Systemic Stress Testing under Central and Non-Central Clearing*

Barbara Casu[†], Elena Kalotychou[‡], Petros Katsoulis[§]

October 2020

Abstract

The new OTC derivatives regulatory framework expanded the role of central clearing and established the collateralization of non-centrally cleared contracts. We assess the effects of this reform on bank-level and systemic risks. By developing a stress-testing network model of the largest market participants we compare defaults due to counterparty and liquidity risks and systemic losses in the regime with and without non-central clearing. We find risk-shifting effects from counterparty to liquidity risk and reduction of systemic risk at the expense of increased contagion from central counterparties. The expansion of central clearing further reduces systemic risk, in accordance with regulatory predictions.

Keywords: Central counterparty, margin, stress testing, financial stability

JEL classification: C61, G01, G20, G21, G28

*We would like to thank participants at the Bank of England and Central Bank of Ireland internal seminars, the IBEFA sessions in the WEAI virtual 2020 annual conference, the British Accounting and Finance Association 2018 conference, the Financial Engineering and Banking Society 2018 conference and the European Financial Management Association 2018 conference for their useful comments.

†Barbara Casu is Professor of Banking and Finance at Cass Business School, City, University of London. Email: b.casu@city.ac.uk

‡Elena Kalotychou is Assistant Professor in Finance at Cyprus University of Technology. Email: eleni.kalotychou@cut.ac.cy

§Petros Katsoulis is PhD Candidate in Finance at Cass Business School, City, University of London (Corresponding Author). Email: petros.katsoulis.1@cass.city.ac.uk

1 Introduction

The lack of market transparency associated with over-the-counter (OTC) derivatives contracts during the financial crisis prompted the response of the regulators who initiated a reform programme aimed at containing counterparty and systemic risks in the financial system. The G20 leaders mandated the clearing of all standardized OTC derivatives contracts through central counterparties by the end of 2012 and the introduction of higher capital requirements for bilateral contracts cleared between counterparties (G20, 2009).[1] The clearing mandates were later strengthened by collateral requirements for bilateral trades (G20, 2011). Non-central clearing, formally introduced in 2016, imposes the mandatory collateralization of bilaterally traded OTC derivatives through the exchange of margins between counterparties.[2]

The OTC derivatives market reforms have two main goals. First, promoting central clearing by creating cost incentives (lower capital and collateral requirements compared to bilateral clearing) with a view to reduce systemic risk by allowing for greater netting of exposures through CCPs. Second, curbing counterparty risk through the establishment of a rigorous and transparent margining mechanism extended to embrace bilateral trades.

As the reforms have reshaped the OTC derivatives markets, understanding their implications is crucial for numerous reasons. First, as a result of the new clearing mandate CCPs have become the dominant counterparties in several derivatives markets. The fraction of centrally cleared CDS contracts increased from 10% to 55% in terms of gross notional from 2010 to 2018 according to Bank for International Settlements (BIS) data. In addition, central clearing is predominant in the OTC interest rate derivatives market with CCPs managing 75% of total positions globally as of December 2018 (BIS, 2019). While other derivative

[1] Central clearing involves trading contracts through a clearing house, aka central counterparty (CCP), which interposes itself between counterparties by becoming the buyer to every seller and the seller to every buyer. As the bilateral trade ceases to exist the CCP concentrates counterparty risk in exchange for collateral in the form of initial margin (IM) and contributions to a default fund (DF) which is used to mutualize losses across clearing members (CMs). CCP protection is further established by daily marking-to-market all positions and transferring cash-flows from losing counterparties to winning ones upon adverse price movements through the collection of variation margin (VM).

[2] The G20 mandate was enforced via the Dodd-Frank Act in the US and the European Market Infrastructure Regulation (EMIR) in the European Union.

asset classes have not seen similar expansion, central clearing is gaining ground in them as well (BIS, 2017). Second, the new clearing regulations may result in redistributing rather than reducing risk in the system. The clearing process that involves rigid margining and marking-to-market has been criticized for being procyclical, creating sharp increases in liquidity demand during periods of shortage in liquidity supply and in this way exacerbating systemic risk (Pirrong, 2014). This was evidenced in March 2020 when market turbulence led to large margin calls and a rush for liquidity, negatively affecting traditionally safe markets such as US government bonds and exacerbating redemptions from money market funds (Bank of England, 2020).

In this paper, we assess the impact of the introduction of the mandatory collateralization of bilaterally traded derivatives, which we refer to as non-central clearing. While non-central clearing of OTC derivatives is expected to reduce counterparty risk and spillover effects, it may do so at the expense of the liquidity of market participants (BCBS-IOSCO, 2015). Motivated by the documented concerns that liquidity risk may be a much more significant source of stress than counterparty risk in cleared OTC derivatives markets (Cont, 2017), our work focuses on disentangling and quantifying the effects of non-central clearing on these two forms of risk for both the largest dealer banks as well as the CCP. Acknowledging new forms of stress that can crystallize in the new regulatory environment is key for preempting potential adverse effects of the new mandates.

The concept of risk transformation, first coined by Cont (2017), posits that clearing does not eliminate counterparty risk but transforms it into liquidity risk because exposures are mitigated via the exchange of initial and variation margins (IM and VM) in the form of liquid assets. Hence, the introduction of non-central clearing may create a risk-shifting effect, reducing potential losses from exposures and the risk of insolvency, but increasing disproportionately the liquidity encumberment of market participants, rendering them more vulnerable to liquidity shocks that can occur in times of market stress. We test the risk transformation hypothesis by using the introduction of non-central clearing as the vehicle for providing counterparty risk protection through the mandatory bilateral exchange of liquid assets.

In addition, improved understanding of the channels through which losses arise in cleared OTC derivatives markets allows for a more accurate appraisal of the risks and the role of the CCP as a potential source of contagion for its members. The increased liquidity stress associated with the collateralization of bilateral exposures, which increases the probability of CM defaults during market stress periods, may result in higher losses for the CCP and the surviving CMs due to the CCP's loss mutualization mechanisms (Pirrong (2014), Domanski et al. (2015), King et al. (2020)). Thus, considering the consequences of non-central clearing and the CCP loss mutualization processes in isolation underestimates the risks imposed to the financial system. In our paper we thus consider the CCP-bank nexus which has come to the forefront of regulatory attention in the recent COVID-19 crisis, in order to assess the systemic implications of the CCP's actions during a crisis (Huang and Takáts, 2020).

We extend the literature which has mainly focused on central clearing, by evaluating the effects of non-central clearing of OTC derivatives on counterparty, liquidity and systemic risks and their interaction. Our contribution is twofold. First, on the methodological front we contribute to existing empirical work on CCP modelling and, in particular, the modelling of the loss allocation mechanisms of the clearing house. Building on the methodology of Heath et al. (2016) we construct a network model of the largest dealer banks in the OTC derivatives markets and a fictitious CCP taking into account the various mechanisms through which the CCP allocates uncollateralized losses to the CMs. The model dynamics unfold in two rounds. In the first round, an exogenous market shock creates VM exchanges in the system and potential defaults due to a) liquidity risk arising from insufficient liquid resources to meet VM obligations, and b) counterparty risk attributed to large equity losses following missed VM gains from defaulted counterparties. The second round captures the way the CCP mutualizes the first-round losses due to missed VM gains across the surviving participants through further default fund contributions (over and above those originally collected) and haircuts on their VM gains. This process can pose both liquidity and counterparty risks to CMs. To our knowledge, this paper is the first to accurately model the CCP's loss mutualization mechanisms to reflect the new regulatory framework.

Second, we contribute to three strands of empirical literature on derivatives clearing. On counterparty risk, Duffie and Zhu (2011) develop a theoretical model and argue that central clearing may not always reduce counterparty risk as fragmenting central clearing services by assigning separate CCPs to each derivative asset class increases exposures. However, Loon and Zhong (2014) find empirically that the introduction of central clearing in the CDS market reduces counterparty risk. Our analysis complements these papers by assessing whether non-central clearing further reduces counterparty risk in the OTC derivatives markets. On liquidity risk, Duffie et al. (2015) show that the introduction of non-central clearing greatly increases the demand for collateral due to the limited netting benefits of bilateral trading, while the expansion of central clearing reduces it due to multilateral netting. We add to this line of research by analyzing the implications of the increased collateral demand due to the introduction of non-central clearing for financial stability. On systemic risk, Heath et al. (2016) examine the effect of increased central clearing on the topology and stability of the financial network and find that CCPs act as a source of stability in the system even in the presence of large market shocks. Paddrik et al. (2020) develop a network model of the cleared CDS market and calibrate it to trade repository data to assess contagion effects under a stress scenario. They document significant losses and defaults of market participants, even though the CCP avoids default by using its pre-funded resources. On this front, our paper assesses whether the CCP's propensity for contagion is affected following the introduction of non-central clearing by considering a range of stress scenarios which could potentially exhaust the CCP's pre-funded resources, and quantifying the amount of stress imposed on its members.[3]

In order to test our hypothesis on the effectiveness of non-central clearing, we calibrate our model using annual report data on the positions of the largest participating banks in the global OTC derivatives markets and compare the systemic losses before and after the

[3]The theoretical branch of the literature concerns the optimal central counterparty design. Biais et al. (2012) examine the implications of full vs. partial protection offered by CCPs in the presence of aggregate risk. Acharya and Bisin (2014) consider the counterparty risk externality generated by the opaqueness of the OTC markets and the CCP's ability to eliminate it. Glasserman et al. (2016) argue for the need for CMs to disclose information about their positions across multiple CCPs in order for the latter to impose accurate margins. Amini et al. (2015) propose a CCP design based on fees and default fund policies that reduces systemic risk and improves aggregate surplus. Menkveld (2016) shows that a certain degree of crowding in trades is socially optimal because it increases overall investment.

introduction of non-central clearing. We measure systemic risk as the total equity losses that occur in the system due to OTC derivatives trading during stress conditions.[4] Importantly, these losses include both first-round (market shock) and second-round (feedback effect) losses, so our model belongs in the class of macroprudential stress testing models which have been developed following the financial crisis to capture the interdependencies between financial institutions which propagated shocks during the crisis. The model allows us to assess whether the feedback effect between the banks and the CCP is amplified with the introduction of non-central clearing during times of stress.

Our main finding is that the introduction of non-central clearing substantially reduces counterparty and systemic risks under all market conditions. However, the reduction of counterparty and systemic risks comes at the expense of higher liquidity risk which becomes substantial during extreme market stress due to large VM obligations. Non-central clearing severely impairs the CMs' ability to pay those obligations in periods of stress due to higher liquidity encumberment, which triggers a significantly higher number of liquidity-driven defaults, although the protection offered by non-central clearing reduces the resulting losses in bilateral trading. As a result of the higher number of defaults, the CCP suffers bigger losses and in turn becomes a significant source of contagion in extremely adverse market conditions, distributing higher losses to the surviving members in the second round. Nonetheless, we find that the reduction of losses due to the collateral in bilateral trades from non-central clearing (first round) more than offsets the increase of losses due to the greater fragility of the CCP (second round), which results in a reduction of overall systemic losses under non-central clearing.

Second, our results provide empirical support for the risk transformation argument. We show through simulations that in extreme market conditions the number of liquidity-triggered defaults increases by 60 percent whereas the counterparty-triggered defaults decrease by 50 percent. Hence, the introduction of non-central clearing creates a significant risk-shifting

[4] In our context, systemic risk propagates among banks through bilateral transactions similarly to Rochet and Tirole (1996) although there exist several other channels of contagion including fire sales (Acharya and Yorulmazer, 2008), liquidity spirals (Brunnermeier and Pedersen, 2009), herding behavior (Acharya (2009), Farhi and Tirole (2012)) and runs (Pedersen (2009), Diamond and Dybvig (1983)). Models introduced to measure individual contributions to systemic risk in terms of market equity losses include SES (Acharya et al., 2017) and CoVaR (Adrian and Brunnermeier, 2016).

effect via the transformation of counterparty to liquidity risk. In addition, we find that liquidity risk is a much more severe source of stress than counterparty risk in cleared markets as it accounts for the vast majority of defaults.

Third, we test the expectation of regulatory authorities that the requirement of non-central clearing may promote financial stability by incentivizing market participants to switch to central clearing due to lower collateral costs (BCBS-IOSCO, 2015). By simulating various proportions of central clearing in the market, we find evidence in favor of the expansion of central clearing because increased multilateral netting reduces exposures and first-round losses following market shocks. The large reduction of first-round losses reduces overall systemic risk even though the second-round losses increase as the CCP becomes more dominant and its propensity for contagion increases. Furthermore, since the expansion of central clearing reduces bilateral trading, the effects of non-central clearing are found to be insignificant when the CCP is the counterparty to most transactions. Overall, our findings provide evidence to suggest that non-central clearing is most effective at reducing counterparty and systemic risks when central clearing is limited.

Against the backdrop of major regulatory overhauls whose impact is expected to be economically significant given the size of the OTC derivatives markets, our results have important policy implications. First, the introduction of non-central clearing appears beneficial for financial stability but at the cost of higher liquidity risk and related defaults during extreme market stress, which has adverse consequences for the stability of the CCP and the surviving market participants. Second, to the extent that non-central clearing prompts market participants to migrate their bilateral positions to centrally-cleared ones, the resulting expansion of the CCP can reduce systemic risk but generates an impetus for reviewing the collateral requirements and loss allocation mechanisms in order to contain its role as a source of contagion in extreme stress (Domanski et al., 2015).

The rest of the paper is organized as follows. Section 2 provides an overview of the key regulations regarding the clearing of OTC derivatives, section 3 describes the model, section 4 presents the data used in our study and section 5 presents the empirical results. Section 6 discusses the results of sensitivity analysis and finally section 7 concludes.

2 Clearing regulations

In this section we describe the main tools at the CCPs' disposal to manage their risk as well as their counterparts in non-centrally cleared transactions that we use in our model to derive our results. The CCP collects IM as collateral at contract initiation from both counterparties which must cover at least 99% of exposures movements over an appropriate time horizon under normal market conditions (CPSS-IOSCO, 2012). In bilateral transactions not cleared through a CCP, the exchange of IM between major dealers was made mandatory in September 2016 with the introduction of non-central clearing (BIS, 2015). The assumed holding period in case of default for these positions is ten days compared to five assumed for centrally cleared positions, highlighting their increased liquidity risk and hence increased collateral requirements (BCBS-IOSCO, 2015).

