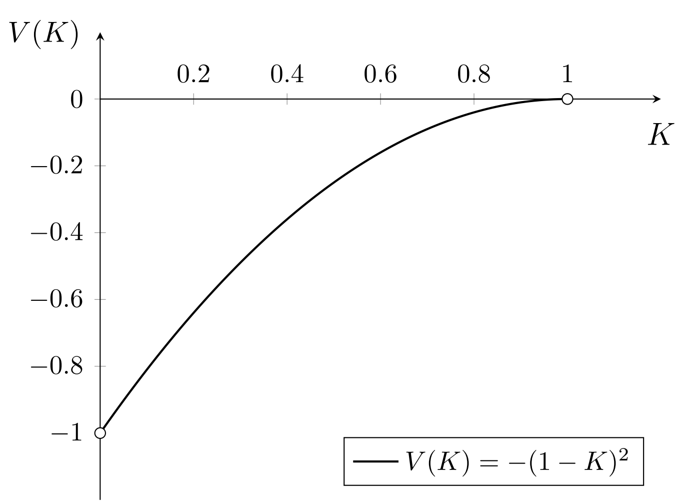
B Figures

Figure 1: Number of Risk Underreporting Cases and Basel Additional Capital Requirements.



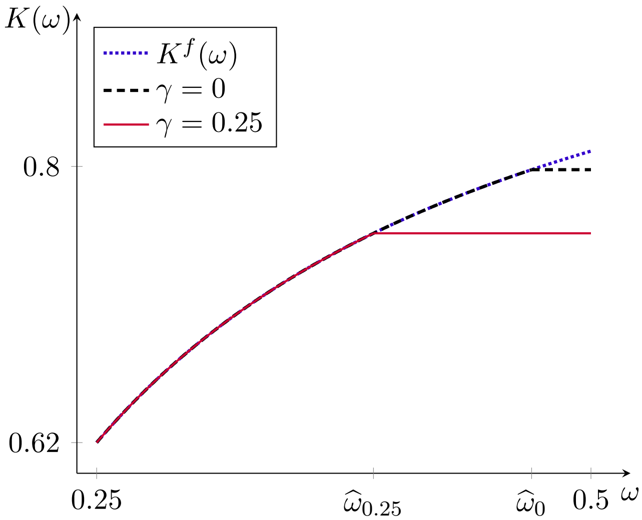
This figure visualizes Basel additional capital requirements for market risk (see Table 1) given the number of days on which risk is underreported over the preceding year. The additionally required capital multipliers ΔCapital according to Basel I and II are marked with black top half circles, whereas ΔCapital multipliers according to Basel III are marked with white top half circles. According to Basel rules, market risk capital requirements (similar to those for credit and operational risk) constitute 8% of market risk-weighted assets. If risk weights are determined internally by banks, their market risk-weighted assets can be represented as $12.5\times(3+\Delta\text{Capital})\times f(\text{Reported Risk})$, where f is an increasing function of risk reported by banks that changes along Basel I, II and III. The additional capital requirement for a given underreporting of risk is halved under Basel III (BCBS, 2019a). Ceteris paribus, the lower is risk reported by banks, the higher is #Underreport due to the higher probability of the reported risk being exceeded by an actual loss.

Figure 2: Regulatory Loss Function V.

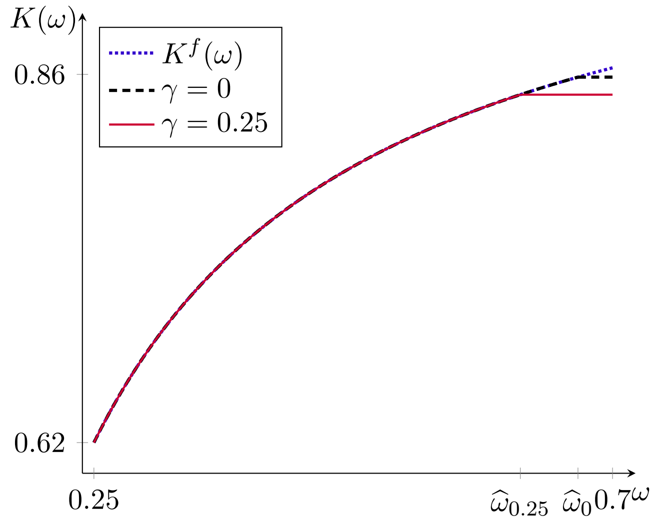


This figure illustrates the regulator's utility function V of capital requirement K used in the numerical analysis and representing the respective social loss in case of failure. The function is non-positive with $V(1) = 0$, increasing ($V' > 0$) and concave ($V'' < 0$). The corner values of capital requirement $K = 0$ and $K = 1$ are excluded in line with Assumption 3 and Assumption 4.

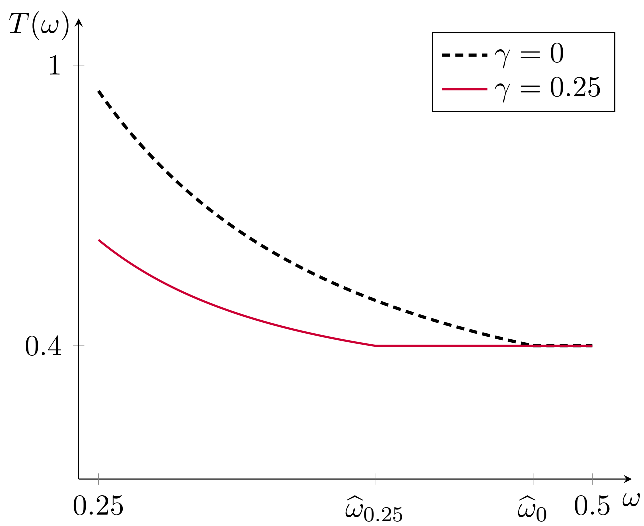
Figure 3: Optimal Regulatory Capital K and Penalties T.



