Systemic Stress Testing under Central and Non-Central Clearing

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Abstract

Following the global financial crisis, central counterparties (CCPs) have become key participants in the OTC derivatives markets by clearing an increasing proportion of these contracts in accordance with international regulations put forth to mitigate systemic risk. Furthermore, since 2016 non-centrally cleared contracts have also been subject to clearing regulations in order to facilitate their effective risk management. We empirically assess the effects of the introduction of non-central clearing in the presence of central clearing on counterparty, liquidity and systemic risks by developing a dynamic macroprudential stress testing network model of the largest market participants in the OTC derivatives market. We show that non-central clearing substantially reduces systemic risk in most cases. However, in extreme market conditions the CCP acts as a source of contagion and its detrimental effects to financial stability are amplified in the presence of non-central clearing because of the increased liquidity risk of the market participants, mitigating the beneficial effects of non-central clearing. For the same reason, the expansion of central clearing may increase systemic risk following the implementation of non-central clearing in contrast to the intention of regulators.

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

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

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1 Introduction

Credit default swaps (CDS) were instrumental in facilitating the collapse of Lehman Brothers and AIG during the financial crisis. These derivative contracts were traded over-the-counter (OTC) and the lack of market transparency prompted the regulators to respond following these extraordinary events.

As a result, the G20 leaders mandated in Pittsburgh in September 2009 that: "All standardized OTC derivative contracts should be traded on exchanges or electronic trading platforms, where appropriate, and cleared through central counterparties by end-2012 at the latest... Non-centrally cleared contracts should be subject to higher capital requirements" [G20, 2009].The aim was to reduce counterparty and systemic risks in the financial markets.

The mandate addresses two key concepts, central and non-central clearing. Central clearing involves trading contracts through clearing houses aka central counterparties (CCPs) which interpose themselves between counterparties by becoming the buyer to every seller and the seller to every buyer. Since CCPs concentrate counterparty risk to themselves, they protect themselves by collecting collateral called Initial Margin (IM) from market participants and marking-to-market all positions daily by transferring cash-flows called Variation Margin (VM) from losing counterparties to winning ones. This results in a reduction of counterparty risk and greater market transparency as all trades are concentrated in a single venue. Non-central clearing was introduced in 2016 and involves the exchange of IM and VM between counterparties for the contracts not traded through a CCP, resulting in further reduction of counterparty risk [BIS, 2015].

In this paper we empirically assess the implications of the introduction of non-central clearing of OTC derivatives in the presence of central clearing for counterparty, liquidity and systemic risks. While the mandatory collateralization of bilaterally traded OTC derivatives is expected to reduce counterparty risk and spillover effects, it is also recognized that it may have a significant impact on the liquidity of the 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], we are interested in quantifying the effects of non-central clearing on these two forms of risk and as an extension assessing its effectiveness as a policy measure in promoting financial stability i.e. mitigating systemic risk.

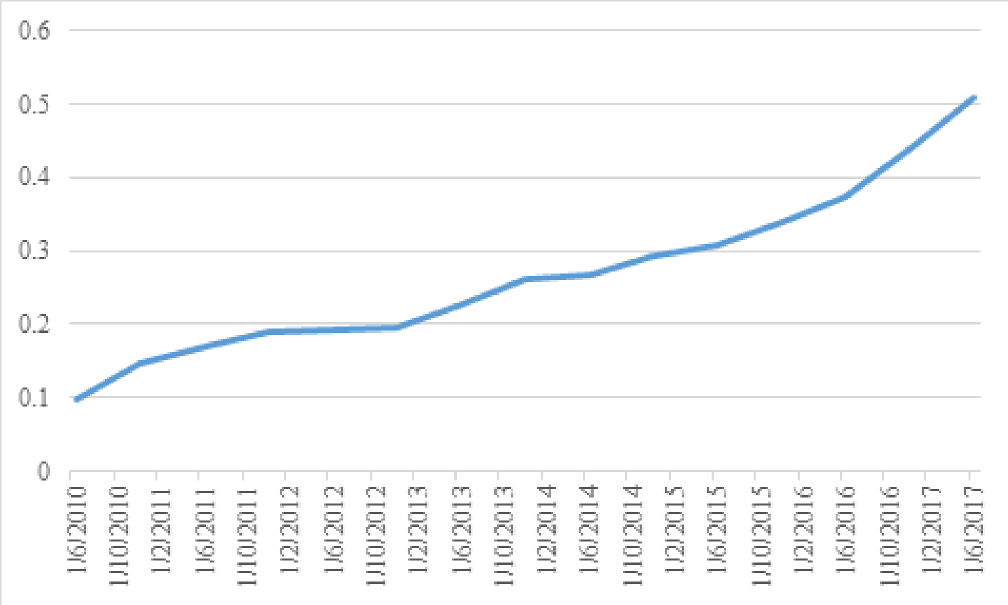
To illustrate ideas, consider first that IM and VM are deposited in the form of liquid assets. Hence, the introduction of non-central clearing increases the liquidity encumberment of market participants, making them more vulnerable to liquidity shocks that can occur in times of market stress. As [Cont, 2017] observes, in cleared markets counterparty risk is replaced by liquidity risk. However, while the major dealer banks' exposure to CCPs is not large relative to their capital cushion, the collateral requirements bind a large proportion of their available liquid resources. As a result, liquidity risk poses a more significant threat than counterparty risk for market participants and any new measures that increase it may be detrimental to financial stability. In addition, CCPs may contribute to financial instability in times of extreme stress due to their loss mutualization mechanisms that distribute losses to their members (Clearing Members – CMs) [Pirrong, 2014] [Domanski et al., 2015]. Once their pre-funded resources are depleted, CCPs may ask from CMs further liquidity contributions or apply haircuts to their VM gains.

Linking the two concepts together, we assess under which conditions the introduction of non-central clearing may prove to be detrimental to financial stability by increasing the number of CMs being in liquidity stress and defaulting on their VM obligations, leading to more losses for the CCP which transmits them back to the surviving participants, propagating contagion.

Assessing the implications of OTC derivatives clearing is crucial for numerous reasons. First, CCPs have become the dominant counterparties in several markets as a result of the new regulations.[1] Figure 1 depicts the fraction of centrally cleared CDS contracts in terms of gross notional from 2010 to 2017, which increased from 10% to 50% according to Bank for International Settlements (BIS) data. In addition, central clearing is predominant in the OTC interest rate derivatives market with CCPs managing 76% of total positions globally as of June 2017. While other derivative asset classes have not seen similar expansion, central clearing is gaining ground in them as well [BIS, 2017]. Second, the impact of major regulatory overhauls is expected to be economically significant given the size of the OTC derivatives market, standing at 542 US$ trillion gross notional as of June 2017. New regulations prompt market participants to readjust their positions and it is the aim of the regulators to incentivise them to migrate non-centrally cleared positions to centrally-cleared ones in order to reduce systemic risk [BCBS-IOSCO, 2015]. Whether such an outcome achieves the intended goal remains to be tested.

[1]The G20 mandate was enforced via the Dodd-Frank Act in the US [US, 2010] and the European Market Infrastructure Regulation (EMIR) in the EU [EU, 2012].

Figure 1: Fraction of centrally cleared CDS contracts



Source: BIS semiannual OTC derivatives statistics

Using data on the positions of the largest participating banks in the global OTC derivatives markets from their annual reports, we develop a dynamic macroprudential stress testing network model of market participants that act as optimizing agents in the presence of OTC derivatives clearing regulations. Macroprudential stress testing models have been developed as a response to the inability of the microprudential counterparts to capture the interdependencies between institutions which were identified as key to the emergence of the financial crisis.

In order to test the effectiveness of non-central clearing, we compare the model results under two configurations, with and without non-central clearing. As a result, we are able to quantify the systemic losses that may crystallize in times of stress in the presence of both central and non-central clearing or only in the presence of central clearing. We measure systemic risk simply as the total equity losses that occur in the system in times of stress due to OTC derivatives trading. Since our aim is to assess the effectiveness of non-central clearing in reducing total losses, we are not interested in the individual contribution of each market participant to these losses. As such, our simple aggregate measure of stress captures the size of capital losses that may occur due to OTC derivatives trading.

