Banks' Next Top Model

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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 risk-sensitive capital and penalties when banks have private information about their risk. I find that the Basel framework can be rationalized provided sufficient variation in banks' risk aversion. I then use hand-collected data on reported risk, penalties and model revisions, to show that current penalties provide only weak incentives for model improvements and in fact incentivize underreporting of risk. My model suggests that Basel recent revisions may be detrimental to the elicitation of truthful reporting.

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

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

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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 the 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 the 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., 2021) studies concerning the use of internal models for market risk.

I model how the regulator should jointly determine optimal capital requirements and penalties under private information about the true risk of banks 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 penalties which depend therefore on banks' risk aversion. To test whether penalties are lower for more risk-averse banks for a given reported risk, I use an instrumental variable approach to recover exogenous variation in penalties and the quality of banks' risk models (their tool to deal with uncertainty) from the instrumented past-year number of risk underreporting incidences. Moreover, I exploit the change in market risk capital regulation for U.S. banks in 2013 as a quasi-exogenous shock to their market risk reporting requirements (Federal Register, 2012). I also run panel regressions to study the ex post risk model outcomes.

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. (2021) for the remaining banks' self-reported data which covers 19 banks from the U.S., Canada and Europe from 2002 to 2016.

My model illustrates that the optimal penalties decrease with banks' risk aversion for a given reported risk level. This is different from existing models in which penalties (if any) are either exogenous (Prescott, 2004) or serve as an unlimited reward to those banks who report risk truthfully (Colliard, 2019). In the data, I find that banks are more likely to report switching to a model that implies higher capital requirements, but the effect is rather small. Moreover, using these risk models corresponds to worse model outcomes ex post. Similarly, the change in regulation intended to better capture market risk of the U.S. banks is followed by the lower reported risk and higher number of risk underreporting incidences among these banks. This result complements Begley et al. (2017) who find that banks with large trading operations at the beginning of 2006 tend to have more risk underreporting cases over the period from 2006 to 2013. Thus, the increasing Basel penalties at a given threshold level (see Table 1) is 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 to the elicitation of truthful reporting: penalties 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 (BCBS, 2019b). These changes seem to only help banks to look safer than they really are as they did in the global financial crisis.

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 larger than in Begley et al. (2017) hand-collected data set, I provide evidence on underreporting of bank risk as well as assess regulation with respect to promoting strong incentives among banks to improve their risk 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 takes the form of an additional capital charge that increases with a number of times when true risk is underreported (see Table 1)[1]. The lower risk reported by banks is, the lower the corresponding capital requirement is. This implies that in the absence of penalties for too low reported risk levels, all banks would simply report the lowest risk possible. Thus, penalties are key to ensure a correct mapping between bank risk and bank capital as well as to achieve the optimal capital requirement. To evaluate the existing Basel regulation, it is therefore necessary to build a model where capital requirements and penalties at the regulator's disposal are risk-sensitive, and where penalties are used as an incentivizing mechanism to mitigate misreporting of bank risk and suboptimal capital requirements ex ante.

There are two types of agents in the model: banks and a regulator[2]. 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

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

[2]The model setup follows Prescott (2004), however, I make a few significant changes: (i) the regulator observes only a signal about the true risk of banks; (ii) the regulatory penalties are endogenized and are risk-dependent; (iii) there is a limited liability condition that determines the maximum feasible capital requirement.

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. When $\omega' < \omega$, the true risk ω is underreported by banks, and when $\omega' > \omega$, the true risk ω is overreported.

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', i.e., a *risk-sensitive capital requirement*. Then, since each bank is of size 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 be protected by limited liability:

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[3]. 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 $V(K)$ which increases with K $(V' > 0)$ and reaches its maximum at zero when $K = 1$ (Figure 2 gives an example of such function V). Formally,

Assumption 2. $V\big(K\big) \leqslant 0 \;\; \forall\, \omega' \in [\underline{\omega}, \overline{\omega}]$ with $V\big(1\big) = 0$.

Since banks have private information about the true probability of failure ω, they would always prefer to report the lowest possible risk $\underline{\omega}$ and hold the lowest possible amount of capital $K(\underline{\omega})$ in the absence of regulation along the risk-based capital. 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 given the signal ω' and are related to the capital $K(\omega')$ through ω'. The penalties are imposed on banks in case the investment fails with probability ω, while there are no penalties with probability $1 - \omega$. The regulation works as follows:

$t = 0$: The regulator specifies a formula linking any reported risk ω' to a capital requirement $K(\omega')$ and penalties $T(\omega')$ in case of failure.

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

[3] This preference can stem, for example, from capital being costly for banks (Dagher et al., 2016).

$t = 2$: Banks make their investment of size one, financed with $K(\omega')$ equity and $1 - K(\omega')$ deposits.

$t = 3$: With probability ω, the investment fails and banks are charged penalties $T(\omega')$.

The regulator wants to achieve the optimal level of risk-based bank capital K and uses T to ensure truthful reporting among banks. It is not, however, in the regulator's interest to maximize the capital requirement. The regulator's objective is to maximize social welfare balancing between the losses from failure measured by V and the losses from liquidity provision using equity[4] measured by the per unit cost of capital c. The penalties T do not represent a direct value to society, therefore, do not enter the regulator's payoff, but they are crucial for having an appropriate level of capital.

The regulator is searching for the 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

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

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

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 given the capital amount K held by banks. The second term $cK(\omega)$ is the cost to banks of issuing capital for a given risk ω. The regulator maximizes his payoff 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 (limited liability (LL) constraint).

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

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

[4]The same objective for the regulator is proposed by Prescott (2004).

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 the high expected losses to society 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 the true risk ω, the first-order condition from solving the regulator's problem combined with the assumptions 3 and 4 would define the interior first-best capital level 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 $K(\omega)$ increases with ω, i.e., the capital requirement increases with the true risk. This positive relationship between the risk and the capital is consistent with the risk-sensitive Basel regulation.

Proposition 1. The first-best capital level $K^f(\omega)$ 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.

Thus, the highest possible failure risk $\overline{\omega}$ is associated with the highest capital requirement $K(\overline{\omega})$. Under full information, the regulator would perfectly observe $\overline{\omega}$ and could assign banks a unique risk-based capital amount $K(\overline{\omega})$. Under incomplete information instead, the regulator would bear the social cost of failure only with an unobserved probability $\overline{\omega}$, but could save on the cost of issuing capital by marginally reducing $K(\overline{\omega})$ and be thus better off. Therefore, the capital requirement $K(\overline{\omega})$ may not be unique in this case and then there exists an interval in the upper tail of the risk distribution $[\widehat{\omega}, \overline{\omega}]$ such that over this interval the capital requirement stays constant which is denoted by $\overline{K}$ (see Figure 3).

Because the true risk ω is private information, the capital schedule $K(\omega)$ as defined in (1) is only feasible for the regulator if it is in the interest of banks to report their risk truthfully. The regulator hence should choose functions K and T such that the (IC) constraint is satisfied:

$$\forall\,(\omega',\omega)\in[\underline{\omega},\overline{\omega}]^2 \quad \omega\in\arg\max_{\omega'} U(\omega',\omega),$$

i.e., reporting the true risk ω should be a solution of the banks' maximization problem. I assume that banks have CRRA preferences[5] with a risk aversion parameter $\gamma\in[0,1)$. Considering this range of γ allows to include both the possibility of banks being risk-neutral[6] and, more generally, being risk-averse[7]. The respective banks' payoff $U(\omega',\omega)$ is:

$$\begin{aligned} U(\omega',\omega) &= (1-\omega)\frac{\big(1-K(\omega')\big)^{1-\gamma}}{1-\gamma}+\omega\left(\frac{\big(1-K(\omega')\big)^{1-\gamma}}{1-\gamma}-\frac{\big(T(\omega')\big)^{1-\gamma}}{1-\gamma}\right)= \\ &= \frac{\big(1-K(\omega')\big)^{1-\gamma}-\omega\big(T(\omega')\big)^{1-\gamma}}{1-\gamma}. \end{aligned} \tag{2}$$

With probability $1-\omega$ the investment succeeds and the banks' payoff is solely based on the amount of deposits $1-K(\omega')$. With probability ω the investment fails, and deposits as well as penalties $T(\omega')$ enter the banks' payoff.

The relationship between the banks' payoff $U(\omega',\omega)$ and the capital $K(\omega')$ is:

$$\begin{aligned} \frac{\partial U(\omega',\omega)}{\partial K(\omega')} &= -\big(1-K(\omega')\big)^{-\gamma}<0, \\ \frac{\partial U^2(\omega',\omega)}{\partial K(\omega')^2} &= -\gamma\big(1-K(\omega')\big)^{-\gamma-1}<0, \end{aligned}$$

i.e., the banks' payoff $U(\omega',\omega)$ is a decreasing and concave function of the capital schedule K ($U'_K<0$, $U''_K<0$). This means that an increase in the capital requirement for a given risk level by a certain amount when the capital level is relatively high is more costly for banks than when

[5] The same type of preferences are used by Cuoco and Liu (2006) in their numerical application.

[6] Both Prescott (2004) and Colliard (2019) assume that banks are risk-neutral.

[7] A risk aversion assumption rests on the traditional explanations for risk aversion behavior including (i) incentive problems such as adverse selection and moral hazard which are associated with regulation (e.g., deposit insurance, failure resolution mechanism, 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; (iv) insufficient owner diversification. See e.g. Ratti (1980), Sealey (1980), Ho and Saunders (1981), Koppenhaver (1985), Angbazo (1997) who treat banks as risk-averse agents. For the most recent empirical evidence on banks being risk-averse see Camba-Méndez and Mongelli (2021).

the capital level is relatively low. This relationship points to diminishing returns for banks when they lower the capital requirement.