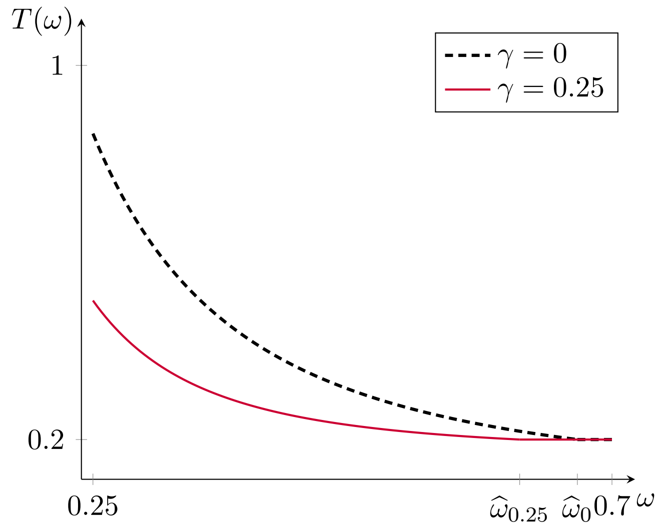
(a) Regulatory Capital K when $\overline{T} = 0.4$



(b) Regulatory Capital K when $\overline{T} = 0.2$



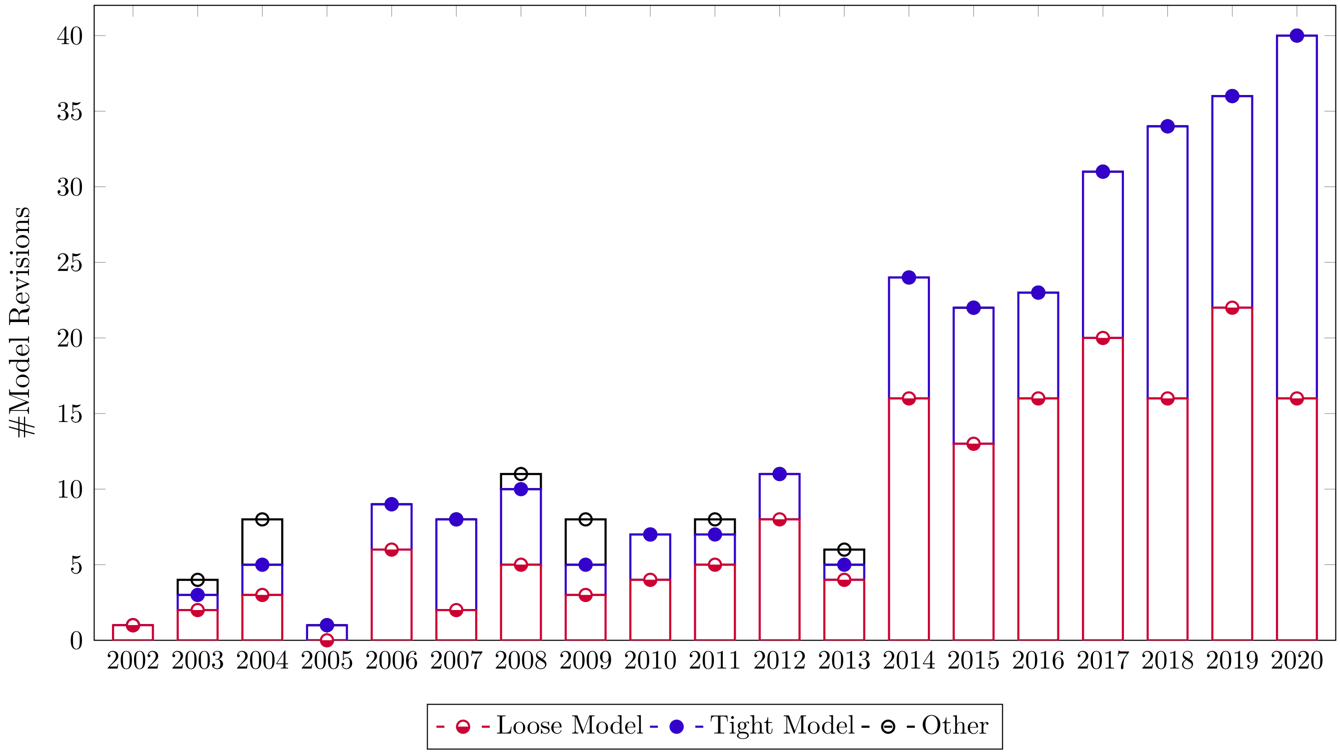
(c) Penalties T when $\overline{T} = 0.4$



(d) Penalties T when $\overline{T} = 0.2$

These four figures visualize the numerical results for optimal capital requirements K (Figures 3a and 3b) and penalties T (Figures 3c and 3d) selectively reported in Table 2. Figures 3a and 3c illustrate the solution characterized in Proposition 2 for the minimum penalty size of 0.4, and Figures 3b and 3d show the solution for the minimum penalty size of 0.2. The black dashed line represents the case when banks are risk-neutral ($\gamma = 0$). The red solid line represents the case when banks are risk-averse with the risk-aversion parameter $\gamma = 0.25$. The blue dotted line represents the first-best solution for capital requirements. The respective sets of parameters are $\underline{\omega} = 0.25$, $\overline{\omega} = 0.5$, $c = 0.19$ when $\overline{T} = 0.4$ and $\underline{\omega} = 0.25$, $\overline{\omega} = 0.7$, $c = 0.19$ when $\overline{T} = 0.2$ which are feasible under (6), (7), (8) and (9).

Figure 4: Risk Model Revisions.



This figure plots the yearly time series of sample banks' risk model revisions over the period from 2002 to 2020. I extract information from banks' financial reports on the disclosed incidences of model revisions and classify them (where possible) into those that ceteris paribus imply higher or lower capital requirements. Red bars marked with half-filled circles represent a total number of model revisions in a given year that imply lower capital requirements (*Loose Model).* Blue bars marked with filled circles represent a total number of model revisions in a given year that imply higher capital requirements (*Tight Model*). Black bars marked with empty circles represent a total number of model revisions in a given year that have no clear effect on capital requirements (*Other*). Red, blue and black bars stacked together represent a total number of model revisions in a given year (*New Model*). The classification is primarily done based on the information from the market risk management section of a particular filing. Also, starting from 2013Q4 in the light of the Basel III regime implementation, some banks begin to report quarterly changes in market risk-weighted assets and its drivers including model revisions. These values, being either positive or negative, allow to detect additional cases of model revisions and to precisely classify those as either *Tight* or *Loose*. 2020 data is excluded from the sample because of extreme market volatility caused by COVID-19 and the respective actions of national supervisors including Fed, ECB and FINMA that disregard underreporting of risk during 2020Q1 for the computation of capital requirements during 2020.