In addition, by considering two time periods we capture the dynamics that unfold during a stress period and the feedback effects originating from the CCP. Following a market shock and potential CM defaults due to liquidity or counterparty risk (first-round effects), we model the loss allocation mechanisms of the CCP and isolate the effects of the various forms of risk it poses to its members in order to include second-round effects into the model. This is key to deriving our results because by only measuring the losses due to the market shock one does not consider a truly systemic view. While non-central clearing indeed reduces counterparty risk and first-round losses in the system, this does not necessarily translate into lower systemic risk because of the negative repercussions for the CCP and as an extension for the surviving market partipants.

Finally, by incorporating optimizing agents we extend the static setup of balance sheet models which has been criticized as a major disadvantage of these models [Demekas, 2015]. The assumption of static market participants may mask the true extent of losses that may crystallize in times of stress because it does not take into account negative externalities that occur due to runs [Pedersen, 2009].

Our main finding is that the introduction of non-central clearing substantially reduces counterparty and systemic risks in all but the most extreme market conditions. The IM posted in bilateral transactions protects CMs from losses due to counterparty default without posing significant strain on their ability to pay their own VM obligations. The CCP has sufficient pre-funded resources to withstand the shocks and does not pose a risk to the CMs.

However, in the most extreme market conditions liquidity risk becomes substantial because of the large VM obligations and the introduction of non-central clearing severely impairs the CMs' ability to pay those obligations. As a result, a considerably higher number of CMs default due to liquidity risk which leads to more losses for the CCP compared to the configuration without non-central clearing. This transforms the CCP into a significant source of contagion which transmits more losses following the introduction of non-central clearing, leading to similar total systemic losses between the two configurations. In fact, the losses faced by the CMs originating from the CCP can be higher under non-central clearing by a factor as high as 12 compared to without non-central clearing.

Second, we empirically verify that liquidity risk is a much more significant source of stress than counterparty risk in cleared markets as predicted by [Cont, 2017] and this is amplified with the introduction of non-central clearing. The potential number of defaults due to liquidity risk is 4 times higher than those due to counterparty risk in extreme market stress without non-central clearing but rises to 13 times higher after its introduction.

Third, we test the prediction of regulatory authorities that the introduction of non-central clearing promotes financial stability by incentivizing market participants to switch to central clearing [BCBS-IOSCO, 2015]. Similarly to our main results, while in most cases the expansion of central clearing reduces systemic risk due to the beneficial effects of multilateral netting in reducing counterparty risk, in the most extreme market conditions systemic risk actually increases following the introduction of non-central clearing. This is because the increase of losses due to the feedback effects of the CCP on the second round more that offset the decrease of losses on the first one. In other words, the CCP transmits more losses on the second round due to its size than it helps reduce on the first one. This is not observed in the configuration without non-central clearing because of the lower number of CMs defaulting due to liquidity risk.

Fourth, we find that the optimizing behavior of each individual market participant may exacerbate systemic risk in extreme market conditions because once large VM obligations crystallize, everyone runs for the exit [Pedersen, 2009]. This makes it harder for distressed participants to close out their positions, leading to more defaults as postulated by [Brunnermeier and Pedersen, 2009]. As such, by only considering a static setup the potential losses may be underestimated in such cases. This has important policy implications because while a static setup clearly favours non-central clearing in terms of minimizing systemic losses, the version incorporating optimizing agents produces more ambiguous results due to its ability to capture more accurately the feedback effects that may occur in time of stress. Such effects may occur both due to direct as well as indirect links which should be captured by macroprudential stress testing models [Bank of England, 2015].

Our contribution to the literature is twofold. First, on the methodological side we extend existing empirical work on the modelling of the CCP's operations and in particular its loss allocation mechanisms [Heath et al., 2016]. This allows for a more clear appraisal of the ways a CCP may become a source of contagion for its members. We also incorporate optimizing agents into our framework in order to accurately capture the dynamics that may unfold due to the collective behaviour of the market participants.

Second, on the empirical side we test the effectiveness of non-central clearing of OTC derivatives in reducing counterparty and systemic risks. While the literature on central clearing has greatly expanded post-crisis due to the increasing importance of CCPs addressing issues such as counterparty risk [Duffie and Zhu, 2011] [Loon and Zhong, 2014], collateral demand [Duffie et al., 2015] and systemic risk

[Pirrong, 2014] [Capponi et al., 2015] [Amini et al., 2015] [Menkveld, 2016], non-central clearing has not been extensively researched partly because it has only been recently introduced. Further, while systemic risk under central clearing has been examined theoretically, empirical research remains scant in terms of contagion spread. The literature has focused instead on how to internalize into margin models externalities arising from crowded trades and high CM portfolio interdependence in order to reduce systemic risk [Cruz Lopez et al., 2017] [Menkveld, 2017]. We address these gaps and test the stability of the financial system in a unified framework that incorporates both central and non-central clearing.

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 reviews the relevant literature, section 4 describes the model, section 5 presents the data used in our study, section 6 presents the main results, section 7 discusses further results of sensitivity analysis and section 8 concludes.

2 Clearing regulations

The G20 mandate to promote central clearing was driven by the view that CCPs reduce counterparty risk and provide transparency in the markets by simplifying the complicated web of exposures in the OTC derivatives network since they concentrate all trades to themselves. However, since they become central nodes in the system they concentrate risk and can be a potential source of contagion in times of market stress if not properly managed.

In order to address those concerns, following the financial crisis the Committee on Payment and Settlement Systems (CPSS) and the International Organization of Securities Commissions (IOSCO) produced a set of standards for the operation of CCPs [CPSS-IOSCO, 2012]. These standards provide guidance for the sound management of various forms of risk including counterparty, liquidity and operational risks.

In addition, recognizing the concentration of risk in these entities due to their increased presence in the financial markets, there has been a focus on developing sound recovery and resolution mechanisms that would allow CCPs to continue their operations in times of extreme stress or default in an orderly manner without disrupting the operation of the markets [CPMI-IOSCO, 2014] [ISDA, 2015] [FSB, 2017].

Below we expose the main tools at the CCP's disposal to manage risk as well as their counterparts in non-centrally cleared transactions that we use in our model to derive our results.

The risk management procedures of the CCP are summarized in a structure called the risk waterfall because it is comprised of multiple lines of defence. The CCP collects IM as collateral at contract initiation from both counterparties. The IM must cover at least 99% of exposures movements over an appropriate time horizon under normal market conditions (see Principle 6 [CPSS-IOSCO, 2012] and Article 41 [EU, 2012]). This implies that CCPs apply a minimum of 99% Value-at-Risk (VaR) as the IM. 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].

As an additional line of defence, in accordance with international standards ([CPSS-IOSCO, 2012] and Article 42 [EU, 2012]), the CCP is obligated to hold a pre-funded mutualized pool of resources called the Guaranty Fund (GF) that can be used in the case losses exceed the IM posted to cover them. The GF 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 GF is funded by the CMs on a pro-rata basis based on their IM contributions.

The CCP also commits part of its capital to absorb losses. This "skin-in-the-game" is typically used after the defaulting member's IM and GF contributions and before other members' GF 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 members. Nonetheless, there has been considerable discussion on the optimal capital pledge that would balance CCP incentives and exposure [ISDA, 2014c].

If all the pre-funded resources are depleted and the CCP still faces losses, it enters into the recovery and resolution mechanisms which are built into its Default Management Process (DMP). Recovery plans include the Powers of Assessment, VM gains haircuts (VMGH) to the winning counterparties and partial tear-up of contracts.

If the losses exceed both the IM and GF resources, the CCP may, under its Powers of Assessment, request from surviving CMs to provide additional resources limited to a certain multiple of their original GF contributions in order to avoid insolvency. 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].

The effectiveness of the Powers of Assessment is a matter of debate. [Duffie, 2014] cites the example of the clearing house of Korea Exchange which requested in December 2013 from its members to replenish its GF resources within one month following the default of HanMag Investment Securities. Some members were unable to do so which resulted in the replenshiment being postponed for three months. In a systemic event with multiple defaults this would likely severely test the CCP's capacity to continue operating. As such, market participants such as JPMorgan have argued in favour of more robust pre-funded resources [JPMorgan, 2017].