Since the positions are marked-to-market daily, the maximum exposure the CCP has at any point in time is due to the daily price variation which the IM covers. Marking-to-market is achieved by the CCP by collecting at the end of each day VM from the losing counterparties and transferring it to the winning counterparties. VM represents the change in value since the last marking-to-market so that at the end of each day the value of the centrally cleared contract is zero if the VM is transferred successfully (no exposure). This prohibits large exposures from accumulating during the life of the contract, thus reducing counterparty risk. In non-centrally cleared trades, the exchange of VM was made mandatory for all market participants in March 2017, although it also existed in various forms before the crisis (Gregory (2014), ISDA (2014b)). It is important to note that in centrally cleared trades VM must typically be paid in cash while IM can be settled using high-quality liquid assets (HQLA). In non-centrally cleared trades, both IM and VM can be settled using HQLA (BCBS-IOSCO, 2015).

As an additional line of defence, in accordance with international standards (CPSS-IOSCO, 2012), the CCP is obligated to hold a pre-funded mutualized pool of resources called the default fund that can be used in the case losses exceed the IM posted to cover them. The DF of systemically important CCPs is calibrated to Cover-2, i.e. expected to cover the uncollateralized losses (losses in excess of IM) arising from the simultaneous default of the two largest CMs in terms of exposures under extreme but plausible market conditions. These conditions are typically modelled by CCPs using stress tests that aim to capture at least 99.9% of exposures movements. The DF is funded by the CMs on a pro-rata basis based on their IM contributions. Furthermore, the CCP also commits part of its capital to absorb losses. This "skin-in-the-game" is typically used after the defaulting CM's IM and DF contributions and before other CMs' DF contributions in order to incentivize the CCP to maintain sound risk management practices. However, this capital is typically small so as not to endanger the solvency of the CCP and compromise its main objective of protecting surviving CMs.

If all the pre-funded resources are depleted and the CCP still faces losses, it activates its recovery mechanisms which are built into its Default Management Process (DMP) and include the Powers of Assessment and VM gains haircuts (VMGH) to the winning counterparties. Under the Powers of Assessment, the CCP may request from surviving CMs to provide additional resources limited to a certain multiple of their original DF contributions in order to repay its obligations. This transforms the CCP into a possible source of contagion by acting as a liquidity consumer in times of extreme market stress when multiple CMs are likely to be constrained as well (Pirrong, 2014). If the Powers of Assessment prove inadequate to cover the losses borne by the CCP, it allocates the residual losses on a pro-rata basis to the winning counterparties by applying a haircut to their VM gains. VMGH has been proposed as an effective loss allocation mechanism at the end of the risk waterfall by simulating the effects of general insolvency.

While under normal conditions the CCP is market-neutral since for every buyer there is a seller, when a default occurs it becomes the owner of the centrally cleared portfolio of the defaulted CM. This exposes the CCP to market risk which would make it liable to unlimited future VM payments to winning counterparties and hence require unlimited resources. As a result, the successful utilization of its resources and the recovery tools is conditional on returning to a matched book. This is achieved via an auction of the defaulting portfolio where the surviving CMs are obligated to act as bidders (ISDA, 2015). While the CMs have the right to bid negatively, i.e. request compensation from the CCP in order to claim ownership of the defaulting portfolio, the CCP incentivizes sensible bidding behavior by allocating uncollateralized losses according to the ranking of the bids. Hence, CMs who do not bid at all will be asked to replenish funds via the Powers of Assessment first in full and then sequentially for other CMs according to bid competitiveness. It follows that the winner of the auction will have its resources claimed last if necessary and hence the probability of it having to replenish the DF with additional resources will be minimal. For a more detailed description of the mechanisms of the DMP see ISDA (2015).

3 Model

Our modelling framework evolves over a period of three days, $t = \{0, 1, 2\}$, in order to capture the key dynamics of clearing that occur following a stress event. The time frame is aligned with the clearing operations that occur at a daily frequency and the daily marking-to-market of positions. Table 1 summarizes the model dynamics.

Table 1: Model dynamics

Time	**Round**	**Description**
$t = 0$	Baseline	Initial configuration
$t = 1$	First day effects	Shock on derivative asset triggers VM obligations; potential defaults on VM due to liquidity risk cause defaults due to counterparty risk
$t = 2$	Second day effects	CCP completes DMP if applicable; unfunded losses are allocated to CMs

At time $t = 0$ we construct the bilateral OTC derivative exposures network based on the available aggregate data as well as a fictitious CCP that clears a fraction of total derivatives activity. While the CMs are real banks, the CCP is not real and there are several reasons for this.

First and most important, we do not consider CCP default in this study. A CCP failure is an extreme event that has unpredictable and long-term consequences and the outcomes are hard to be modelled accurately as they will vary according to prevailing market conditions.

Historically there have been three CCP defaults, the last and most severe one being the Hong Kong Futures Exchange occurring in 1987.[5] Second, data limitations do not allow us to model the breakdown of total exposures of CMs to real CCPs. That is, we do not observe the fraction of exposures centrally cleared by various real CCPs. Since our focus is on equity losses borne by the CMs, a fictitious CCP that acts as a market representative is not a drawback in this context. Its operation is modelled according to prevailing regulations in order to simulate dynamics as realistically as possible.

We start the analysis by calculating the IM that is collected by the CCP and calibrating its DF to Cover-2. These calculations are simplified in the sense that we only consider the cost of protection against market risk while in reality CCPs also charge for other risks, e.g. for highly concentrated positions in the market. We abstract from more detailed margin calculations because we are more interested in the relative difference of our results before and after the introduction of non-central clearing. In this sense, higher CCP margin requirements, which remain constant before and after the introduction of non-central clearing, would affect our results in an absolute rather than relative manner.[6]

Following this calculation, we consider two different configurations, one in which the CMs also post IM between themselves in bilateral trades (non-central clearing) and one in which they don't. This allows us to assess the effects of non-central clearing on our model results. In both cases the CCP remains active and clears the same fraction of derivatives activity, collecting the same amount of collateral. We treat the asset class as a representative risky asset that the CMs trade with each other.

The clear-cut distinction between the two configurations enables the straightforward evaluation of the effects of collateralizing bilateral trades. It is important to note that this distinction is stylized since some bilateral trades exchanged collateral even before the introduction of non-central clearing, although they tended to be under-collateralized (Gregory, 2014). In addition, we do not endogenize the change of market activity in response to the implemen-

[5] For a description and empirical analysis of CCP failures see Bignon and Vuillemey (2018) and Cox (2015).

[6] In subsection 6.1 we discuss the model results when the CCP collects double the resources it does in the baseline configuration in order to assess the effect on overall systemic risk. Our results on the effects of the introduction of non-central clearing are robust.

tation of non-central clearing in our model, i.e. we assume that the positions remain the same before and after introducing non-central clearing. Ghamami and Glasserman (2017) find several cases in which bilateral trading remains more capital and collateral efficient even after the introduction of non-central clearing than a full migration to central clearing. As such, the extent of change in the market activity as a result of the new regulation remains ambiguous.[7] Nonetheless, comparing the two configurations in this way allows us to capture the transformation of counterparty to liquidity risk and its systemic implications through the introduction of non-central clearing in a simplified framework that incorporates the key drivers behind these risks.

At time $t = 1$ we commence the stress test by applying exogenous shocks of various magnitudes on the asset which create VM losses and gains in the system. We assume that VM is exchanged in bilateral transactions even without non-central clearing because as stated in section 2 the majority of contracts already had such arrangements in place before the introduction of the new regulations. In our context, the additional collateral demand is due to the exchange of IM in bilateral transactions which puts additional liquidity strain on the CMs.

We allow the CMs to react to the shock by attempting to close their positions and regain liquidity through the return of IM in order to fulfill their VM obligations. This behavior follows from Brunnermeier and Pedersen (2009) who model budget-constrained dealers in a similar way. Hence, after the shock we perform an optimization in which the CMs trade the asset with each other subject to their budget constraints. The larger the shock, the less likely it is that everyone will be able to achieve their goal, which leads to more defaults.

We assume that the CMs pay their IM and VM obligations using their HQLA (which include cash reserves) as discussed in the previous section and, in the baseline scenario, that they are under liquidity stress if their liquidity coverage ratio (LCR) drops to less than 100%. LCR is a regulatory ratio introduced in Basel III that requires banks to have enough HQLA to repay their obligations under a severe 30-day stress scenario where funding sources are withdrawn. This ratio under normal market conditions must be at least 100%,

[7] In subsection 5.2 we consider the case where a higher fraction of trades are cleared through the CCP to assess the potential effects of a migration to central clearing.

i.e. banks must have HQLA equal or greater than the projected obligations during the stress period, although during stress the banks are expected to use their HQLA reserves. The banks typically hold HQLA reserves in excess of their projected obligations and we assume that they have those excess reserves available for derivatives obligations, with the rest used for other operations. Hence, CMs whose VM obligations breach their LCR minimum requirements are assumed to default due to liquidity risk.[8] We treat the non-cash portion of HQLA as infinitely liquid and readily convertible to cash without the risk of fire sales, given that VM obligations for centrally cleared trades are settled in cash.[9]

CMs whose counterparties default on their VM obligations suffer equity losses through profit and loss. We assume that CMs default due to counterparty risk if their Capital Adequacy Ratio (CAR) drops to less than 8% as a result of these losses. CAR is a regulatory ratio of minimum capital requirements that banks must always satisfy, introduced in Basel III.

At time $t = 2$ the CCP assigns uncollateralized losses it suffers, if any, to the surviving CMs. It first performs an auction of the defaulting portfolio in order to return to a matched book. It then uses the available IM and DF resources to cover losses. If these pre-funded resources are insufficient, it calls on its Powers of Assessment by asking surviving CMs to replenish the DF according to their bidding behavior, posing a liquidity risk to them. As such, our model quantifies the domino effects that may originate from the loss allocation mechanisms of the CCP that have been theoretically documented. Domanski et al. (2015) argue that the unexpected liquidity demands originating from the CCP's recovery mechanisms may stress the CMs and in extreme cases cause a default cascade. We estimate the potential number of defaults in such cases due to liquidity stress.

In the most extreme cases when the Powers of Assessment prove inadequate, the CCP proceeds to VMGH, which translates into additional equity losses for the CMs that expect

[8]We discuss the model results assuming a minimum LCR of 70% in subsection 6.2.

[9]In unreported results, we have run the model assuming that banks have a fraction of HQLA available to pay their derivatives obligations based on the reported ratio of projected derivatives outflows to total outflows. The pool of available HQLA is smaller compared to our baseline methodology leading to more banks being under liquidity stress, but the results are qualitatively similar.

VM receipts from the CCP, posing a counterparty risk to them. Since this occurs only in the most extreme market conditions when the CMs are stressed as well, our model captures the wrong-way risk that has been reported by Pirrong (2014). In such cases the activation of the CCP's recovery mechanisms is likely to put additional pressure on the system exactly when it is at its most vulnerable. We quantify the systemic losses that may crystallize under such conditions due to VMGH.

The completion of the DMP typically occurs within five working days (ISDA, 2015) but for simplicity we assume it takes place on a single day, $t = 2$. While this may overestimate the amount of stress the CCP can realistically impose on the CMs on a single day, by not considering multiple days we are also neglecting the potential amplification of losses if asset price movements create further VM obligations for the CCP.

Our aggregate measure of systemic risk is the total equity losses of CMs on days 1 and 2 which we use to assess the effectiveness of non-central clearing. We proceed with a detailed discussion of each step.

3.1 Initial Configuration ($t = 0$)

Consider a population of n banks belonging in the set of network nodes $N = \{1, 2, \ldots, n\}$. The presence or absence of a connection between any two banks through derivative exposures is determined by the adjacency matrix $\boldsymbol{I}$. This is a $n \times n$ matrix that takes values of 1 if there is an edge between banks i and j ($I_{ij} = 1$) and 0 otherwise. The main diagonal of the matrix is zero since the banks do not have exposures to themselves ($I_{ii} = 0 \; \forall \; i \in N$). The network is directed since a bank may have an exposure to a counterparty but the reverse need not be true.

We assume a core-periphery network structure which has been identified in OTC derivatives markets among others by Craig and Von Peter (2014) and Markose (2012). To configure the network, we use the connectivity priors assumed in a study by the Macroeconomic Assessment Group on Derivatives (MAGD) to construct the adjacency matrix (MAGD, 2013). Specifically, we assume that the core (large) banks trade with each other with 100% probability, they trade with the periphery (small) banks with 50% probability and the latter trade with each other with 25% probability and generate random numbers from the Bernoulli distribution in accordance with these priors.[10] In total, we generate 100 adjacency matrices and repeat the stress testing exercise for each random network, providing results as averages of the 100 simulations.

Next, we construct the $n \times n$ bilateral exposures matrix $\boldsymbol{X^0}$. We define the OTC derivatives obligation owed by bank i to bank j as X_{ij}^0. Thus, the sum of columns for row i represents the observable total gross liabilities (L_i^0) of bank i while the sum of rows for column i represents the observable total gross assets (A_i^0) as given by the balance sheet data. We infer the bilateral gross exposures X_{ij}^0 by minimizing the errors in the row and column sums, following Heath et al. (2016):

$$\min_{X_{ij}^0, X_{ji}^0} \sum_i \left[\left| A_i^0 - \sum_j X_{ji}^0 \right| + \left| L_i^0 - \sum_j X_{ij}^0 \right| \right] \tag{1}$$

subject to:

$$X_{ij}^0 = 0 \text{ if } I_{ij} = 0$$

$$0 \leq X_{ij}^0 \leq \min(A_j^0, L_i^0)$$

The goal of optimization (1) is to estimate the bilateral exposures matrix by providing column and row sums as close as possible to the available bank data of liabilities and assets respectively. If the adjacency matrix has an element with a value of zero then the corresponding exposure is also zero and the upper bound is the minimum of the total assets for the specific column and the total liabilities for the specific row. By construction, the optimization equates total assets and total liabilities, $\sum_i \sum_j X_{ji}^0 = \sum_i \sum_j X_{ij}^0$, hence the solution of the objective function is equal to the difference between the total assets and total liabilities of the data. This implies that the system is assumed to form a complete economy.