C Tables

Table 1: Basel Framework for Market Risk - Traffic Light Approach (BCBS, 1996, 2019a).

Risk Model Quality Class	Annual Number of Risk Underreporting Cases	ΔCapital Basel I & II	ΔCapital Basel III	Supervisory action
Green	0	0.00	0.00	None
	1	0.00	0.00	
	2	0.00	0.00	
	3	0.00	0.00	
	4	0.00	0.00	
Yellow	5	0.40	0.20	May disallow use of the model
	6	0.50	0.26	
	7	0.65	0.33	
	8	0.75	0.38	
	9	0.85	0.42	
Red	$\geqslant 10$	1.00	0.5	Disallows use of the model

This table reports the framework proposed by the Basel Committee for the supervisory assessment of banks' internal models for market risk (so called "Traffic Light Approach"). The first column represents three risk model quality classes: green, yellow and red. A bank's risk model is assigned to one of them on a quarterly basis upon the supervisory review. The classification is based on the number of cases when risk is underreported over the preceding year. More specifically, it is a yearly number of trading days when the actual daily loss of a bank exceeds its risk estimate (Value-at-Risk) for that particular day. The third and fourth columns represent the additionally required capital multipliers ΔCapital according to Basel I and II, and Basel III, respectively. According to Basel rules, market risk capital requirements (similar to those for credit and operational risk) constitute 8% of market risk-weighted assets. If risk weights are determined internally by banks, their market risk-weighted assets can be represented as $12.5 \times (3 + \Delta\text{Capital}) \times f(\text{Reported Risk})$, where f is an increasing function of risk reported by banks that changes along Basel I, II and III. The last column presents an additional supervisory action with respect to a bank's risk model given its quality class.

Table 2: Optimal Regulatory Capital K and Penalties T.

ω	(1) T $\gamma=0$	(2) T $\gamma=0.1$	(3) T $\gamma=0.25$	(4) T $\gamma=0.5$	(5) T $\gamma=0.75$	(6) K $\gamma=0$	(7) K $\gamma=0.1$	(8) K $\gamma=0.25$	(9) K $\gamma=0.5$	(10) K $\gamma=0.75$	(11) $\max K$ $\gamma=0$	(12) $\max K$ $\gamma=0.1$	(13) $\max K$ $\gamma=0.25$	(14) $\max K$ $\gamma=0.5$	(15) $\max K$ $\gamma=0.75$
$\overline{T}=0.4$															
$\underline{\omega}=0.25$	0.97	0.69	0.67	0.58	0.41	0.62	0.62	0.62	0.62	0.62	0.76	0.80	0.76	0.71	0.71
$\widehat{\omega}_{0.75}=0.28$	0.82	0.61	0.59	0.40	0.40	0.66	0.66	0.66	0.66	0.66	0.77	0.81	0.77	0.79	0.71
$\widehat{\omega}_{0.5}=0.33$	0.65	0.52	0.50	0.40	0.40	0.71	0.71	0.71	0.71	0.66	0.79	0.81	0.78	0.77	0.70
$\widehat{\omega}_{0.25}=0.39$	0.52	0.46	0.40	0.40	0.40	0.76	0.76	0.76	0.71	0.66	0.80	0.80	0.80	0.75	0.68
$\widehat{\omega}_{0.1}=0.44$	0.46	0.40	0.40	0.40	0.40	0.78	0.78	0.76	0.71	0.66	0.80	0.81	0.78	0.73	0.67
$\widehat{\omega}_{0}=0.47$	0.40	0.40	0.40	0.40	0.40	0.80	0.78	0.76	0.71	0.66	0.81	0.80	0.77	0.73	0.67
$\overline{\omega}=0.50$	0.40	0.40	0.40	0.40	0.40	0.80	0.78	0.76	0.71	0.66	0.80	0.79	0.76	0.72	0.66
$\overline{T}=0.2$															
$\underline{\omega}=0.25$	0.86	0.53	0.51	0.39	0.21	0.62	0.62	0.62	0.62	0.62	0.78	0.85	0.82	0.81	0.85
$\widehat{\omega}_{0.75}=0.51$	0.29	0.24	0.23	0.21	0.20	0.81	0.81	0.81	0.81	0.81	0.85	0.87	0.86	0.85	0.83
$\widehat{\omega}_{0.5}=0.56$	0.25	0.22	0.22	0.20	0.20	0.83	0.83	0.83	0.83	0.81	0.86	0.87	0.86	0.85	0.83
$\widehat{\omega}_{0.25}=0.62$	0.23	0.21	0.20	0.20	0.20	0.85	0.85	0.85	0.83	0.81	0.86	0.86	0.86	0.84	0.82
$\widehat{\omega}_{0.1}=0.65$	0.22	0.20	0.20	0.20	0.20	0.85	0.85	0.85	0.83	0.81	0.86	0.86	0.86	0.84	0.82
$\widehat{\omega}_{0}=0.67$	0.20	0.20	0.20	0.20	0.20	0.86	0.85	0.85	0.83	0.81	0.87	0.86	0.85	0.84	0.82
$\overline{\omega}=0.70$	0.20	0.20	0.20	0.20	0.20	0.86	0.85	0.85	0.83	0.81	0.86	0.85	0.85	0.83	0.82

This table reports the selection of numerical results. Cases $\gamma = 0$ and $\gamma = 0.25$ are visualized in Figure 3. Columns (1)-(5) show the optimal values of penalties T for different levels of banks' risk aversion from $\gamma = 0$ (risk-neutral case) to $\gamma = 0.75$. Similarly, columns (6)-(10) report the optimal values of capital requirements K, whereas columns (11)-(15) demonstrate the maximum feasible levels of capital requirements as defined by (PC). The top panel reports the values when the minimum penalty size is 0.4 and the bottom panel shows the values when the minimum penalty size is 0.2. The respective sets of parameters are $\underline{\omega} = 0.25$, $\overline{\omega} = 0.5$, $c = 0.19$ when $\overline{T} = 0.4$ and $\underline{\omega} = 0.25$, $\overline{\omega} = 0.7$, $c = 0.19$ when $\overline{T} = 0.2$ which are feasible under (6), (7), (8) and (9). The optimal second-best values of K and T are determined using the following algorithm:

1. The first-best capital requirements $K^f(\omega)$ are calculated for the chosen range $[\underline{\omega}, \overline{\omega}]$ and the equity cost c.