The corresponding relationship between the banks' payoff $U(\omega')$ and the penalties $T(\omega')$:

$$\frac{\partial U(\omega',\omega)}{\partial T(\omega')} = -wT(\omega')^{-\gamma} < 0,$$
$$\frac{\partial U^2(\omega',\omega)}{\partial T(\omega')^2} = \omega\gamma\big(T(\omega')\big)^{-\gamma-1} > 0,$$

i.e., the banks' payoff $U(\omega',\omega)$ is a decreasing and convex function of penalties T ($U'_T < 0$, $U''_T > 0$). This implies that an increase in the penalties by a certain amount when the penalty level is relatively low is more costly for banks than when the penalty level is relatively high. This relationship is consistent with the Basel framework (see Table 1 and Figure 1) where the penalties increase in a non-linear way between different classes of risk models.

If banks were risk-neutral ($\gamma = 0$), the payoff would simply be:

$$U^{RN}(\omega',\omega) = (1-\omega)\big(1-K(\omega')\big) + \omega\big(1-K(\omega')-T(\omega')\big) = 1-K(\omega')-\omega T(\omega'), \qquad (3)$$

with U^{RN} linearly decreasing with K and T ($U^{RN'}_K < 0, U^{RN''}_K = 0, U^{RN'}_T < 0, U^{RN''}_T = 0$). This implies that a non-linear impact of the capital K and the penalties T on the banks' payoff is present as long as banks are risk-averse. A linear trend in the Basel penalties within the Yellow model quality class (see Figure 1), but the absence of the linearity in penalties moving from one model class to another suggests a special preventive role that a potential supervisory action is intended to play for banks.

For the (IC) constraint to hold, $\omega' = \omega$ must constitute a maximum of the banks' payoff function $U(\omega',\omega)$. This requires that the first-order condition holds in $\omega' = \omega$:

$$\frac{\partial U(\omega',\omega)}{\partial \omega'} = -\big(1-K(\omega')\big)^{-\gamma}K'(\omega') - \omega\big(T(\omega')\big)^{-\gamma}T'(\omega'), \qquad (4)$$

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

Here the marginal change in the capital for a given amount of deposits is set equal to the expected marginal change in the penalties for a given level of penalties. Also, since from (1) $K' > 0$, (5) implies that $T(\omega)$ decreases with ω, i.e, the penalties decrease with the true risk. This negative relationship between the true risk and the penalties reflects their complementary role to the capital for a given risk level.

Because the banks' payoff $U(\omega', \omega)$ decreases with the penalties T ($U'_T < 0$) and the capital K remains constant for all $\omega \geqslant \widehat{\omega}$, banks have incentives to misreport ω if $\omega \geqslant \widehat{\omega}$ due to the lower expected penalties $T(\omega)$. This implies that the only penalty schedules that are incentive-compatible over the interval $[\widehat{\omega}, \overline{\omega}]$ where the capital is constant, are where T stays constant as well.

(5) is a differential equation that pins down the optimal risk-sensitive capital and penalty schedules, so that it is in the interest of banks to report risk truthfully. The regulator also cares about the (LL) constraint, i.e, that the banks' payoff $U(\omega, \omega)$ is never below zero:

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

This constraint puts limits on the possible penalties $T(\omega)$ and the capital schedule $K(\omega)$:

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

$$\forall\, \omega \in [\underline{\omega}, \overline{\omega}] \quad K(\omega) \leqslant 1 - \omega^{\frac{1}{1-\gamma}} T(\omega). \tag{7}$$

(6) means that the expected regulatory penalties cannot exceed the amount of deposits at banks' disposal. According to (7), 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.

Proposition 2 describes the optimal regulatory capital and penalty schedules:

Proposition 2. *The second-best capital schedule $K^s(\omega)$ 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:

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

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

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

In the optimal contract, when the true risk is relatively high ($\omega > \widehat{\omega}$), there is no risk variation in either the capital requirement K or the penalties T. In this case, banks are required to hold the highest possible capital amount $\overline{K}$. On the other hand, when the true risk is relatively low ($\omega \leqslant \widehat{\omega}$), the capital requirement K as well as the penalties T are risk-sensitive and defined by the first-order conditions (1) and (5). Because the banks' payoff $U(\omega', \omega)$ decreases in both the capital K and the penalties T, whereas $K' > 0$ and $T' < 0$, banks face a trade-off between a lower capital requirement K and potentially higher penalties T for a given risk. Proposition 3 summarizes additional implications for the sensitivity of the penalties relative to that of the capital:

Proposition 3. In the optimal contract, the lower risk ω is, the higher banks' risk aversion γ is, the higher penalty $T(\omega)$ and capital $K(\omega)$ levels are, the more risk-sensitive the penalties $T(\omega)$ should be relative to the capital $K(\omega)$:

$$\forall\, \omega \in [\underline{\omega}, \widehat{\omega}] \qquad -\frac{T'(\omega)}{K'(\omega)} = \frac{1}{\omega} \left(\frac{T(\omega)}{1 - K(\omega)} \right)^{\gamma}.$$

The effect of Basel regulation for market risk can be characterized using Proposition 3. Basel capital requirement varies with risk, but the sensitivity of the capital with respect to risk is constant. Basel penalties vary with risk as well, but the sensitivity of penalties increases as the risk level becomes lower and there are more risk underreporting incidences (see column 3 in Table 1). Therefore, the relationship between the ratio of penalties' and capital sensitivities $\frac{T'(\omega)}{K'(\omega)}$ and the risk ω is consistent with Basel rules. If all banks were risk-neutral, i.e., $\gamma = 0$, the optimal rate of the penalty sensitivity relative to that of capital would solely depend on the risk ω, and this is where the Basel framework fits completely. What is different, however, and plays a crucial role is risk aversion. If banks are indeed risk-averse, the sensitivities' ratio does not depend only on the risk level, but also on the penalty $T(\omega)$ and the capital $K(\omega)$ levels at place. In the Basel framework, the sensitivity of penalties indeed increases with the penalty itself. However, according to Proposition 3, there should be a positive relationship between the amount of capital $K(\omega)$ and the optimal sensitivities' ratio $\frac{T'(\omega)}{K'(\omega)}$. This is where the Basel framework may potentially deviate from the theoretical prediction if the penalties' sensitivity does not increase in the total amount of risk-based capital. The lower risk ω has a direct positive effect on the optimal sensitivities' ratio as well as two indirect effects of the opposite signs through higher penalties T and lower capital K. To evaluate the effect of the Basel regulation, it is therefore crucial to check whether the total capital requirement with penalties for a given misrepresentation of risk actually increases with penalties.

2.1 Numerical Analysis of Optimal Capital and Penalties

Proposition 2 and Proposition 3 are illustrated with a numerical example. The first-best solution is computed as well to compare it with the second-best. For the numerical example, a simple quadratic loss function V is considered: $V(K) = -(1-K)^2$ with $V(1) = 0$, $V' > 0$ and $V'' < 0$ (see Figure 2). Assuming this form for the regulatory function V allows to define K^f using (1):

$$K^f(\omega) = 1 - \frac{c}{2\omega}, \tag{8}$$

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

The regulator aims at implementing the full-information capital strategy K^f, which is feasible only if there exists $T(\omega)$ such that (5), (6) and (7) hold. The range of the optimal $T(\omega)$ can be found solving the differential equation (5) for different values of the risk-aversion parameter γ:

$$\forall\, \gamma \in (0,1) \quad T(\omega) = c\left(\frac{1-\gamma}{8\omega^2}\right)^{\frac{1}{1-\gamma}} + c_1, \tag{9}$$

where $T' = -\left((1-\gamma)^{\gamma} 2^{-2-\gamma} c^{1-\gamma} \omega^{-3+\gamma}\right)^{\frac{1}{1-\gamma}} < 0$, i.e., T decreases with ω as in the model.

When banks are risk-neutral, i.e., when $\gamma = 0$, penalties $T(\omega)$ take a special form $T^{RN}(\omega) = \frac{c}{4\omega^2} + c_1$ with $T' = -\frac{c}{2\omega^3} < 0$.

Figure 3 and Table 2 demonstrate the solution for two scenarios of the lower bound of T following the structure of the Basel penalties (see Figure 1 and Table 1): $T(\overline{\omega}) = \overline{T} = 0.4$ and $\overline{T} = 0.2$. (6), (7), (8) and (9) define the feasible sets of parameters in both cases. 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 $\overline{T} = 0.2$.

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 and volatility data. I use hand-collected data from publicly available quarterly and annual reports as well as Pillar III Disclosures. I extract information on the reported incidences of risk model revisions (*New Model*) and classify them (where possible) based on their descriptions into those that ceteris paribus imply higher (*Tight Model*) or lower (*Loose Model*) capital requirements. Both the number and the distribution of risk model revisions vary significantly across banks over time (see Figure 4). There are on average more model revisions that imply lower capital requirements, especially before and after the global financial crisis. During the crisis in 2007-2008, however, banks seemed to switch more actively to more stringent risk models.

For the remaining self-disclosed bank data to study the reported risk and penalties, I use the sample from Mariathasan et al. (2021). The sample selection follows Begley et al. (2017) and the final sample covers 19 largest banks from the U.S., Canada and Europe who provide sufficient quarterly information on market risk models, estimated exposures and the number of days when the realized daily loss of a bank exceeds its risk estimate (which is essential to measure penalties) from 2002Q1 to 2016Q4. The sample comprises 813 bank-quarter observations and, when bank balance sheet information is taken into account, 676 bank-quarter observations[8].

