Model Risk at Central Counterparties: Is Skin in the Game a Game Changer?*

Wenqian Huang[a] and Előd Takáts[a,b,c]
[a]Bank for International Settlements
[b]Corvinus University of Budapest
[c]London School of Economics

As central counterparties (CCPs) have become systemic, their credit risk modeling has become critical for the global financial system. This paper empirically investigates CCPs' incentives to model credit risk. Our hypothesis is that the more CCPs stand to lose from mismanagement, the more conservatively they model credit risk. Accordingly, we find that the higher the skin in the game, i.e., the CCP capital dedicated to credit risk, the lower the model risk is. The results are significant and robust across different model risk proxies. Consistent with our hypothesis, the association with other forms of capital is not significant. Our findings inform the policy debate on CCP capital regulation.

JEL Codes: F34, F42, G21, G38.

1. Introduction

Central counterparties (CCPs) have become systemic players in over-the-counter (OTC) derivatives markets. A CCP stands between clearing member banks: each bank faces the CCP as its counterparty.

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This provides transparency. For instance, during the Lehman bankruptcy, CCPs unwound derivatives trades fast, while bilateral trades took years to resolve. This impressed regulators, who mandated central clearing for standardized OTC derivatives. Market forces, chiefly network externalities, amplified the regulatory drive for central clearing further. As a result, today almost four-fifths of interest rate derivatives and half of credit default swaps are cleared centrally through CCPs, up from one-third and one-tenth, respectively, in 2009 (Aramonte and Huang 2019). Furthermore, CCPs have become very concentrated, with just a handful of them dominating the major product lines (Huang and Takáts 2020). Thus, large CCPs have become systemically important.

One critical function of CCPs is to manage counterparty credit risk through margining (Faruqui, Huang, and Takáts 2018). By clearing a transaction, the CCP severs the bilateral link between banks and becomes the counterparty to each of them. While the derivative transaction has zero market value initially, its value changes with market movements. The bank that has incurred a mark-to-market loss has to post variation margin (VM) with the CCP (while the "winning" bank receives VM from the CCP). In order to manage the risk of potential non-payment of VM, the CCP requires banks to post initial margin (IM) to serve as collateral.

Model risk at CCPs is the risk of loss resulting from using insufficiently accurate IM models. For instance, Nasdaq Clearing almost failed in September 2018 due to undersizing IM. A single trader, Einar Aas, could not post VM, which far exceeded his IM. The resulting losses wiped out the CCP's capital that is dedicated to credit risk, the so-called skin in the game. Consequently, CCP members also had to bear significant losses (Bell and Holden 2018). Similar near-failure of large CCPs could disrupt the global financial system with systemic consequences.

Strikingly, given the systemic risks, managing model risk (i.e., right-sizing initial margin) is the sole responsibility of CCPs. The reason is that right-sizing IM requires expert judgment that outside parties, including regulators, do not fully possess. Right-sizing requires, among all else, correctly assessing future volatility, future correlations across various derivatives (and across other markets), the concentration of portfolios, and the time required to close failing portfolios amid severe market stress.[1] This information is not available for outsiders. Therefore, regulators rely on CCPs having the right incentives and provide only general guidelines for IM setting.

The question is, how well are CCP incentives aligned to manage model risk, i.e., to right-size initial margin? Surprisingly, there is a gap in the literature about how these incentives work in practice, despite the systemic importance of CCPs. In this paper we start to fill the gap.

We are the first to empirically investigate model risk and its relationship with CCP skin in the game (SITG), i.e., the specific element of CCP capital which is allocated to absorb credit risk. Our hypothesis is straightforward: the more the CCP stands to lose from mismanaging model risk, the more carefully it sets IM. Indeed, we find robust evidence that the higher the skin in the game, the lower the model risk is.

We collect data from quantitative disclosures of 39 CCP groups between 2015:Q3 and 2018:Q4. The data cover all internationally relevant CCPs. The 39 CCP groups have 120 separate CCP product lines. The collected data set contains information such as balance sheets, earnings, and the quality of credit risk management at the product line level.

Model risk at CCPs can be measured by back-testing IM models. IM is typically modeled as value-at-risk (VaR) of an expected loss distribution in which the loss is the non-payment of VM (see details in Section 3). The ex post performance of IM models is not directly observable through a single variable. Therefore we use five proxies of model risk from the quantitative disclosures: (1) number of margin breaches (i.e., how many times the VM exceeds the IM), (2) achieved coverage (i.e., what percentage of trades resulted in lower VM than IM), (3) difference between achieved coverage and target coverage (the latter being the targeted coverage ex ante from the model), (4) average size of margin breaches, and (5) maximum size of margin breaches.

[1] Closing concentrated derivative portfolios takes longer and can disrupt markets more, as the recent collapse of Archegos shows, for instance. Banks suffered losses over USD 10 billion from the failure of the relatively small firm, with Credit Suisse alone losing more than USD 5 billion (*Financial Times*, April 27, 2021).