2. The upper bounds for $\overline{K}$ are determined from (PC) for each value of the risk aversion parameter γ given the predefined values of $\overline{\omega}$ and $\overline{T}$ (these upper bounds are reported in the last row of top and bottom panels in columns (11)-(15)).

3. If $\overline{K}$ does not exceed an upper bound with a associated risk aversion, then the first-best capital requirements $K^f(\omega)$ can be achieved for all $\omega \in [\underline{\omega}, \overline{\omega}]$ and the optimal second-best values of capital requirements $K^s(\omega)$ are set equal to $K^f(\omega)$. The corresponding penalties $T^s(\omega)$ are then determined from (9) given c, γ, ω, c_1 and c_2, where $c_1 = \overline{T} - \frac{c}{4\overline{\omega}^2}$ if $\gamma = 0$ and $c_2 = \overline{T} - c\left(\frac{1-\gamma}{8\overline{\omega}^2}\right)^{\frac{1}{1-\gamma}}$ for all $\gamma \in (0, 1)$.

4. If $\overline{K}$ exceeds an upper bound with a associated risk aversion, the highest $K(\omega) < \overline{K}$ needs to be found such that it does not happen. The corresponding ω is $\widehat{\omega}$. The second-best values of $K^s(\omega)$ are set equal to $K^f(\omega)$ for all $\omega \in [\underline{\omega}, \widehat{\omega}]$ and $K(\widehat{\omega})$ for all $\omega \in [\widehat{\omega}, \overline{\omega}]$. The corresponding penalties $T^s(\omega)$ are then set equal to $\overline{T}$ for all $\omega \in [\widehat{\omega}, \overline{\omega}]$ and for all $\omega \in [\underline{\omega}, \widehat{\omega}]$ they are determined from (9) given c, γ, ω, c_1 and c_2, where $c_1 = \overline{T} - \frac{c}{4\widehat{\omega}^2}$ if $\gamma = 0$ and $c_2 = \overline{T} - c\left(\frac{1-\gamma}{8\widehat{\omega}^2}\right)^{\frac{1}{1-\gamma}}$ for all $\gamma \in (0, 1)$.

Table 3: Summary Statistics.

Bank	#New	#Tight	#Loose	Tight ($M)	Loose ($M)	ΔCapital	Reported Risk ($M)	ΔCapital ($M)	#Underreport
Bank of America	5	2	3			0.09	220.40	20.92	0.47
Bank of Montreal	18	5	13	34.95	61.27	0.09	51.02	4.35	0.38
Bank of NY Mellon	4	1	3			0.00	21.45	0.00	0.13
Canadian IBC	17	7	9	8.62	4.28	0.00	20.27	0.00	0.11
Citi Group	28	10	18	143.75	173.75	0.00	299.65	0.00	0.13
Credit Agricole	7	1	5			0.12	48.08	5.87	0.63
Credit Suisse Group	36	17	18	61.03	81.93	0.14	235.70	33.88	0.70
Deutsche Bank	7	5	2	7.65	24.26	0.05	225.74	11.01	0.62
Goldman Sachs	4	0	2			0.12	279.61	34.41	0.29
ING Group	3	0	3			0.01	59.64	0.78	0.22
JPMorgan Chase	28	4	23	202.67	330.68	0.06	304.22	18.30	0.23
Morgan Stanley	6	1	4			0.15	327.60	49.64	0.25
Royal Bank of Canada	27	11	15	38.43	32.87	0.08	70.43	5.96	0.37
Société Générale	9	7	2	22.90	29.21	0.17	115.19	19.37	0.88
Bank of Nova Scotia	21	10	11	15.55	35.59	0.00	35.56	0.00	0.06
TD Bank	8	5	3		46.93	0.00	57.19	0.00	0.07
UBS Group	24	10	12	17.86	43.68	0.18	217.45	38.29	1.23
Total	252	96	146	51.53	125.57	0.08	148.80	11.21	0.38

This table reports summary statistics for the sample covering 17 banks from the U.S., Canada and Europe over the period from 2002 to 2019. Data is hand-collected from banks' quarterly and annual reports as well as Pillar III disclosures. I extract information on the reported incidences of model revisions (*New*) and classify them (where possible) into those that ceteris paribus imply higher (*Tight*) or lower (*Loose*) capital requirements. *#New* is a number of model revisions reported by a given bank over the sample period. *#Tight* is a number of model revisions reported by a given bank over the sample period that imply higher capital requirements. *#Loose* is a number of model revisions reported by a given bank over the sample period that imply lower capital requirements. Starting from 2013Q4 in the light of the Basel III regime implementation, some banks begin to report quarterly changes in market risk-weighted assets and its drivers including model revisions. These values allow to compute the corresponding changes in capital requirements provided that the capital requirement constitutes 8% of risk-weighted assets. *Tight* ($M) represents the average quarterly positive change in capital requirements attributed to model revisions and expressed in million U.S. dollars. *Loose* ($M) represents the average quarterly negative change in capital requirements attributed to model revisions and expressed in million U.S. dollars. $\Delta Capital$ represents the mean values for the additional capital requirement multiplier imposed on a given bank over the sample period according to the Basel framework (see Table 1). *Reported Risk* ($M) represents the average 10-day 99% Value-at-Risk self-reported by a given bank and expressed in million U.S. dollars. In case it is unavailable, a one-day 99% Value-at-Risk self-reported by a given bank scaled by a square root of 10 is used. 10-day 99% Value-at-Risk is the maximum potential loss over a 10-day horizon that should not be exceeded in 99% cases. Under Basel I, market risk capital requirements are mostly determined as the product of *Reported Risk* and *Capital* multiplier which includes $\Delta Capital$ (if any). Basel II and III use a more complex measure for market risk capital requirements which is still based on the 10-day Value-at-Risk and if anything takes a value further in the tail of risk distribution. These changes in the Basel approach to market risk unfortunately make it impossible to accurately estimate the monetary component of penalties (an additional capital charge for the detected misrepresentation of risk) over the sample period. Therefore, I compute its lower bound denoted by $\Delta Capital$ ($M) as the product of $\Delta Capital$ multiplier and *Reported Risk* measure. $\Delta Capital$ ($M) hence represents the average quarterly U.S. dollar amount of a minimum additional capital requirement imposed on a given bank over the sample period. *#Underreport* is the average number of days in a quarter on which the actual daily loss of a given bank exceeds its daily Value-at-Risk estimate. Thus, it represents a quarterly number of cases when true risk is underreported. *#Underreport* is winsorized at 1% and 99% level.