Table 3 shows summary statistics on self-reported model revisions, risk exposures[9], its underreporting cases and penalties. All 19 banks change their model at least once during the sample period. There are 98 risk model revisions in total, with the vast majority constituting those model revisions that imply lower capital requirements. Non-U.S. banks tend to report model revisions more often, UBS and Credit Suisse lead in this component with 12 and 17 quarterly model revisions, respectively. The only bank that tightens its risk model substantially more often is Toronto-Dominion Bank: all five model revisions reported by this bank are classified as implying higher capital requirements. All other banks, especially U.S. banks, seem to do more often model revisions that imply lower capital requirements.

The average number of risk underreporting incidences in the sample is 0.4. 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 0.09, between 2007 and 2010 it is 1.05, and between 2011 and 2016 it is 0.19. Thus, risk tends to be overreported during normal times, whereas underreporing of risk is concentrated in crisis times, i.e., when truthful risk reporting would matter the most.

Data on risk underreporting makes it possible to compute risk-sensitive penalties as outlined in the Basel framework (see Table 1). Combining these penalties with the self-reported risk exposures allows to calculate the minimum monetary cost of the penalties[10]. The average penalty in the sample is 0.09, the average self-reported risk exposure is just above \$150 million which results in at least \$13 million monetary cost of penalties on average. The estimated lower bound for penalties

[8]Accounting data is obtained from Fitch, Orbis and SNL, whereas data to measure exchange rate, interest rate, market and commodity volatilities is from the St. Louis Fed, International Financial Statistics and Thomson Reuters Eikon (Mariathasan et al., 2021).

[9]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.

[10]Under Basel I, market risk capital charges are determined in most cases as the product of the quarterly average 10-day Value-at-Risk and the multiplier that includes penalties. Basel II and III use a more complex measure for market risk capital charges 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 capital charges unfortunately make it impossible to accurately estimate the penalties, but its lower bound can be reasonably determined.

varies a lot across banks from zero for seven banks who face no penalties over the sample period[11] to nearly $70 million for Morgan Stanley.

3.2 Empirical Strategy

In the model, banks' risk aversion is a determinant of banks' reporting strategy. In the optimal contract, penalties decrease with the bank's risk aversion for a given risk level at the lower tail of risk distribution (see Figure 3). To test this relation empirically, I use the number of risk underreporting cases in the preceding year to measure the quality of a bank's risk model as a tool to deal with uncertainty and the associated penalties. The past-year number of risk underreporting incidences determines where in the Basel framework banks' risk model fits in the current quarter, the corresponding penalty and whether an additional supervisory action may take place (see Table 1). Therefore, if banks are more cautious towards risk when the expected penalties are relatively lower, banks should have strong incentives to revise their risk models if its past-year performance is unsatisfactory (or the supervisor may come and explicitly ask them to) and if so, switch to a more stringent model.

A key identification challenge stems from the fact that risk model revisions are endogenous. I employ two strategies to alleviate this concern. First, I use an instrumental variable (IV) approach where I exploit the product of banks' trading assets scaled by total assets and the S&P 500 index volatility as an instrument. The shares of banks' trading portfolios measure their differential exposure to common market shocks that are correlated with the incidences when market risk estimates are exceeded by actual trading losses but can be seen as exogenous to banks' decision to change their risk model[12]. I examine whether worse risk model performance in the past year makes model

[11]These seven banks include Bank of New York Mellon, Canadian Imperial Bank of Commerce, Citi, ING, SunTrust Bank, Bank of Nova Scotia and Toronto-Dominion Bank.

[12]I therefore assume that the relative exposure of banks' trading book to market volatility in the preceding quarter affects banks' decision to change their model only through the total number of past-year risk underreporting incidences. This number serves as a whistleblower for revising a model and is the main criterion for the supervisor to disallow the use of a model (see Table 1). However, the discretion in the decision to change the model critically depends on the nature of risk underreporting, and in particular the model change is substantially less likely to take place if underreporting of risk happens just due to high market volatility. In addition to selecting the instrument based on an economic argument (exclusion restriction), I ensure that the coefficient for the instrument is statistically significant in the first-stage regressions (t-statistic = -5.47 and F-statistic = 29.88 in the first-stage regressions in columns (5) and (7) of Table 4), supporting the relevance of the instrument.

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 $\sum_{t-4}^{t-1} Underreport_{it}$ which is a number of days from quarter $t-4$ to quarter $t-1$ such that the actual daily loss of bank i exceeds its risk estimate for that particular day. In other words, $\sum_{t-4}^{t-1} Underreport_{it}$ captures the total number of risk underreporting cases in the past year which is a key model performance criterion in 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:

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

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 book assets), leverage (proxied by the equity ratio) and profitability (proxied by the ratio of the net income to book 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[13]. α_t represents year-quarter fixed effects that capture the effect of period-specific global shocks on risk model performance (including, especially the crisis)[14].

[13]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.

[14]Recall that seven out of 19 banks face no penalties over the sample period. Hence, including bank fixed effects would limit the attention to model revisions enforced by the supervisor ex post while the goal is to analyze the model revisions driven by cross-sectional differences in banks' risk preferences. Table 11 shows that the main results

The next step is to analyze the risk model outcomes following the model changes. Even if banks revise their risk models when it is needed, it is not clear whether these revisions lead to the improved reporting of bank risk ex post. I use three main outcome variables: $Risk_{it}$, $\#Underreport_{it}$ and $NoPenalty_{it}$. $Risk_{it}$ 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. Therefore, $Risk_{it}$ represents bank i's estimated risk exposure at time t. I estimate the OLS regressions of the following form:

$$Risk_{it} = \beta_1 Model_{it} + [\beta_2 Model_{it} \times Penalty_{it-1} + \beta_3 Penalty_{it-1}] + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \varepsilon_{it}, \quad (11)$$

where $Model_{it}$ is either $NewModel_{it}$, $TightModel_{it}$ or $LooseModel_{it}$ which is an indicator for a model revision by bank i at quarter t to a model that ceteris paribus implies lower capital requirements. In the first set of regressions (11), I include only one of $Model$ indicators and β_1 is the coefficient of interest. If banks' reporting of model revisions corresponds to reality, those model revisions that imply higher capital requirements ($TightModel$) should be associated with higher $Risk$ whereas those that imply lower capital requirements ($LooseModel$) - with lower $Risk$. In the second set of regressions (11), I additionally include the interaction between one of $Model$ indicators and $Penalty_{it-1}$ which is an indicator for penalties imposed on bank i at quarter $t-1$. β_2 thus captures the effect on $Risk$ of those model revisions that occur in line with the recommendations from the Basel Committee (see Table 1).

Another way to assess the risk model performance is to look at how many times the true risk is underreported after the model change. I construct a variable $\#Underreport_{it}$ measuring a number of days at quarter t such that the actual daily loss of bank i exceeds its risk estimate for that particular day. $\#Underreport$ 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 more suitable for count data. More specifically, I consider a zero-inflated negative binomial (ZINB) regression model[15]. I use

are robust to the inclusion of bank and country fixed effects.

[15] 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.

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. I estimate the ZINB regressions of the following form:

$$\#Underreport_{it} = \beta_1 Model_{it} + [\beta_2 Model_{it} \times Penalty_{it-1} + \beta_3 Penalty_{it-1}] + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \varepsilon_{it}. \tag{12}$$

Similar to (11), in the first set of regressions (12), 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 cases, especially those model revisions that imply higher capital requirements ($TightModel$). In the second set of regressions (12), I additionally include the interaction between one of $Model$ indicators and $Penalty_{it-1}$. β_2 thus captures the effect on $\#Underreport$ of those model revisions that occur in line with the recommendations from the Basel Committee (see Table 1).

Finally, I investigate whether model revisions make it more likely to belong to the highest model quality class and less likely to have penalties. I construct a variable $NoPenalty_{it}$ which is an indicator for zero penalties imposed on bank i at quarter t under the Basel framework (see Table 1). In other words, $NoPenalty_{it}$ is an indicator for bank i's risk model being classified as green at quarter t. I estimate the OLS and probit regressions of the following form:

$$NoPenalty_{it} = \beta Model_{it} + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \varepsilon_{it}. \tag{13}$$

β is the coefficient of interest. If risk model revisions improve its quality, they should be associated with a higher likelihood to belong to the highest quality class and to have zero penalties. The effect (if any) should be stronger in cases when banks report switching to a more stringent risk model ($TightModel$).

To improve further upon the identification, I exploit the change in market risk capital regulation in the U.S. as an exogenous shock to banks' risk reporting requirements. In particular, I look at the introduction of the Market Risk Capital Rule enforced by Fed in 2013[16]. Starting from January 2013, 30 U.S. banks are required to report more detailed market risk information to Fed (Federal Register, 2012). All eight U.S. banks in the sample have been affected by the Rule. I construct a variable $MRCR_{it}$ which is an indicator for bank i being affected by the Market Risk Capital Rule at quarters t from 2013Q1 onwards. I estimate the probit, linear and ZINB regressions:

$$Y_{it} = \beta MRCR_{it} + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \alpha_i + \varepsilon_{it}. \tag{14}$$

Here the outcome variable Y_{it} is either $NewModel_{it}$, $Risk_{it}$ or $\#Underreport$. If the Market Risk Capital Rule is effective, banks should enhance their reporting standards and have stronger incentives to revise their models accordingly.