We empirically test our hypothesis. We find that higher skin in the game is associated with lower model risk, consistent with our hypothesis. For instance, higher skin in the game is associated with less frequent margin breaches. The results are significant and robust across all five model risk proxies. Our results also support the auxiliary hypothesis: we do not find a similar significant relationship between model risk and CCP capital other than skin in the game (i.e., capital not exposed to credit risk).

Our results should be interpreted as being consistent with the theoretical arguments that higher SITG lowers model risk. Importantly, we do not determine causality unambiguously from the regression results themselves. Yet, our empirical evidence is consistent with the theoretical priors that higher SITG lowers model risk.

Our results are policy relevant. The results suggest that higher skin in the game incentivizes CCPs to reduce model risks. This matters for financial stability due to the systemic role CCPs play at the center of the financial system. This also matters for major clearing member banks and end users (such as asset managers), who face huge potential losses should major CCPs mismanage model risk on a large scale. In sum, the results suggest that policymakers might want to think about potential CCP capital requirements, especially as franchise value does not seem to incentivize CCPs strongly enough to manage model risk.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 briefly discusses how CCPs function. Section 4 introduces our hypotheses. Section 5 details our data set, and Section 6 discusses our proxies for model risk. Section 7 shows our analysis. Section 8 discusses robustness. The final section concludes with caveats and policy implications.

2. Literature Review

Our work contributes to two streams of literature. First, our work adds empirical evidence to the small but fast-growing literature on incentives and risks resulting from the mutualization of counterparty credit risk. Biais, Heider, and Hoerova (2012) highlight the diversification benefits from central clearing but warn of moral hazard in the case of fully insured credit risk. Biais, Heider, and Hoerova (2016) show, however, that margin requirements can prevent such moral hazard.[2] Carter and Garner (2015) and Saguato (2017) sketch the conceptual framework of CCP skin in the game. Huang (2019) develops this line of thinking towards our question by theoretically examining the link between CCP capitalization and risk-taking incentives.

Second, we complement the nascent literature that investigates CCP risk management empirically. In this area, Bignon and Vuillemey (2020) describe a high-profile central clearinghouse failure. The documentation of this rare failure is particularly relevant when thinking about potential triggers for failure. Huang (2019) focuses on the role of CCP skin in the game, including its association with the aggregate amount of collateral, i.e., initial margin (IM). We depart from Huang (2019) by focusing explicitly on the model risk of CCP credit risk management. Thus, instead of aggregate IM size, we look at the performance (i.e., the back-testing) of the margin models. The main reason is that a high aggregate amount of IM does not necessarily preclude CCP failures, because IM is not fungible across members. A member's IM can only cover risks from his own portfolio. For example, if NASDAQ Clearing had prescribed IM on trades other than those of Mr. Aas, it would not have safeguarded the CCP during the near failure.

Furthermore, analyzing model risk based on back-testing results as opposed to aggregate IM can help identification by excluding a confounding factor. Namely, a greater amount of skin in the game may induce clearing members to take more risks, because trades are safer due to the CCP's higher loss-absorbing capacity. Reflecting this higher risk-taking, the CCP might increase aggregate IM. This effect could confound estimates that aim to analyze the impact of skin in the game based on aggregate IM: it would remain unclear if higher skin in the game induces more risk-taking by members and thereby leads indirectly to higher aggregate IM, or if higher skin in the game increases the CCP's incentive to manage risks more conservatively, which raises aggregate IM. This issue is not present

[2] In addition, an entire school of papers is dedicated to investigate netting benefits (Duffie and Zhu 2011; Cont and Kokholm 2014; Duffie, Scheicher, and Vuillemey 2015). Several others examine how central clearing can alleviate OTC derivative market opacity: Acharya and Bisin (2009, 2014); Koeppl and Monnet (2010, 2013); Koeppl, Monnet, and Temzalides (2012).

in our approach based on back-testing results: model performance proxies already include the effects of increased risk-taking by members. Therefore, while we build on the argument in Huang (2019), we move from investigating aggregate initial margin to portfolio-specific initial margin and model risk.