If a situation was to arise where the Powers of Assessment are not enough 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. Losses are allocated to the "creditors", in this case winning counterparties without the costs and delays associated with insolvency proceedings [Gibson et al., 2013]. As such taxpayers and other members of the CCP are protected [ISDA, 2013]. However, in contrast to normal creditors who are aware of the losses in case of counterparty default as well as their claim priority, loss allocation in this case is unpredictable since it is not known in advance which parties would sustain the losses [Duffie, 2014].

If all recovery plans fail and in the absence of a resolution authority, the CCP initiates a full tear-up by closing all outstanding positions it retains with CMs and paying any remaining default resources to the surviving CMs on a pro-rata basis. This marks the CCP's default.

Effective use of the CCP's resources is implied as long as it can successfully return to a matched book following a CM's default and obtaining its centrally cleared portfolio. This is because market exposure would make the CCP liable to unlimited future VM payments to winning counterparties and hence require unlimited resources. The main tool at the CCP's disposal to offload a defaulting portfolio is the auction. Under present clearing rules, the CCP can perform an auction of a defaulted CM's portfolio with surviving CMs being obligated to act as bidders [ISDA, 2015].

While 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 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 GF with additional resources will be minimal. For a more detailed description of the mechanisms of the DMP see [ISDA, 2015].

3 Literature review

The literature on systemic risk has seen a substantial expansion post-crisis; models introduced to measure it in terms of market equity losses include SES [Acharya et al., 2017] and CoVaR [Adrian and Brunnermeier, 2016]. 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, 2014]. 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].

There have been several theoretical contributions on systemic risk specifically related to central clearing.[2] [Capponi et al., 2015] show that central clearing increases market

[2] A relevant branch of the literature concerns with optimal central counterparty design. [Biais et al., 2012] examine the implications of full vs. partial protection offered by CCPs in the pres-

concentration and argue that the build-up of systemic risk is a feature of the system rather than due to the behavior of individual agents.

[Amini et al., 2015] propose a CCP design based on fees and guaranty fund policies that reduces systemic risk and improves aggregate surplus. The authors argue that the CCP always mitigates the propagation of contagion but its effectiveness in reducing counterparty and systemic risks depends on its capitalization. We take the CCP design as exogenously given according to the prevailing regulations and test its effectiveness in reducing counterparty and systemic risks under different stress scenarios.

[Menkveld, 2016] shows that a certain degree of crowding in trades is socially optimal because it increases overall investment. A higher level of crowding lowers the fire sale premium that can be demanded by investors from the CCP when it needs to liquidate defaulting portfolios which in turns reduces the size of the GF and frees up capital for investment.

[Cont, 2017] argues that OTC derivatives clearing does not eliminate counterparty risk but merely transforms it into liquidity risk via the exchange of collateral in the form of IM and VM which has systemic implications. The author observes that in such a system liquidity risk is a much more likely source of stress than counterparty risk. We empirically verify those concerns and show that the potential number of defaults due to liquidity constraints is much higher than due to capital depletion and that the introduction of non-central clearing can further amplify this effect.

Our model quantifies the domino effects that may originate from the operation 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.

[Pirrong, 2014] reports that even though CCPs reduce bilateral connections in the system, they create new indirect ones e.g. through the GF. In particular, the high collateralization through the IM creates wrong-way risk because the GF is likely to be stressed only under the most extreme market conditions when multiple CMs are likely to be stressed as well. 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 vulnera-

ence 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., 2015] argue for the need for CMs to disclose information about their positions across multiple CCPs in order for the latter to impose accurate margins.

ble. We quantify the systemic losses that may crystallize under such conditions due to VMGH.

We document the role of the CCP in enhancing the "robust-yet-fragile" property of the financial network [Haldane, 2013] [Acemoglu et al., 2015] i.e. its role as a system stabilizer in small to medium shocks but as a system destabilizer in extreme shocks. While multilateral netting reduces exposures and realized losses during mild market conditions, once all pre-funded resources have been depleted the CCP acts as a source of contagion exacerbating systemic risk. Importantly, we show that the potential losses the CCP distributes to the CMs increase following the introduction of non-central clearing, enhancing the fragility of the network.

On the empirical side, [Duffie et al., 2015] use a proprietary CDS positions dataset to estimate the impact on collateral demand arising from the new clearing regulations. They 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 collateral demand due to multilateral netting. Our paper investigates the implications of this increase for collateral demand due to non-central clearing for liquidity, counterparty and systemic risks. In general, the CCP is most efficient at reducing counterparty risk and required collateral via multilateral netting when it nets through all products and all counterparties. [Duffie and Zhu, 2011] show theoretically that fragmenting central clearing services by assigning separate CCPs to each asset class increases exposures and hence counterparty risk.

[Heath et al., 2016] examine the implications of increased central clearing for the topology and stability of the financial network. They report that CCPs that are funded according to the regulatory requirements outlined in the previous section act as a source of stability in the system even in the presence of large market shocks. Uncollateralized losses are allocated to CMs sufficiently widely such that the stress is well contained. However, their methodology does not model the entire DMP of the CCP isolating the different sources of risk, neither does it consider CMs as optimizing agents that react in times of stress which may mask the true magnitude of crystallized losses. We use as a basis but substantially expand their methodology and address both these limitations in our study in order to provide more realistic results.

[Ghamami and Glasserman, 2017] use a proprietary dataset of banks' derivatives portfolios to investigate the effectiveness of the introduction of non-central clearing at incentivizing market participants to switch to central clearing. They find that there are several cases in which bilateral trading remains more capital and collateral efficient than a full migration to central clearing hence the goal of promoting central clearing may not be achieved. In our work we do not endogenize the change of market activity in response to the implementation of non-central clearing (i.e. we assume that the positions remain the same before and after non-central clearing) but if the regulation provides little motivation for banks to switch to central clearing then our results are more robust in this regard.

[Boissel et al., 2017] find that during the peak of the European sovereign debt crisis in 2011 participants in the repo market collateralized using sovereign debt perceived the CCP to pose similar counterparty risk as bilateral counterparties. This led to the repricing of these contracts with adverse effects on interbank liquidity. In a similar vein, we show that the introduction of non-central clearing increases the probability that the CCP will default on its obligations in extreme stress by applying VMGH. If this is also the perception of market participants, it could have implications similar to the ones described by [Boissel et al., 2017].

Our model belongs in the class of macroprudential stress testing models that have been developed for the banking sector by regulatory agencies including the Bank of England (BoE) [Burrows et al., 2012] and the European Central Bank (ECB) [Henry and Kok, 2013] and are based on balance sheet data due to their tractability. Their attractiveness lies in their ability to trace the impact of a shock via various propagation mechanisms thus offering transparency in contrast to market price-based models which rely on market data and complex statistical techniques. However, they rely on static balance sheet data and tend to impose behavioral rules-of-thumb rather than consider optimizing agents [Demekas, 2015]. The BoE states in its stress testing framework document that it intends to expand this class of models beyond the core banking sector to include among others CCPs [Bank of England, 2015]. We develop such a model and contribute to the literature by incorporating optimizing agents and improving on the results of [Heath et al., 2016] who consider a static setup.

Finally, our paper also relates to the auction theory literature. We develop a simple model that incorporates the CCPs' rules that govern the auctions of the defaulting portfolios. We show that CMs are faced with Knightian uncertainty when assessing their expected payoffs to derive their bids and that under some simplifying assumptions the auction can be modelled using the Independent Private Values (IPV) model for first-price sealed bid auctions [Milgrom and Weber, 1982] with budget constrained bidders [Che and Gale, 1998]. In contrast to the Bayesian rationality framework that assumes perfect information about the future states of nature and their associated probabilities, our setup is characterized by the inability to identify these states i.e. the agents are faced with an infinite set of priors to characterize them. Hence in the face of Knightian uncertainty they adopt the minimax operator proposed by [Gilboa and Schmeidler, 1989]. Auction models with uncertainty averse bidders have been developed in the literature, see e.g. [Lo, 1998]. To our knowledge, the only paper to have analyzed CCP auctions is [Ferrara and Li, 2017] but their approach is theoretical while ours is grounded in an empirical setting.

4 Model

Our model takes place over a period of three days, $t = \{0, 1, 2\}$ in order to capture the key dynamics of clearing that occur in a stress event. We focus on such a limited timeframe because the operations of clearing occur at a daily frequency i.e. contracts are marked-to-market daily. The completion of the DMP typically occurs within 5 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 uncollateralized VM obligations for the CCP.