Following Heath et al. (2016), the bilateral gross notional positions are estimated by multiplying the values in each row of the exposures matrix $\boldsymbol{X^0}$ by the ratio of gross notional liabilities to gross market value of liabilities. The gross notional positions matrix is denoted $\boldsymbol{G^0}$. Finally, the net notional positions matrix is simply calculated as $\boldsymbol{N^0} = \boldsymbol{G^0} - (\boldsymbol{G^0})^{\mathbf{T}}$,

[10] Our results are robust to denser and sparser network configurations.

i.e. the difference between the gross notional positions matrix and its transpose. The matrix $\boldsymbol{N^0}$ is skew symmetric such that $N^0_{ij} = -N^0_{ji}$.

We introduce the CCP by augmenting the matrix $\boldsymbol{N^0}$ with an additional row and column to create the new matrix $\boldsymbol{W^0}$. Let $s \in [0, 1]$ denote the fraction of centrally cleared transactions. Then $W^0_{ij} = (1 - s)N^0_{ij} \ \forall\ i, j \in N$ and $W^0_{ij} = \sum_{p=1}^{n} sN^0_{ip} \ \forall\ i \in N$ and $j = n + 1$. In addition, $W^0_{ij} = -W^0_{ji} \ \forall\ j \in N$ and $i = n + 1$. The matrix $\boldsymbol{W^0}$ remains skew symmetric.

We can now calculate the IM using the matrix $\boldsymbol{W^0}$. As stated in section 2, the minimum requirement for the calculation of the IM is to cover at least 99% of exposures movements, which is typically estimated with a Value-at-Risk (VaR) model. We adopt a Monte Carlo approach in order to be able to update the IM at $t = 2$. Specifically, we model the asset as a representative interest rate swap with price dynamics following an Ornstein-Uhlenbeck process:

$$d\Pi_t = -k\Pi_t dt + \sigma_t dZ_t \tag{2}$$

where k is the speed of mean reversion, σ_t is the time-varying volatility and Z_t is a one-dimensional Brownian Motion under the real-world probability measure. We assume that the long-run mean value of the contract is zero which implies a "fair" contract. The value of k is irrelevant so we set it arbitrarily at 1. However, the volatility parameter is crucial in setting the IM. We discuss the calibration of this parameter in section 4.

We simulate 1000 paths and calculate the margin as the maximum between the lower 1% and upper 99% percentiles of the price differences $d\Pi_t$ as done in practice by CCPs in order to protect themselves from both upswings and downswings. Denote this value as m_0:

$$m_0 = \max(|P_1(d\Pi_t)|, |P_{99}(d\Pi_t)|) \tag{3}$$

where P_a denotes the percentile at the a% level. For simplicity, we assume that all CMs set the same margin m_0 for their trades in the presence of non-central clearing. The IM for each position is then calculated as:

$$IM^0_{ij} = m_0|W^0_{ij}|$$

In accordance with the regulations outlined in section 2, centrally cleared OTC derivatives positions are assumed to have a holding period of five days, i.e. the CCP would be able to unwind the positions within five days. As such, the IM is scaled by the square root of five for centrally cleared positions:

$$IM_{ij}^0 = m_0\sqrt{5}|W_{ij}^0| \;\forall\; i \in N \text{ and } j = n+1 \tag{4}$$

Similarly, non-centrally cleared positions are assumed to have a holding period of ten days due to their increased liquidity risk and smaller netting efficiencies. As such:

$$IM_{ij}^0 = m_0\sqrt{10}|W_{ij}^0| \;\forall\; i, j \in N \tag{5}$$

Note that the IM is posted in bilateral transactions only when non-central clearing is enabled. In the alternative configuration without non-central clearing we have:

$$IM_{ij}^0 = 0 \;\forall\; i, j \in N \tag{6}$$

Denote $IM_i^0 = \sum_{j=1}^{n+1} IM_{ij}^0$ as the total IM requirements for each CM i at time 0. We subtract the total IM requirements from the CMs' liquid assets under the two different configurations in order to calculate their unencumbered resources. Naturally, since IM_i^0 is higher under non-central clearing, the CMs are more encumbered in this configuration which is the key driver behind our results.

Finally, we calculate the CCP's DF. As stated in section 2, the international regulations require systemically important CCPs to be able to withstand the simultaneous default of their two largest CMs under extreme but plausible market conditions. We calculate the uncollateralized losses as follows:

$$SC_i = z\sqrt{5}|W_{ij}^0| - IM_{ij}^0 \;\forall\; i \in N \text{ and } j = n+1 \tag{7}$$

where z captures 99.9% of movements:[11]

[11]Note that this is a conservative approach to size the DF because by using the absolute value of net notional positions in (7) we consider the maximum losses that each CM may incur either due to a positive or a negative shock. Alternatively, two separate shocks could be applied to all CMs as different stress scenarios, one positive and one negative, and the DF would be

$$z = \max(|P_{0.1}(d\Pi_t)|, |P_{99.9}(d\Pi_t)|) \tag{8}$$

We rank SC_i from largest to smallest and sum the first two entries in order to calculate the DF:

$$DF = SC_{i(1)} + SC_{i(2)} \tag{9}$$

Each CM contributes to the DF on a pro-rata basis according to their IM contribution. Denoting individual DF contributions as F_i we have:

$$F_i = \frac{IM^0_{ij}}{\sum_i IM^0_{ij}} DF \;\forall\; i \in N \text{ and } j = n+1 \tag{10}$$

This completes the initial system configuration. All positions are assumed to be marked-to-market, i.e. there are no outstanding VM payments as of time 0.

3.2 First day effects ($t = 1$)

We begin the stress testing exercise by shocking the asset in order to create mark-to-market gains and losses (VM). We measure the shocks in terms of standard deviations of price changes σ_0. In total we apply four shocks which are measured as multiples of σ_0, $2.33\sigma_0$, $3\sigma_0$, $10\sigma_0$ and $20\sigma_0$.[12] The first two are "mild" shocks and are not expected to stress the system significantly since the IM posted is larger than the VM generated. The latter two are severe shocks with $20\sigma_0$ signifying an extreme market event. We discuss the calibration of these shocks and their interpretation in section 4.

Let Δp denote the change in the asset's price as a result of the shock. The VM obligation of i to j is calculated as:

$$VM^1_{ij} = \max(W^0_{ij}\Delta p, 0) \tag{11}$$

sized as the maximum between the sums of the two largest losses among those scenarios which would result in a slightly smaller DF. Nonetheless, the normality assumption already results in a modest DF so our conservative calculation does not oversize it.

[12] We also apply negative shocks of corresponding magnitudes. The results are qualitatively and quantitatively similar.

A positive W_{ij}^0 signifies i being short and j being long. Hence, a positive (negative) Δp creates a VM obligation (gain) for i and VM gain (obligation) for j if W_{ij}^0 is positive and vice versa. Denote $VML_i^1 = \sum_{j=1}^{n+1} VM_{ij}^1$ the total VM requirements for each CM i at time 1. The CMs can pay their VM obligations using their available HQLA AL_i^0 (net of the IM requirements calculated at $t = 0$).

While the study of Heath et al. (2016) assumed static CMs, we allow for portfolio rebalancing by solving an optimization problem to take into account the fact that the contracts are cleared end-of-day hence some CMs may manage to close out their positions and avoid default.

Denote the updated assets and liabilities of each CM i as A_i^1 and L_i^1. Each CM attempts to close out its positions by minimizing the difference between its assets and liabilities. A zero net position would require zero IM ($IM_i^1 = 0$) and the CM would be able to regain the full amount of IM_i^0 to help repay the VM. Specifically, each CM solves the following optimization problem:

$$\min_{A_i^1, L_i^1} |A_i^1 - L_i^1| \tag{12}$$

subject to:

$$LCR_i^1 = \frac{AL_i^0 - (IM_i^1 - IM_i^0) - VML_i^1}{stress_i} \geq 100\%$$
$$(A_i^1 - L_i^1) - \Big(\sum_j X_{ji}^0 - \sum_j X_{ij}^0\Big) = RE_i^0$$

where $stress_i$ are the CM's projected obligations in a stress period for the LCR calculation, R indicates return and E_i^0 is the CM's total equity.

The first condition is the budget constraint stating that the sum of the perceived net IM receipt or payment and the VM obligation must not make the CM's LCR drop to less than 100%. The updated IM (IM_i^1) is a function of the positions A_i^1, L_i^1 and is calculated by updating the matrix $\boldsymbol{X^0}$ and repeating the calculations shown in subsection 3.1. We only consider IM gains here because the IM posted remains in the ownership of the CM that posted it. In contrast, VM gains are subject to counterparty risk because it is not certain that they will be delivered by the counterparty. As such, the CMs do not take them into account in their budget constraint, i.e. they do not rely on uncertain VM gains to pay their own obligations.

The second condition states that the CMs expect a small return R on their equity E_i^0 by holding slightly unbalanced portfolios. This reflects their views on the market and we set R to 1 basis point (bp) which signifies the expected daily return. This is included in order to prohibit the CMs from taking unrealistically large net positions which is not reflected in the data. Since the principal operation of the banks in this setup is market making, they tend to hold balanced inventories in order to avoid excessive directional risk. However, CMs that violate their budget constraint still try to achieve zero net positions.

Each CM performs the optimization by assuming that its counterparties will accept these changes. This implies that the markets are liquid enough to execute these trades. In essence, the IM amounts calculated in (12) are the ones they perceive they can achieve, not the realized ones. Defaults occur when we take into account all CMs' optimal values to form the updated exposures matrix and some CMs are unable to deleverage enough to satisfy their constraints. This is much more likely to happen under extreme stress since the VM requirements are larger.

We solve the optimization for all CMs simultaneously by minimizing the sum of the individual objective functions subject to the vectors of budget and return constraints in order to impose the market clearing condition:

$$\sum_i A_i^1 = \sum_i L_i^1 \tag{13}$$

Since this is a complete economy, the total values of assets and liabilities in the system remain constant throughout time:

$$\sum_i A_i^1 = \sum_i \sum_j X_{ji}^0$$

$$\sum_i L_i^1 = \sum_i \sum_j X_{ij}^0$$

Once this is achieved, we create the updated bilateral exposures matrix $\boldsymbol{X^1}$ as before using the solutions of (12) as the target column and row sums in optimization (1). We calculate the updated matrices $\boldsymbol{G^1}$, $\boldsymbol{N^1}$ and $\boldsymbol{W^1}$ using $\boldsymbol{X^1}$ and calculate the realized IM obligations from $\boldsymbol{W^1}$.

A CM defaults due to liquidity risk if it breaches its LCR requirements. Hence, in order to avoid default the following condition must be satisfied:

$$LCR_i^1 = \frac{AL_i^0 - (IM_i^1 - IM_i^0) - VML_i^1}{stress_i} \geq 100\% \;\forall\; i \in N \tag{14}$$

Equation (14) captures liquidity risk and is central to our analysis. Since the CMs' available liquidity AL_i^0 is net of the IM posted, it follows that it is lower under non-central clearing due to the increased IM requirements in the bilateral transactions. This then translates into higher liquidity risk under this configuration as there are fewer resources to pay the VM obligations VML_i^1.[13]

A secondary default occurs if a CM that satisfies condition (14) does not receive a VM gain due to counterparty default that translates into an equity loss and results in a breach of its CAR minimum requirement of 8%. Denote H the subset of CMs defaulting due to their inability to satisfy (14). Hence, an additional condition for liquid CMs not belonging in this subset to avoid default is:

$$CAR_i^1 = \frac{E_i^0 - \sum_h \max(VM_{hi}^1 - IM_{hi}^0, 0)}{RWA_i} \geq 8\% \;\; \forall\; i \in N \backslash H \text{ and } h \in H \tag{15}$$

where RWA_i is the CM's risk weighted assets used for the calculation of CAR.

Equation (15) captures counterparty risk. If non-central clearing is disabled then $IM_{hi}^0 = 0$ and the CMs translate the whole missed VM receipt as an equity loss. In the alternative configuration, the IM protects the CMs to an extent which is the reasoning behind the introduction of non-central clearing. Denote D the subset of all CMs that default at $t = 1$ by failing to satisfy any of conditions (14) and (15). We assume that CMs that default due to counterparty risk, i.e. due to violation of (15) repay their VM obligations since they have

[13]For completeness we also considered market risk, i.e. the revaluation of positions as a source of risk. However, it has a negligible effect on our results and is not relevant to our analysis, hence we do not report it.

sufficient liquid resources to do so.

The liquid resources available to surviving CMs at the end of $t = 1$ are:

$$AL_i^1 = AL_i^0 - (IM_i^1 - IM_i^0) - (VML_i^1 - VMG_i^1) \; \forall \; i \in N \backslash D \tag{16}$$

where VMG_i^1 denotes the realized VM gains for CM i.

Similarly, the equity available to surviving CMs at the end of $t = 1$ is:

$$E_i^1 = E_i^0 - \sum_h \max(VM_{hi}^1 - IM_{hi}^0, 0) \; \forall \; i \in N \backslash D \text{ and } h \in H \tag{17}$$

We measure systemic risk (SR_1) as the total equity loss in the system:

$$SR_1 = \sum_i (E_i^1 - E_i^0) \; \forall \; i \in N \tag{18}$$

In contrast to the CMs, the CCP does not translate uncollateralized losses into equity losses but it manages them in accordance with its DMP which is modelled next.

While technically this is a zero-sum game as a CM's devaluation of its assets corresponds to an equal reduction of the defaulted counterparty's liabilities, it is important to consider those losses as part of the overall social welfare. Systemic risk poses an externality because failing banks may require ex-post bailouts and equity losses lead to under-capitalization of the financial system with adverse consequences for the real economy (Acharya et al. (2017), Brunnermeier and Cheridito (2019)).

3.3 Second day effects ($t = 2$)

At $t = 2$ the CCP manages the defaulting portfolios and uncollateralized losses it sustains at $t = 1$, if any. If there are no defaults on the first day, there are no further losses in the system and the stress testing exercise stops there.

