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Author: Alex Heath Gerard Kelly Mark Manning Sheri Markose Ali Rais Shaghaghi

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CCPs and Network Stability in OTC Derivatives Markets

Alex Heath#, Gerard Kelly#, Mark Manning#, Sheri Markose*[1] and Ali Rais Shaghaghi**

#Reserve Bank of Australia, 65 Martin Pl, Sydney NSW, Australia, *** University of Essex,**

Wivenhoe Park, Colchester CO4 3SQ, United Kingdom, ****Centre for Risk Studies**, Cambridge Judge Business School, University of Cambridge, Trumpington St Cambridge CB2 1AG, UK

Abstract

Among the reforms to OTC derivative markets since the global financial crisis is a commitment to collateralize counterparty exposures and to clear standardized contracts via central counterparties (CCPs). The reforms aim to reduce interconnectedness and improve counterparty risk management in these important markets. At the same time, however, the reforms necessarily concentrate risk in one or a few nodes in the financial network and also increase institutions' demand for high-quality assets to meet collateral requirements. This paper looks more closely at the implications of increased CCP clearing for both the topology and stability of the financial network. Building on Heath, Kelly and Manning (2013) and Markose (2012), the analysis supports the view that the concentration of risk in CCPs could generate instability if not appropriately managed. Nevertheless, maintaining CCP prefunded financial resources in accordance with international standards and dispersing any unfunded losses widely through the system can limit the potential for a CCP to transmit stress even in very extreme market conditions. The analysis uses the Bank for International Settlements Macroeconomic Assessment Group on Derivatives (MAGD) data set on the derivatives positions of the 41 largest bank participants in global OTC derivative markets in 2012.

Keywords: OTC Derivatives Reforms; OTC derivatives reforms; Central Counterparty (CCP); Netting Efficiency; Collateralization

JEL Classification: G; G1; G20; G21; G28; N2

[1] Sheri Markose is the corresponding author, email:scher@essex.ac.uk.
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CCPs and Network Stability in OTC Derivatives Markets

1. Introduction

Since the global financial crisis, the G20 has overseen an ambitious program of regulatory reform in financial markets. One goal of the reform program is to 'make derivative markets safer' by reducing interconnectedness, improving counterparty risk management and increasing transparency. Important steps towards meeting this objective are the 2009 commitment by G20 Leaders that 'all standardized OTC derivative contracts should be …cleared through central counterparties (CCPs)…'and the development of standards that require current and potential future counterparty exposures to be collateralizedfor contracts that cannot be centrally cleared.

More recently, as progress has been made in meeting these commitments, concerns have been expressed in both industry and regulatory circles about the increasing system reliance on CCPs. As banks become more exposed to CCPs, questions are being askedas to whether CCPs' risk management frameworks, and arrangements for their recovery and resolution in the event of a severe financial shock, are adequate to support financial stability.

In this paper, we bring together methodological and conceptual frameworks from two recent contributions to the literature on OTC derivative markets – Markose (2012) and Heath, Kelly and Manning (2013) – to gain a better understanding of the implications for the stability of the financial system of CCP clearing and the collateralization of OTC derivative trades.

A key insight from Heath, Kelly and Manning (2013) is that while collateralization reduces credit risk, at the same time it increases liquidity risk by encumbering banks' high-qualityassets. Introducing a CCP can help to reduce these liquidity implications because a CCP can generally support more efficient netting of positions and associated collateral. Heath, Kelly and Manning (2013) consider stability and contagion under different assumptions about the degree of CCP clearing and collateral coverage, and under different assumptions about the severity of price shocks. This paper extends this analysis in three main directions.

First, we use actual rather than simulated data on banks' derivative positions. Our sample is based on the data collected for the Macroeconomic Assessment Group on Derivatives (MAGD) coordinated by the Bank for International Settlements (BIS) and includes the 41 largest bank participants in global OTC derivative markets in the fourth quarter of 2012. This extends well beyond the core of 16 highly interconnected dealer banksto also include banks that have fewer counterparties.We consider positions in five OTC derivative asset classes: interest rates, credit, currency, commodities and equity.We also supplement the OTC derivative position data with balance sheet data on banks'Tier 1 capital and liquid asset holdings.