3. Institutional Background

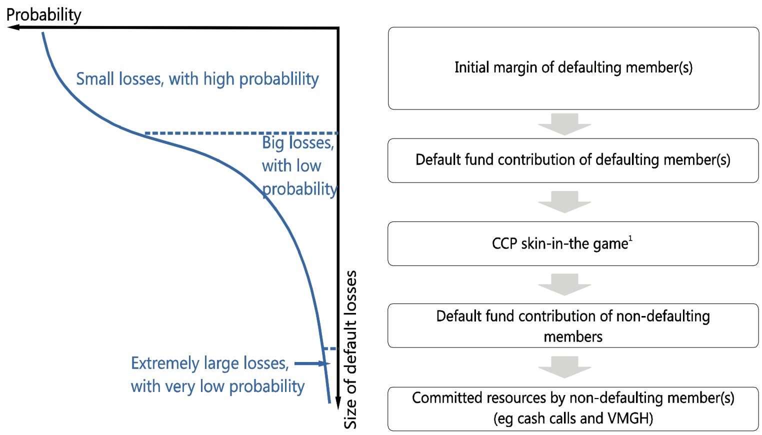
CCPs are financial market infrastructures that provide clearing services. CCPs essentially stand between two counterparties (for instance, banks) and assume the credit risk from the contracting parties. In this section, we briefly review how CCPs work. We focus on two features, which are particularly relevant for our argument. First, we outline how central clearing works—in particular, how CCPs manage counterparty credit risk through initial margin setting. Second, we discuss the special loss-absorbing setup of CCPs, called the default waterfall—in particular, the role of skin in the game.

3.1 Initial Margin Setting

As discussed in the introduction, the CCP severs the link between the contracting parties. The resulting counterparty credit risk is measures by setting trade-specific initial margin.

CCPs set IM to cover, with a high likelihood, the potential VM payments over a period long enough to close the failing positions even in stressed market conditions. Setting IM involves expert judgment. Typically, CCPs model IM as a value-at-risk measure, which is a quantile of the loss distribution (Pirrong 2011). Many CCPs target the 99th percentile, for instance. Another key determinant is the time expected to close a position: this tends to be longer in stressed market conditions and for concentrated positions. In addition, the precise IM setting involves expert judgment about correlations across different derivatives, the nature of stressed market conditions, and the behavior of concentrated exposures, among many other factors. Therefore, regulators provide only broad guidelines on IM setting.

Figure 1. Default Waterfall



Source: Faruqui, Huang, and Takáts (2018).
Note: The left-hand panel shows the default loss distribution and the right-hand panel shows the financial resources used in the default waterfall.

3.2 Default Waterfall

To withstand losses from the materialization of a counterparty credit risk event, CCPs rely on a range of resources through the so-called default waterfall (Faruqui, Huang, and Takáts 2018). In the event of a clearing member bank's default, a CCP first absorbs losses by drawing on the IM that the defaulting bank has posted (Figure 1).[3] Importantly, IM is not fungible across members: a bank's IM can only be used to cover its own losses, not other banks' losses (Wang, Capponi, and Zhang 2019).

If the defaulter's IM is insufficient, the CCP has access to the defaulting bank's contribution to the default fund. Banks need to contribute to the CCP's default fund in order to be able to trade with the CCP.

The next layer in the waterfall is the CCP capital dedicated to absorb credit risk, called "skin in the game." SITG is the layer that

[3] To ease exposition, we refer to members as banks in the following. While not all members are necessarily banks, many of the most important clearing members are indeed banks.

we focus on, because the risk of losing SITG might provide incentives for the CCP to manage risks prudently (Huang 2019). Importantly, CCPs have capital other than SITG. This other capital underwrites, for instance, operational risks. Critically from our perspective, unlike banks, CCPs do not have regulatory SITG requirements. This lack of minimum SITG requirement allows for heterogeneity in SITG across CCPs that we can utilize in our empirical investigations.[4]

Furthermore, CCPs also differ from banks in that they can continue as going concerns even after exhausting their SITG: they have other resources to absorb credit losses. First, CCPs can rely on member banks' prefunded resources, such as non-defaulting banks' default fund contributions. Second, CCPs can call on surviving banks to provide committed resources. Depending on the CCP rulebook, the CCP can call on the surviving members for more cash or can haircut the receivable VM payments owing to their winning positions (Singh 2014; Singh and Turing 2018).

Quantitatively, the overwhelming majority of CCPs' prefunded resources is IM (Figure 2, left-hand panel). Around 90 percent of all prefunded resources are IM (red area), and only around 10 percent are default fund contributions (yellow area). The SITG is dwarfed by IM and default fund contributions (indeed the blue area is so tiny that it is not visible on the figure). SITG amounts to only around USD 5 billion (center panel). In sum, CCP capital is very sparse, as compared with other collateral or with bank capital (right-hand panel).

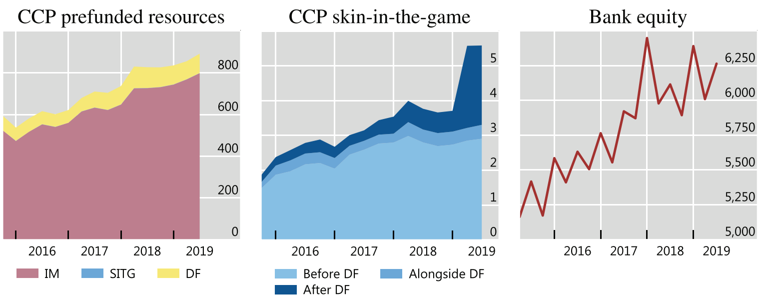
The data shows that SITG is small and could play a limited role in absorbing credit losses. Therefore, our inquiry focuses on its incentive role: that is, whether CCPs with higher SITG manage model risk more prudently.