We assume that on the second day the CCP performs a margin update, i.e. it updates its IM requirements upwards to take into account the increased volatility of the market. This effect is known as margin procyclicality and is a standard practice of CCPs which may have negative consequences for systemic stability given that margins act as destabilizing factors in illiquid markets (Brunnermeier and Pedersen, 2009). If the shock is large enough to be considered a tail scenario by the VaR model, the IM increases exerting further liquidity pressure on CMs. Margin procyclicality is a major concern for regulators who plan to incorporate it into stress testing methodologies considering the increasing importance of CCPs in derivatives markets (Bank of England, 2015). Empirically, CCPs are found to quickly raise margins following a shock but are slower in lowering them after volatility declines (Abruzzo and Park, 2016).

Following the default of at least one CM, the CCP becomes the owner of its centrally cleared portfolio. Its first act is to offload the portfolio from its books in order to become market neutral again and avoid potential future VM obligations to the counterparties. As explained in section 2, the main tool at the CCP's disposal in order to achieve this is the auction.

The clearing rules specify the set-up of the auction (see e.g. section 9 ICEU (2017) and Ferrara et al. (2017)). It is a first-price sealed bid auction where all CMs are obligated to participate. The CMs have the right to bid negatively, i.e. request resources from the CCP in order to obtain the defaulting portfolio (for example because it consists of net short positions and the CMs request the premium or due to its excessive riskiness). As mentioned before, the CCP incentivizes CMs to bid sensibly by allocating uncollateralized losses according to the bidding behavior. This implies the existence of a loss function in the payoff of the bidders in contrast to the standard auction setting where losers walk away with nothing.

We adopt the standard auction setting where the bidders are risk-neutral (Milgrom and Weber, 1982). For simplicity, the CCP is assumed to combine all defaulting portfolios together in case of multiple defaults and auctions it off as one item. The total value of this portfolio (PV) is:

$$PV = \sum_{d} \sum_{j} (X^1_{jd} - X^1_{dj}) s \ \forall \ d \in D \text{ and } j \in N \tag{19}$$

which is the sum of the total assets minus total liabilities of centrally cleared positions as captured by the clearing fraction s of defaulted CMs belonging in the subset D.

Since the CCP marks-to-market the portfolio, its price is known to be PV. However, the incorporation of the defaulting portfolio into each CM's existing one creates unique new IM gains or losses which differentiate each bidder's valuation. Each surviving CM's IM posted to the CCP at the end of $t = 1$ was:

$$IM_{ij}^1 = m_0\sqrt{5}|W_{ij}^1| \ \forall \ i \in N\backslash D \text{ and } j = n+1$$

Let $WD = \sum_d W_{dj}^1 \ \forall \ d \in D$ and $j = n+1$ denote the net notional of the defaulting portfolio. The net IM gain or loss from incorporating the defaulting portfolio into each CM's existing one is calculated as:

$$IM_{ij}^2 - IM_{ij}^1 = m_1\sqrt{5}|W_{ij}^1 + WD| - m_0\sqrt{5}|W_{ij}^1| \ \forall \ i \in N\backslash D \text{ and } j = n+1 \tag{20}$$

where m_1 is the updated VaR estimated as in (3) but including the change in the asset price Δp due to the shock into the Monte Carlo paths to capture margin procyclicality.

The fair private value of each CM for the defaulting portfolio is thus given as:

$$u_i = PV - (IM_{ij}^2 - IM_{ij}^1) \ \forall \ i \in N\backslash D \text{ and } j = n+1 \tag{21}$$

Note that PV is constant and known to all CMs since the CCP marks-to-market the portfolio which makes this auction a private value auction. A positive (negative) PV implies an asset (liability) for the CM, hence it posts (requests) compensation to (from) the CCP to acquire the portfolio. A positive (negative) net IM ($IM_{ij}^2 - IM_{ij}^1$) is a future payment (receipt) to (from) the CCP hence the CM requests (posts) this amount from (to) the CCP.

As in the standard auction setting, we assume that the CMs' valuations u_i are independent and drawn from a known to all distribution F with density f and support $[\underline{u}, \overline{u}]$. We assume a uniform distribution with support $\underline{u} = -0.1$ and $\overline{u} = 0.1$ in US$ trillion.[14]

Each CM places a bid $b_i = b(u_i)$. In a standard setting the payoff π_i would be:

$$\pi_i = \begin{cases} u_i - b_i \text{ if } b_i > \max_{j \neq i} b_j \\ 0 \text{ otherwise} \end{cases}$$

[14] The uniform distribution is the standard assumption in the auction theory literature. Selecting broader bounds results in lower overall bids while tighter bounds increase them. Alternative bounds do not have a significant effect on our results.

That is, the winner places the highest bid and profits the difference between his valuation and his bid while losers walk away with nothing, i.e. zero payoff.

However, in this case the CCP punishes losers by requesting contributions via the Powers of Assessment according to the ranking of the bids. The contributions are capped to a multiple of the original DF contribution, typically two. CMs cannot calculate the loss function ex-ante for several reasons.

First, it requires the ordering of the bids to be known which is obviously not possible before the auction is complete. Second, the bids are sealed so only the CCP knows the ranking ex-post. Third, the CMs are not aware of the total losses faced by the CCP, nor the individual contributions to the DF from all the CMs. Hence, we depart from the usual notion of risk estimation to model CMs that face Knightian uncertainty, i.e. an unmeasurable risk.

Under such a setting, agents are said to be Knightian uncertainty averse and maximize expected utility given the least favorable state of nature. In other words, they maximize expected utility under the worst-case scenario according to the maximin expected payoff representation introduced by Gilboa and Schmeidler (1989). However, the worst-case scenario is known to everyone: it is the one where the losses are so large that the CMs pay the capped amount which is equal to twice their original DF contribution irrespectively of the bidding order. That is, the losses are not fully covered by the addition of twice the original DF to the available resources.

In Appendix A we prove that in this case the loss function becomes irrelevant and the auction boils down to the standard independent private value (IPV) case where the bid function is given by:

$$b(u_i) = \begin{cases} \frac{(M-1)\int_{\underline{u}}^{u_i} x_i F(x_i)^{M-2} f(x_i) dx_i}{F(u_i)^{M-1}} \text{ if } \underline{u} < u_i \leq \overline{u} \\ -\infty \text{ if } u_i = \underline{u} \end{cases} \tag{22}$$

where M is the number of bidders, i.e. the number of surviving CMs. A CM whose valuation coincides with the lower bound of the distribution $\underline{u}$ would be a certain loser and ask an infinite amount of compensation from the CCP. Our bounds are broad enough to never observe this case.

Since the CMs have a finite amount of liquid resources available, they bid in accordance to their budget constraint (Che and Gale, 1998):

$$b^*(u_i) = \min(b(u_i), AL_i^1) \tag{23}$$

Once all bids (23) have been placed, the CCP assigns the portfolio to the highest bidder. If the highest bid is negative, the CCP is assumed to always be able to pay the winner.[15]

Next, if the CCP faces uncollateralized losses that exceed the defaulted CMs' IM and DF contributions as well as a small equity tranche of US$100 million, it calls on its Powers of Assessment. Each surviving CM is obligated to contribute up to twice its original DF amount starting from the lowest bidder and ascending until the losses have been covered or every CM has pledged the capped amount and the losses are still not fully covered. The CMs use their remaining liquid assets to pay the additional funds. If any CM does not have enough liquid resources, i.e. it breaches its LCR requirements, it defaults due to liquidity stress. Hence, the following condition must hold in order to avoid default:

$$LCR_i^2 = \frac{AL_i^1 - P_i}{stress_i} \geq 100\% \quad \forall\, i \in N \backslash D \tag{24}$$

where P_i is the amount asked by the CCP under the Powers of Assessment.

In the most extreme case when there are still unfunded losses after the Powers of Assessment, the CCP assigns these residual losses via VMGH to the winning counterparties. This haircut is applied pro-rata and is directly translated into an equity loss for the CMs since the CCP does not post IM to them. Any CM whose updated CAR drops below 8% defaults due to counterparty risk. In other words, the following condition must hold to avoid default:

$$CAR_i^2 = \frac{E_i^1 - VM_{ji}^2}{RWA_i} \geq 8\% \quad \forall\, i \in N \backslash D \text{ and } j = n + 1 \tag{25}$$

where VM_{ji}^2 is the VM loss due to VMGH.

We measure systemic risk for $t = 2$ (SR_2) as:

[15] In reality, it may occur that the CCP does not have enough resources of its own to pay the bid in which case it has to rely on its DF and then its Powers of Assessment to replenish it. This adds an additional layer of complexity and also introduces the possibility of CCP default hence we eschew it.

$$SR_2 = \sum_i (E_i^2 - E_i^1) \; \forall \; i \in N \backslash D \tag{26}$$

The total equity loss (SR_T) in the system is:

$$SR_T = SR_1 + SR_2 \tag{27}$$

which gives the total measure of systemic risk.

Any CMs that default at $t = 2$ would require the repeat of the auction process, although there are no uncollateralized losses in this case. We do not perform this step as it does not add substantial information to our analysis.

3.4 Model implications

The model has several implications for the redistribution of risks across the CCP and the CMs following the introduction of non-central clearing. First, the model predicts that the liquidity risk of the CMs will increase because they have fewer unencumbered liquid assets to pay their VM obligations, as captured by equation (14). Second, it is also expected that their counterparty risk will decrease as the presence of the IM in the bilateral transactions will protect them from losses due to counterparty default, as seen in equation (15). Third, holding the CCP's resources constant, non-central clearing can increase the CCP's losses if more CMs default on their obligations due to liquidity risk. Hence, the effect on systemic risk is ambiguous as the collateralization of bilateral transactions can reduce losses due to default but can lead to higher losses for the CCP which will be subsequently mutualized across the surviving CMs.

We finish this section by highlighting certain model simplifications and abstractions from real life. First, due to data limitations we do not include non-banks or non-financial institutions (end-users). These entities are more likely to lie in the periphery of the network although their significant presence in the OTC interest rate derivatives market is recognized (ISDA, 2014a). Second, the available aggregate data do not allow for the correct identification of connections. While we simulate 100 random networks in order to average out the results, there remains the possibility of considerable model error. Nonetheless, we base our network formation on existing literature which is based on actual data of bilateral exposures. Third, we do not account for banks' additional sources to raise liquidity such as the repo market. Equally however, systemic events are characterized by multiple market failures as was evident in the recent financial crisis and their orderly operation cannot be guaranteed (Gorton and Metrick, 2012). While macroprudential stress test models add general equilibrium dimensions to improve on their microprudential counterparts, there is a limit to the degree of generalization that is possible without losing tractability (Demekas, 2015). Stress testing models remain partial equilibrium exercises but they can be extended in order to balance the trade-off between reality and model tractability.

4 Data

We test the model implications by running simulations using data on 39 banks that act as CMs. The selection of these banks is based on a study by the Macroeconomic Assessment Group on Derivatives (MAGD), also adopted by Heath et al. (2016), which uses proprietary data and simulates a core-periphery structure of the OTC derivatives network that comprises the 16 largest global derivatives dealers forming the densely connected core and a number of smaller banks representing individual jurisdictions forming the sparsely connected periphery (MAGD, 2013). The list of banks is provided in Table 5 in Appendix B.

We obtain the following data for the banks from their 2018 annual reports: total interest rate derivatives gross assets and liabilities, gross notional, liquid assets defined as their High Quality Liquid Assets (HQLA) required under Basel III regulation and used among others for derivatives activities, as well as their total equity (Tier 1 plus Tier 2 capital). The annual reports include data for five major derivatives asset classes, those being equity, currency, commodity, credit and interest rate. For simplicity, in this study we focus on one asset class and we choose the interest rate one since it dominates all other classes in terms of notional and exposures. In this way we capture more than 85% of the total OTC derivatives markets activity in terms of gross notional which stood at US$544 trillion at the end of 2018 (BIS, 2019). We set the central clearing fraction s equal to 75% in line with current estimates for interest rate derivatives (BIS, 2019), with the rest 25% of trading activity being bilaterally traded.

A summary of the data is given in Table 2. Figures are in US$ trillion.

Table 2: Data summary (US$ trillion)

	Total	**Core-16**	**Periphery-23**
Gross assets	2.78	2.22	0.56
Gross liabilities	2.66	2.07	0.59
Gross notional	465.40	386.32	79.08
Liquid assets	8.76	4.44	4.32
Equity	3.19	1.81	1.38

Source: Annual reports and own calculations

The majority of trading activity is concentrated in the Core-16 banks, accounting for approximately 80% of total assets, liabilities and notional, with the rest 20% shared among the Periphery-23 banks. Approximately 50% of total liquid assets are in the core and the rest 50% in the periphery, while 57% of total equity belongs to the Core-16 banks and 43% in the Periphery-23 banks. The derivatives data represent the aggregates for each bank which we use to infer the unobservable bilateral connections as explained in the previous section. Using this data to calibrate our model, the CCP collects US$224.3 billion in IM and US$13.1 billion for its default fund, approximately twice as much as the resources collected by LCH, the leading CCP for interest rate swaps.[16] When non-central clearing is enabled, CMs post US$449 billion in IM between themselves. The fact that the CMs post almost twice as much IM in the bilateral transactions (covering 25% of total notional) compared to the centrally cleared ones (covering 75% of total notional) highlights the netting benefits arising from the dominance of CCPs.

Regarding the volatility parameter σ_0, since we don't have any prior knowledge of its value we refer to the study of MAGD (2013) which estimates the daily volatility of the interest rate derivatives class using proprietary data equal to 0.068%.[17] We use this parameter value

[16]According to the 2017 EU-wide CCP stress test published by the European Securities and Markets Authority (ESMA), LCH had approximately EUR 110 billion in IM and EUR 7 billion in its default fund (ESMA, 2018).

[17]While a different value of σ_0 would change our absolute results, we are more interested in the relative results, i.e. comparing before and after the introduction of non-central clearing, and we expect those to be robust to different parameter values.

to calculate the market shocks which we interpret as parallel movements of the swap curve used to price interest rate swaps, the dominant contract of interest rate derivatives.