Since the introduction of the Market Risk Capital Rule, U.S. banks have changed their risk models only a few times and, interestingly, all such model revisions in the current sample are identified as those that imply lower requirements. Relaxing risk models is not something that raises concerns on its own, unless it results in worse model outcomes in the future. To test this, I estimate the OLS and ZINB regressions of the following form:

$$Y_{it} = \beta_1 LooseModel_{it} + [\beta_2 LooseModel_{it} \times Penalty_{it-1} + \beta_3 Penalty_{it-1}] + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \varepsilon_{it}. \tag{15}$$

Here the outcome variable Y_{it} is either $\#Underreport_{it+1}$ or $NoPenalty_{it+1}$. $\#Underreport_{it+1}$ is, similarly to $\#Underreport_{it}$, a number of days such that the actual daily loss of bank i exceeds its risk estimate for that particular day, but at quarter $t+1$. Along the same lines, $NoPenalty_{it+1}$ is an indicator for zero penalties imposed on bank i under the Basel framework at quarter $t+1$. As in (11) and (12), in the first set of regressions (15) I include only $LooseModel$ indicator, whereas in the second set of regressions (15), I additionally include the interaction between $LooseModel$ and $Penalty_{it-1}$. β_1 captures the stand-alone effect of relaxing the risk model on future model outcomes, whereas β_2 captures the effect of relaxing the risk model on future outcomes when the model requires revision under the Basel rules (see Table 1).

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

4 Results

Table 4 reports the findings from examining the relation between the past-year performance of banks' risk model and their incentives 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 positive. This indicates that banks are more 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 6% and 3%, respectively (columns 5, 6 and 8). Using the probit estimator, I also compute marginal effects for a given change in $\sum_{t-4}^{t-1} Underreport$ conditional on its residual (i.e., conditional on the level of endogeneity in the model). For example, the marginal effect of having one (five) incidence(s) of risk underreporting versus having none in the past year on the probability of having $NewModel$ is only around 17 (89) bps, whereas the marginal effect of having 10 incidences of risk underreporting versus having none in the past year on the same probability is nearly 1.85%. For $TightModel$, the same marginal effects are slightly higher, constituting 22 bps, 1.28% and 3%, respectively. Provided that the penalties take place in approximately 10% cases in the sample, the results suggest that, on one hand, the national supervisors seem to be more lenient towards banks with regard to their internal models than the Basel Committee proposes, and on the other hand, banks' own incentives to revise their risk models when it is needed (after underestimating risk 10+ times in a given year) seem to be rather weak.

Table 5 presents the findings from investigating the relation between risk model revisions and the reported risk. Estimates in columns (1)-(3) correspond to the general case of revising a model, columns (4)-(6) feature the case of switching to a more stringent risk model and columns (7)-(9) reflect the case of relaxing a risk model. The coefficient on $NewModel$ in column (1) is 0.30 and is statistically significant suggesting that the model revision on its own is associated with approximately 35% higher self-reported risk exposure. The coefficient on $TightModel$ in column (4) is 0.52 and is statistically significant suggesting that the model revision on its own is associated with approximately 68% higher self-reported risk exposure. These stand-alone effects, however, seem to fade once the interaction with having penalties in the previous quarter is added to the model. In particular, switching to a more stringent model when a bank is penalized in the preceding quarter corresponds to more than twice higher reported risk level (columns 5 and 6). On the other hand, switching to a more optimistic model when the penalties are imposed on a bank right before corresponds to significantly lower reported risk level that almost cancels out the effect of penalties on the reported risk (columns 8 and 9). Thus, reporting a more stringent or more optimistic model is in line with the reported risk level ex post, however, these effects on the reported risk are mainly present when models are revised after having penalties in the past quarter (i.e., after having 5+ risk underreporting incidences in the past year).

Table 6 reports the findings from examining the relation between risk model revisions and the number of risk underreporting incidences. Here I focus on the effects of revising a model in general $NewModel$ (columns 1-3) and of switching to a more stingent model $TightModel$ (columns 4-6) given that the chances of observing these two increase with worse performance of the old model (see Table 4). Bringing back the results for the self-reported risk exposures from Table 5, both $NewModel$ and $TightModel$ are expected to be associated with lower numbers of risk underreporting cases among banks, especially after them being penalized. The results in Table 6 demonstrate quite the opposite. The coefficients on $NewModel$ and $TightModel$ in columns (1) and (4) are significantly positive. Interpreting these coefficients in terms of incidence-rate ratios, revising a risk model versus not corresponds to 2.84 times higher number of risk underreporting cases in a given quarter, whereas switching to a more stringent model corresponds to 2.86 times higher number of risk underreporting cases. Similar to the results in Table 5, these effects are mainly observed after penalties take place and if anything become stronger in this case: revising a risk model after having penalties is associated with 3.02 times more risk underreporting incidences and switching to a more stringent risk model at the same time is associated with 3.08 times more risk underreporting incidences. These results suggest that even though using certain risk models correspond to higher reported risk on average, misrepresentation of true risk persists on a more granular level for these models and is even further exacerbated.

Table 7 presents the findings from studying the relation between risk model revisions and the quality of a newly chosen risk model. Again as in Table 6, I focus on the effect of revising a model $NewModel$ (columns 1-2 and 5-6) and switching to a more stringent risk model $TightModel$ (columns 3-4 and 7-8). The outcome variable $NoPenalty$ indicates that a risk model is of the highest quality class (green from Table 1) and as a consequence there are no penalties which are set by the Basel Committee *"to maintain strong incentives for the continual improvement of banks' internal risk measurement models"* (BCBS, 1996). Unfortunately, the results given in Table 7 do not support the argument. The coefficients on $NewModel$ and $TightModel$ are significantly negative, implying that banks tend to adopt worse risk models. Similar to the results in Table 6, estimates are somewhat higher when banks report switching to a more stringent model. In particular, the average marginal effect of having a new model on its chances to belong to the highest quality class is -10.86% (column 5), whereas the same marginal effect of reporting a more stringent model is -20.45% (column 7). These results together with those in Table 6 raise concerns about the true incentives of banks when they introduce a new risk model, especially when it implies higher reported risk and higher capital requirements. Such models produce relatively more conservative estimates for banks' risk exposures on average, but neither do so with sufficient precision (see Table 6), nor help to avoid the regulatory penalties.

Table 8 reports the findings from examining the effect of the shock to bank risk estimation and reporting requirements on risk model revisions and model outcomes. In particular, I look at the Market Risk Capital Rule enforced by Fed in 2013 (Federal Register, 2012). The Rule targets the 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 Rule is expected to be positive on the chances of updating a risk model $NewModel$ and the reported risk $Risk$, and negative on the number of risk underreporting incidences $\#Underreport$ provided banks have stronger incentives to develop better risk models and better account for different sources of market risk after the change in regulation. However, I discover totally the opposite. The coefficient on $NewModel$ is significantly negative (columns 1-2) as it is on $Risk$ (columns 3-4), whereas the coefficient on $\#Underreport$ is significantly positive (columns 5-6). More specifically, the average marginal effect of the shock on the probability of updating a model is almost -6.5% for the U.S. banks as compared to the others. Moreover, following the implementation of the Rule, U.S. banks tend to report approximately 43% lower risk exposure than the other banks (around 82% lower risk exposure after controlling for bank size, leverage and profitability). Finally, U.S. banks tend to have 2.46 times more risk underreporting incidences after the shock. These findings indicate that the Fed enforcement of Basel post-crisis rules is inefficient, since banks seem to hide their risk even more than before the introduction of the Rule.

Table 9 and Table 10 report the results from investigating the relation between relaxing risk models and future model outcomes. In the data, the U.S. banks report only few model revisions but all of them are identified as those that imply lower capital requirements. This observation seems to be consistent with the results given in Table 8, however, it does not necessarily mean that relaxing a risk model is per se worrying. Basel rules enforce risk-sensitive capital requirements, implying that the capital requirements should be lower when the true risk exposure is lower and it is not misreported. The results in Table 9, however, reveal that this is not the case. Using a more optimistic risk model corresponds to approximately 2.33 times more risk underreporting incidences in the quarter following the model change (column 1). This effect is taken over by the interaction with having penalties before the model change which has even higher incidence-rate ratio of approximately 3.17 (column 4). At the same time, the negative effect of switching to a more optimistic risk model when there are penalties on the model quality seems to be more instantaneous (columns 3-6 in Table 10). These results suggest that a risk model that implies lower capital requirements has a strong link with worse future model outcomes.

Table 11 presents the results from numerous robustness tests to exclude potential concerns about the identification. First, I show that the main result in Table 6 (column 3) is robust to the inclusion of bank and country fixed effects in columns 1 and 2, respectively. For the same result, I run the placebo test with the interaction between having a new model and penalties five quarters before, which should have no effect in contrast to the penalties determined a quarter before based on the past-year outcomes (column 3). I also run the placebo test for the introduction of the Market

Risk Capital Rule and falsely assume that it was enforced in 2005 when actually Basel II pre-crisis rules for market risk were set (BCBS, 2005). In column 5, I drop 2008Q3 data, which corresponds to Lehman Brothers' collapse and find the results are not driven simply by this event. In column 6, I show that the results are robust to clustering the standard errors at the bank level. Finally, the results from examining the relation between the past-year risk model performance and the probability of relaxing a risk model are consistent with the results in Table 4 (columns 7-8).