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 causes VM payments; potential counterparty losses due to defaults on VM
$t = 2$	Second day effects	CCP completes DMP if applicable; unfunded losses are allocated to CMs

At time $t = 0$ we construct the bilateral OTC derivatives exposures network based on the available aggregate data as well as a synthetic 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. The reason for this is that 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. For example, resolution authorities may intervene at any time if they deem the CCP to be too-important-to-fail or they may allow the CCP to default by proceeding to full tear-up of outstanding contracts. Historically there have been three CCP defaults, the last and most severe one being the Hong Kong Futures Exchange occurring in 1987. For an empirical analysis of CCP failure see [Bignon and Vuillemey, 2017].

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 synthetic 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 based on a realistic context.

We calculate the IM that is collected by the CCP and we calibrate its GF to Cover-2. Then we consider two different configurations, one in which the CMs also post IM between themselves in bilateral trades (non-central clearing enabled) and one in which they don't (non-central clearing disabled). In both cases the CCP remains active and clears the same fraction of derivatives collecting the same amount of collateral. We treat the asset class as a representative risky asset that the CMs trade with each other.

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. This is done in order to make the results comparable between the two configurations and 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 on 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. Hence after the shock we perform an optimization in which the CMs trade the asset with each other in order to satisfy their budget constraints. The larger the shock the less likely it is that everyone can achieve their goal which leads to more defaults. CMs with insufficient liquid assets default on their VM obligations due to liquidity risk. CMs whose capital is wiped out due to the missed VM gains default due to counterparty risk. This is because missed VM gains due to counterparty default in excess of collateral posted (if any) translate into an equity loss for the CMs in accordance with international accounting standards [IASB, 2011].

At time $t = 2$ the CCP assigns uncollateralized losses, 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 GF 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 GF according to their bidding behavior, posing a liquidity risk to them. In the most extreme cases where this proves inadequate, it proceeds to VMGH which translates into additional equity losses for the CMs that expect VM receipts from the CCP, posing a counterparty risk to them.

Our aggregate measure of systemic risk is the total equity losses of CMs on days 1 and 2. We proceed with a detailed discussion of each step.

4.1 Initial Configuration ($t = 0$)

A network is defined by a set of vertices or nodes and a set of lines or edges. For financial networks the nodes typically represent financial institutions (banks in our case) and the edges represent their connections (derivatives exposures in our case). We have a population of n banks belonging in the set of nodes $N = \{1, 2, \dots, n\}$. The presence or absence of a connection between any two banks 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.e. $I_{ij} = 1$ and 0 otherwise. The main diagonal of the matrix is zero since the banks do not have exposures to themselves i.e. $I_{ii} = 0$. Note that the matrix is not symmetric since a bank may have an exposure to a counterparty but the reverse need not be true. In graph theory terminology, our network is directed.

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]. We use the connectivity priors assumed in [MAGD, 2013] to construct the adjacency matrix. 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. This configuration captures the core-periphery structure of the network. We generate random numbers from the Bernoulli distribution to construct the matrix in accordance with these priors. 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^0_{ij}. Thus the sum of columns for row i represents the observable total gross liabilities of bank i while the sum of rows for column i represents the observable total gross assets as given by the balance sheet data. We infer the bilateral gross exposures by minimizing a loss function. Specifically, denote A^0_i and L^0_i the initial gross assets and liabilities values of bank i respectively. We estimate the matrix entries X^0_{ij} by minimizing the errors in the row and column sums:

$$\min_{X^0_{ij}, X^0_{ji}} \sum_i \left[\left| A^0_i - \sum_j X^0_{ji} \right| + \left| L^0_i - \sum_j X^0_{ij} \right| \right] \tag{1}$$

subject to:

$$X^0_{ij} = 0 \text{ if } I_{ij} = 0$$

$$0 \leq X^0_{ij} \leq \min(A^0_j, L^0_i)$$

The goal of optimization (1) is to populate the bilateral exposures matrix by providing column and row sums as close as possible to the available data of liabilities and assets respectively for each bank. 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 i.e. $\sum_i \sum_j X^0_{ji} = \sum_i \sum_j X^0_{ij}$ 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. Most banks report gross notional for the sum of assets and liabilities hence we need to infer the notional amounts for each one. Notional assets are inferred from total notional amounts by multiplying the latter with the ratio of gross market value of assets to the sum of gross asset and liability values. Notional liabilities are then the difference between total notional value and notional assets. The gross notional positions matrix is denoted $\boldsymbol{G^0}$.

Finally, the net notional positions matrix is simply calculated as $\boldsymbol{N^0} = \boldsymbol{G^0} - (\boldsymbol{G^0})^{\mathbf{T}}$ 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 a 99% VaR. 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 (IRS) with price dynamics following an Ornstein-Uhlenbeck (OU) 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. Since we don't have any prior knowledge of the value of σ_0, 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%. As such we set $\sigma_0 = 0.068\%$.[3]

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 is done in practice by CCPs which need 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:

$$IM_{ij}^0 = m_0 |W_{ij}^0|$$

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 with non-central clearing enabled. In the alternative configuration without non-central clearing we have:

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

[3]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.

Denote $IM_i^0 = \sum_{j=1}^{n+1} IM_{ij}^0$ the total IM requirements for each CM i at time 0. We subtract the total IM requirements from the CMs' liquid assets defined in section 5 under the two different configurations in order to calculate their unencumbered resources. Naturally, since IM_i^0 is higher under non-central clearing compared to without, the CMs are more encumbered in the former configuration.

Finally, we calculate the CCP's GF. 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:

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

Note that this is a conservative approach to size the GF 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 GF would be sized as the maximum between the sums of the two largest losses among those scenarios which would result in a slightly smaller GF. Nonetheless, the normality assumption already results in a modest GF so our conservative calculation does not oversize it.

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

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

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

$$F_i = \frac{IM_{ij}^0}{\sum_i IM_{ij}^0} GF \ \forall \ i \in N \text{ and } j = n+1 \tag{10}$$

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 day 0.

4.2 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 i.e. VM. We measure the shocks in terms of standard deviations σ_0. In total we apply four shocks, $2.33\sigma_0$, $3\sigma_0$, $10\sigma_0$ and $20\sigma_0$.[4] 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 do not specify the origin of the shocks but they may occur e.g. due to macroeconomic factors.

It is important to note that the purpose of the stress testing exercise is not to assess the likelihood of such events, rather to highlight potential sources of stress under different market conditions. While extreme events are highly unlikely, by testing the system's stability under such conditions we are able to show the effects of the regulations on it. A $20\sigma_0$ event is beyond what CCPs consider a plausible scenario but we are interested in examining what happens once all the pre-funded resources of the CCP are depleted.

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

$$VM_{ij}^1 = \max(W_{ij}^0 \Delta p, 0) \tag{11}$$

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 liquid assets AL_i^0. We assume conservatively that the CMs have 20% of total liquid assets dedicated to their derivatives activities and can only use that amount to repay their obligations (after subtracting the day 0 IM requirements). Similarly, we only use 20% of their equity values to symbolize the capital dedicated to this activity.

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 solves the following problem in order to minimize its expected costs:

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

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

subject to:

$$(IM_i^1 - IM_i^0) + VML_i^1 \leq AL_i^0$$

$$(A_i^1 - L_i^1) - \Big(\sum_j X_{ji}^0 - \sum_j X_{ij}^0\Big) = RE_i^0$$

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.

The first condition is the budget constraint stating that the sum of the perceived net IM receipt or payment and the VM obligation is less than the available liquid assets AL_i^0. 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 before. 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 the counterparty will deliver them. 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 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 market is market making, they tend to hold balanced inventories in order to avoid excessive directional risk. However, CMs who violate their budget constraint will still try to achieve zero net positions.

Each CM performs the optimization by assuming that its counterparties will accept these changes. This implies that they assume 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:

$$\min_{X_{ij}^1, X_{ji}^1} \sum_i \left[\left| A_i^1 - \sum_j X_{ji}^1 \right| + \left| L_i^1 - \sum_j X_{ij}^1 \right| \right] \tag{14}$$

subject to:

$$X_{ij}^1 = 0 \text{ if } I_{ij} = 0$$

$$0 \leq X_{ij}^1 \leq \min(A_j^1, L_i^1)$$

Optimization (14) achieves almost perfect convergence i.e. the objective function is almost zero because unlike the original data A_i^0 and L_i^0, the updated values A_i^1 and L_i^1 are equal in sum by construction.