To give context to the magnitude of the shocks we apply to the system, a $2.33\sigma_0 \approx$ 15.8bps movement is approximately one-third the shock to the USD Libor swap rate on the day Lehman Brothers defaulted, which was 45bps according to a report by the Commodity Futures Trading Commission (CFTC) (CFTC, 2019). A $3\sigma_0 \approx 20.4$bps movement is equivalent to approximately one-half the Lehman shock, a $10\sigma_0 \approx 60.8$bps movement is 1.5 times the Lehman shock, while a $20\sigma_0 \approx 136$bps movement is 3 times the Lehman shock. Hence, a $10\sigma_0$ shock can be described as "extreme but plausible" while a $20\sigma_0$ is probably beyond what CCPs would consider plausible. The reason we apply such a shock is because we can simulate an extreme scenario where the CCP's pre-funded resources are depleted, which has happened in rare cases historically.

5 Empirical results

5.1 Baseline analysis

We report the baseline model results for each of the two rounds (days 1 and 2) in Table 3. The table presents mean values across the 100 simulated networks for the defaults due to liquidity and counterparty risk as well as the overall systemic and CCP losses. The results derived from the simulations are compared between the two configurations, with and without non-central clearing (NCC), for shocks of various magnitudes. We calculate the % reduction of effects achieved through NCC (negative value indicates increase) and assess the statistical significance through a two-sample t-test.[18]

[18] We also apply the Welch's t-test to control for unequal variances between the two samples. The results remain the same.

Table 3: Baseline configuration results. This table reports the baseline results of the analysis. The CCP is assumed to clear 75% of all derivatives transactions, and the banks default due to liquidity risk if their LCR drops to less than 100% and due to counterparty risk if their CAR drops to less than 8%. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

	Shock	With NCC	Without NCC	% Reduction
Panel A: Day 1 results				
Defaults due to liquidity risk	$2.33\sigma_0$	0.51	0.07	−628.57***
	$3\sigma_0$	0.63	0.13	−384.62***
	$10\sigma_0$	4.56	2.79	−63.44***
	$20\sigma_0$	11.53	8.48	−35.97***
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.06	100.00*
	$3\sigma_0$	0.00	0.33	100.00**
	$10\sigma_0$	16.91	54.41	68.93***
	$20\sigma_0$	189.59	254.59	25.53***
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.02	100.00
	$20\sigma_0$	0.13	0.67	80.60***
CCP uncollateralized losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	33.20	25.40	−30.69***
	$20\sigma_0$	221.12	194.79	−13.52***
Panel B: Day 2 results				
Defaults due to liquidity risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.15	0.04	−275.00***
	$20\sigma_0$	0.36	0.33	−9.09
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	4.38	1.04	−319.79***
	$20\sigma_0$	125.58	105.02	−19.58***
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.00	0.00
	$20\sigma_0$	1.65	1.48	−11.49
Panel C: Days 1&2 results				
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.06	100.00*
	$3\sigma_0$	0.00	0.33	100.00**
	$10\sigma_0$	21.29	55.46	61.62***
	$20\sigma_0$	315.16	359.61	12.36***

5.1.1 First day defaults and losses ($t = 1$)

The results from day 1 for shocks ranging from 2.33 to 20 standard deviations are reported in Panel A of Table 3. Defaults due to liquidity risk occur due to the violation of condition (14), that is, if the net IM and the VM obligations make the banks breach their LCR requirement. The introduction of NCC significantly increases the liquidity-driven default frequency for all market shocks due to the higher liquidity encumberment of the banks, with the increase being most pronounced for mild shocks (628.57% at $2.33\sigma_0$) and least pronounced during extreme market stress (35.97% at $20\sigma_0$). This is because when large market shocks occur many banks cannot repay their VM obligations even in the absence of the liquidity encumberment caused by the introduction of NCC. In absolute terms, the number of defaults is substantial, reaching an average of 11.53 under NCC and 8.48 without in the most extreme case. The results indicate that NCC leads to a significant increase in liquidity risk which affects a large number of banks.

The day 1 systemic equity losses defined in (18) caused by the defaults due to liquidity risk are discussed next. For mild shocks NCC eliminates all systemic losses due to the added protection offered by the IM in the bilateral transactions. As the shock magnitude increases, the crystallized losses become larger as expected, and NCC decreases the overall losses. The loss reduction is both statistically and economically significant. Specifically, NCC caps the overall systemic losses at US$189.59 billion or 5.94% of the total equity of all banks. Without NCC the losses are as high as US$254.59 billion or 7.97% of total equity, an increase of 25.53% or US$65 billion. Even though the number of defaults due to liquidity risk is higher under NCC in extreme market conditions, leading to higher raw losses before taking into account the collateral, the IM posted in bilateral transactions protects the surviving participants. Our findings provide support for the role of NCC as a mechanism for obtaining economically significant savings in systemic losses attributed to extreme market shocks in the OTC derivatives markets.

Even though NCC significantly reduces systemic losses, the reduction of defaults due to counterparty risk as a result of these losses is more limited. This is because defaults due to counterparty risk are zero or near zero with or without NCC in all but the most extreme market shock case. The banks have sufficient capital to withstand the losses that occur, and while under a $20\sigma_0$ scenario there is a statistically significant reduction of defaults of 81%, the actual number of defaults is very small, 0.13 under NCC and 0.67 without. This finding corroborates Cont (2017) who argues that liquidity risk is the main source of stress in cleared markets. It also shows that the small benefits of introducing NCC in terms of decreasing counterparty risk are overshadowed by the accompanying increase of liquidity risk which adds to the evidence for the effect of risk transformation.

The CCP sustains zero uncollateralized losses under mild stress since its resources remain constant under both configurations and are sufficient to cover losses due to default. However, due to the dominance of the CCP in our model which clears 75% of total trading activity, the uncollateralized losses in the most extreme scenario are very large, standing at US$221.12 billion under NCC and US$194.79 billion without. NCC increases the losses sustained by the CCP by 14% in the most extreme case because of the higher number of defaults due to liquidity risk. Nonetheless, since some of those losses are owed to other defaulted counterparties, we assume that the CCP is only liable to repay surviving CMs. As such, the magnitude of losses presented in Table 3 overestimates the true level of stress imposed on the CCP.

While NCC appears effective at reducing counterparty and systemic risks when considering the first-round results, the increased liquidity risk in the most extreme shock scenario leads to a higher number of total defaults, so the CCP sustains larger losses in this case. This has important implications for financial stability because these losses are transmitted back to the surviving CMs in accordance with the DMP as reported in the ensuing analysis.

5.1.2 Second day defaults and losses ($t = 2$)

On the second day, the CCP distributes any losses in excess of the defaulted CMs' posted IM and DF contributions and a small tranche of its own equity to the surviving CMs. The results are presented in Panel B of Table 3.

Defaults due to liquidity risk (i.e. due to insufficient liquid assets to meet the Powers of Assessment (24)) and counterparty risk (i.e. due to equity losses caused by VMGH (25)) only occur under severe stress when the CCP's pre-funded resources are depleted and the recovery tools are activated. The defaults due to liquidity risk remain small with and without NCC, reaching 0.36 and 0.33 on average respectively, due to the cap on the amount of resources that the CCP can ask for. As such, we do not find that the CCP poses a substantial liquidity risk to its members, alleviating concerns about the repercussions of the stress imposed on CMs due to the Powers of Assessment (Domanski et al., 2015).

The equity losses sustained by CMs due to VMGH defined in (26) reach US$125.58 billion under NCC or 4.18% of remaining total equity from day 1 and US$105.02 billion without or 3.57% of remaining equity in the most extreme market scenario. Interestingly, the introduction of NCC seems to amplify the CCP's potential for contagion in the most extreme market conditions, increasing average losses by US$20.56 billion or, equivalently, by 19.58%. The increased liquidity risk leads to more initial defaults and more uncollateralized losses for the CCP, which transmits them back to the surviving CMs leading to higher secondary losses. As such, the CCP's propensity to act as a source of contagion in the most extreme cases is amplified with the introduction of NCC. Nonetheless, the increase in losses transmitted by the CCP is not enough to significantly increase the number of defaults occurring due to counterparty risk, implying that the CMs are able to withstand the additional losses distributed by the CCP under NCC. The number of defaults due to counterparty risk is virtually zero for all shocks except the most extreme one, where they average 1.65 under NCC and 1.48 without, statistically the same.

5.1.3 Overall systemic losses

We report the overall systemic losses that occur over the two days of the clearing process derived using (27) in Panel C of Table 3.

NCC significantly reduces overall systemic losses under all market conditions. Under NCC, losses remain zero for small to moderate shocks, rising to US$21.29 billion or 0.67% of total initial equity for a $10\sigma_0$ shock and US$315.16 billion for the most extreme $20\sigma_0$ shock or 9.87% of total initial equity. Without NCC, losses occur in all cases, rising to US$55.46 billion or 1.74% of total initial equity for a $10\sigma_0$ shock and US$359.61 billion or 11.26%

of total initial equity for a $20\sigma_0$ shock. The findings suggest that the introduction of NCC reduces losses by 62% and 12%, respectively for shock sizes of $10\sigma_0$ and $20\sigma_0$, which amounts to economically significant savings of US$34.17 billion and US$44.45 billion or 1.07% and 1.39% of total initial equity respectively.

We can thus deduce that the introduction of NCC promotes financial stability in terms of reducing total equity losses. The exchange of IM in bilateral transactions mitigates the losses arising from counterparty risk at the expense of an increase of liquidity risk. However, this increase has implications for the stability of the CCP since it faces larger losses in adverse market conditions and as a result the knock-on effects are also more severe. We further analyze the implications of the expansion of central clearing for systemic risk in the next subsection.

5.2 Central clearing and systemic risk

In this subsection we examine the impact of the expansion of central clearing on systemic risk. Post-crisis regulations have heavily promoted the expansion of CCPs as a result of them being regarded as bulwarks that provide stability to the financial system, and the introduction of non-central clearing is an additional step towards that goal by incentivizing market participants to switch to central clearing in order to benefit from lower margin costs (BCBS-IOSCO, 2015).

We repeat the stress testing exercise twice by setting the clearing fraction s equal to 0.5 and 0.95, i.e. we assume that 50% and 95% of positions are centrally cleared compared to 75% in the earlier configuration. That is, we consider a scenario with reduced central clearing and another one with increased central clearing compared to the earlier configuration. For each repetition a new set of 100 random adjacency matrices is generated. The results are presented in Table 4.

On day 1, liquidity risk remains the main source of stress but the corresponding number of defaults decreases with the expansion of the CCP because the increasing netting benefits lower the exposures and the amount of collateral required so the CMs have lower liquidity encumberment. When the CCP clears 50% of transactions, the number of liquidity-driven defaults is 17.91 and 11.28 with and without NCC respectively, compared to 6.20 and 5.83 when 95% of transactions are centrally cleared. In addition, because of the decreasing role of non-central clearing, which affects only 5% of transactions in the increased central clearing configuration, the % increase in the number of defaults is lower when the CCP is dominant.

The decrease in the number of defaults due to liquidity risk leads to a sizable decrease in systemic losses on day 1. With decreased central clearing, the losses in the most extreme market scenario under NCC are US$528.76 billion or 16.55% of total equity while with increased central clearing they are US$23.55 billion or 0.74% of total equity, reduced by a factor of 21. Without NCC the corresponding losses are US$664.06 billion or 20.79% of total equity and US$36.30 billion or 1.14% of total equity, reduced by a factor of 17. These results illustrate the very significant reduction of exposures and counterparty risk due to market shocks that can be achieved with the proliferation of CCPs. NCC reduces these losses even further which corroborates our baseline results from section 5.1.

Defaults due to counterparty risk are completely eliminated with a clearing fraction of 95% as fewer CMs default on their VM obligations due to liquidity risk, leading to smaller systemic losses and hence zero defaults due to counterparty risk, with or without NCC. Under reduced central clearing, the number of defaults due to counterparty risk is reduced with NCC but similarly with the baseline results they are low, 1.44 and 2.89 with and without NCC respectively. This shows that even with very large equity losses of up to 20% of total capital most banks do not breach their capital adequacy ratios.

Table 4: Alternative central clearing configurations results. This table reports results assuming that the CCP clears 50% and 95% of all derivatives transactions in the Reduced central clearing and Increased central clearing configurations respectively. The banks default due to liquidity risk if their LCR drops to less than 100% and due to counterparty risk if their CAR drops to less than 8%. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

		Reduced central clearing			Increased central clearing		
	Shock	With NCC	Without NCC	% Reduction	With NCC	Without NCC	% Reduction
Panel A: Day 1 results							
Defaults due to liquidity risk	$2.33\sigma_0$	1.29	0.03	-4200.00^{***}	0.22	0.13	-69.23^{*}
	$3\sigma_0$	1.65	0.10	-1550.00^{***}	0.37	0.21	-76.19^{**}
	$10\sigma_0$	9.39	4.29	-118.88^{***}	2.00	1.81	-10.50
	$20\sigma_0$	17.91	11.28	-58.78^{***}	6.20	5.83	-6.35^{*}
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00	0.00	0.02	100.00^{**}
	$3\sigma_0$	0.00	1.28	100.00^{**}	0.00	0.05	100.00^{***}
	$10\sigma_0$	62.53	156.60	60.07^{***}	1.67	7.05	76.33^{***}
	$20\sigma_0$	528.76	664.06	20.38^{***}	23.55	36.30	35.13^{***}
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.34	100.00^{***}	0.00	0.00	0.00
	$20\sigma_0$	1.44	2.89	50.17^{***}	0.00	0.00	0.00
CCP uncol. losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00	0.00	0.00	0.00
	$10\sigma_0$	34.88	22.67	-53.86^{***}	24.47	23.16	-5.69
	$20\sigma_0$	166.70	147.16	-13.28^{***}	201.30	193.62	-3.97
Panel B: Day 2 results							
Defaults due to liquidity risk	$2.33\sigma_0$	0.00	0.00	0.00	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00	0.00	0.00	0.00
	$10\sigma_0$	0.21	0.03	-600.00^{***}	0.07	0.06	-16.67
	$20\sigma_0$	0.64	0.42	-52.38^{***}	0.10	0.12	-16.67
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00	0.00	0.00	0.00
	$10\sigma_0$	9.85	2.43	-305.50^{***}	0.65	0.59	-10.30
	$20\sigma_0$	41.69	43.76	4.73	137.29	133.13	-3.13
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.04	100.00^{**}	0.00	0.00	0.00
	$20\sigma_0$	0.24	0.37	35.14	0.82	0.96	14.58
Panel C: Days 1&2 results							
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00	0.00	0.02	100.00^{**}
	$3\sigma_0$	0.00	1.28	100.00^{**}	0.00	0.05	100.00^{***}
	$10\sigma_0$	72.39	159.03	54.48^{***}	2.32	7.64	69.61^{***}
	$20\sigma_0$	570.45	707.82	19.41^{***}	160.84	169.44	5.07

On the other hand, the expansion of central clearing also increases the systemic importance of the CCP and its propensity for contagion under severe stress. The uncollateralized losses faced by the CCP in the most extreme market scenario with 50% of positions centrally cleared are US$166.70 billion under NCC and US$147.16 billion without, compared to US$201.30 billion and US$193.62 billion respectively with 95% of positions centrally cleared. Interestingly, even though the number of CMs that default on their VM obligations due to liquidity stress decreases, the losses incurred by the CCP increase as it expands its operations. This highlights the fact that in a configuration where the CCP is most dominant, the exposures that manifest when shocks occur are so large that only a small number of defaults is sufficient to generate losses comparable to those in a configuration with a smaller CCP.