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 upon the supervisor's approval. This creates an asymmetric information problem where the regulator has to rely on the 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 upon 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 the 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 the existing regulation concerning truthful reporting, and providing empirical evidence on the deteriorating quality of models using hand-collected data on banks' self-reported risk levels, 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) and Colliard (2019). The theoretical contribution of this paper is to consider a simple model where the regulator jointly determines the optimal capital and penalty schedules given the risk reported by banks and their risk aversion. This allows me to capture well the main features of the Basel framework.

My empirical findings indicate that the current combination of Basel 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.

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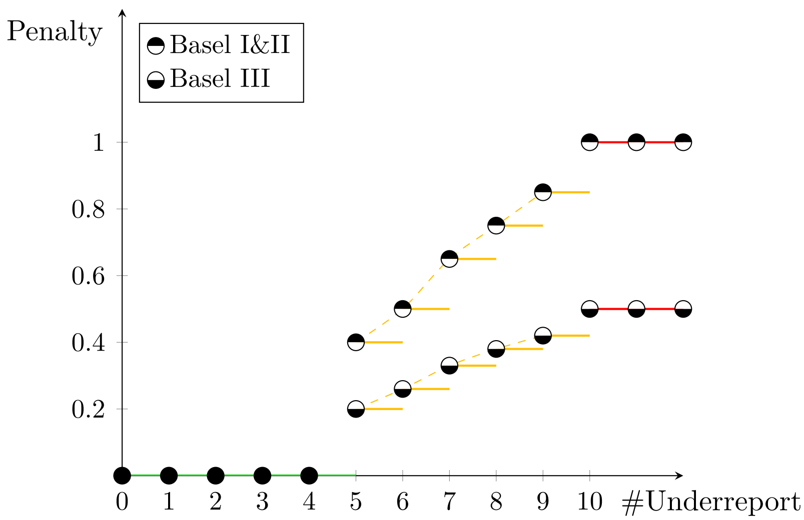
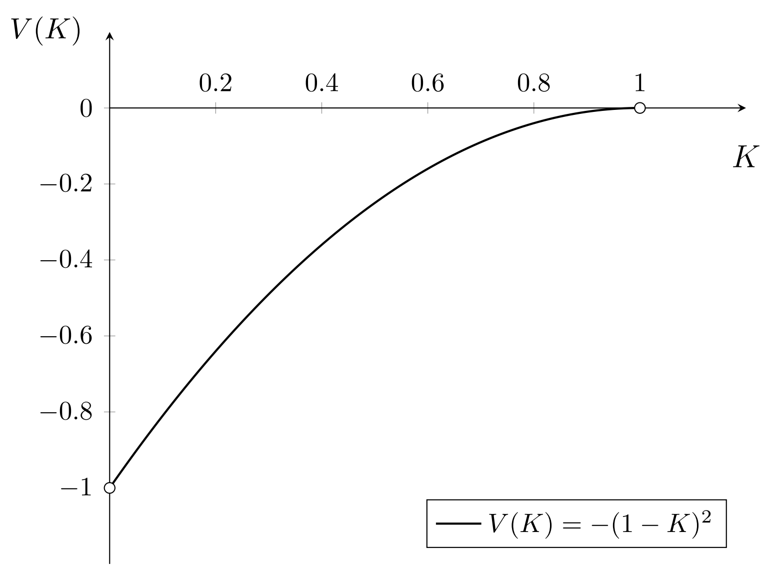
A Figures

Figure 1: Number of Risk Underreporting Cases and Basel Penalties.



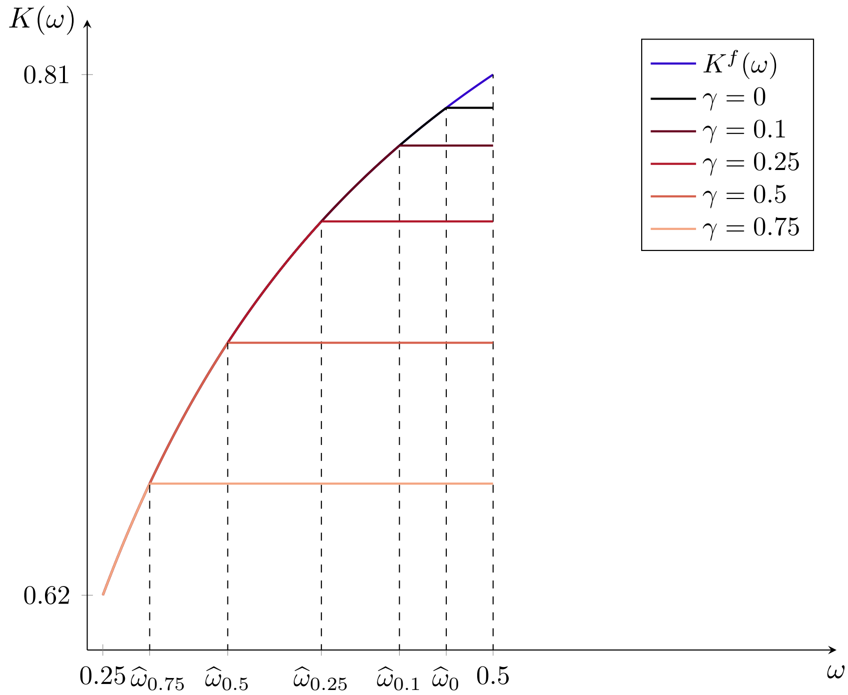
This figure visualizes the Basel penalties (see Table 1) given the number of days when risk is underreported over the preceding year. The values of penalties according to Basel I and II are marked with black top half circles, whereas the values of penalties according to Basel III are marked with white top half circles. Penalties are embedded in market risk capital requirement which constitutes 8% of market risk-weighted assets. If risk weights are determined internally by banks, their market risk-weighted assets can be represented as $12.5\times(3+\text{Penalties})\times f(\text{Reported Risk})$, where f is an increasing function of risk reported by banks that changes along Basel I, II and III. The lower risk reported by banks is, the higher #Underreport is due to the higher probability of the reported risk being exceeded by an actual loss.

Figure 2: Regulatory Loss Function V.

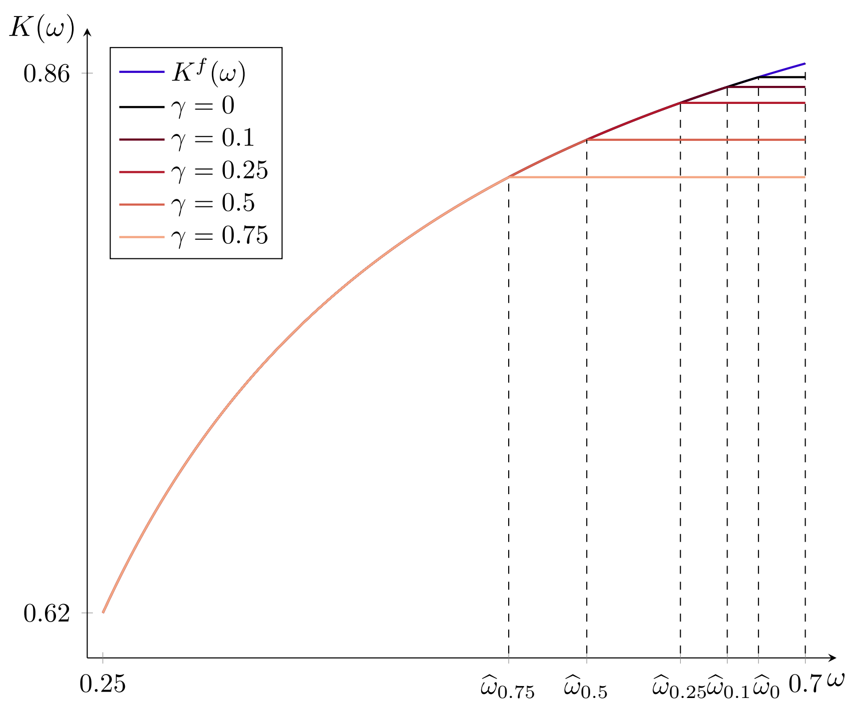


This figure illustrates an example of V, i.e., the regulator's utility function of capital K representing the respective social loss in case of failure and used in the numerical analysis. The function is non-positive with $V(1) = 0$, increasing ($V' > 0$) and concave ($V'' < 0$). The corner values of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

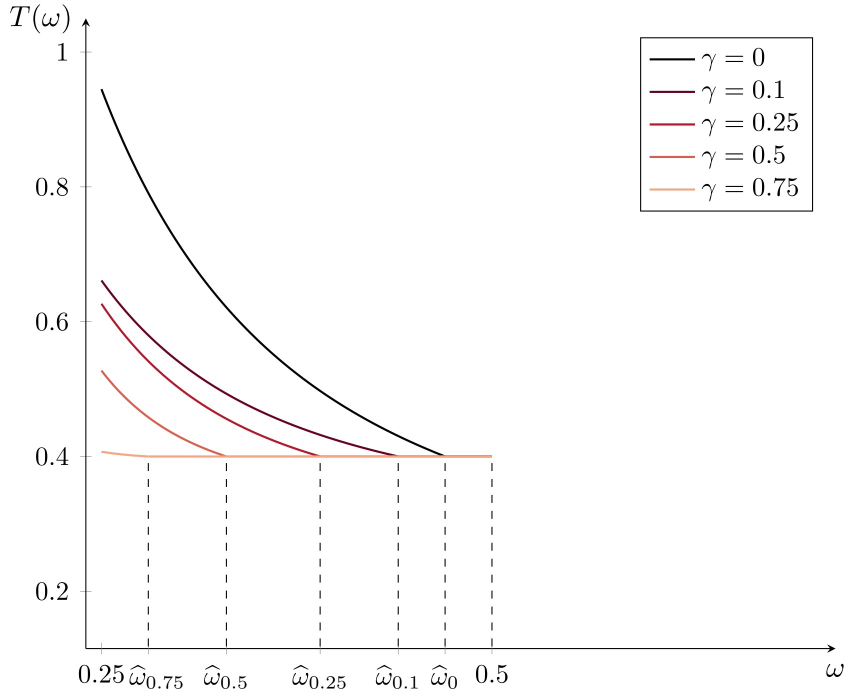
Figure 3: Optimal Regulatory Capital K and Penalties T.