Table 4: Past-Year Risk Model Performance and Model Revisions.

	(1) New Model	(2) New Model	(3) Tight Model	(4) Tight Model	(5) New Model	(6) New Model	(7) Tight Model	(8) Tight Model
$\sum_{s=1}^{s=4}$ #Underreport$_{t-s}$	-0.19***	-0.28***	-0.16***	-0.28***	-0.10***	-0.30***	-0.04**	-0.10**
	(0.038)	(0.050)	(0.052)	(0.060)	(0.038)	(0.098)	(0.018)	(0.042)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
Model	IV Probit	IV Probit	IV Probit	IV Probit	IV 2SLS	IV 2SLS	IV 2SLS	IV 2SLS
Observations	876	748	876	589	876	876	876	876

This table reports the results for the instrumental variable (IV) probit and linear (2SLS) models in columns (1)-(4) and columns (5)-(8), respectively. I use the product of a supervisory enforcement index and the past-year S&P 500 index volatility as an instrument. The supervisory enforcement index is based on the number of enforcement powers available to the supervisory agency according to the World Bank's *Bank Regulation and Supervision Survey* (BRSS) completed in 2019. The magnitude of the supervisory enforcement index depends on the answer to the following question: *11.1 Please indicate whether the following enforcement powers are available to the supervisory agency.* Using other supervision strength proxies based on the 2019 BRSS, e.g., disclosure power of supervisors (*10.10 Do supervisors require banks to publicly disclose ...*), supervisory frequency (*12.23.2 How frequently are onsite inspections conducted in a year in the 10 largest banks by asset size?*), supervisory training hours (*12.43 How many hours of training (at the supervisory agency or elsewhere) on average have supervisors had in the last year?*), number of supervisors per bank (*12.39 How many professional bank supervisors are there in total (excluding all support functions and management)?*), yield qualitatively similar estimates. I ensure that the coefficient for the instrument is statistically significant in the first-stage regressions (t-statistic = 4.35 and F-statistic = 18.94 in the first-stage regressions in columns (5) and (7) of Table 4), hence indicating that the chosen instrument is relevant. Moreover, I select the instrument based on an economic argument (exclusion restriction) provided that the number of past-year risk underreporting incidences is the one and only criterion for the supervisor to disallow the use of a model (see Table 1), and the decision to enforce a model revision critically depends on the supervision strength combined with the origin of observed underreporting of risk given market volatility. I run the regression:

$$Y_{it} = \beta \sum_{s=1}^{s=4} \#Underreport_{it-s} + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \varepsilon_{it}.$$

In columns (1), (2), (5) and (6), Y_{it} is $NewModel_{it}$ which equals one if bank i reports a model revision that occurs at quarter t. In columns (3), (4), (7) and (8), Y_{it} is $TightModel_{it}$ which equals one if bank i reports a model revision that occurs at quarter t and implies higher capital requirements. $\sum_{s=1}^{s=4} \#Underreport_{it-s}$ is the number of days from quarter $t-4$ to quarter $t-1$ on which the actual daily loss of bank i exceeds its risk estimate. X_{it} represents a vector of bank characteristics to control for bank size (proxied by total assets), leverage (proxied by the equity ratio) and profitability (proxied by the ratio of the net income to total assets). V_{it-1} is a vector of lagged volatility measures to control for interest rate, exchange rate and commodity volatilities. α_t represents year-quarter fixed effects. The sample covers 17 banks from the U.S., Canada and Europe over the period from 2002 to 2019. Year-quarter clustered errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Market Risk Capital Rule and Model Outcomes.

	(1) #Underreport	(2) #Underreport	(3) #Underreport	(4) #Underreport	(5) Reported Risk	(6) Reported Risk	(7) Reported Risk	(8) Reported Risk
MRCR	0.43*	4.96***	2.32***	3.82**	-0.30***	-0.17*	-0.29***	-0.58***
	(0.261)	(0.991)	(0.573)	(1.604)	(0.066)	(0.094)	(0.069)	(0.113)
MRCR × TA_{2012Q1}		-0.25***				-0.01***		
		(0.075)				(0.005)		
MRCR × High TA_{2012Q1}			-3.66**				-0.31***	
			(1.446)				(0.066)	
MRCR × G-SIB $Bucket_{2012}$				-1.17				0.15***
				(0.753)				(0.051)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Model	ZINB	ZINB	ZINB	ZINB	OLS	OLS	OLS	OLS
Observations	842	787	787	842	842	787	787	842
R-squared					0.908	0.911	0.912	0.908

This table reports the results for the zero-inflated negative binomial and linear models in columns (1)-(4) and columns (5)-(8), respectively. In columns (1) and (5), I run the regression:

$$Y_{it} = \beta MRCR_{it} + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \alpha_i + \varepsilon_{it}.$$