The number of defaults due to liquidity risk on day 2 is further reduced with the expansion of central clearing to 0.10 and 0.12 with and without NCC respectively since the CMs are less liquidity encumbered which allows them to meet their Powers of Assessment obligations.

The CCP's expansion leads to substantially higher systemic losses on day 2 in the most extreme market scenario, from US$41.69 billion or 1.56% of remaining capital under NCC and US$43.76 billion or 1.73% of remaining capital without NCC with reduced central clearing, to US$137.29 billion or 4.33% of remaining capital under NCC and US$133.13 billion or 4.22% of remaining capital without NCC with increased central clearing, an increase of 3.3 times and 3 times respectively. Hence, once the CCP exhausts its pre-funded resources it becomes a source of contagion and the losses it distributes are amplified with its increased presence in the market.

The defaults due to counterparty risk increase with the expansion of central clearing because the CCP distributes larger uncollateralized losses to the surviving CMs via VMGH. However, these defaults remain low as banks are well-capitalized, at 0.24 and 0.37 with and without NCC respectively when the CCP clears 50% of all transactions, to 0.82 and 0.96 when the CCP clears 95% of all transactions.

Finally, the total systemic losses for days 1 and 2 decrease with the expansion of central clearing under all market scenarios due to the beneficial effect of multilateral netting in reducing exposures. In the most extreme market scenario, the losses decrease by 255% with

NCC as central clearing expands, from US$570.45 billion or 17.86% of total equity with reduced central clearing to US$160.84 billion or 5.04% of total equity with increased central clearing. Without NCC, total systemic losses decrease by 318% from US$707.82 billion or 22.16% of total equity with reduced central clearing to US$169.44 billion or 5.31% of total equity with increased central clearing.

The results indicate that the expansion of central clearing is beneficial for financial stability as it substantially reduces total systemic losses, driven by the reduction of first-round losses originating from market shocks due to increasing netting benefits. However, this reduction is accompanied by an increase of second-round losses due to the feedback effect, such that the CCP can distribute losses that are much higher than those due to the market shock when it is dominant in the market. Hence, even though the net reduction is positive (decrease of first-round losses more than offsets increase of second-round ones), the fact that the CCP has the potential to become the main source of stress in the system requires a careful appraisal of its pre-funded resources in the new regulatory environment to ensure it does not contribute to financial instability.

Examining the effect of NCC as the CCP expands, we observe that its effects (both positive and negative) become subdued when it affects only 5% of market activity. In terms of total systemic losses, we observe that the only insignificant difference in means occurs in the increased central clearing configuration under extreme stress. In general, NCC is most effective at reducing systemic losses when central clearing is limited as observed by the reduction of losses between the two configurations for various levels of central clearing. This is intuitive given that bilateral transactions capture a larger fraction of market activity when central clearing is limited.

6 Sensitivity analysis

6.1 Increased CCP resources

In this subsection we discuss the model results when the CCP increases its pre-funded resources, the IM and the DF, by 100% compared to the baseline configuration. Such an increase would better protect the CCP, reducing the losses it distributes in the second round, at the cost of higher liquidity encumberment of CMs and higher losses in the first round. We can thus use the model to assess which effect dominates and what is the net effect on overall systemic risk.[19] The results are reported in Table 6 in Appendix B.

On day 1, the number of defaults due to liquidity risk is slightly higher compared to the baseline configuration under all market conditions due to the higher liquidity encumberment, reaching 12.87 and 9.79 with and without NCC respectively during extreme stress compared to 11.53 and 8.48 in the baseline configuration. The resulting systemic losses also increase, reaching US$205.86 billion or 6.45% of total equity under NCC compared to US$189.59 billion or 5.94% of total equity in the baseline configuration, and US$273.46 billion or 8.56% of total equity without NCC compared to US$254.59 billion or 7.97% of total equity in the baseline configuration. The number of defaults due to counterparty risk increases marginally due to the increased systemic losses, reaching 0.17 under NCC and 0.80 without, compared to 0.13 and 0.67 respectively in the baseline configuration. The CCP suffers uncollateralized losses only in the most extreme market scenario due to its increased resources, reaching US$141.36 billion under NCC and US$127.24 billion without, significantly reduced compared to the baseline configuration losses of US$221.12 billion and US$194.79 billion respectively.

On day 2, the number of defaults due to liquidity risk increases slightly, up to 0.74 under NCC and 0.55 without in the most extreme market scenario, compared to 0.36 and 0.33 with and without NCC respectively in the baseline configuration. This is because the CCP has a larger DF so it asks for more resources to replenish it from the CMs. The systemic losses are greatly reduced, at US$54.96 billion or 1.84% of remaining equity under NCC compared to US$125.58 billion or 4.18% of remaining equity in the baseline configuration, and US$44.29 billion or 1.52% of remaining equity without NCC compared to US$105.02 billion or 3.57% of remaining equity in the baseline configuration. As a result, the defaults due to counterparty risk also decrease, at 0.65 under NCC and 0.80 without compared to 1.65 and 1.48 respectively in the baseline configuration.

Finally, the total systemic losses decrease under severe stress conditions, reaching

[19] This analysis is partial in the sense that it does not capture the change in CMs' incentive to centrally clear if CCP margin costs double. As such, systemic risk could increase if they migrate transactions outside of CCPs.

US$260.82 billion or 8.17% of total equity under NCC compared to US$315.16 billion or 9.87% of total equity in the baseline configuration, and US$317.74 billion or 9.95% of total equity without NCC compared to US$359.61 billion or 11.26% of total equity in the baseline configuration. In other words, a more robust CCP decreases overall systemic risk because the increase in first-round losses due to the higher liquidity risk of CMs is more than offset by the decrease in second-round losses allocated by the CCP due to its larger resources.

6.2 Alternative LCR threshold

In this subsection we discuss the model results assuming that the banks default due to liquidity risk if their LCR drops below 70% instead of 100% as in the baseline configuration. In general, the reported effects are reduced if the banks have more available liquidity to pay their VM obligations, although the actual resources that they can utilize for their derivatives activities are likely to be only a fraction of their total HQLA. The results are reported in Table 7 in Appendix B.

The number of defaults due to liquidity risk on day 1 is substantially reduced since banks have more HQLA available, reaching 2.98 in extreme stress under NCC and 1.92 without, higher under NCC by 55.21%, compared to 11.53 and 8.48 respectively in the baseline configuration, higher under NCC by 35.97%. This leads to systemic losses of up to US$52.34 billion under NCC and US$65.83 billion without, or 1.64% and 2.06% of total equity respectively, reduced by 20.50% under NCC. These compare to the baseline results of US$189.59 billion or 5.94% of the total equity under NCC and US$254.59 billion or 7.97% of total equity without, reduced by 25.53% under NCC. As a result, the number of defaults due to counterparty risk is also lower, reaching 0.03 under NCC and 0.19 without in extreme stress, decreased by 84.21% under NCC, compared to 0.13 and 0.67 respectively in the baseline configuration, decreased by 80.60% under NCC. The CCP's uncollateralized losses reach US$58.55 billion under NCC and US$50.25 billion without, increased by 16.52% with the introduction of NCC, compared to US$221.12 billion and US$194.79 billion respectively in the baseline configuration, increased by 13.52% with NCC. Hence, even though the magnitude of day 1 defaults and losses decreases when we lower the minimum LCR bound, the relative difference between the two configurations with and without NCC remains similar, which provides support to our baseline results regarding the effects of NCC.

On day 2, the number of defaults due to liquidity risk again decreases, reaching only 0.01 under extreme stress with and without NCC compared to 0.36 and 0.33 in the baseline configuration. The systemic losses are also lower, at US$23.53 billion under NCC or 0.75% of remaining equity, and US$16.61 billion without or 0.53% of remaining equity, higher under NCC by 41.64%. These compare to the baseline results of US$125.58 billion under NCC or 4.18% of remaining total equity and US$105.02 billion without or 3.57% of remaining equity, increased by 19.62% under NCC. The resulting defaults due to counterparty risk reach 0.09 under NCC and 0.19 without, compared with 1.65 and 1.48 in the baseline configuration.

Finally, the total systemic losses reach US$75.87 billion or 2.38% of total equity under NCC and US$82.44 billion or 2.58% of total equity without, decreased by US$6.6 billion or 7.98% under NCC. This decrease is not statistically significant, in contrast to the decrease of 12.36% in total systemic losses in the baseline configuration from US$359.61 billion without NCC to US$315.16 billion following its introduction. This is because the decrease of day 1 losses of US$13.49 billion is more comparable to the increase of day 2 losses of US$6.92 billion, compared to the baseline configuration decrease of day 1 losses of US$65 billion and increase of day 2 losses of US$20.56 billion. In other words, when the banks utilize more resources to pay their VM obligations the beneficial effect of NCC at reducing first-round losses is almost entirely offset by the increase of second-round losses due to the CCP's operations, so the net effect on total systemic losses is less pronounced. This result further highlights the importance of containing the potential of the CCP to act as a source of contagion during extreme stress, as it can potentially negate the reduction of systemic losses originating from the market shock with the introduction of NCC.

6.3 Static market participants

In this subsection we discuss results from a static variant of the model. Under this configuration the CMs are not allowed to rebalance their portfolios following the shock on the first day but they passively accept the resulting losses as they crystallize. This mimics the methodology of Heath et al. (2016) and serves as a useful benchmark in order to compare with our baseline configuration's results. We report the results in Table 8 in Appendix B.

Overall, we observe that the number of defaults on day 1 tends to be higher for mild shocks but slightly lower for severe shocks under the static configuration compared to the baseline one. This is because in the presence of small shocks and few distressed market participants, healthy CMs are able to accommodate the needs of the former so they are able to avoid default. However, once extreme shocks occur everyone runs for the exit due to large VM obligations and the system becomes more fragile (Pedersen, 2009).

In the most extreme market scenario, the first-round losses in the static setup are US$198.15 billion or 6.20% of total equity under NCC and US$249.63 billion or 7.82% of total equity without, compared to US$189.59 billion or 5.94% of total equity and US$254.59 billion or 7.97% of total equity respectively in the baseline configuration. While the number of defaults due to liquidity risk is higher in the baseline configuration, the systemic losses are comparable. This is because in the baseline configuration there is a higher number of defaults of small (periphery) banks and lower number of defaults of core (large) banks. Intuitively, larger banks would be more resilient to liquidity shocks than smaller ones and be able to more quickly adapt to changing market conditions.

Due to the similar systemic losses, the number of defaults due to counterparty risk remains virtually the same, at 0.13 and 0.66 with and without NCC respectively, compared to 0.13 and 0.67 in the baseline configuration. The CCP also sustains similar losses, US$220.49 billion with NCC and US$192.94 billion without compared to US$221.12 billion and US$194.79 billion in the baseline configuration respectively, leading to similar second-round losses. These are capped at US$120.98 billion or 4.04% of remaining equity under NCC and US$104.31 billion or 3.54% of remaining equity without, compared to US$125.58 billion or 4.18% of remaining equity and US$105.02 billion or 3.57% of remaining equity respectively in the baseline configuration.

Finally, the total systemic losses in the most extreme market scenario under the static setup are US$319.13 billion or 9.99% of total equity under NCC and US$353.94 billion or 11.08% of total equity without, compared to US$315.16 billion or 9.87% of total equity and

US\$359.61 billion or 11.26% of total equity respectively under the baseline configuration. While the results in terms of total systemic risk are similar between the baseline and static configurations, which provides robustness to our main findings, the change in the composition of defaulting banks highlights the fragility of the system during times of stress.

6.4 CCP interoperability

In the final subsection we discuss results from an alternative model configuration which showcases how our framework can be used to assess a variety of different policies. In particular, we consider the case of two competing CCPs which may or may not be linked to each other through interoperability arrangements. Such arrangements allow for a buyer and a seller to clear their trade through different CCPs, which makes the CCPs clearing members to each other.

The main benefit arising from interoperability is the reduction of exposures in a fragmented clearing market since positions can be netted across CCPs, thus lowering the margin costs of market participants. On the other hand, interoperability arrangements can potentially increase systemic risk because they create exposures between CCPs so a CM default in one CCP can lead to spillover losses to CMs of the other CCP. Furthermore, CCPs do not have control over the amount of exposure that can build up between them as it depends on the CMs' trades.

To date, CCP interoperability has been mainly applied in vanilla securities rather than derivatives CCPs due to the inherently higher complexity of managing risks of derivatives contracts with long maturities, which has hampered its widespread adoption (McPartland and Lewis, 2016). Theoretical research has found that CCP interoperability can lead to significant reduction of exposures in fragmented clearing markets, but at the same time it can also increase systemic risk due to under-collateralization of cross-CCP exposures (Mägerle and Nellen, 2015). In our paper, we attempt to quantify the trade-off between decreased exposures and increased CCPs' propensity for contagion. While our results are stylized and do not take into account all the complexities that would arise from derivatives CCP interoperability arrangements, we contribute by providing empirical estimates of the trade-off to assess which effect dominates.