We calculate the updated matrices $\boldsymbol{G^1}$, $\boldsymbol{N^1}$ and $\boldsymbol{W^1}$ as before using $\boldsymbol{X^1}$ and calculate the realized IM obligations from $\boldsymbol{W^1}$.

A CM defaults if the revaluation of its positions wipes outs its available equity or if the budget constraint is not satisfied. Hence both of the following conditions must hold in order to avoid default:

$$E_i^1 = E_i^0 + \left(\sum_j X_{ji}^1 - \sum_j X_{ij}^1 \right) - \left(\sum_j X_{ji}^0 - \sum_j X_{ij}^0 \right) > 0 \tag{15}$$

$$(IM_i^1 - IM_i^0) + VML_i^1 \leq AL_i^0 \tag{16}$$

A secondary default occurs if a CM that satisfies conditions (15) and (16) does not receive a VM gain due to counterparty default that translates into equity loss and results in its equity being wiped out. Denote H the subset of CMs defaulting due to their inability to satisfy either (15) or (16). Hence an additional condition for CMs who satisfy the above conditions to avoid default is:

$$E_i^1 = E_i^0 + \Big(\sum_j X_{ji}^1 - \sum_j X_{ij}^1\Big) - \Big(\sum_j X_{ji}^0 - \sum_j X_{ij}^0\Big) - \sum_h \max(VM_{hi}^1 - IM_{hi}^0, 0) > 0$$

$$\forall\ i \in N \backslash H \text{ and } h \in H \tag{17}$$

It is obvious that 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 (15), (16) or (17). We assume that CMs that default due to contagion i.e. due to violation of (17) repay their VM obligations since they have sufficient liquid resources to do so.

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

$$AL_i^1 = AL_i^0 - (IM_i^1 - IM_i^0) - (VML_i^1 - VMG_i^1)\ \forall\ i \in N \backslash D \tag{18}$$

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

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

$$SR_1 = \sum_i (E_i^1 - E_i^0)\ \forall\ i \in N \tag{19}$$

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. To the extent that the propagation of contagion leads to multiple defaults, this may require the government to intervene with potential bailouts which impose social costs as discussed in section 3.

4.3 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 such that the VaR model considers it a tail scenario, 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 and Li, 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. 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 is:

$$PV = \sum_{d} \sum_{j} (X_{jd}^1 - X_{dj}^1) s \ \forall \ d \in D \text{ and } j \in N \tag{20}$$

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:

$$IM_{ij}^2 - IM_{ij}^1 = m_1\sqrt{5}|W_{ij}^1 + WD| - m_0\sqrt{5}|W_{ij}^1| \ \forall \ i \in N \backslash D \text{ and } j = n+1 \quad (21)$$

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

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

$$u_i = PV - (IM_{ij}^2 - IM_{ij}^1) \ \forall \ i \in N \backslash D \text{ and } j = n+1 \quad (22)$$

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.[5]

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

[5] 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.

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

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 GF 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 GF 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 GF contribution irrespectively of the bidding order. That is, the losses are not fully covered by the addition of twice the original GF 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 IPV case where the bid function is given by:

$$b(u_i) = \begin{cases} \frac{(M-1)\int_{\underline{u}}^{u_i} x_i F(x_i)^{M-2} f(x_i) dx_i}{F(u_i)^{M-1}} \text{ if } \underline{u} < u_i \leq \overline{u} \\ -\infty \text{ if } u_i = \underline{u} \end{cases} \tag{23}$$

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 with their available budget:

$$b^*(u_i) = \min(b(u_i), AL_i^1) \tag{24}$$

Once all bids (24) 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. 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 GF 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.

Next, if the CCP faces uncollateralized losses that exceed the defaulted CMs' IM and GF contributions as well as a small equity tranche of 100 US$ million, it calls on its Powers of Assessment. Each surviving CM is obligated to contribute up to twice its original GF 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 after the margin update to pay the additional funds. If any CM does not have enough liquid resources, it defaults due to liquidity stress.

In the most extreme case where 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 equity E_i^2 is wiped out defaults due to counterparty risk. We measure systemic risk for $t = 2$:

$$SR_2 = \sum_i (E_i^2 - E_i^1) \ \forall \ i \in N \backslash D \tag{25}$$

The total equity loss in the system is:

$$SR_T = SR_1 + SR_2 \tag{26}$$

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. Suffice to say, our results are on the conservative side since we do not capture potential default cascades due to the operation of the CCP's DMP.

This ends the stress testing exercise. 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]. It is important to note however that non-financial entities are recommended to be exempt from non-central clearing regulations due to their limited contribution to systemic risk hence their omission is not significant [BCBS-IOSCO, 2015].

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 include Non-Clearing Members (NCMs) due to lack of available data. In reality CMs are in turn connected to NCMs and provide clearing services to them as intermediaries to the CCP. This fragments the network further and has implications for CCP exposures [Galbiati and Soramäki, 2013].

Fourth, we do not account for banks' additional sources to raise liquidity such as repos in the interbank network. 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. 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 tradeoff between reality and model tractability.

5 Data

We calibrate our model 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 comprised of 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].

We obtain data for the banks from their 2015 annual reports comprised of their total held-for-trading 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 market value of equity. 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 90% of the total OTC derivatives market activity in terms of gross notional which stood at 493 US$ trillion at the end of 2015 [BIS, 2016]. We set the central clearing fraction s equal to 75% in line with current estimates for interest rate derivatives [BIS, 2017].

Four periphery banks in our sample do not provide data on HQLA and we proxy their liquid assets as the sum of cash and cash equivalents and available-for-sale assets in the spirit of [Heath et al., 2016]. In addition, three periphery banks do not provide equity market values and we use their balance sheet equity values instead.

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**
Derivative assets	5.52	4.78	0.74
Derivative liabilities	5.29	4.57	0.72
Gross notional	450.83	387.33	63.50
Liquid assets	6.67	4.11	2.56
Equity	2.66	1.55	1.11

Source: Annual reports and own calculations

It can be readily observed that the majority of trading activity is concentrated in the Core-16 banks, accounting for approximately 86% of total assets, liabilities and notional, with the rest 14% shared among the Periphery-23 banks. Approximately 60% of total liquid assets and equity are in the core and the rest 40% in the periphery. The derivatives data represent the aggregates for each bank which we use to infer the unobservable bilateral connections as explained in the previous section.

The list of banks belonging in the core and the periphery of the network is reported in Table 3.

Table 3: 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]

6 Baseline results

We report the results for each day of the model separately in order to isolate the different sources of risk. Results are presented as averages over 100 simulations and are compared between the two different configurations, with non-central clearing (NCC) enabled and with NCC disabled.

6.1 First day results $(t = 1)$

On Table 4 we report the total number of defaults occurring on day 1.

Table 4: Day 1 total number of defaults

Shock	With NCC	Without NCC
$2.33\sigma_0$	1.71	2.03
$3\sigma_0$	2.19	2.41
$10\sigma_0$	6.22	8.81
$20\sigma_0$	27.11	19.72

It is apparent that as the shock intensity increases the number of defaults also increases. While they remain lower under NCC for mild to moderate shocks, in the most extreme scenario they are higher under NCC compared to without, at 27.11 and 19.72 respectively. We present a breakdown of these results due to liquidity and counterparty risks in the next two tables in order to shed light on the effects of various sources of stress.

Table 5: Day 1 number of defaults due to liquidity risk

Shock	With NCC	Without NCC
$2.33\sigma_0$	1.48	1.58
$3\sigma_0$	1.80	1.92
$10\sigma_0$	5.44	7.48
$20\sigma_0$	25.17	15.66

Table 5 reports the number of defaults due to the violation of the budget constraint (condition (16)). As can be seen, they comprise the majority of total defaults shown on Table 4 which shows that liquidity risk is the main source of stress as already documented by [Cont, 2017]. While the number of defaults is comparable between the two configurations for mild shocks, in the most extreme case the introduction of NCC causes a significantly higher number of defaults compared to the alternative configuration. Hence we document the significant increase in liquidity risk faced by CMs under extreme stress with NCC enabled.