$MRCR_{it} = 1$ if bank i is based in the U.S. and is affected by the Market Risk Capital Rule (MRCR) enforced by Fed starting from 2013Q1. To understand how different bank characteristics affect the MRCR implementation, I also include bank-specific interaction variables I_i, capturing banks' trading exposure pre-MRCR and the additional capital requirements set out for the global systemically important banks (G-SIBs) in November 2012. In columns (2)-(4) and (6)-(8), the model therefore becomes:

$$Y_{it} = \beta_1 MRCR_{it} + \beta_2 MRCR_{it} \times I_i + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \alpha_i + \varepsilon_{it}.$$

In columns (1)-(4), Y_{it} is $\#Underreport_{it}$, i.e., the number of days during quarter t on which the actual daily loss of bank i exceeds its risk estimate. Thus, it represents a quarterly number of cases when true risk is underreported. $\#Underreport_{it}$ is winsorized at 1% and 99% level. In columns (5)-(8), Y_{it} is $ReportedRisk_{it}$, i.e., the natural logarithm of the 10-day 99% Value-at-Risk self-reported by bank i at quarter t. In case it is unavailable, a one-day 99% Value-at-Risk self-reported by bank i at quarter t scaled by a square root of 10 is used. In columns (2) and (6), $TA_{i2012\mathrm{Q1}}$ is the ratio of trading assets to total assets of bank i freezed at 2012Q1 level. In columns (3) and (7), $HighTA_{i2012\mathrm{Q1}} = 1$ if the ratio of trading assets to total assets of bank i as of 2012Q1 is above the sample mean. In columns (4) and (8), $G\text{-}SIBBucket_{i2012}$ is the additional capital requirement (in %) according to the G-SIB list disclosed by the Financial Stability Board in November 2012. X_{it} represents a vector of bank characteristics to control for bank size (proxied by total assets), leverage (proxied by the equity ratio) and profitability (proxied by the ratio of the net income to total assets). V_{it-1} is a vector of lagged volatility measures to control for market, interest rate, exchange rate and commodity volatilities. α_t and α_i represent year-quarter and bank fixed effects, respectively. For the zero-inflated estimation, I use the natural logarithm of VIX to distinguish between two latent groups of observations which can be always zero by construction, or reflect the realization of the negative binomial distribution and constitute either zero or positive integers. In column (1), the estimates for the specification without bank fixed effects are reported, since the ZINB model with two-way fixed effects does not converge in this case. The sample covers 17 banks from the U.S., Canada and Europe over the period from 2002 to 2019. Year-quarter clustered errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Model Revisions, Additional Capital Requirements and Model Outcomes.

	(1) #Underreport	(2) #Underreport	(3) #Underreport	(4) Reported Risk	(5) Reported Risk	(6) Reported Risk
New Model	-0.11	-0.06	-0.27	0.03	0.04	0.03
	(0.296)	(0.323)	(0.272)	(0.035)	(0.043)	(0.033)
New Model × Supervisory Oversight	-0.90*			0.02		
	(0.494)			(0.048)		
Supervisory Oversight	0.59			-0.11**		
	(0.491)			(0.049)		
New Model × G-SIB		-0.94*			-0.02	
		(0.512)			(0.059)	
G-SIB		2.01***			-0.12**	
		(0.715)			(0.057)	
New Model × G-SIB Bucket			-0.45			0.06*
			(0.298)			(0.031)
G-SIB Bucket			0.86***			-0.21***
			(0.319)			(0.035)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Model	ZINB	ZINB	ZINB	OLS	OLS	OLS
Observations	842	842	842	842	842	842
R-squared				0.905	0.905	0.908

This table reports the results for the zero-inflated negative binomial and linear models in columns (1)-(3) and columns (4)-(6), respectively. I run the regression:

$$Y_{it} = \beta_1 NewModel_{it} + \beta_2 I_{it} + \beta_3 NewModel_{it} \times I_{it} + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \alpha_i + \varepsilon_{it}.$$

In columns (1)-(3), Y_{it} is $\#Underreport_{it}$, i.e., the number of days during quarter t on which the actual daily loss of bank i exceeds its risk estimate. Thus, it represents a quarterly number of cases when true risk is underreported. $\#Underreport_{it}$ is winsorized at 1% and 99% level. In columns (4)-(6), Y_{it} is $ReportedRisk_{it}$, i.e., the natural logarithm of the 10-day 99% Value-at-Risk self-reported by bank i at quarter t. In case it is unavailable, a one-day 99% Value-at-Risk self-reported by bank i at quarter t scaled by a square root of 10 is used. $NewModel_{it} = 1$ if bank i reports a model revision that occurs at quarter t. To understand how a model revision affects model outcomes once additional capital burden appears, I also include interaction variables I_{it}, capturing the introduction of supervisory tools to oversee more closely additional capital requirements, and of the additional capital requirements for the global systemically important banks (G-SIBs). In columns (1) and (4), $SupervisoryOversight_{it}$ is an indicator based on the answer to the question 12.34.1 in the World Bank's *Bank Regulation and Supervision Survey* given additional capital requirements are selected and the respective date of introduction is specified (*12.34.1 Does the banking supervisor have any tools to oversee more closely and/or limit the activities of large/interconnected institutions?*). In columns (2) and (5), $GSIB_{it} = 1$ if bank i is in a G-SIB list disclosed by the Financial Stability Board at quarter t. In columns (3) and (6), $G\text{-}SIBBucket_{it}$ is the additional capital requirement (in %) according to G-SIB lists published during 2014-2017. I choose this time period because there is a 14-month gap between the G-SIB list publication date and the actual implementation date, and G-SIB buckets have been implemented since 2016. X_{it} represents a vector of bank characteristics to control for bank size (proxied by total assets), leverage (proxied by the equity ratio) and profitability (proxied by the ratio of the net income to total assets). V_{it-1} is a vector of lagged volatility measures to control for market, interest rate, exchange rate and commodity volatilities. α_t and α_i represent year-quarter and bank fixed effects, respectively. For the zero-inflated estimation, I use the natural logarithm of VIX to distinguish between two latent groups of observations which can be always zero by construction, or reflect the realization of the negative binomial distribution and constitute either zero or positive integers. The sample covers 17 banks from the U.S., Canada and Europe over the period from 2002 to 2019. Year-quarter clustered errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Model Revisions, Pecuniary Penalties and Underreporting of Risk.