Second, we analyse the stability properties of networks under alternative clearing structures and different price change assumptions using the maximum eigenvalue/eigenvector centrality (eigen-pair) methodology in Markose (2012, 2013) and Markose *et al* (2012). This method allows tipping points to be identified and also supports the ranking of institutions according to both their systemic importance and their systemic vulnerability.We use this method to examine the incidence of stress when financial institutions incur losses that exceed a given threshold of their available financial resources. We also extend this methodology to capture the observation that constraints on a bank's liquidity can also be a direct source of instability. In particular, the encumbrance of assets to meetinitial margin and prefunded contributions to the CCP's financial resources mayconstrain a bank's access to liquid assets to meet obligations on a timely basis.

Third, we apply a variant of the methodology in Heath *et al* (2013) – further elaborated in Heath, Kelly and Manning (2015) – that simulates extreme changes to OTC derivative prices and directly traces the propagation of contagion through the system. The methodologycaptures key aspects of CCP design, including how losses would be allocated to participants if the CCP's prefunded resources were exhausted.

The analysis of network stability illustrates how CCP clearing transforms the financial network by concentrating risk in just one or few nodes. These highly interconnected nodes are found to be the most systemically vulnerable in the system, in the sense that they are highly exposed to the default of connected counterparties. However, given their design, CCPs are not found to be among the most prominent sources of stress transmission in this system. A CCP has a very different risk profile to that of a bank. Unlike a bank, a CCP does not take on discretionary risks; it only assumes financial risks that arise from the positions it clears for its participants and maintains a fully 'balanced book' unless a participant defaults. Further, in accordance with international standards, a large, systemically important CCP would holdprefunded financial resources sufficient to fully withstand the default of its largest two participants in 'extreme but plausible' market conditions. Only ifeither one or more large participants defaulted in adverse market conditions that were 'beyond plausible', or more than two of its participants defaulted, would a CCP transmit stress by allocating any remaining unfunded losses among its participants. By contrast, a bank that relied on its capital to support proprietary risk positions in multiple markets would begin to transmit stress once only a portion of its available capital was exhausted.

Our analysis supports the view that a well-designed CCP can be a source of stability in the system, rather than a source of instability. We demonstrate that even in a range of very extreme scenarios, any unfunded losses would be expected to beallocated sufficiently widely that stress would be well contained.

After beginning with some background on the role of CCPs in Section 2, we turn in Section 3 to the dataset, the scenarios under consideration, and some of the key exposure metrics used in the analysis. Section 4 introduces the network analysis used to derive the metricsfor the systemic importance and vulnerability of individual financial institutions, and the stability of the system under alternative clearing structures and OTC derivative price shock assumptions. Section 5 goes on to present results from the analysis of contagion, while Section 6 considers the implications for policy.Section 7 concludes.

2. The Role of Central Counterparties

A CCP assists institutions in the management of counterparty credit risk by interposing itself between counterparties to become the buyer to every seller, and the seller to every buyer. These arrangements support anonymous trading, deepen market liquidity, and generally maximize the netting of exposures across participants.

At the same time, however, CCPs become central nodes in the financial system (Pirrong, 2011). The concentration in risk this implies can crystallize if a participant defaults on its obligations to aCCP, since the CCP must continue to meet its obligations to all of the non-defaulting participants. The CCP may incur losses should the replacement trades be executed at an unfavourable price. This is known as replacement cost risk.In this way, while a CCP does not assume discretionary financial risk, it can still be a channel for the transmission of stress to other participants and the financial system more widely. Policymakers acknowledge thatconfidence in underlying markets could be severely tested if a CCP's activitieswere disrupted, leaving market participants unable to establish new positions or manage existing exposures.[2]

How widely stress could be transmitted depends crucially on the CCP's design and its risk management arrangements: whether the CCP is sufficiently collateralized; how quickly it can liquidate non-cash collateral assets (or cash collateral that has been reinvested); how effectively it manages the default and closes out the risk associated with the defaulted participant's trades; etc. Any shortcomings in the design or risk management framework of the CCP could, in the event of a shock, have spillover effects throughout the system (RBA 2014).