Next, we report the number of defaults due to contagion i.e. due to missed VM receipts that wipe out healthy CMs' equity (condition (17)).

Table 6: Day 1 number of defaults due to contagion

Shock	**With NCC**	**Without NCC**
$2.33\sigma_0$	0	0.10
$3\sigma_0$	0	0.08
$10\sigma_0$	0.03	0.99
$20\sigma_0$	1.89	3.80

With NCC enabled the number of defaults is zero for mild shocks due to the protection of the IM. In the more extreme cases we document defaults under both configurations but they remain lower under NCC because of the presence of IM in bilateral transactions. Hence we conclude that NCC reduces counterparty risk. However, the number of defaults due to counterparty risk is much lower than due to liquidity risk which corroborates [Cont, 2017].

Day 1 systemic losses (19) as reported in Table 7 follow a similar pattern. Under NCC CMs are protected from counterparty risk hence systemic equity losses are zero for mild shocks while without NCC there are small losses. As the shock magnitude increases, the crystallized losses become larger but NCC caps them at 116.45 US$ billion or 21.8% of total equity dedicated to derivatives trading while without NCC the losses are up to 185.73 US$ billion or 34.8% of total equity.

Table 7: Day 1 systemic losses (US$ billion)

Shock	**With NCC**	**Without NCC**
$2.33\sigma_0$	0	1.42
$3\sigma_0$	0	2.56
$10\sigma_0$	8.37	59.48
$20\sigma_0$	116.45	185.73

The CCP's uncollateralized losses are reported in Table 8. Since its resources remain constant under the two configurations the CCP sustains zero losses under mild stress in both cases. However, due to the dominance of the CCP in our model which clears 75% of total trading activity, the sustained losses in the most extreme scenario are very large, standing at 231.53 US$ billion under NCC and 194.80 US$ billion without. 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 8 is not indicative of the stress imposed on the CCP.

Table 8: Day 1 CCP uncollateralized losses (US$ billion)

Shock	**With NCC**	**Without NCC**
$2.33\sigma_0$	0	0
$3\sigma_0$	0	0
$10\sigma_0$	16.92	35.78
$20\sigma_0$	231.53	194.80

Because of the higher number of initial defaults under NCC in the most extreme market scenario, 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 such the CCP's propensity to act as a source of contagion in the most extreme cases is amplified with the introduction of NCC, enhancing the robust-yet-fragile property of the network.

6.2 Second day results $(t = 2)$

On the second day the CCP distributes any losses in excess of the defaulted CMs' posted IM and GF contributions and a small tranche of its own equity to the surviving CMs. Table 9 reports the number of CMs defaulting due to liquidity risk i.e. due to insufficient liquid assets to meet the Powers of Assessment.

Table 9: Day 2 number of defaults due to liquidity risk

Shock	With NCC	Without NCC
$2.33\sigma_0$	0	0
$3\sigma_0$	0	0
$10\sigma_0$	0.17	0.35
$20\sigma_0$	0.24	0.73

As can be seen, defaults only occur under severe stress when the CCP's pre-funded resources are depleted but they remain small under both configurations due to the limited liability of the CMs in the form of a cap on the additional contributions.

Table 10 presents the number of defaults due to the depletion of equity from VMGH.

Table 10: Day 2 number of defaults due to counterparty risk (VMGH)

Shock	With NCC	Without NCC
$2.33\sigma_0$	0	0
$3\sigma_0$	0	0
$10\sigma_0$	0	0
$20\sigma_0$	2.18	0.14

Counterparty risk becomes relevant only in the severe cases when VMGH is activated and leads to more defaults under NCC due to the higher losses sustained by the CCP on day 1 (Table 8) as shown in Table 10.

In Table 11 we present the actual equity losses sustained by CMs due to VMGH (25) which comprise the systemic equity losses for day 2.

Table 11: Day 2 systemic losses (US$ billion)

Shock	With NCC	Without NCC
$2.33\sigma_0$	0	0
$3\sigma_0$	0	0
$10\sigma_0$	0.81	0
$20\sigma_0$	72.34	5.98

Consistent with Table 10, VMGH becomes relevant only under severe market stress. In the most extreme scenario the systemic equity losses reach 72.34 US$ billion under NCC or 17.3% of remaining total equity from day 1 and 5.98 US$ billion without or 1.72% of remaining equity.

Interestingly, the introduction of NCC seems to amplify the CCP's potential for contagion in the most extreme market scenarios. 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 secondary losses which are higher by a factor of more than 12 compared to without NCC.

6.3 Final results

We report the overall systemic equity losses (26) in Table 12.

Table 12: Days 1&2 systemic losses (US$ billion)

Shock	**With NCC**	**Without NCC**
$2.33\sigma_0$	0	1.42
$3\sigma_0$	0	2.56
$10\sigma_0$	9.18	59.48
$20\sigma_0$	188.79	191.72

With NCC enabled losses remain zero for small to moderate shocks, rising to 9.18 US$ billion or 1.72% of total initial equity for a $10\sigma_0$ shock and 188.79 US$ billion for the most extreme $20\sigma_0$ shock or 35.4% of total initial equity. With NCC disabled, losses occur in all cases rising to 59.48 US$ billion or 11.1% of total and 191.72 US$ billion or 35.9% of total equity for the most extreme cases.

We can thus deduce that the introduction of NCC is overall beneficial for financial stability. The exchange of IM in bilateral transactions mitigates losses arising from counterparty risk at the expense of an increase in liquidity risk. However, this increase has implications for the stability of the CCP because it reports larger losses in severe market conditions and as a result the knock-on effects are also more severe. In the most extreme case, the total losses are only marginally smaller under NCC compared to without which suggests that the increased liquidity risk counteracts the benefits arising from reduced counterparty risk. We further analyze the implications of the expansion of central clearing for systemic risk in subsection 7.2.

7 Sensitivity analysis

7.1 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 dynamic/baseline model's results. For brevity we report the results in Appendix B in Tables 13 - 21. For ease of comparison we restate the results of the previous section under the Baseline column along with the ones from the sensitivity analysis under the Static column.

Overall, we observe that the number of defaults and the resulting losses for day 1 tend to be larger for mild shocks but smaller for severe shocks under the static configuration compared to the dynamic one (Table 13). In the most extreme market scenario the losses in the static setup are 88.84 US$ billion or 16.6% of total equity under NCC and 175.09 US$ billion or 32.8% of total equity without, compared to 116.45 US$ billion or 21.8% of total equity and 185.73 US$ billion or 34.8% of total equity respectively in the dynamic setup (Table 16).

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 hence they are able to avoid default. However, once extreme shocks occur everyone runs for the exit due to large margin calls and the system becomes more fragile [Pedersen, 2009]. Even though each agent acts rationally, systemic risk is increased showcasing the robust-yet-fragile property of the network [Acemoglu et al., 2015]. This in turn transforms the CCP into a source of contagion, further enhancing this property [Domanski et al., 2015].

While the number of defaults due to liquidity risk on day 1 are comparable under the static setup in the most extreme case with and without NCC, at 15.20 and 11.23 respectively, they differ significantly under the dynamic setup at 25.17 and 15.66 respectively (Table 14). This in turn causes the CCP to transmit more losses to the surviving CMs under NCC in the dynamic setup, leading to day 2 systemic losses of 72.34 US$ billion or 17.3% of remaining equity under NCC and 5.98 US$ billion or 1.72% of remaining equity without, compared to 55.52 US$ billion or 12.5% of remaining equity under NCC and 49.28 US$ billion or 13.7% of remaining equity without in the static setup (Table 20). As such, we find that the CCP is a more prominent source of stress under NCC in a dynamic and more realistic setting than what a static setup would indicate.

As a result, the total systemic losses in the most extreme market scenario under the static setup are 144.36 US$ billion or 27% of total equity under NCC and 224.38 US$ billion or 42% of total equity without, compared to 188.79 US$ billion or 35.4% of total equity and 191.72 US$ billion or 35.9% of total equity respectively under the dynamic setup (Table 21). While the static setup clearly favors NCC, the dynamic model's results are more ambiguous. By only considering passive CMs there exists the risk of overestimating losses under mild stress while underestimating losses in the most extreme cases because of the presence of negative externalities caused by herding behavior and runs.