	(1) #Underreport	(2) #Underreport	(3) #Underreport	(4) #Underreport
New Model	-0.40*		-0.77***	
	(0.221)		(0.268)	
Tight Model		-0.54*		-0.68**
		(0.325)		(0.301)
New Model × $\mathbb{1}_{t-1}^{\Delta \text{Capital}}$			1.53***	
			(0.512)	
Tight Model × $\mathbb{1}_{t-1}^{\Delta \text{Capital}}$				1.64**
				(0.667)
$\mathbb{1}_{t-1}^{\Delta \text{Capital}}$			0.41	0.56*
			(0.283)	(0.292)
Controls	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Model	ZINB	ZINB	ZINB	ZINB
Observations	842	842	782	782

This table reports the results for the zero-inflated negative binomial model. For the zero-inflated estimation, I use the natural logarithm of VIX to distinguish between two latent groups of observations which can be always zero by construction, or reflect the realization of the negative binomial distribution and constitute either zero or positive integers. The dependent variable is $\#Underreport_{it}$ is the number of days during quarter t on which the actual daily loss of bank i exceeds its risk estimate. Thus, the dependent variable represents a quarterly number of cases when true risk is underreported. $\#Underreport_{it}$ is winsorized at 1% and 99% level. In columns (1)-(2), I run the regression:

$$\#Underreport_{it} = \beta Model_{it} + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \alpha_i + \varepsilon_{it}.$$

To understand how a model revision relates to underreporting of risk in the presence of the additional capital requirement specifically for market risk, I also consider the interaction with an indicator variable $\mathbb{1}_{it-1}^{\Delta \text{Capital}}$ for ΔCapital of bank i taking non-zero values at quarter $t-1$ (see Table 1). In columns (3)-(4), the model therefore becomes:

$$\#Underreport_{it} = \beta_1 Model_{it} + \beta_2 \mathbb{1}_{it-1}^{\Delta \text{Capital}} + \beta_3 Model_{it} \times \mathbb{1}_{it-1}^{\Delta \text{Capital}} + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \alpha_i + \varepsilon_{it}.$$

$Model_{it}$ is $NewModel_{it}$ and $TightModel_{it}$ in columns (1) and (3), and columns (2) and (4), respectively. $NewModel_{it} = 1$ if bank i reports a model revision that occurs at quarter t. $TightModel_{it} = 1$ if bank i reports a model revision that occurs at quarter t and implies higher capital requirements. X_{it} represents a vector of bank characteristics to control for bank size (proxied by total assets), leverage (proxied by the equity ratio) and profitability (proxied by the ratio of the net income to total assets). V_{it-1} is a vector of lagged volatility measures to control for market, interest rate, exchange rate and commodity volatilities. α_t and α_i represent year-quarter and bank fixed effects, respectively. The sample covers 17 banks from the U.S., Canada and Europe over the period from 2002 to 2019. Year-quarter clustered errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Model Revisions, Pecuniary Penalties, Supervision Strength and Model Outcomes.

	(1) #Underreport	(2) #Underreport	(3) Reported Risk	(4) Reported Risk
New Model	-0.17	-0.50	-0.08	0.09*
	(0.447)	(0.354)	(0.066)	(0.049)
New Model × $\mathbb{1}_{t-1}^{\Delta\text{Capital}}$ × #Supervisors per Bank	1.41		-0.28	
	(1.114)		(0.241)	
New Model × #Supervisors per Bank	-0.95*		0.13*	
	(0.558)		(0.066)	
New Model × $\mathbb{1}_{t-1}^{\Delta\text{Capital}}$ × #Hours of Supervisory Training		-0.06***		-0.00
		(0.020)		(0.002)
New Model × #Hours of Supervisory Training		-0.00		-0.00
		(0.005)		(0.001)
New Model × $\mathbb{1}_{t-1}^{\Delta\text{Capital}}$	0.79	2.43***	0.23	0.08
	(0.963)	(0.587)	(0.209)	(0.166)
$\mathbb{1}_{t-1}^{\Delta\text{Capital}}$ × #Supervisors per Bank	0.59		0.01	
	(0.364)		(0.082)	
$\mathbb{1}_{t-1}^{\Delta\text{Capital}}$ × #Hours of Supervisory Training		-0.01		-0.00
		(0.005)		(0.001)
$\mathbb{1}_{t-1}^{\Delta\text{Capital}}$	-0.05	1.35***	0.09	0.18*
	(0.405)	(0.349)	(0.094)	(0.090)
#Hours of Supervisory Training		0.00		
		(0.003)		
Controls	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Bank FE	Yes	No	Yes	Yes
Model	ZINB	ZINB	OLS	OLS
Observations	782	782	782	782
R-squared			0.908	0.909

This table reports the results for the zero-inflated negative binomial and linear models in columns (1)-(2) and columns (3)-(4), respectively. I run the regression:

$$Y_{it} = \beta_1 NewModel_{it} + \beta_2 \mathbb{1}_{it-1}^{\Delta\text{Capital}} + \beta_3 NewModel_{it} \times \mathbb{1}_{it-1}^{\Delta\text{Capital}} + \beta_4 NewModel_{it} \times I_i + \beta_5 \mathbb{1}_{it-1}^{\Delta\text{Capital}} + \\ + \beta_6 NewModel_{it} \times \mathbb{1}_{it-1}^{\Delta\text{Capital}} \times I_i + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \alpha_i + \varepsilon_{it}.$$