The systemic importance of CCPs has long been acknowledged (Bernanke 1990; Moser 1998; Kroszner 2006). However, the G20-led initiative to expand the scope of CCP clearing to OTC derivative markets (G20 2009) has moved the resilience of CCPs higher up the international regulatory policy agenda. Accordingly, the need for sound risk management arrangements to address concentration risks is well recognized both by policymakers (Tucker 2011, 2014; Bailey 2014; Cœuré 2014, 2015; Powell 2014) and by industry participants (JPMorgan Chase 2014; ISDA 2015).

In particular, new international standards, the Principles for Financial Market Infrastructures (PFMIs) (CPSS-IOSCO 2012),have been developed for the design, operation and risk management arrangements of CCPs and other financial market infrastructures (FMIs). Among other things, they establish minimum requirements in all

2 Wendt (2015) describes a range of contagion channels in the event of a shock – either to a participant of a CCP, or to the CCP itself – that arise from the connections that a CCP has with the financial markets that it serves, its participants, linked CCPs and other financial market infrastructures.

areas of risk management: e.g. credit, liquidity, investment, business, legal and operational risks. A particular focus in recent years has been how to ensure continuity of critical CCP services in the event of very extreme market conditions that could threaten the CCP's viability. To deal with such scenarios, the PFMIs require that CCPs establish recovery plans (FSB 2013; CPMI-IOSCO 2014). As a backstop to these arrangements, special resolution regimes for CCPs and other FMIs are being developed (FSB 2014).At the time of writing, standard-setters are reviewing the need for refinements to these standards to strengthen the resilience of CCPs and their recovery and resolution arrangements (FSB 2015).

2.1 Collateral

CCPs typically manage replacement cost risk through the use of variation and initial margin. Variation margin is typically exchanged at least daily – usually in cash – to reflect mark-to-market price changes on participants' outstanding positions. Initial margin is collected to cover, with a high probability (typically at least a 99 per cent confidence level), potential future exposure arising between the last variation margin payment and the closeout or replacement of a defaulted counterparty's trades. Initial margin requirements may be met either in cash or using high-quality non-cash assets that carry low credit, market and liquidity risk. Only the defaulted participant's initial margin can be used in the event of a default.

In recent years, the use of margin has also become more commonplace in non-centrally cleared markets, although bilateral collateral agreements have, to date, typically covered only variation margin (ISDA 2014). However, new regulatory standards will make the exchange of both variation and initial margin mandatory between bilateral derivative market counterparties from September 2016(BCBS-IOSCO 2015). These standards will also establish a minimum level of initial margin coverage of 99 per cent.

A CCP's initial margin resources are supplemented with a pool of resources, typically prefunded by contributions from all participants (along with a layer of CCP equity), known as the default fund. Fora large CCP that is systemically important in multiple jurisdictions,thePFMIs require that the combination of default fund resources and defaulted participants' margin be calibrated to withstand the default of its largest two participants (*Cover 2*) in 'extreme but plausible' market conditions. There is not yet a consistent interpretation of 'extreme but plausible', but some CCPs target market stress equivalent to a 'once-in-30-years' price change.The PFMIs similarly require that a CCP use liquidity stress tests to ensure access to sufficient liquidity to meet its payment obligations on time with a high degree of confidence under a wide range of potential stress scenarios.

Should market conditions prove to be more severe than considered by the CCP in calibrating its prefunded resources, or should more than two participants default, the CCP's prefunded resources could be depleted. In such scenarios, a CCP's recovery plans must provide for the allocation of uncovered losses. One mechanism for uncovered loss allocation that has been widely debated, and in some cases adopted, is 'variation margin gains haircutting' (VMGH) (see Elliott (2013), Gibson (2013), ISDA (2013), CPMI-IOSCO (2014), and Duffie (2014)). This involves writing down a CCP's variation margin outflow in proportion to the amount owed to each 'winning' participant, so as to fully allocate the loss.