4. Hypotheses

Exposing capital to losses encourages prudent behavior (Diamond and Rajan 2000; Hellmann, Murdock, and Stiglitz 2000). The evidence shows, for instance, that higher bank capital is associated

[4]The European Market Infrastructure Regulation (EMIR) requires that CCPs' SITG should be at least 25 percent of their operational capital. Such a requirement, however, is not a binding constraint for most CCPs.

Figure 2. CCP and Bank Resources (unit: USD bn)



Source: Clarus CCPview, Fitch.
Note: The left-hand panel shows the prefunded resources of CCPs. Skin in the game is not visible, because it is dwarfed by other prefunded resources. The central panel zooms in on the different layers of CCP SITG. The right-hand panel shows the equity of large banks. IM: initial margin; SITG: skin in the game; DF: default fund; Before DF: CCP skin in the game that will be used to absorb default losses before default fund being used; Alongside DF: CCP skin in the game that will be used together with default fund; After DF: CCP skin in the game that will be used after default fund.

with less risk-taking (Furlong and Keeley 1989): as shareholders stand to lose more if losses materialize, they are more prudent in terms of risk-taking. In the same vein, Huang (2019) provides a theoretical model and empirical evidence that a higher CCP SITG is associated with a higher aggregate IM.

In this paper, we depart from aggregate margin levels to look at margin model back-testing results. The reason is that a high aggregate amount of IM does not necessarily preclude CCP failures. Even if aggregate IM is high, the CCP remains exposed to the particular IM set for a particular trader's portfolio. In contrast to aggregate IM, the back-testing results identify whether CCPs right-sized portfolio-specific IM.

An additional advantage of using back-testing results is that it reduces a potential confounding factor arising from banks' risk-taking. Recall that according to the CCP default waterfall, default losses will be born by CCP skin in the game before depleting the members' default fund. Therefore, higher skin in the game makes banks less likely to face losses through their default fund. Lower default fund exposure, in turn, may induce banks to take more risks. This higher risk-taking, and the resulting higher risk of trades, might compel the CCP to increase aggregate IM. Thereby, the relationship between model performance and aggregate IM might also reflect banks' risk-taking. This effect can confound estimates on the relationship between SITG and CCPs' risk management, should one rely on aggregate IM.

This confounding factor, however, is not present in our approach. The reason is that our data shows the relationship between model performance and SITG after any changes in bank risk-taking and resulting CCP IM setting. The data, as the next section details, is essentially the back-testing of the risk model: for instance, it shows how often margin breaches arise. In short, we observe how the CCP risk model works after the CCP has adjusted its IM, including aggregate IM, for any changes in bank risk-taking. Hence, the above confounding effect (from higher risk-taking to higher IM) is not present when using back-testing results.

Therefore, we formulate our risk-taking hypotheses in terms of model back-testing results:

Hypothesis 1. *A higher CCP skin in the game is associated with lower model risk as measured by model back-testing results.*

A related argument is that CCP capital other than SITG should not affect credit risk management. The reason is, as mentioned in Section 3: when a credit event happens, capital other than SITG is not exposed to credit losses. Therefore, such operating capital should not provide incentives for credit risk management. That leads to our next hypothesis.

Hypothesis 2. *A higher amount of CCP operating capital is not significantly associated with model risk as measured by model back-testing results.*

We turn to our data to empirically test these two hypotheses.

5. Data

We use public CCP quantitative disclosures to test the two hypotheses. The CPMI-IOSCO Principles for Financial Market

Table 1. Summary Statistics

	Mean	Std.	Min.	Median	Max.
A. Default Waterfall					
Initial Margin (IM) ($bn)	9	19	0.0002	3	138.1
Skin in the Game (SITG) ($bn)	0.039	0.0595	0.00001	0.0164	0.272
Default Fund (DF) ($bn)	1.3	2.2	0.0002	0.3	15
B. Financial Information					
Return on Equity (ROE)	20%	27%	–29%	13%	169%
Profit ($m)	117.1	309.2	–14.46	51.9	4,063.4
Equity ($bn)	1.4	4.6	0.02	0.3	26
Other Equity ($bn)	1.4	4.6	0.01	0.2	25.8
Assets ($bn)	71.7	113.6	0.08	21.7	470.3

Source: CCP quantitative disclosures, Clarus CCPview, and authors' calculations.
Note: This table summarizes the financial variables. The summary statistics are taken across CCPs and quarters. The variables are divided into two groups: panel A reports the statistics for variables in CCP default waterfall. Panel B shows the balance sheet variables for CCPs. Note that Equity is the sum of SITG and Other Equity.

Infrastructures (PFMI) (CPMI-IOSCO 2012, 2015) require CCPs to publish them at a quarterly frequency. We use disclosure data collected by Clarus FT's CCPView.