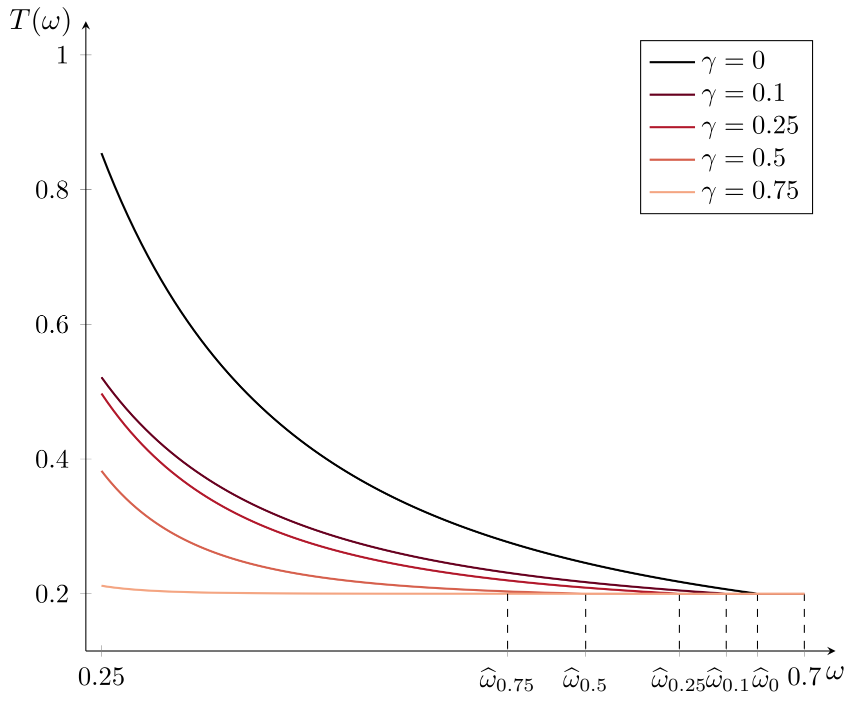
(a) Capital Schedule K when $\overline{T} = 0.4$



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



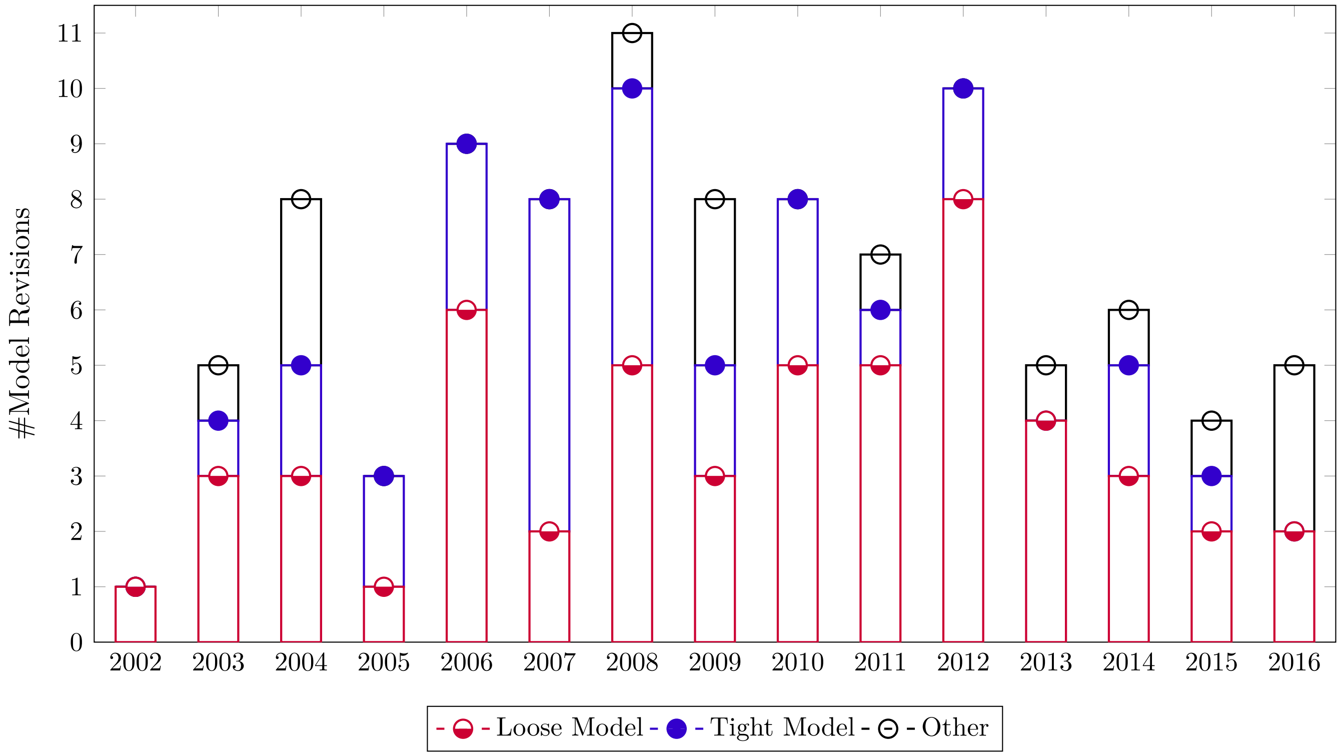
(c) Penalty Schedule T when $\overline{T} = 0.4$



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

These four figures visualize the numerical results for the optimal capital 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 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. I extract information from banks' financial reports on the reported 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 that imply lower capital requirements and occur at a particular year (*Loose Model)*. Blue bars marked with filled circles represent a total number of model revisions that imply higher capital requirements and occur at a particular year (*Tight Model*). Black bars marked with empty circles represent a total number of model revisions that have no clear effect on capital requirements and occur at a particular year (*Other*). Red, blue and black bars stacked together represent a total number of model revisions occured at a particular year (*New Model*).

B Tables

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

Risk Model Quality Class	Annual Number of Risk Underreporting Cases	Penalties Basel I & II	Penalties 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 such that 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 values of penalties according to Basel I and II, and Basel III, respectively. Penalties are embedded in market risk capital requirement which constitutes 8% of market risk-weighted assets. If risk weights are determined internally by banks, their market risk-weighted assets can be represented as $12.5\times(3+\text{Penalties})\times f(\text{Reported Risk})$, 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 which 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 K, whereas columns (11)-(15) demonstrate the maximum feasible levels of capital as defined by (LL). 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 levels $K^f(\omega)$ 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 (LL) 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 $K^f(\omega)$ can be achieved for all $\omega \in [\underline{\omega}, \overline{\omega}]$ and the optimal second-best values of capital $K^s(\omega)$ are set equal to $K^f(\omega)$. The corresponding penalties $T^s(\omega)$ are then determined from (9) given c, γ, ω and c_1, where $c_1 = \overline{T} - c\left(\frac{1-\gamma}{8\overline{\omega}^2}\right)^{\frac{1}{1-\gamma}}$ for all $\gamma \in (0, 1)$ and $c_1 = \overline{T} - \frac{c}{4\overline{\omega}^2}$ if $\gamma = 0$.

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 and c_1, where $c_1 = \overline{T} - c\left(\frac{1-\gamma}{8\widehat{\omega}^2}\right)^{\frac{1}{1-\gamma}}$ for all $\gamma \in (0, 1)$ and $c_1 = \overline{T} - \frac{c}{4\widehat{\omega}^2}$ if $\gamma = 0$.

Table 3: Summary Statistics.

Bank	#New Model	#Tight Model	#Loose Model	Penalty	$Risk	$Penalty	#Underreport	N
Bank of America	4	1	3	0.11	251.26	28.87	0.52	60
Bank of Montreal	7	1	6	0.09	58.7	5.36	0.47	51
Bank of NY Mellon	1	0	1	0.00	23	0.00	0.14	57
Canadian IBC	4	2	1	0.00	20.7	0.00	0.12	42
Citi Group	4	2	2	0.00	359.89	0.00	0.14	36
Credit Agricole	6	0	5	0.12	70.9	8.18	0.33	12
Credit Suisse Group	17	5	6	0.18	262.39	46.42	0.81	48
Deutsche Bank	1	1	0	0.07	263.55	18.18	0.75	32
Goldman Sachs	4	0	2	0.15	321.75	48.57	0.31	16
ING Group	3	0	3	0.00	71.16	0.00	0.03	34
JPMorgan Chase	5	1	3	0.07	332.47	24.21	0.27	48
Morgan Stanley	5	1	3	0.19	366.38	68.09	0.29	48
PNC Financial Services	3	0	3	0.08	15.2	1.23	0.26	46
Royal Bank of Canada	5	1	3	0.10	89.58	9.30	0.46	50
Societe Generale	3	2	1	0.23	127.81	29.56	1.14	36
SunTrust Bank	5	1	4	0.00	28.51	0.00	0.05	37
Bank of Nova Scotia	4	2	2	0.00	36.81	0.00	0.07	59
TD Bank	5	5	0	0.00	57.99	0.00	0.09	56
UBS Group	12	5	5	0.21	245.61	52.35	1.51	45
Total	98	30	53	0.09	151.91	13.08	0.4	813