The expansion of CCP clearing to OTC derivative markets and the margining of non-centrally cleared derivative transactions will increase market participants' demand for high-quality assets and change how collateral markets operate (Singh 2013). There have been a number of attempts to estimate the magnitude of this increase in demand (Heller and Vause 2012; ISDA, IIF and AFME 2012;Levels and Capel 2012; Sidanius and Zikes 2012; CGFS 2013;Duffie, Scheicher and Vuillemey 2014). These studies have delivered a wide range of estimates, which largely reflect assumptions about the underlying volatility of OTC contracts, the share of the market that is centrally cleared, and the netting efficiency of alternative clearing arrangements (Cheung, Manning and Moore 2014).

2.2 Netting

Netting efficiency depends on the product and counterparty scope of a given clearing arrangement, the profile of positions, and the margining methodology applied:

- Variation margin is calculated as a net payment/receipt, based on observed price changes across *all* products covered by the clearing arrangement. In the case of non-centrally cleared trades, separate variation margin payments/receipts are calculated vis-à-vis eachbilateral counterparty. In the case of central clearing, variation margin payments/receipts are multilaterally netted across all counterparties.
- Initial margin is calculated separately vis-à-vis eachbilateral counterparty in non-centrally cleared arrangements, and multilaterally across all counterparties where positions are centrally cleared. There is, however, typically less scope for netting across products in calculating initial margin requirements. For CCPs, 'margin offsets' are generally limited to combinations of products where prices are significantly and reliably correlated.

Prior to the financial crisis, most OTC derivative transactions were cleared directly between the transacting counterparties, with netting occurring across products within a given bilateral relationship. It has become common for some products – notably, interest rate and credit derivatives – to be cleared by product-specific CCPs, or for a single CCP to clear unrelated products via separate services that do not permit margin offsets and are supported by segregated default funds. Under such arrangements, netting occurs separately across counterparties for each product class.

Generally, the greatest netting efficiency would arise where a single CCP cleared the full range of derivative products via a single service and allowed netting across both products and counterparties. The netting advantage of central clearing will, however, be smaller when activity is concentrated in a few counterparties, central clearing is more fragmented, and participants' positions are more directional (Duffie and Zhu 2011; Heath*et al* 2013).

3. Data and methodology

The first step in exploring the question of how collateralization and CCP clearing affect the stability of a financial system is to construct a matrix of bilateral positions between counterparties. Unfortunately, detailed data on bank-to-bank positions is not yet currently available. We therefore generate these fromdata on the total derivative assets and liabilities of 41 financial institutions across five categories of OTC derivatives at the end of 2012. These data were compiled for the Macroeconomic Assessment Group on Derivatives (MAGD 2013). The original data, and the transformations that we use to create a matrix of bilateral net notional positions, are described in Section 3.1.

The next step is to derive the bilateral exposure matrices, which are a function of the bilateral positions and the opportunities for netting. The set of clearing arrangements that we consider is described in Section 3.2. To illustrate the dataset and establish some stylized facts that are relevant for the analysis in the remainder of the paper, we also present and discuss how exposures and collateral requirements change under each alternative clearing arrangement.

3.1 The dataset and the position matrix

The MAGD data on OTC derivativesconsist of reported balancesheet data on derivative assets and liabilities for 41 banks that are involved in OTC derivative trading. To support the analysis of stability and contagion (in Sections 4 and 5), we supplement these data with published balance sheet data for each bank on Tier 1 capital and liquid resources (which we define here as the sum of cash and cash equivalents and available-for-sale assets) (Table 1).[3] All data are based on banks' 2012 financial reports.

Table 1: Balance Sheet Data

($US trillion)

	Total	Core (16 Banks)	Periphery (25 Banks)
Derivative Liabilities	14.34	12.16	2.18
Derivative Assets	14.48	12.35	2.13
Gross Notional Outstanding	755.08	633.49	121.58
Cash and Cash Equivalents	2.44	1.20	1.25
Available for Sale Assets	5.57	2.83	2.74
Tier 1 Capital	2.39	1.34	1.05

Note: Based on 2012 Financial Reports. Some adjustments made for missing values.