7.2 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 baseline configuration. That is, we consider a scenario with reduced central clearing and another one with increased central clearing compared to the baseline configuration. For each repetition a new set of 100 random adjacency matrices is generated. The results are presented in Tables 22 - 30 provided in Appendix B. We repost the results from the baseline configuration under the column $s = 0.75$.

Table 22 shows the total number of defaults on day 1. As central clearing expands, the number of defaults decreases both before and after the introduction of NCC due to the increasing netting benefits. The effect is more pronounced under extreme stress ($20\sigma_0$) where the number of defaults decreases by more than half when 95% of positions are centrally cleared compared to only 50%, from 35.16 to 12.59 under NCC and from 25.35 to 11.91 without.

Tables 23 and 24 report the number of defaults due to liquidity and counterparty risks respectively. Liquidity risk remains the main source of stress under all configurations but it decreases with the expansion of the CCP. Counterparty risk is almost eliminated with a clearing fraction of 95% as very few CMs default even under extreme market stress.

The decrease in the number of defaults leads to a sizeable decrease in systemic equity losses for day 1 (Table 25). In the most extreme market scenario the losses under NCC are 105.12 US$ billion or 19.7% of total equity with $s = 0.5$ and 19.70 US$ billion or 3.7% of total equity with $s = 0.95$, reduced more than five-fold. Without NCC the corresponding losses are 282.32 US$ billion or 52.9% of total equity and 30.68 US$ billion or 5.7% of total equity, reduced more than nine times. Hence the expansion of central clearing protects the CMs from losses originating from market stress.

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 163.52 US$ billion under NCC and 137.82 US$ billion without, compared to 217.27 US$ billion and 207.92 US$ billion respectively with 95% of positions centrally cleared (Table 26).

Table 27 presents the number of defaults due to liquidity risk on day 2 i.e. due to the inability of the CMs to meet the Powers of Assessment. These are reduced with the expansion of central clearing because of the lower liquidity encumberment due to the increased netting benefits and the limited liability resulting in more CMs being able to meet the requirements. However, defaults due to counterparty risk increase with the expansion of central clearing because the CCP distributes larger uncollateralized losses to the surviving CMs (Table 28).

This leads to substantially higher systemic equity losses for day 2 in the most extreme market scenario, from 7.69 US$ billion or 1.8% of remaining equity under NCC and 2.11 US$ billion or 0.84% of remaining equity without with $s = 0.5$ to 146.50 US$ billion or 28.5% of remaining equity under NCC and 139.89 US$ billion or 27.8% of remaining equity without with $s = 0.95$, an increase of 19 times and 66 times respectively (Table 29). 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.

Finally, the total equity losses for days 1 and 2 are reported in Table 30. We observe that they significantly decrease with the expansion of central clearing in all but the most extreme market scenario due to the stabilizing effect of multilateral netting. In the most extreme market scenario the losses still decrease by 40% without NCC as central clearing expands, from 284.44 US$ billion or 53.3% of total equity with $s = 0.5$ to 170.57 US$ billion or 31.9% of total equity with $s = 0.95$. However, following the introduction of NCC total equity losses actually increase by 47% from 112.81 US$ billion or 21.1% of total equity with $s = 0.5$ to 166.21 US$ billion or 31.1% of total equity with $s = 0.95$. This occurs because the reduction of losses from day 1 is more than offset by the increase of losses on day 2 due to the higher number of initial defaults.

Our results imply that the introduction of NCC amplifies the potential of the CCP to act as a source of contagion under extreme market stress. While total losses remain lower under NCC, a CCP that clears almost 100% of market activity may transmit losses that greatly exceed those generated by an initial market shock, diminishing any benefits arising from the collateralization of bilateral transactions as seen by the similar total losses occurring under such a scenario (166.21 US$ billion and 170.57 US$ billion with and without NCC respectively). In fact, as the CCP becomes more dominant the bulk of the losses shift from day 1 to day 2 in extreme market stress. Crucially, contrary to the intentions of the regulators [BCBS-IOSCO, 2015], the expansion of central clearing does not appear to be beneficial for financial stability in times of extreme stress after the introduction of NCC since total equity losses actually increase. This is not observed in a system without NCC where the CCP's expansion is beneficial in all market scenarios.

8 Conclusion and policy implications

The proliferation of central clearing has had important implications for the distribution of risks in the financial system. As new regulations come to the fore, it is imperative to understand the dynamics that may crystallize in a stress scenario as a result of their implementation and assess their effects on financial stability.

In this paper we have developed a model incorporating the largest dealer banks in the OTC derivatives market as well a CCP that is the dominant counterparty. We have considered 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 document the effectiveness of non-central clearing in reducing counterparty and systemic risks under most market conditions. The IM posted in bilateral trades protects market participants from counterparty risk which results in lower systemic losses compared to a market configuration without non-central clearing. However, the implications for the relationship between central and non-central clearing are less clear-cut. A higher initial number of bank defaults due to increased liquidity risk leads to higher losses for the CCP which in turn transmits them back to surviving market participants, mitigating the benefits of non-central clearing. Furthermore, our results suggest that this effect is amplified as the CCP becomes more dominant in the market such that the knock-on losses originating from the CCP may surpass those due to the initial market shock. As a result, under extreme stress systemic risk increases as central clearing expands following the introduction of non-central clearing.

Hence, 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 [Domanski et al., 2015]. To the extent that the introduction of non-central clearing increases liquidity risk in the system and the probability of default of the CMs, the CCP would be incentivized to increase its pre-funded resources in order to protect itself. Highly volatile markets with more risky CMs favour the increase of the IM over the GF resources because the cost of loss mutualization increases for the surviving CMs [Nahai-Williamson et al., 2013]. Indeed, the losses shared between the surviving CMs on day 2 of our model are more than 12 times larger under extreme stress with non-central clearing enabled compared to the alternative configuration. An increase of IM requirements would reduce those losses at the expense of further ex-ante liquidity encumberment.

We also document the role of the CCP in enhancing the robust-yet-fragile property of the network and how by only considering a static setup without optimizing agents the magnitude of losses may be underestimated in the most extreme market scenarios. While a static setup would indicate that the introduction of non-central clearing is clearly beneficial under all market conditions, reducing overall losses, the dynamic model provides results that suggest that in the most extreme cases the collective reaction of the market participants may prove to be detrimental to financial stability. By underestimating the potential number of defaults the static model is unable to capture the true extent of losses that may crystallize under such conditions.

There are two main theoretical questions arising from our work. First, is it socially optimal to make the CCP more robust to tail risk by requesting further resources from the CMs given the unlikeliness of extreme events? Second, is there an optimal fraction of central clearing s that minimizes systemic risk? These questions are related to optimal central clearing design and we leave them for future research.

Our analysis can be expanded along several dimensions. For simplicity we have only included one asset class but the model could be extended to include all five (equity, credit, commodity, interest rate and currency). This would allow a more refined (yet more complex) analysis with several CCPs and a richer dataset. The existence of multiple CCPs would allow the modelling of further channels of contagion such as through overlapping CMs' membership [Pirrong, 2014]. It would also test the efficiency of central clearing in reducing exposures when the service is fragmented across multiple CCPs.

The development of a more refined auction model adhering to the rules of the CCP is worthy a paper in itself and is left for future research. While Knightian uncertainty conveniently solves the circularity problem faced by the bidders, the unique setup of this auction remains to be properly researched from an empirical perspective. It would be interesting for example, given the appropriate dataset, to examine whether CMs bid responsibly in reality as we assume in our model or they request excessive compensation from the CCP in order to maximize their profits and what are the implications for the sustainability of the CCP and financial stability overall.

Finally, another important point to consider is the endogenous change of market activity due to the changing regulatory environment. We use data as of end-2015 to test the effectiveness of a regulation that was introduced in 2016. It is possible that the market participants will rebalance their portfolios in anticipation of the change in order to benefit from lower margin requirements. Our results show that this may not always lead to a reduction of systemic risk. A more recent dataset will allow the analysis to be repeated in the new regulatory environment after the changes have taken place to verify whether the results remain consistent.

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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 GF 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 GF, the skin-in-the-game equity and any other bidders' Powers of Assessment contributions used according to the bidding behavior. Except for its own GF contribution, the equity contribution of the CCP and the total GF 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 $\sum_{h \in H} VM^0_{hi}$. Note that CMs that defaulted due to missed VM receipts violating condition (17) have successfully repaid their VM obligations since they satisfy condition (16) hence they do not owe VM to the CCP. As such we only consider here the subset H that includes the CMs that violated either (15) or (16) and not D that also includes those that failed condition (17). The function is of the form:

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

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 GF 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 GF.