Our data set is in panel form. The time series ranges from 2015:Q3 to 2018:Q4 at a quarterly frequency, i.e., 14 quarters. The data set spans 120 CCP entities or product lines (which are grouped into 39 CCP groups). Therefore, our data allow us to control for specific product lines. The full panel has at most 1,680 observations. We divide our data description into two categories (Table 1): (i) default waterfall (panel A) and (ii) financial information (panel B).[5]

Default waterfall data reveal that IM and default fund account for the majority of the default waterfall in our sample (Table 1, panel A). The average of IM at a given CCP entity is around USD 9 billion and that of the default fund is around USD 1.3 billion. Compared with IM and DF, SITG is small, with an average value of USD

[5]We discuss the third broad element, the model back-testing results, in the next section among the proxies for model risk management.

Table 2. Credit Risk Management

	Mean	Std.	Min.	Median	Max.
Number of Breaches	12.6	37.7	0	1	394
Number of Trades in Margin Model	148,492	1,038,522	239	13,154	14,148,135
Target Coverage (%)	99.2	0.3	99	99	99.9
Achieved Coverage (%)	99.9	0.03	96.17	100	100
Difference between Achieved and Target (%)	0.7	0.6	–8.96	0.9	1
Maximum Breach Size ($m)	61.6	130.1	0.01	7.2	1,228
Average Breach Size ($m)	4.7	9.1	0.01	1.4	67.1

Source: CCP quantitative disclosures, Clarus CCPview, and authors' calculations.
Note: This table summarizes the credit risk variables. The statistics are taken across CCPs and quarters.

40 million. These data are consistent with the CCP data discussed in the Institutional Background section. In addition, all three variables are heavily skewed to the right with median values far below the averages. Furthermore, all variables show high variation, with a standard deviation almost twice as large as the average. Importantly, the average CCP equity (i.e., the sum of skin in the game and other operational capital) is around USD 1.4 billion. Therefore, most CCP capital is operational capital and is not exposed to credit losses (Table 1, panel B).[6]

6. Proxies for Model Risk Management

CCP quantitative disclosures contain information on back-testing of CCPs' IM models (Table 2). The back-testing results show how carefully CCPs set individual, portfolio-specific IM to manage counterparty credit risk. Therefore, back-testing data allows us to test our hypotheses.

The back-testing results from quantitative disclosures inform us about portfolio-specific IM model performance through margin

[6]The financial information reveals high CCP profits. Return on equity (RoE) is 20 percent on average across entities in the sample period, with the maximum reaching 169 percent. Yet, in absolute value profits do not appear that high, as they average only around USD 117 million.

breaches. Recall that CCPs calculate IM as a value-at-risk measure and aim to achieve a quantile of an expected loss distribution. The targeted quantile is called the target coverage. The PFMI requires that CCPs should target at least 99 percent coverage (CPMI-IOSCO 2012). The 99 percent percentile target coverage implies that 99 percent of VM payments are aimed to be less than the required IM. As the target coverage is never 100 percent, some actual VM payments are expected to exceed the IM. In our example of 99 percent target coverage, 1 percent of VM is expected to exceed IM. These events are called margin breaches.

The back-testing results from quantitative disclosures provide information on margin breaches from five different perspectives:

- the number of breaches,
- achieved coverage,
- difference between achieved and target coverage,
- average size of margin breaches,
- maximum size of margin breaches.

First, the number of margin breaches is a straightforward metric of model risk. Controlling for CCP size, fewer margin breaches imply less model risk.

Second, achieved coverage scales margin breaches by the number of trades, as the following formula shows:

$$\begin{aligned}&\textit{Achieved coverage}\\&\quad = 1 - (\textit{Number of margin breaches})/(\textit{Number of trades}).\end{aligned}$$

Achieved coverage shows the proportion of trades that did not result in a margin breach. Its advantage over the numerical breach number is that it scales the number of breaches to the number of trades.

Third, the difference between achieved and target coverage shows how effective the CCP is at in reaching its own risk model target. Not all product lines and not all CCPs target the same coverage level. While the PFMI requires at least 99 percent coverage, most CCPs aim for a higher level. The difference proxy controls for these differences in targets.

Fourth, the average size of margin breaches informs about the potential losses that margin breaches could have affected. As an example, more frequent but smaller margin breaches might constitute less model risk than rarer but larger breaches.

Fifth and finally, the maximum size of margin breaches focuses our attention to the largest, and potentially most threatening, margin breach. As CCPs have a number of credit risk-absorbing layers, small breaches do not constitute a major risk—in contrast to large ones. The size difference is not trivial: the maximum breach in our sample reaches USD 1.3 billion, while the average margin breach hovers around USD 5 million.

All in all, these five proxies provide five different angles to consider model risk. None of them is perfect in isolation. However, taken together, especially when they point to a consistent picture, they provide useful information. Therefore, in our empirical analysis we consider all five proxies and look for consistent results across all five of them.