As mentioned before, we consider two competing CCPs. In the case where there are no interoperability arrangements, we assume that the first CCP manages the majority of the trades of the Core-16 banks, while the second CCP caters for the trades of the Periphery-23 banks between themselves and with the Core-16 banks. In other words, with no interoperability the Core-16 banks are CMs of both CCPs, while the Periphery-23 banks are CMs of the second CCP only. As a result, in this configuration collateral requirements are not efficient since the Core-16 banks' exposures are fragmented across two CCPs, leading to higher IM requirements. Specifically, the first CCP collects US$156.2 billion in IM while the second CCP collects US$123.2 billion, so the total IM collected is US$279.4 billion. This is 25% higher than the IM posted in the baseline configuration of US$224.3 billion, a significant increase.

When interoperability arrangements exist, the Core-16 banks do not need to be CMs of the second CCP in order to accommodate the Periphery-23 banks' trades. Hence, in this case the Core-16 banks are CMs of the first CCP only while the Periphery-23 banks are CMs of the second CCP as before. However, the CCPs now have an exposure between themselves equal to the value of the trades between the Core-16 and Periphery-23 banks. This configuration lowers the IM requirements to the same level as in the baseline configuration because of the netting benefits, with the first CCP collecting US$172.9 billion in IM and the second one collecting US$51.4 billion for a total of US$224.3 billion.

Apart from these changes the model works as before, although in the case of interoperability if a CM of one CCP indirectly connected to the CM of the other defaults and creates losses for the CCP that are not covered by its pre-funded resources, these losses can be transmitted to the other CCP and mutualized across its CMs. For ease of exposition, we assume that non-central clearing is present in both configuration in order not to confound our results. The results are presented in Table 9 in Appendix B.

On day 1, defaults due to liquidity risk remain significantly lower under interoperability compared to without in all cases, reaching 11.63 and 13.17 on average respectively in the most extreme market scenario. This is because as explained before the presence of interoperability lowers the system-wide IM requirements and hence the CMs' liquidity encumberment. This translates into lower day 1 systemic losses, reaching US$189.78 billion or 5.94% of initial equity under interoperability and US$220.51 billion or 6.90% of initial equity without, reduced by 13.93%. The resulting defaults due to counterparty risk are thus also lower under interoperability compared to without, at 0.11 and 0.16 respectively, although there is no statistical difference between them.

The first CCP suffers slightly lower uncollateralized losses under interoperability compared to without as a result of the lower number of defaults due to liquidity risk, reaching US$183.98 billion and US$185.88 billion respectively under extreme market stress, statistically the same. However, the second CCP's losses under interoperability are significantly lower compared to without, reaching US$31.37 billion and US$93.01 billion respectively, a reduction of 66.28%. This is because without interoperability it includes all 39 banks as CMs while with interoperability only the Periphery-23 banks are its CMs. As a result, its exposures are greatly reduced under interoperability as the Core-16 banks do not need to act as its CMs to accommodate the Periphery-23 banks' trades, leading to lower losses in times of stress.

On day 2, defaults due to liquidity risk are slightly higher under interoperability compared to without, at 0.43 and 0.28 respectively. The systemic losses reach US$101.59 billion or 3.38% of remaining equity under interoperability and US$122.99 billion or 4.14% of remaining equity without, reduced by 17.40%. This is because even though under interoperability there is transmission of losses across CCPs, they only reach US$250 million after taking into account the collateral which are more than offset by the significant reduction of the second CCP's uncollateralized losses and their subsequent mutualization across its CMs. As a result, the number of defaults due to counterparty risk due to VMGH decreases by 24.41% with the introduction of interoperability from 1.68 to 1.27. Finally, the total systemic losses always remain lower under interoperability compared to without, reaching US$291.37 billion or 9.12% of total equity and US$343.49 billion or 10.75% of total equity respectively, reduced by 15.17%.

Our results indicate that interoperability arrangements can in fact reduce liquidity, counterparty and systemic risks. As long as their introduction leads to smaller CCPs in terms of membership base, the resulting reduction in CCP uncollateralized losses more than offsets cross-CCP losses that can occur even under extreme market conditions, while the netting benefits result in lower CM liquidity encumberment and further reduction of CCP losses. To the best of our knowledge, this is a novel finding in the small literature on CCP interoperability arrangements. While it is not intended to guide policy due to the stylized nature of the model, it indicates that further research should be conducted to assess how interoperability can affect systemic risk.

7 Conclusion

In this paper we develop a network model incorporating the largest dealer banks in the OTC derivatives markets as well a fictitious CCP that is the dominant counterparty. We consider two system configurations, one in which the banks post collateral between themselves in bilateral transactions and one in which they don't in order to assess the effects of non-central clearing on counterparty, liquidity and systemic risks.

We report the effectiveness of non-central clearing at reducing counterparty and systemic risks under mild and severe market conditions. Even though a higher number of market participants default on their obligations due to liquidity risk under extreme stress following the introduction of non-central clearing, the collateral posted in bilateral trades results in lower systemic losses and protects market participants from counterparty risk.

However, the implications for the relationship between central and non-central clearing are less clear-cut. A higher number of defaulting banks due to increased liquidity risk leads to higher losses for the CCP which in turn transmits them back to the surviving market participants. This effect is reduced as the CCP becomes more dominant in the market but the knock-on losses originating from the CCP may surpass those due to the initial market shock as a result. Hence, our analysis suggests that the introduction of non-central clearing also necessitates the review of CCP collateral requirements and/or loss allocation mechanisms in order to avoid amplifying their role as system destabilizers in extreme stress as already theoretically documented. Indeed, our model results suggest that an increase in

CCPs' resources reduces overall systemic risk although the analysis remains partial as it does not take into account the potential migration of trades outside of CCPs as a result of the higher CCP margin costs.

To conclude, our paper provides a quantitative assessment of the potential sources of stress in the cleared OTC derivatives markets. We highlight the importance of liquidity risk during times of stress and its potential to destabilize the CCP, leading to significant feedback effects. We have used the framework to empirically assess various recommendations regarding the optimal CCP design that will maximize the welfare of itself and its members such as interoperability arrangements. Future work can expand the framework to provide further insights.

References

Abruzzo, N. and Park, Y.-H. (2016). An empirical analysis of futures margin changes: determinants and policy implications. *Journal of Financial Services Research*, 49(1):65–100.

Acharya, V. V. (2009). A theory of systemic risk and design of prudential bank regulation. *Journal of Financial Stability*, 5:224–255.

Acharya, V. V. and Bisin, A. (2014). Counterparty risk externality: Centralized versus over-the-counter markets. *Journal of Economic Theory*, 149:153–182.

Acharya, V. V., Pedersen, L. H., Philippon, T., and Richardson, M. (2017). Measuring systemic risk. *The Review of Financial Studies*, 30(1):2–47.

Acharya, V. V. and Yorulmazer, T. (2008). Cash-in-the-market pricing and optimal resolution of bank failures. *The Review of Financial Studies*, 21(6):2705–2742.

Adrian, T. and Brunnermeier, M. K. (2016). CoVaR. *American Economic Review*, 106(7):1705–41.

Amini, H., Filipović, D., and Minca, A. (2015). Systemic risk and central clearing counterparty design. Swiss Finance Institute Research Paper No. 13-34.

Bank of England (2015). The Bank of England's approach to stress testing the UK banking system.

Bank of England (2020). Interim Financial Stability Report May 2020.

BCBS-IOSCO (2015). Margin requirements for non-centrally cleared derivatives.

Biais, B., Heider, F., and Hoerova, M. (2012). Clearing, counterparty risk, and aggregate risk. *IMF Economic Review*, 60(2):193–222.

Bignon, V. and Vuillemey, G. (2018). The failure of a clearinghouse: Empirical evidence. *Review of Finance*, pages 1–30.

BIS (2015). Summary of changes to the implementation of the margin requirements for non-centrally cleared derivatives. Retrieved from https://www.bis.org/bcbs/publ/d317_summarytable.pdf.

BIS (2017). OTC derivatives statistics at end-december 2016.

BIS (2019). OTC derivatives statistics at end-december 2018.

Brunnermeier, M. and Cheridito, P. (2019). Measuring and allocating systemic risk. *Risks*, 7(2).

Brunnermeier, M. K. and Pedersen, L. H. (2009). Market liquidity and funding liquidity. *The Review of Financial Studies*, 22(6):2201–2238.

CFTC (2019). CCP Supervisory Stress Tests: Reverse Stress Test and Liquidation Stress Test.

Che, Y.-K. and Gale, I. (1998). Standard auctions with financially constrained bidders. *The Review of Economic Studies*, 65(1):1–21.

Cont, R. (2017). Central clearing and risk transformation. Financial Stability Review 21, Banque de France.

Cox, R. T. (2015). Central counterparties in crisis: The Hong Kong Futures Exchange in the crash of 1987. *Journal of Financial Market Infrastructures*, 4(2):73–98.

CPSS-IOSCO (2012). Principles for financial market infrastructures.

Craig, B. and Von Peter, G. (2014). Interbank tiering and money center banks. *Journal of Financial Intermediation*, 23(3):322–347.

Demekas, D. G. (2015). Designing effective macroprudential stress tests: Progress so far and the way forward. IMF Working Paper 15/146.

Diamond, D. W. and Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *Journal of Political Economy*, 91(3):401–419.

Domanski, D., Gambacorta, L., and Picillo, C. (2015). Central clearing: trends and current issues. BIS Quarterly Review.

Duffie, D., Scheicher, M., and Vuillemey, G. (2015). Central clearing and collateral demand. *Journal of Financial Economics*, 116(2):237–256.

Duffie, D. and Zhu, H. (2011). Does a central clearing counterparty reduce counterparty risk? *The Review of Asset Pricing Studies*, 1(1):74–95.

ESMA (2018). EU-wide CCP Stress Test 2017.

Farhi, E. and Tirole, J. (2012). Collective moral hazard, maturity mismatch, and systemic bailouts. *American Economic Review*, 102(1):60–93.

Ferrara, G., Li, X., and Marszalec, D. (2017). Central counterparty auction design. Bank of England Staff Working Paper No. 669.

G20 (2009). G20 leaders statement: The Pittsburgh Summit.

G20 (2011). G20 leaders statement: The Cannes Summit.

Ghamami, S. and Glasserman, P. (2017). Does OTC derivatives reform incentivize central clearing? *Journal of Financial Intermediation*, 32:76–87.

Gilboa, I. and Schmeidler, D. (1989). Maximin expected utility with non-unique prior. *Journal of Mathematical Economics*, pages 141–153.

Glasserman, P., Moallemi, C. C., and Yuan, K. (2016). Hidden illiquidity with multiple central counterparties. *Operations Research*, 64(5):1143–1158.

Gorton, G. and Metrick, A. (2012). Securitized banking and the run on repo. *Journal of Financial Economics*, 104(3):425–451.

Gregory, J. (2014). *Central Counterparties: Mandatory Central Clearing and Initial Margin Requirements for OTC Derivatives*. John Wiley & Sons.

Heath, A., Kelly, G., Manning, M., Markose, S., and Shaghaghi, A. R. (2016). CCPs and network stability in OTC derivatives markets. *Journal of Financial Stability*, 27:217–233.

Huang, W. and Takáts, E. (2020). The CCP-bank nexus in the time of Covid-19. BIS Bulletin No. 13.

ICEU (2017). ICE Clear Europe Clearing Rules. Retrieved from https://www.theice.com/publicdocs/clear_europe/rulebooks/rules/Clearing_Rules.pdf.

ISDA (2014a). Dispelling Myths: End-User Activity in OTC Derivatives.

ISDA (2014b). ISDA Margin Survey 2014.

ISDA (2015). CCP default management, recovery and continuity: A proposed recovery framework.

King, T. B., Nesmith, T. D., Paulson, A. L., and Prono, T. (2020). Central clearing and systemic liquidity risk. FEDS Working Paper.

Loon, Y. C. and Zhong, Z. K. (2014). The impact of central clearing on counterparty risk, liquidity, and trading: Evidence from the credit default swap market. *Journal of Financial Economics*, 112(1):91–115.

MAGD (2013). Macroeconomic impact assessment of OTC derivatives regulatory reforms. Technical report, BIS.

Markose, S. (2012). Systemic risk from global financial derivatives: A network analysis of contagion and its mitigation with super-spreader tax. IMF Working Paper 12/282.

McPartland, J. and Lewis, R. (2016). The challenges of derivatives central counterparty interoperability arrangements. *Journal of Financial Market Infrastructures*, 4(4):41–51.

Menkveld, A. J. (2016). Systemic risk in central clearing: Should crowded trades be avoided? Working paper, VU Amsterdam.

Milgrom, P. R. and Weber, R. J. (1982). A theory of auctions and competitive bidding. *Econometrica*, 50(5):1089–1122.

Mägerle, J. and Nellen, T. (2015). Interoperability between central counterparties. *Journal of Financial Market Infrastructures*, 4(2):49–71.

Paddrik, M., Rajan, S., and Young, H. P. (2020). Contagion in Derivatives Markets. *Management Science*, pages 1–14.

Pedersen, L. H. (2009). When everyone runs for the exit. *International Journal of Central Banking*, 5(4):177–199.

Pirrong, C. (2014). A bill of goods: central counterparties and systemic risk. *Journal of Financial Market Infrastructures*, 2(4):55–85.

Rochet, J.-C. and Tirole, J. (1996). Interbank lending and systemic risk. *Journal of Money, Credit and Banking*, 28(4):733–762.

A CCP auction optimal bidding function

In this section we derive the optimal bidding function of our auction setup which coincides with the one from the IPV model.

Consider M risk-neutral bidders (the participating CMs), each assigning a private and independent value u_i on the auction item, in this case the defaulting CMs' portfolio. Each bidder knows its valuation and the fact that the opponents' valuations are drawn independently from the same distribution F with density f and support $[\underline{u}, \overline{u}]$. Note that it may be that $\underline{u} < 0$ and $\overline{u} > 0$ since the CMs may assign both positive and negative values to the portfolio depending on their existing positions as explained in the main text.