This table reports summary statistics for the current sample. The sample comprises 813 year-quarter observations for 19 banks from the U.S., Canada and Europe over the period from 2002 to 2016. 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 and classify them (where possible) into those that ceteris paribus imply higher or lower capital requirements. *#NewModel* is a total number of model revisions reported by a given bank over the sample period. *#TightModel* is a total number of model revisions reported by a given bank over the sample period that imply higher capital requirements. *#LooseModel* is a total number of model revisions reported by a given bank over the sample period that imply lower capital requirements. *Penalty* represents the mean penalty values imposed on a given bank over the sample period which are calculated based on the framework proposed by the Basel Committee (see Table 1). $*Risk* 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 represents the maximum potential loss over a 10-day horizon that should not be exceeded in 99% cases. $*Penalty* represents the average dollar amount of minimum penalty values imposed on a given bank over the sample period which is calculated as the product of the average *Penalty* multiplier and the average self-reported *Risk* measure. *#Underreport* is the average number of days in a quarter such that the actual daily loss of a given bank exceeds its daily Value-at-Risk estimate for that particular day. In other words, it represents a quarterly number of cases when the 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
$\sum_{t-4}^{t-1}$ Underreport	0.23***	0.32***	0.28***	0.23***	0.06**	0.06**	0.04*	0.03**
	(0.077)	(0.095)	(0.075)	(0.081)	(0.029)	(0.024)	(0.022)	(0.018)
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	612	449	612	176	612	612	612	612

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 the ratio of trading assets to total assets and the S&P 500 index volatility as an instrument. I ensure that the coefficient for the instrument is statistically significant in the first-stage regressions (t-statistic = -5.47 and F-statistic = 29.88 in the first-stage regressions in columns (5) and (7) of Table 4), hence indicating that the chosen instrument is relevant. In columns (1), (2), (5) and (6), I run the regression:

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

$NewModel_{it} = 1$ if bank i reports a model revision that occurs at quarter t. $\sum_{t-4}^{t-1} Underreport_{it}$ is a number of days from quarter $t-4$ to quarter $t-1$ such that the actual daily loss of bank i exceeds its risk estimate for that particular day. X_{it} represents a vector of bank characteristics to control for bank size (proxied by book assets), leverage (proxied by the equity ratio) and profitability (proxied by the ratio of the net income to book 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. In columns (3), (4), (7) and (8), I run the regression:

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

$TightModel_{it} = 1$ if bank i reports a model revision that occurs at quarter t and implies higher capital requirements. The sample covers 19 banks from the U.S., Canada and Europe over the period from 2002 to 2016. Year-quarter clustered errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Risk Models and Reported Risk.

	(1) Risk	(2) Risk	(3) Risk	(4) Risk	(5) Risk	(6) Risk	(7) Risk	(8) Risk	(9) Risk
New Model	0.30**	0.24	0.14						
	(0.145)	(0.146)	(0.155)						
Tight Model				0.52***	0.23	0.09			
				(0.240)	(0.245)	(0.248)			
Loose Model							0.18	0.26	0.18
							(0.189)	(0.202)	(0.230)
New Model × Penalty$_{t-1}$		0.52	0.49						
		(0.339)	(0.332)						
Tight Model × Penalty$_{t-1}$					0.82**	0.81**			
					(0.318)	(0.315)			
Loose Model × Penalty$_{t-1}$								-0.70**	-0.67*
								(0.272)	(0.362)
Penalty$_{t-1}$		0.73***	0.63***		0.70***	0.62***		0.80***	0.70***
		(0.136)	(0.183)		(0.139)	(0.181)		(0.137)	(0.184)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	676	621	621	676	621	621	676	621	621
R-squared	0.037	0.062	0.095	0.038	0.061	0.095	0.033	0.058	0.093

This table reports the results for the linear model. In columns (1)-(3), I run the regression:

$$Risk_{it} = \beta_1 NewModel_{it} + [\beta_2 NewModel_{it} \times Penalty_{it-1} + \beta_3 Penalty_{it-1}] + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \varepsilon_{it}.$$

$Risk_{it}$ 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 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. $Penalty_{it-1} = 1$ if penalties are imposed on bank i at quarter $t-1$. X_{it} represents a vector of bank characteristics to control for bank size (proxied by book assets), leverage (proxied by the equity ratio) and profitability (proxied by the ratio of the net income to book 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. In columns (4)-(6), I run the regression:

$$Risk_{it} = \beta_1 TightModel_{it} + [\beta_2 TightModel_{it} \times Penalty_{it-1} + \beta_3 Penalty_{it-1}] + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \varepsilon_{it}.$$

$TightModel_{it} = 1$ if bank i reports a model revision that occurs at quarter t and implies higher capital requirements. In columns (7)-(9), I run the regression:

$$Risk_{it} = \beta_1 LooseModel_{it} + [\beta_2 LooseModel_{it} \times Penalty_{it-1} + \beta_3 Penalty_{it-1}] + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \varepsilon_{it}.$$

$LooseModel_{it} = 1$ if bank i reports a model revision that occurs at quarter t and implies higher capital requirements. The sample covers 19 banks from the U.S., Canada and Europe over the period from 2002 to 2016. Year-quarter clustered errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Risk Models and a Number of Risk Underreporting Cases.

	(1) #Underreport	(2) #Underreport	(3) #Underreport	(4) #Underreport	(5) #Underreport	(6) #Underreport
New Model	1.04***	0.65**	0.12			
	(0.203)	(0.298)	(0.307)			
Tight Model				1.05**	1.16*	0.17
				(0.438)	(0.614)	(0.462)
New Model × Penalty$_{t-1}$		0.33	1.11**			
		(0.968)	(0.507)			
Tight Model × Penalty$_{t-1}$					-0.33	1.12*
					(1.307)	(0.637)
Penalty$_{t-1}$		1.73***	1.32***		1.73***	1.41***
		(0.205)	(0.344)		(0.212)	(0.360)
Controls	No	Yes	Yes	No	Yes	Yes
Year-Quarter FE	No	No	Yes	No	No	Yes
Observations	813	621	621	813	621	621

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. In columns (1)-(3), I run the regression:

$$\#Underreport_{it} = \beta_1 NewModel_{it} + [\beta_2 NewModel_{it} \times Penalty_{it-1} + \beta_3 Penalty_{it-1}] + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \varepsilon_{it}.$$

$\#Underreport_{it}$ is a number of days at quarter t such that the actual daily loss of bank i exceeds its risk estimate for that particular day. In other words, the dependent variable represents a quarterly number of cases when the true risk is underreported. $\#Underreport_{it}$ is winsorized at 1% and 99% level. $NewModel_{it} = 1$ if bank i reports a model revision that occurs at quarter t. $Penalty_{it-1} = 1$ if penalties are imposed on bank i at quarter $t-1$. X_{it} represents a vector of bank characteristics to control for bank size (proxied by book assets), leverage (proxied by the equity ratio) and profitability (proxied by the ratio of the net income to book 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. In columns (4)-(6), I run the regression:

$$\#Underreport_{it} = \beta_1 TightModel_{it} + [\beta_2 TightModel_{it} \times Penalty_{it-1} + \beta_3 Penalty_{it-1}] + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \varepsilon_{it}.$$

$TightModel_{it} = 1$ if bank i reports a model revision that occurs at quarter t and implies higher capital requirements. The sample covers 19 banks from the U.S., Canada and Europe over the period from 2002 to 2016. Year-quarter clustered errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Risk Models and Penalties.

	(1) No Penalty	(2) No Penalty	(3) No Penalty	(4) No Penalty	(5) No Penalty	(6) No Penalty	(7) No Penalty	(8) No Penalty
New Model	-0.11**	-0.07**			-0.47***	-0.62***		
	(0.041)	(0.028)			(0.134)	(0.237)		
Tight Model			-0.13**	-0.16*			-0.76***	-0.96**
			(0.065)	(0.086)			(0.221)	(0.482)
Controls	No	No	No	Yes	No	No	No	Yes
Year-Quarter FE	No	Yes	Yes	Yes	No	Yes	No	Yes
Model	OLS	OLS	OLS	OLS	Probit	Probit	Probit	Probit
Observations	850	850	850	665	850	387	850	261
R-squared	0.011	0.449	0.450	0.376				

This table reports the results for the linear and probit models in columns (1)-(4) and columns (5)-(8), respectively. In columns (1), (2), (5) and (6), I run the regression:

$$NoPenalty_{it} = \beta NewModel_{it} + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \varepsilon_{it}.$$

$NoPenalty_{it} = 1$ if no penalties are imposed on bank i at quarter t. $NewModel_{it} = 1$ if bank i reports a model revision that occurs at quarter t. X_{it} represents a vector of bank characteristics to control for bank size (proxied by book assets), leverage (proxied by the equity ratio) and profitability (proxied by the ratio of the net income to book 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. In columns (3), (4), (7) and (8), I run the regression:

$$NoPenalty_{it} = \beta TightModel_{it} + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \varepsilon_{it}.$$

$TightModel_{it} = 1$ if bank i reports a model revision that occurs at quarter t and implies higher capital requirements. The sample covers 19 banks from the U.S., Canada and Europe over the period from 2002 to 2016. Year-quarter clustered errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Market Risk Capital Rule, Model Revisions and Model Outcomes.