One advantage of the quantitative disclosure data is the large number of margin breach observations. Margin breaches might be rare relative to the number of trades, but the huge number of trades generates a steady stream of breaches for our empirical analysis. Therefore, we are able to deploy econometric tools to analyze all five above.

Importantly, the CCP quantitative disclosure data report the margin breaches for the past 12 months. Hence, the raw reported variables are autocorrelated. To address the autocorrelation, we use only the annual data of the size measures, i.e., the average size and the maximum size of margin breaches. For the frequency measures, it is possible to calculate the quarterly increment. We can calculate the quarterly number of margin breaches, which in turn allows us to calculate the achieved coverage and the difference between the achieved and the target coverage on a quarterly basis (see Appendix B for calculation details).

7. Regression Analysis

We test our hypotheses in a panel regression framework. Formally, we estimate

$$\begin{aligned} ModelRisk_{i,t} = \beta_0 + \beta_1 SITG_{i,t} + \beta_2 OtherEquity_{i,t} + \beta_3 Profit_{i,t} \\ + \gamma IMs_{i,t} + \delta Assets_{i,t} + \alpha_t + \iota_i + \varepsilon_{i,t}. \end{aligned} \tag{1}$$

Table 3. Regression Results with Skin in the Game

	Number of Breaches	Achieved Coverage	Diff. Coverage	Avg. Breach	Max. Breach
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
SITG	**–0.24****	**0.07***	**0.09****	**–0.04***	**–1.51***
	(–2.08)	**(1.88)**	**(2.28)**	**(–1.82)**	**(–1.90)**
IM	–0.16	–0.04	0.01	–0.04	–1.91**
	(–0.68)	(–1.07)	(0.17)	(–0.65)	(–2.53)
Asset	–0.01	0.01	0.01	0.00	–0.06
	(–0.20)	(1.59)	(1.53)	(0.36)	(–1.09)
Constant	45.65***	9,990.11***	140.73***	3.80***	108.13***
	(8.32)	(6,134.00)	(65.80)	(3.68)	(3.35)
R-squared	0.008	0.003	0.000	0.012	0.095
N	557	557	557	168	168

Note: This table presents the regression results with skin in the game. The panel regressions incorporate the time and CCP entity fixed effects. t-statistics are in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

Following the usual panel notation, index i stands for CCP entities (product lines) and t stands for quarters throughout.

Our dependent variable $ModelRisk_{i,t}$ denotes one of the five proxies defined in the previous section.

Our main explanatory variables stem from the two hypotheses we test: skin in the game and other equity. In addition, we control for profit, aggregate IM, and CCP assets in each quarter. Finally, we apply both entity and time fixed effects to capture unobserved CCP business line heterogeneity (such as ownership structure, governance, and product-specific features) and time-varying market conditions, respectively. Appendix A provides a summary of the variables used in regressions.

Our first set of regressions focuses on SITG (Table 3). We examine all five model risk proxies (see Models 1–5). Consistent with Hypothesis 1, we find that a higher SITG is associated with fewer breaches (Model 1), higher achieved coverage (Model 2), relatively higher difference between achieved and targeted coverage (Model 3), lower average (Model 4), and lower maximum size of margin breaches (Model 5). In short, all five proxies point consistently in the same direction: higher SITG is associated with lower model risk proxies, as Hypothesis 1 would suggest.[7]

Notice that our sample size drops for the average and maximum size proxies (Models 4 and 5). The reason is that here we have to use annual frequency data to avoid overlapping windows. Recall that CCPs are required to report model back-testing data over a 12-month period and it is only possible to uncover quarterly increments for number of breaches, achieved coverage, and the difference between average and target coverage.

Our second set of regressions extends our analysis to include other capital and profits (Table 4). Again, we consider all five proxies of model risk (Models 1–5).

The regressions confirm our first set of results about SITG: higher SITG continues to associate significantly with lower model risk across all five proxies even after controlling for other capital.

The regression results on other capital show a mixed picture—broadly consistent with our Hypothesis 2. The coefficient estimates on number of breaches (Model 1) and average breach size (Model 4) are insignificant. Achieved coverage (Model 2) and difference between achieved and targeted coverage (Model 3) show a negative relationship: higher other capital is associated with higher model risk across these two proxies. In contrast, maximum breach size (Model 5) suggests the exact opposite: higher other capital is associated with lower model risk. In short, no consistent picture emerges for capital other than SITG.

In sum, our results are strongly consistent with Hypothesis 1: a CCP with a higher SITG has smaller model risk for credit risk management, and hence more prudent risk management. The results also broadly support Hypothesis 2: there is no consistent, statistically significant relationship between other capital and CCP risk management. In the next section we examine the robustness of these results.

[7]One should be cautious about interpreting the regression results as direct causality. It is possible that CCPs with lower model risk are more willing to expose more capital to default losses, in order to signal their confidence in the IM models.