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:

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

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:

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

or simply:

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

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:

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

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:

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

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 (23).

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 13: Day 1 total number of defaults – Static configuration comparison
(With NCC/Without NCC)

Shock	Static	Baseline
$2.33\sigma_0$	3.82/2.96	1.71/2.03
$3\sigma_0$	4.34/3.68	2.19/2.41
$10\sigma_0$	10.18/7.28	6.22/8.81
$20\sigma_0$	17.66/15.82	27.11/19.72

Table 14: Day 1 number of defaults due to liquidity risk – Static configuration comparison
(With NCC/Without NCC)

Shock	Static	Baseline
$2.33\sigma_0$	3.44/2.36	1.48/1.58
$3\sigma_0$	3.86/2.95	1.80/1.92
$10\sigma_0$	9.16/5.48	5.44/7.48
$20\sigma_0$	15.20/11.23	25.17/15.66

Table 15: Day 1 number of defaults due to contagion – Static configuration comparison
(With NCC/Without NCC)

Shock	Static	Baseline
$2.33\sigma_0$	0/0.22	0/0.10
$3\sigma_0$	0/0.25	0/0.08
$10\sigma_0$	0.02/0.80	0.03/0.99
$20\sigma_0$	1.47/3.59	1.89/3.80

Table 16: Day 1 systemic losses (US$ billion) – Static configuration comparison
(With NCC/Without NCC)

Shock	Static	Baseline
$2.33\sigma_0$	0/4.62	0/1.42
$3\sigma_0$	0/9.43	0/2.56
$10\sigma_0$	19.03/62.15	8.37/59.48
$20\sigma_0$	88.84/175.09	116.45/185.73

Table 17: Day 1 CCP uncollateralized losses (US$ billion) – Static configuration comparison
(With NCC/Without NCC)

Shock	Static	Baseline
$2.33\sigma_0$	0/0	0/0
$3\sigma_0$	0/0	0/0
$10\sigma_0$	49.39/36.83	16.92/35.78
$20\sigma_0$	201.00/176.99	231.53/194.80

Table 18: Day 2 number of defaults due to liquidity risk – Static configuration comparison
(With NCC/Without NCC)

Shock	Static	Baseline
$2.33\sigma_0$	0/0	0/0
$3\sigma_0$	0/0	0/0
$10\sigma_0$	0.35/0	0.17/0.35
$20\sigma_0$	0.86/0.23	0.24/0.73

Table 19: Day 2 number of defaults due to counterparty risk (VMGH) – Static configuration comparison
(With NCC/Without NCC)

Shock	**Static**	**Baseline**
$2.33\sigma_0$	0/0	0/0
$3\sigma_0$	0/0	0/0
$10\sigma_0$	0.26/0.19	0/0
$20\sigma_0$	1.65/2.19	2.18/0.14

Table 20: Day 2 systemic losses (US$ billion) – Static configuration comparison
(With NCC/Without NCC)

Shock	**Static**	**Baseline**
$2.33\sigma_0$	0/0	0/0
$3\sigma_0$	0/0	0/0
$10\sigma_0$	16.21/7.18	0.81/0
$20\sigma_0$	55.52/49.28	72.34/5.98

Table 21: Days 1&2 systemic losses (US$ billion) – Static configuration comparison
(With NCC/Without NCC)

Shock	**Static**	**Baseline**
$2.33\sigma_0$	0/4.62	0/1.42
$3\sigma_0$	0/9.43	0/2.56
$10\sigma_0$	35.25/69.33	9.18/59.48
$20\sigma_0$	144.36/224.38	188.79/191.72

Table 22: Day 1 total number of defaults – Alternative clearing fraction comparison
(With NCC/Without NCC)

Shock	***s*=0.5**	***s*=0.75**	***s*=0.95**
$2.33\sigma_0$	2.04/2.97	1.71/2.03	1.74/1.60
$3\sigma_0$	2.48/3.88	2.19/2.41	1.93/1.71
$10\sigma_0$	11.31/13.17	6.22/8.81	5.94/6.20
$20\sigma_0$	35.16/25.35	27.11/19.72	12.59/11.91

Table 23: Day 1 number of defaults due to liquidity risk – Alternative clearing fraction comparison
(With NCC/Without NCC)

Shock	***s*=0.5**	***s*=0.75**	***s*=0.95**
$2.33\sigma_0$	1.94/2.30	1.48/1.58	1.47/1.42
$3\sigma_0$	2.19/3.06	1.80/1.92	1.60/1.45
$10\sigma_0$	10.52/10.10	5.44/7.48	5.33/5.57
$20\sigma_0$	33.73/19.79	25.17/15.66	12.21/11.35

Table 24: Day 1 number of defaults due to contagion – Alternative clearing fraction comparison
(With NCC/Without NCC)

Shock	***s*=0.5**	***s*=0.75**	***s*=0.95**
$2.33\sigma_0$	0/0.06	0/0.10	0/0
$3\sigma_0$	0/0.05	0/0.08	0/0.01
$10\sigma_0$	0.18/2.74	0.03/0.99	0.05/0.08
$20\sigma_0$	1.42/5.39	1.89/3.80	0.14/0.33

Table 25: Day 1 systemic losses (US$ billion) – Alternative clearing fraction comparison (With NCC/Without NCC)

Shock	s**=0.5**	s**=0.75**	s**=0.95**
$2.33\sigma_0$	0/5.72	0/1.42	0/0.16
$3\sigma_0$	0/9.80	0/2.56	0/0.26
$10\sigma_0$	26.05/157.51	8.37/59.48	1.93/8.48
$20\sigma_0$	105.12/282.32	116.45/185.73	19.70/30.68

Table 26: Day 1 CCP uncollateralized losses (US$ billion) – Alternative clearing fraction comparison
(With NCC/Without NCC)

Shock	s**=0.5**	s**=0.75**	s**=0.95**
$2.33\sigma_0$	0/0	0/0	0/0
$3\sigma_0$	0/0	0/0	0/0
$10\sigma_0$	16.99/28.65	16.92/35.78	36.36/35.79
$20\sigma_0$	163.52/137.82	231.53/194.80	217.27/207.92

Table 27: Day 2 number of defaults due to liquidity risk – Alternative clearing fraction comparison
(With NCC/Without NCC)

Shock	s**=0.5**	s**=0.75**	s**=0.95**
$2.33\sigma_0$	0/0	0/0	0/0
$3\sigma_0$	0/0	0/0	0/0
$10\sigma_0$	0.24/0.61	0.17/0.35	0.13/0.13
$20\sigma_0$	0.51/0.74	0.24/0.73	0.34/0.26

Table 28: Day 2 number of defaults due to counterparty risk (VMGH) – Alternative clearing fraction comparison
(With NCC/Without NCC)

Shock	s**=0.5**	s**=0.75**	s**=0.95**
$2.33\sigma_0$	0/0	0/0	0/0
$3\sigma_0$	0/0	0/0	0/0
$10\sigma_0$	0.04/0	0/0	0.03/0.05
$20\sigma_0$	0.45/0.14	2.18/0.14	3.90/3.91

Table 29: Day 2 systemic losses (US$ billion) – Alternative clearing fraction comparison
(With NCC/Without NCC)

Shock	s**=0.5**	s**=0.75**	s**=0.95**
$2.33\sigma_0$	0/0	0/0	0/0
$3\sigma_0$	0/0	0/0	0/0
$10\sigma_0$	2.29/0	0.81/0	3.59/2.97
$20\sigma_0$	7.69/2.11	72.34/5.98	146.50/139.89

Table 30: Days 1&2 systemic losses (US$ billion) – Alternative clearing fraction comparison
(With NCC/Without NCC)

Shock	s**=0.5**	s**=0.75**	s**=0.95**
$2.33\sigma_0$	0/5.72	0/1.42	0/0.16
$3\sigma_0$	0/9.80	0/2.56	0/0.26
$10\sigma_0$	28.35/157.51	9.18/59.48	5.53/11.46
$20\sigma_0$	112.81/284.44	188.79/191.72	166.21/170.57