	(1) New Model	(2) New Model	(3) Risk	(4) Risk	(5) #Underreport	(6) #Underreport
MRCR	-0.50**	-0.52**	-0.36***	-0.60***	0.90*	1.84***
	(0.226)	(0.230)	(0.062)	(0.070)	(0.543)	(0.571)
Controls	No	Yes	No	Yes	No	Yes
Year-Quarter FE	No	No	Yes	Yes	Yes	Yes
Bank FE	No	No	Yes	Yes	Yes	Yes
Model	Probit	Probit	OLS	OLS	ZINB	ZINB
Observations	1022	772	813	676	813	676
R-squared			0.881	0.901		

This table reports the results for the probit and linear and zero-inflated negative binomial models in columns (1)-(2), columns (3)-(4) and columns (5)-(6), respectively. I run the regression:

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

In columns (1)-(2), Y_{it} is $NewModel_{it} = 1$ if bank i reports a model revision that occurs at quarter t. In columns (3)-(4), Y_{it} is $Risk_{it}$, 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 (5)-(6), Y_{it} is $\#Underreport_{it}$, i.e., a number of days at quarter t such that the actual daily loss of bank i exceeds its risk estimate for that particular day. In other words, it represents a quarterly number of cases when the true risk is underreported. $\#Underreport_{it}$ is winsorized at 1% and 99% level. $MRCR_{it} = 1$ if bank i is based in the U.S. and is affected by the Market Risk Capital Rule enforced by Fed starting from 2013Q1. X_{it} represents a vector of bank characteristics to control for bank size (proxied by book assets), leverage (proxied by the equity ratio) and profitability (proxied by the ratio of the net income to book 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 19 banks from the U.S., Canada and Europe over the period from 2002 to 2016. Year-quarter clustered errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Optimistic Risk Models and a Future Number of Risk Underreporting Cases.

	(1) $\#\text{Underreport}_{t+1}$	(2) $\#\text{Underreport}_{t+1}$	(3) $\#\text{Underreport}_{t+1}$	(4) $\#\text{Underreport}_{t+1}$	(5) $\#\text{Underreport}_{t+1}$	(6) $\#\text{Underreport}_{t+1}$
Loose Model	0.85**	1.02***	0.26	0.49	0.26	-0.09
	(0.371)	(0.277)	(0.412)	(0.333)	(0.494)	(0.466)
Loose Model × Penalty_{t-1}			1.22***	1.15***	1.74**	1.99***
			(0.413)	(0.428)	(0.885)	(0.599)
Penalty_{t-1}			1.44***	1.33***	2.03***	1.72***
			(0.261)	(0.329)	(0.218)	(0.371)
Controls	No	No	No	No	Yes	Yes
Year-Quarter FE	No	Yes	No	Yes	No	Yes
Observations	790	790	709	709	600	600

This table reports the results for the zero-inflated negative binomial regression:

$$\#Underreport_{it+1} = \beta_1 LooseModel_{it} + [\beta_2 LooseModel_{it} \times Penalty_{it-1} + \beta_3 Penalty_{it-1}] + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \varepsilon_{it}.$$

$\#Underreport_{it+1}$ is a number of days at quarter $t+1$ such that the actual daily loss of bank i exceeds its risk estimate for that particular day. In other words, the dependent variable represents a quarterly number of cases when the true risk is underreported. $\#Underreport_{it+1}$ is winsorized at 1% and 99% level. $LooseModel_{it} = 1$ if bank i reports a model revision that occurs at quarter t and implies lower capital requirements. $Penalty_{it-1} = 1$ if penalties are imposed on bank i at quarter $t-1$. X_{it} represents a vector of bank characteristics to control for bank size (proxied by book assets), leverage (proxied by the equity ratio) and profitability (proxied by the ratio of the net income to book 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 19 banks from the U.S., Canada and Europe over the period from 2002 to 2016. Year-quarter clustered errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Optimistic Risk Models and Future Penalties.

	(1) No Penalty	(2) No Penalty$_{t+1}$	(3) No Penalty	(4) No Penalty	(5) No Penalty$_{t+1}$	(6) No Penalty$_{t+1}$
Loose Model	-0.02	0.00	-0.01	-0.01	0.00	-0.01
	(0.053)	(0.046)	(0.034)	(0.041)	(0.035)	(0.046)
Loose Model × Penalty$_{t-1}$			-0.15*	-0.18**	-0.24**	-0.25***
			(0.086)	(0.074)	(0.093)	(0.069)
Penalty$_{t-1}$			-0.77***	-0.72***	-0.67***	-0.60***
			(0.066)	(0.075)	(0.074)	(0.082)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	No	Yes	No	Yes
Observations	665	655	627	627	611	611
R-squared	0.368	0.362	0.630	0.705	0.469	0.597

This table reports the results for the linear regression:

$$NoPenalty_{it[+1]} = \beta_1 LooseModel_{it} + [\beta_2 LooseModel_{it} \times Penalty_{it-1} + \beta_3 Penalty_{it-1}] + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \varepsilon_{it}.$$

$NoPenalty_{it[+1]} = 1$ if no penalties are imposed on bank i at quarter t or $t+1$, respectively. $LooseModel_{it} = 1$ if bank i reports a model revision that occurs at quarter t and implies lower capital requirements. $Penalty_{it-1} = 1$ if penalties are imposed on bank i at quarter $t-1$. X_{it} represents a vector of bank characteristics to control for bank size (proxied by book assets), leverage (proxied by the equity ratio) and profitability (proxied by the ratio of the net income to book 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. The sample covers 19 banks from the U.S., Canada and Europe over the period from 2002 to 2016. Year-quarter clustered errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Robustness.

	(1) #Underreport	(2) #Underreport	(3) #Underreport	(4) #Underreport	(5) #Underreport	(6) #Underreport	(7) Loose Model	(8) Loose Model
New Model	0.13	0.14	0.07		0.14	0.12		
	(0.456)	(0.371)	(0.383)		(0.501)	(0.266)		
Penalty_{t-1}	0.89**	1.30***			0.97**	1.32***		
	(0.383)	(0.396)			(0.457)	(0.378)		
New Model × Penalty_{t-1}	0.90*	0.98**			0.95*	1.11***		
	(0.538)	(0.484)			(0.541)	(0.393)		
Penalty_{t-5}			0.70					
			(0.659)					
New Model × Penalty_{t-5}			0.77					
			(1.013)					
MRCR_{2005Q3}				-0.29				
				(0.620)				
$\sum_{t-4}^{t-1}$ Underreport							-0.05*	-0.00**
							(0.026)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Bank FE	Yes	No	No	Yes	Yes	No	No	No
Country FE	No	Yes	No	No	No	No	No	No
Cluster	YQ	YQ	YQ	YQ	YQ	Bank	YQ	YQ
Model	ZINB	ZINB	ZINB	ZINB	ZINB	ZINB	Probit	OLS
Period	Full Sample	Full Sample	Full Sample	Full Sample	Drop 2008Q3	Full Sample	Full Sample	Full Sample
Observations	621	621	578	676	612	621	645	645
R-squared								0.017

This table reports the results for robustness tests. In columns (1) and (2), I run the zero-inflated binomial regression:

$$\#Underreport_{it} = \beta_1 NewModel_{it} + \beta_2 NewModel_{it} \times Penalty_{it-1} + \beta_3 Penalty_{it-1} + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \alpha_i/\alpha_c + \varepsilon_{it},$$

where bank fixed effects α_i or country fixed effects α_c are included. In column (3), I run the zero-inflated binomial regression:

$$\#Underreport_{it} = \beta_1 NewModel_{it} + \beta_2 NewModel_{it} \times Penalty_{it-5} + \beta_3 Penalty_{it-5} + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \varepsilon_{it},$$

where $Penalty_{it-5} = 1$ if penalties are imposed on bank i at quarter $t-5$ ("placebo test" for penalties). In column (4), I run the zero-inflated binomial regression:

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

where $MRCR_{2005Q3} = 1$ 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 (5), I exclude the third quarter of 2008 from the sample (Lehman Brothers' collapse) and run the same zero-inflated binomial regression as in column 3 of Table 6. For the same specification, I use standard errors clustered at the bank level in column (6). In columns (7) and (8), I run the probit and linear regression:

$$LooseModel_{it} = \beta \sum_{t-4}^{t-1} Underreport_{it} + \gamma X_{it} + \theta V_{it-1} + \alpha_t + \varepsilon_{it}$$

to check the validity of IV results in Table 4. $\#Underreport_{it}$ is a number of days at quarter t such that the actual daily loss of bank i exceeds its risk estimate for that particular day. In other words, it represents a quarterly number of cases when the true risk is underreported. $\#Underreport_{it}$ is winsorized at 1% and 99% level. $\sum_{t-4}^{t-1} Underreport_{it}$ is a number of days from quarter $t-4$ to quarter $t-1$ such that the actual daily loss of bank i exceeds its risk estimate for that particular day. $NewModel_{it} = 1$ if bank i reports a model revision that occurs at quarter t. $LooseModel_{it} = 1$ if bank i reports a model revision that occurs at quarter t and implies lower capital requirements. $Penalty_{it-1} = 1$ if penalties are imposed on bank i at quarter $t-1$. X_{it} represents a vector of bank characteristics to control for bank size (proxied by book assets), leverage (proxied by the equity ratio) and profitability (proxied by the ratio of the net income to book 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 19 banks from the U.S., Canada and Europe over the period from 2002 to 2016. Standard errors are reported in parentheses; *** p<0.01, ** p<0.05, * p<0.1.