Table 4. Regression Results with SITG, Other Capital, and Profit

	Number of Breaches	Achieved Coverage	Diff. Coverage	Avg. Breach	Max. Breach
	(1)	(2)	(3)	(4)	(5)
SITG	**–0.24****	**0.07***	**0.09****	**–0.04***	**–1.51***
	(–2.07)	**(1.96)**	**(2.35)**	**(–1.81)**	**(–1.89)**
Other Capital	**1.16**	**–1.09*****	**–1.38*****	**–0.16**	**–1.91***
	(0.60)	**(–3.34)**	**(–3.54)**	**(–1.25)**	**(–1.79)**
Profit	0.00	–0.00	–0.00	–0.00	0.00
	(0.15)	(–1.45)	(–1.32)	(–0.23)	(0.09)
IM	–0.15	–0.05	0.01	–0.04	–1.92**
	(–0.66)	(–1.09)	(0.10)	(–0.66)	(–2.53)
Asset	–0.01	0.01*	0.01*	0.00	–0.06
	(–0.22)	(1.83)	(1.78)	(0.38)	(–1.06)
Constant	43.92***	9,992.18***	143.72***	4.03***	110.91***
	(6.29)	(5,119.94)	(63.79)	(3.63)	(3.32)
R-squared	0.008	0.010	0.000	0.012	0.095
N	557	557	557	168	168

Note: This table presents the regression results with skin in the game, other capital, and profit. The panel regressions incorporate the time and CCP entity fixed effects. t-statistics are in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

8. Robustness

We examine the robustness of our results in Table 3 and Table 4 along two directions. First, we investigate intermediate steps when extending the separate analysis of SITG to the joint triple investigation of SITG, other capital, and profits. In our main analysis, we introduced other capital and profits at once. Here, we add them separately. When we add only other capital to SITG in (Table C.1, in Appendix C) the results remain robust: higher SITG remains consistently associated with lower model risk, while no similar consistent association emerges for other capital. When we add only profits to SITG in (Table C.2, in Appendix C), we also observe results very similar to those in the main analysis: higher SITG remains consistently associated with lower model risk, while the association with profits remain consistently insignificant.

Second, we remove the controls for aggregate IM and CCP assets from our main specifications. We replicate the results of Table 3 without IM and asset controls (Table C.3, in Appendix C). Our main results remain robust: higher SITG continues to significantly associate with less model risk. Additionally, we replicate Table 4 without controls (Table C.4, in Appendix C). Again our results remain robust. Higher SITG continues to significantly associate with less model risk. The relationship with other capital remains broadly insignificant.

9. Conclusion

The incentives for CCPs to manage model risk is critical for financial stability. CCPs have become systemic over the last decade. Yet, CCPs can and do fail, if they mismanage model risk—and the failure of large CCPs could shake the global financial system. However, regulators only provide broad guidance and essentially rely on CCPs to manage model risk. Therefore, it is critical that CCPs have the right incentives to manage model risk well.

We investigate how well CCP incentives are aligned to manage model risk, i.e., to right-size portfolio-specific initial margin. To the best of our knowledge, we are the first to investigate this question empirically. We examine portfolio-specific initial margin setting, while the literature has—so far—investigated only aggregate IM setting.

Our hypotheses on how these incentives might work build on the literature that shows that the more a CCP stands to lose from mismanaging model risk, the more carefully it sets IM (Carter and Garner 2015; Saguato 2017; Huang 2019). First, and most important, higher SITG is expected to associate with lower model risk. Second, other capital, as it is not affected by credit losses, is not expected to associate with model risk. We find robust evidence that supports our first hypothesis.

The results are policy relevant, particularly for central banks and financial regulators concerned about financial stability. Unlike for banks' minimum capital requirement, there is no broadly accepted minimum requirement for CCPs' SITG. Our results suggest that such SITG requirements might strengthen CCP incentives to reduce model risk—and thereby strengthen financial stability. Importantly, this effect seems to work only through SITG and not other capital. Therefore, our findings serve as a useful starting point for thinking about SITG requirements.

One important caveat is that our results should not be read as a policy prescription. We do not undertake a detailed cost-benefit analysis of SITG capital regulation. The results suggest that higher skin in the game is associated with lower model risk. However, this is only one part of the relevant policy trade-off. On the other side, there might be other consequences that need to be evaluated carefully. For instance, higher SITG might lead to higher IM, which could increase the cost of clearing derivative trades centrally. The resulting higher trading costs could prevent hedging trades for real economic actors—thereby increasing financial risks in the real economy. Future research should explore such trade-offs further before arriving at firm policy recommendations.

Appendix A. Variable Summary

Table A.1. Variables Used in Regressions

Variable	Definition
SITG	Dollar amount of CCP skin in the game
IM	Dollar amount of initial margin
Asset	Dollar amount of total asset
Number of Breaches	The number of margin breaches which occurs when the required VM payment exceeds the required IM
Achieved Coverage	The percentage of the trades that do not have margin breaches in the total number of trades
Diff. Coverage	The difference between the achieved coverage and the target coverage set by CCPs ex ante
Avg. Breach	The average size of margin breaches
Max. Breach	The maximum size of margin breaches

Note: This table summarizes the variables used in regressions in the paper.