Let the payoff of each bidder be:

$$\pi_i = \begin{cases} u_i - b_i - q_i \text{ if } b_i > \max_{j \neq i} b_j \\ -q_i \text{ otherwise} \end{cases} \tag{A.1}$$

where u_i is the private valuation, b_i is the bid and q_i is a loss function that depends on the bidder's DF contribution, the uncollateralized losses faced by the CCP and the resources used by the CCP prior to the bidder's Powers of Assessment contribution which include the defaulted CMs' IM, the entire DF, the skin-in-the-game equity and any other bidders' Powers of Assessment contributions used according to the bidding behavior. Except for its own DF contribution, the equity contribution of the CCP and the total DF amount, all other quantities are unknown to the bidder.

The total VM owed to the CCP by defaulted CMs belonging in the set H is $\sum_{h \in H} VM_{hi}^0$. Note that CMs that defaulted due to missed VM receipts violating condition (15) have successfully repaid their VM obligations since they satisfy condition (14) hence they do not owe VM to the CCP. As such we only consider here the subset H that includes the CMs that violated (14) and not D that also includes those that failed condition (15). The function is of the form:

$$q_i = \min\left\{2F_i, \max\left\{0, \sum_{h \in H} VM_{hi}^0 - \left(\sum_{h \in H} IM_{hi}^0 + T + DF + \sum_{k \in K} 2F_k\right)\right\}\right\} \text{ for } j = n+1 \tag{A.2}$$

where T is the equity tranche used by the CCP and K is the set of bidders having posted lower bids than bidder i and have responded to the Powers of Assessment in full by contributing twice their original DF amounts F_k. The number of bidders belonging in this set increases as the bid posted by bidder i increases in ranks. Hence, if the losses are sufficiently covered by the Powers of Assessment the function decreases to zero as the ranking of the bid increases. However, the only known variables to CM i are F_i, T and DF.

Since the function is capped at $2F_i$, the worst-case scenario is the one where the expected payoff is minimized, i.e. the one where the loss function is maximized in every state of nature irrespectively of the bidding order. Formally, each bidder chooses a value $x_i \in [\underline{u}, \overline{u}]$ to assign to the bid $b_i = b(x_i)$ to maximize the expected payoff $\pi_i = \pi(x_i)$ given the least favorable state of nature according to the maximin operator:

$$\max_{x_i} \min_{q_i \in Q} \left\{ [u_i - b_i - q_i] \mathrm{P}\left[b_i > \max_{j \neq i} b_j \right] - \sum_{m=3}^{M} q_i \mathrm{P}\left[b_i > \{b\} \right] - q_i \mathrm{P}\left[b_i < \min_{j \neq i} b_j \right] \right\} \quad \text{(A.3)}$$

where $\mathrm{P}[\cdot]$ denotes the probability, Q denotes the set of all possible values of q_i and $\{b\} = \{b_m, \ldots, b_M\}$ denotes the set of ordered bids.

This equals:

$$\max_{x_i} \left\{ [u_i - b_i - 2F_i] \mathrm{P}\left[b_i > \max_{j \neq i} b_j \right] - \sum_{m=3}^{M} 2F_i \mathrm{P}\left[b_i > \{b\} \right] - 2F_i \mathrm{P}\left[b_i < \min_{j \neq i} b_j \right] \right\} \quad \text{(A.4)}$$

or simply:

$$\max_{x_i} \left\{ [u_i - b_i] \mathrm{P}\left[b_i > \max_{j \neq i} b_j \right] - 2F_i \right\} \quad \text{(A.5)}$$

since the loss $2F_i$ occurs in all states of nature, i.e. with probability 1.

The probability that a bid is the k-th highest among M bids is given by order statistics:

$$\mathrm{P}[b(x_1), ..., > b(x_{k-1}) > b(x_k) > b(x_{k+1}), ..., > b(x_M)]$$

$$= \mathrm{P}[x_1, ..., > x_{k-1} > x_k > x_{k+1}, ..., > x_M]$$
$$= \binom{M-1}{k-1} (1 - F(x_i))^{k-1} F(x_i)^{M-k}$$

Note that the second line uses the assumption of b being strictly increasing in x.

Hence the probability of winning ($k = 1$) is equal to:

$$\mathrm{P}\Big[b_i > \max_{j \neq i} b_j\Big] = F(x_i)^{M-1} \tag{A.6}$$

As such the payoff becomes:

$$\max_{x_i} \Big\{[u_i - b_i]F(x_i)^{M-1} - 2F_i\Big\} \tag{A.7}$$

First order condition (FOC) yields:

$$\frac{\vartheta \pi(x_i)}{\vartheta x_i} = \pi'(x_i) = 0 \Leftrightarrow (M-1)F(x_i)^{M-2}f(x_i)(u_i - b(x_i)) - b'(x_i)F(x_i)^{M-1} = 0 \tag{A.8}$$

As can be seen, the Powers of Assessment contribution $2F_i$ disappears in the FOC. In that case, this is the standard IPV model.

In a symmetric equilibrium the expected profit is maximized at $x_i = u_i$.

We solve for the optimal bid as follows. From (A.8):

$$\begin{aligned} b'(u_i)F(u_i)^{M-1} &= (M-1)F(u_i)^{M-2}f(u_i)(u_i - b(u_i)) \\ \Leftrightarrow [b(u_i)F(u_i)^{M-1}]' &= u_i(M-1)F(u_i)^{M-2}f(u_i) \end{aligned} \tag{A.9}$$

This is an ordinary differential equation which can be solved by integration:

$$\begin{aligned} \int_{\underline{u}}^{u_i} d[b(x_i)F(x_i)^{M-1}]' &= \int_{\underline{u}}^{u_i} x_i(M-1)F(x_i)^{M-2}f(x_i)dx_i \\ \Leftrightarrow b(u_i)F(u_i)^{M-1} - b(\underline{u})F(\underline{u})^{M-1} &= \int_{\underline{u}}^{u_i} x_i(M-1)F(x_i)^{M-2}f(x_i)dx_i \end{aligned}$$

Since $F(\underline{u}) \to 0$ solving for $b(u_i)$ yields the optimal equilibrium bid:

$$b(u_i) = \begin{cases} \frac{(M-1)\int_{\underline{u}}^{u_i} x_i F(x_i)^{M-2} f(x_i) dx_i}{F(u_i)^{M-1}} \text{ if } \underline{u} < u_i \leq \overline{u} \\ -\infty \text{ if } u_i = \underline{u} \end{cases} \tag{A.10}$$

i.e. equation (22).

To verify that $x_i = u_i$ is indeed an equilibrium it suffices to show from (A.8) that:

$$\begin{aligned} &(M-1)F(x_i)^{M-2}f(x_i)(u_i - b(x_i)) - b'(x_i)F(x_i)^{M-1} = 0 \\ &\Leftrightarrow (M-1)F(x_i)^{M-2}f(x_i)(u_i - x_i) = 0 \end{aligned} \tag{A.11}$$

Hence from (A.11) if $x_i < u_i$ then $\pi'(x_i) > 0$ and if $x_i > u_i$ then $\pi'(x_i) < 0$ so $x_i = u_i$ maximizes the expected payoff and the optimal solution is an equilibrium.

B Additional tables

Table 5: Market participants

Core-16	**Periphery-23**
Bank of America Merrill Lynch	ANZ Banking Group
Barclays	Banca IMI SpA
BNP Paribas	Banco Santander
Citigroup	Bank of China
Crédit Agricole	Bank of New York Mellon
Credit Suisse	BBVA
Deutsche Bank	Commerzbank
Goldman Sachs	Commonwealth Bank
HSBC	Danske Bank
JP Morgan Chase	Dexia
Morgan Stanley	DZ Bank
Nomura Group	Intesa
Royal Bank of Scotland	LBBW
Société Générale	Lloyds Banking Group
UBS Mitsubishi	UFJ
Wells Fargo	Mizuho
	National Australia Bank
	Nordea Bank
	Rabobank
	Standard Chartered
	State Street
	UniCredit Group
	Westpac

Source: MAGD (2013)

Table 6: Increased CCP resources configuration results. This table reports results assuming that the CCP has double the resources it collects in the baseline configuration. The CCP is assumed to clear 75% of all derivatives transactions, and the banks default due to liquidity risk if their LCR drops to less than 100% and due to counterparty risk if their CAR drops to less than 8%. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Panel A: Day 1 results				
	Shock	With NCC	Without NCC	% Reduction
Defaults due to liquidity risk	$2.33\sigma_0$	1.36	0.53	-156.60^{***}
	$3\sigma_0$	1.77	0.62	-185.48^{***}
	$10\sigma_0$	5.76	4.00	-44.00^{***}
	$20\sigma_0$	12.87	9.79	-31.46^{***}
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.85	100.00^{***}
	$3\sigma_0$	0.00	1.41	100.00^{***}
	$10\sigma_0$	19.34	68.95	71.95^{***}
	$20\sigma_0$	205.86	273.46	24.72^{***}
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.01	100.00
	$20\sigma_0$	0.17	0.80	78.75^{***}
CCP uncollateralized losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.00	0.00
	$20\sigma_0$	141.36	127.24	-11.10^{***}
Panel B: Day 2 results				
Defaults due to liquidity risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.00	0.00
	$20\sigma_0$	0.74	0.55	-34.55^{**}
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.00	0.00
	$20\sigma_0$	54.96	44.29	-24.09^{***}
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.00	0.00
	$20\sigma_0$	0.65	0.80	18.75
Panel C: Days 1&2 results				
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.85	100.00^{***}
	$3\sigma_0$	0.00	1.41	100.00^{***}
	$10\sigma_0$	19.34	68.95	71.95^{***}
	$20\sigma_0$	260.82	317.74	17.92^{***}

Table 7: Alternative LCR threshold configuration results. This table reports results assuming a lower LCR threshold. The CCP is assumed to clear 75% of all derivatives transactions, and the banks default due to liquidity risk if their LCR drops to less than 70% and due to counterparty risk if their CAR drops to less than 8%. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

	Shock	With NCC	Without NCC	% Reduction
Panel A: Day 1 results				
Defaults due to liquidity risk	$2.33\sigma_0$	0.07	0.01	−600.00**
	$3\sigma_0$	0.06	0.02	−200.00
	$10\sigma_0$	0.30	0.12	−150.00**
	$20\sigma_0$	2.98	1.92	−55.21***
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.01	100.00
	$10\sigma_0$	1.07	3.38	68.42**
	$20\sigma_0$	52.34	65.83	20.50***
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.01	100.00
	$20\sigma_0$	0.03	0.19	84.21***
CCP uncollateralized losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	2.49	2.02	−23.17
	$20\sigma_0$	58.55	50.25	−16.52*
Panel B: Day 2 results				
Defaults due to liquidity risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.00	0.00
	$20\sigma_0$	0.01	0.01	0.00
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.00	0.00
	$20\sigma_0$	23.53	16.61	−41.64**
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.00	0.00
	$20\sigma_0$	0.09	0.19	52.63*
Panel C: Days 1&2 results				
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.01	100.00
	$10\sigma_0$	1.07	3.38	68.42**
	$20\sigma_0$	75.87	82.44	7.98

Table 8: Static configuration results. This table reports results assuming that the banks do not rebalance their portfolios following the market shock. The CCP is assumed to clear 75% of all derivatives transactions, and the banks default due to liquidity risk if their LCR drops to less than 100% and due to counterparty risk if their CAR drops to less than 8%. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Panel A: Day 1 results				
	Shock	With NCC	Without NCC	% Reduction
Defaults due to liquidity risk	$2.33\sigma_0$	3.34	1.21	-176.03^{***}
	$3\sigma_0$	3.58	1.37	-161.31^{***}
	$10\sigma_0$	6.42	3.78	-69.84^{***}
	$20\sigma_0$	10.85	8.14	-33.29^{***}
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	3.05	100.00^{***}
	$3\sigma_0$	0.00	5.36	100.00^{***}
	$10\sigma_0$	24.49	66.70	63.28^{***}
	$20\sigma_0$	198.15	249.63	20.62^{***}
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.02	100.00
	$20\sigma_0$	0.13	0.66	80.30^{***}
CCP uncollateralized losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	49.48	31.84	-55.42^{***}
	$20\sigma_0$	220.49	192.94	-14.28^{***}
Panel B: Day 2 results				
Defaults due to liquidity risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.25	0.01	-2400.00^{***}
	$20\sigma_0$	0.56	0.03	-1766.67^{***}
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	15.57	3.73	-317.17^{***}
	$20\sigma_0$	120.98	104.31	-15.98^{***}
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.00	0.00
	$20\sigma_0$	1.62	1.45	-11.72
Panel C: Days 1&2 results				
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	3.05	100.00^{***}
	$3\sigma_0$	0.00	5.36	100.00^{***}
	$10\sigma_0$	40.06	70.43	43.12^{***}
	$20\sigma_0$	319.13	353.94	9.84^{***}

Table 9: Interoperability configuration results. This table reports results assuming that two CCPs clearing 75% of all derivatives transactions may or may not form interoperability arrangements. The banks default due to liquidity risk if their LCR drops to less than 100% and due to counterparty risk if their CAR drops to less than 8%. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

	Shock	With Interop.	Without Interop.	% Reduction
Panel A: Day 1 results				
Defaults due to liquidity risk	$2.33\sigma_0$	0.71	0.73	2.74
	$3\sigma_0$	0.72	1.00	28.00**
	$10\sigma_0$	4.71	5.78	18.51***
	$20\sigma_0$	11.63	13.17	11.69***
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	16.38	20.09	18.45***
	$20\sigma_0$	189.78	220.51	13.93***
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.00	0.00
	$20\sigma_0$	0.11	0.16	31.25
CCP 1 uncollateralized losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	30.95	35.23	12.15**
	$20\sigma_0$	183.98	185.88	1.02
CCP 2 uncollateralized losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.65	9.95	93.44***
	$20\sigma_0$	31.37	93.01	66.28***
Panel B: Day 2 results				
Defaults due to liquidity risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.10	0.11	9.09
	$20\sigma_0$	0.43	0.28	−53.57**
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	4.10	7.52	45.42***
	$20\sigma_0$	101.59	122.99	17.40***
Defaults due to counterparty risk	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	0.00	0.00	0.00
	$20\sigma_0$	1.27	1.68	24.41***
Panel C: Days 1&2 results				
Systemic losses (US$ billion)	$2.33\sigma_0$	0.00	0.00	0.00
	$3\sigma_0$	0.00	0.00	0.00
	$10\sigma_0$	20.49	27.61	25.79***
	$20\sigma_0$	291.37	343.49	15.17***