In columns (1)-(2), Y_{it} is $\#Underreport_{it}$, i.e., the number of days during quarter t on which the actual daily loss of bank i exceeds its risk estimate. Thus, it represents a quarterly number of cases when true risk is underreported. $\#Underreport_{it}$ is winsorized at 1% and 99% level. In columns (3)-(4), Y_{it} is $ReportedRisk_{it}$, i.e., the natural logarithm of the 10-day 99% Value-at-Risk self-reported by bank i at quarter t. In case it is unavailable, a one-day 99% Value-at-Risk self-reported by bank i at quarter t scaled by a square root of 10 is used. $NewModel_{it} = 1$ if bank i reports a model revision that occurs at quarter t. $\mathbb{1}_{it-1}^{\Delta\text{Capital}}$ is an indicator for ΔCapital of bank i taking non-zero values at quarter $t-1$ (see Table 1). To understand how a model revision affects model outcomes in the presence of the additional capital requirement for market risk given supervisory scrutiny, I also include interaction variables I_i, capturing the number of supervisors per bank and the number of hours of supervisory training obtained from the World Bank's *Bank Regulation and Supervision Survey* (*12.39 How many professional bank supervisors are there in total (excluding all support functions and management)?; 12.43 How many hours of training (at the supervisory agency or elsewhere) on average have supervisors had in the last year (2016)?*) X_{it} represents a vector of bank characteristics to control for bank size (proxied by total assets), leverage (proxied by the equity ratio) and profitability (proxied by the ratio of the net income to total assets). V_{it-1} is a vector of lagged volatility measures to control for market, interest rate, exchange rate and commodity volatilities. α_t and α_i represent year-quarter and bank fixed effects, respectively. For the zero-inflated estimation, I use the natural logarithm of VIX to distinguish between two latent groups of observations which can be always zero by construction, or reflect the realization of the negative binomial distribution and constitute either zero or positive integers. In column (2), the estimates for the specification without bank fixed effects are reported, since the ZINB model with two-way fixed effects does not converge in this case. The sample covers 17 banks from the U.S., Canada and Europe over the period from 2002 to 2019. Year-quarter clustered errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Robustness.

	(1) #Underreport	(2) #Underreport	(3) #Underreport	(4) #Underreport	(5) #Underreport	(6) #Underreport	(7) Tight Model
New Model	-0.12	-0.65***	-0.77**	-0.70***	-0.58***		
	(0.074)	(0.223)	(0.308)	(0.255)	(0.214)		
New Model × $\mathbb{1}^{\Delta\text{Capital}}_{t-1}$	1.67*	1.53***	1.53***	0.99*			
	(0.977)	(0.550)	(0.486)	(0.583)			
$\mathbb{1}^{\Delta\text{Capital}}_{t-1}$	0.64***	0.72**	0.41	0.41			
	(0.214)	(0.367)	(0.318)	(0.290)			
New Model × $\mathbb{1}^{\Delta\text{Capital}}_{t-5}$					0.85		
					(0.969)		
$\mathbb{1}^{\Delta\text{Capital}}_{t-5}$					-0.02		
					(0.799)		
$\text{MRCR}_{2005\text{Q3}}$						-0.43	
						(1.005)	
$\sum_{s=1}^{s=4}$ $\#\text{Underreport}_{t-s}$							-0.0003
							(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	No	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	No	No	No	No
Cluster	YQ	YQ	Bank	YQ	YQ	YQ	YQ
Model	OLS	ZINB	ZINB	ZINB	ZINB	ZINB	OLS
Period	Full Sample	Full Sample	Full Sample	Drop 2008Q4	Full Sample	Full Sample	Full Sample
Observations	782	782	782	773	736	842	876
R-squared	0.409						0.197

This table reports the results for robustness tests. In columns (1)-(4), I run the regression:

$$\#Underreport_{it} = \beta_1 NewModel_{it} + \beta_2 \mathbb{1}^{\Delta\text{Capital}}_{t-1} + \beta_3 NewModel_{it} \times \mathbb{1}^{\Delta\text{Capital}}_{t-1} + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \alpha_i + \varepsilon_{it}.$$

In column (1), I report the OLS estimates. In column (2), I replace bank fixed effects α_i with country fixed effects α_c. In column (3), I use standard errors clustered at the bank level. In column (4), I exclude the fourth quarter of 2008 from the sample, i.e., the quarter following Lehman Brothers' collapse. In column (5), I run the regression:

$$\#Underreport_{it} = \beta_1 NewModel_{it} + \beta_2 \mathbb{1}^{\Delta\text{Capital}}_{t-5} + \beta_3 NewModel_{it} \times \mathbb{1}^{\Delta\text{Capital}}_{t-5} + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \alpha_i + \varepsilon_{it},$$

where $\mathbb{1}^{\Delta\text{Capital}}_{t-5}$ is an indicator for ΔCapital of bank i taking non-zero values at quarter $t-5$ ("placebo test" for pecuniary penalties). In column (6), I run the regression:

$$\#Underreport_{it} = \beta MRCR_{2005\text{Q3}} + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \alpha_i + \varepsilon_{it},$$

where $MRCR_{2005\text{Q3}} = 1$ if bank i is based in the US and is exposed to Basel II pre-crisis rules for market risk set in 2005Q3 (BCBS, 2005, "placebo test" for the Market Risk Capital Rule). In column (7), I run the linear regression:

$$TightModel_{it} = \beta \sum_{s=1}^{s=4} \#Underreport_{it-s} + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \alpha_i + \varepsilon_{it}$$

to provide support for the IV results in Table 4. $\#Underreport_{it}$ is the number of days during quarter t on which the actual daily loss of bank i exceeds its risk estimate. Thus, it represents a quarterly number of cases when true risk is underreported. $\#Underreport_{it}$ is winsorized at 1% and 99% level. $\sum_{s=1}^{s=4} \#Underreport_{it-s}$ is the number of days from quarter $t-4$ to quarter $t-1$ on which the actual daily loss of bank i exceeds its risk estimate. $NewModel_{it} = 1$ if bank i reports a model revision that occurs at quarter t. $\mathbb{1}^{\Delta\text{Capital}}_{it-1}$ is an indicator for ΔCapital of bank i taking non-zero values at quarter $t-1$ (see Table 1). X_{it} represents a vector of bank characteristics to control for bank size (proxied by total assets), leverage (proxied by the equity ratio) and profitability (proxied by the ratio of the net income to total assets). V_{it-1} is a vector of lagged volatility measures to control for market, interest rate, exchange rate and commodity volatilities. α_t represents year-quarter fixed effects. For the zero-inflated estimation, I use the natural logarithm of VIX to distinguish between two latent groups of observations which can be always zero by construction, or reflect the realization of the negative binomial distribution and constitute either zero or positive integers. The sample covers 17 banks from the U.S., Canada and Europe over the period from 2002 to 2019. Standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.