Appendix B. Quarterly Increment in the Number of Margin Breaches

In the quantitative disclosure data, CCPs report the number of margin breaches for the past 12 months. Let X_t denote the number of breaches reported at time t, where $t = 0, 1, 2, \hat{a}e|T$. Let Y_t denote the quarterly increment at time t where $t = -3, -2, \hat{a}e|T$. Thus,

$$X_0 = Y_{-3} + Y_{-2} + Y_{-1} + Y_0.$$

To back out the quarterly increment for all periods, we assume $Y_{-3} = Y_{-2} = Y_{-1} = Y_0$, which equals $X_0/4$. With that, we have

$$Y_t = X_t - X_{t-1} + Y_{t-4}. \tag{B.1}$$

Appendix C. Appendix Robustness Tables

Table C.1. Regression Results with SITG and Other Equity

	Number of Breaches	**Achieved Coverage**	**Diff. Coverage**	**Avg. Breach**	**Max. Breach**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
SITG	–0.24**	0.07*	0.09**	–0.04*	–1.51*
	(–2.07)	(1.89)	(2.29)	(–1.81)	(–1.89)
Other Capital	1.19	–2.37***	–2.58***	–0.16	–1.87
	(0.66)	(–3.99)	(–5.51)	(–1.15)	(–1.47)
IM	–0.15	–0.05	0.00	–0.04	–1.92**
	(–0.66)	(–1.12)	(0.04)	(–0.66)	(–2.54)
Asset	–0.01	0.01*	0.01*	0.00	–0.06
	(–0.22)	(1.77)	(1.73)	(0.38)	(–1.06)
Constant	43.89***	9,993.63***	144.55***	4.04***	110.88***
	(6.33)	(4,836.83)	(61.52)	(3.64)	(3.33)
R-squared	0.008	0.005	0.000	0.012	0.095
N	557	557	557	168	168

Note: t-statistics are in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

Table C.2. Regression Results with SITG and Profit

	Number of Breaches	Achieved Coverage	Diff. Coverage	Avg. Breach	Max. Breach
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
SITG	–0.24**	0.07*	0.10**	–0.04*	–1.51*
	(–2.08)	(1.96)	(2.35)	(–1.81)	(–1.89)
Profit	0.00	–0.01	–0.00	–0.00	–0.00
	(0.89)	(–1.53)	(–1.45)	(–0.71)	(–0.46)
IM	–0.16	–0.04	0.01	–0.04	–1.91**
	(–0.68)	(–1.07)	(0.16)	(–0.65)	(–2.53)
Asset	–0.01	0.01*	0.01*	0.00	–0.06
	(–0.20)	(1.76)	(1.69)	(0.36)	(–1.08)
Constant	45.60***	9,990.61***	141.21***	3.82***	108.30***
	(8.27)	(6,099.26)	(65.07)	(3.68)	(3.34)
R-squared	0.008	0.010	0.000	0.012	0.095
N	557	557	557	168	168

Note: t-statistics are in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

Table C.3. Regression Results with SITG (without controls)

	Number of Breaches	Achieved Coverage	Diff. Coverage	Avg. Breach	Max. Breach
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
SITG	–0.21**	0.13**	0.15***	–0.04**	–1.12**
	(–2.17)	(2.34)	(2.67)	(–2.20)	(–2.24)
Constant	41.59***	9,988.44***	135.54***	3.28***	68.77***
	(11.08)	(4,526.88)	(61.15)	(5.22)	(3.65)
R-squared	0.006	0.010	0.000	0.010	0.045
N	603	603	603	186	186

Note: t-statistics are in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

Table C.4. Regression Results with SITG, Other Equity, and Profit (without controls)

	Number of Breaches	Achieved Coverage	Diff. Coverage	Avg. Breach	Max. Breach
	(1)	(2)	(3)	(4)	(5)
SITG	–0.21**	0.13**	0.15***	–0.04**	–1.12**
	(–2.16)	(2.39)	(2.72)	(–2.19)	(–2.23)
Other Capital	1.32	–0.82	–1.32**	–0.12	–1.28
	(0.65)	(–1.59)	(–2.63)	(–0.93)	(–1.27)
Profit	–0.00	–0.00	–0.00	–0.00	–0.00
	(–0.05)	(–1.50)	(–1.33)	(–0.19)	(–0.18)
Constant	39.78***	9,990.97***	137.81***	3.45***	70.52***
	(7.60)	(3,738.72)	(54.60)	(5.01)	(3.63)
R-squared	0.006	0.016	0.000	0.010	0.045
N	603	603	603	186	186

Note: t-statistics are in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

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