Of the 41 banks, 16 are widely recognized as forming the 'core' of the OTC derivative markets. The

3 The sum of cash, cash equivalents and available-for-sale assets is used as an imperfect proxy for a bank's liquid assets. It is acknowledged that 'available for sale' represents an accounting convention that does not necessarily capture the underlying liquidity of the asset.

remaining 25 banks were chosen because they participate in OTC derivative markets, interact with CCPs, and/or are large regional banks (MAGD 2013, Table 3). These banks are typically smaller and are more likely to be involved in OTC derivative markets as part of their client business rather than as dealers with a market-making role. We have not included non-banks or any non-financial institutions (end users) in this network.

For B banks, wedefine the OTC derivative obligations owed by bank i to bank j in product-class $k$to be X_{ij}^{k}**.** Bank i's total derivative liabilities in product-class k will be given by the sum of its obligations to all other banks, $\sum_{j=1}^{B} X_{ij}^{k}$, andits total derivative assetswill be given by $\sum_{j=1}^{B} X_{ji}^{k}$. The available data provide us with these aggregates, which can be thought of as the row and column sums of a matrix of bilateral gross market values – that is, current exposures arising from accumulated past price movements.

We infer the bilateral gross market values for each product class using a genetic algorithm that distributes the aggregate gross market asset and liability values across bilateral relationships. As in Markose, Giansante and Shaghaghi (2012) and Shaghaghi and Markose (2012), the algorithm does this in a way that minimizes the errors in the relevant row and column sums, subject to the constraint that the bilateral relationships are consistent with a core-periphery structure. In particular, we use the 'connectivity priors' about the nature of relationships between counterparties that were used in the MAGD exercise. That is, the 16 core banks are assumed to have transactions with all the other banks in this group with 100 per cent probability; peripheral banks are assumed to have a 50 per cent probability of having a relationship with a core bank and a 25 per cent probability of having a relationship with another peripheral bank. These assumptions are similar in spirit to those used in Heath, Kelly and Manning (2013).[4]

The bilateral gross notional positions are estimated by multiplying the values in each row of the product matrices by the ratio of gross notional liabilities to gross market value liabilities.In cases where gross notional liabilities are not reported (five banks in the sample), the average ratio for the remaining banks is used. The matrix of bilateral gross notional positions for each product class is denoted $\mathbf{G}^{k}$. The matrix of bilateral net notional OTC derivative positions is then given by $\mathbf{N}^{k} = \mathbf{G}^{k} - \mathbf{G}^{k'}$, and is skew symmetric such that $N_{ij}^{k} = -N_{ji}^{k}$.

3.2 Clearing scenarios and netting

We estimate the exposures between two counterparties and the associated collateral demand arising from the need to pay initial margin under alternative scenarios, summarized in Table 2, for the way transactions are cleared. To implement scenarios that involve central clearing, the matrices of bilateral net notional positions,N,are augmented by additional rows and columns representing CCPs to create new matrices, W. For

4 The genetic algorithm we use is different to the standard maximum entropy algorithm that was used in the MAGD exercise because it does not aim to distribute exposures evenly across the transaction matrix (possibly subject to the constraints). The genetic algorithm fits the firm-level gross market asset and liability aggregates with only an 8 per cent error rate.

each bank$i$(within the population of B banks) that novates a proportion s^k of its net notional derivative positions N_{ij}^k to CCP c, bilateral net notional amounts outstanding with another bank j are given by $W_{ij}^k = (1 - s^k)N_{ij}^k$, and those with CCP c are given by $W_{i(B+c)}^k = \sum_{j=1}^{B} s^k N_{ij}^k$. It is also true that $W_{(B+c)j}^k = \sum_{i=1}^{B} s^k N_{ij}^k = -W_{j(B+c)}^k$.

Scenario 1 assumes that 75 per cent of interest rate derivatives, 50 per cent of credit positions, 20 per cent of commodity positions and 15 per cent of both equity and currency positions are cleared centrally through separate CCP services for each product class. The proportions are similar to the 'central' post-reform scenario used in the MAGD exercise for interest rates, credit and currency, but lower for commodity and equity derivatives, acknowledgingthat progress towards central clearing of these product classes has been slower than expected since the MAGD exercise was undertaken in 2012.

Scenario 2 assumes that the same proportions of each product class are cleared centrally as in Scenario 1, but that this is done through a single CCP service. In this case, $W_{i(B+1)}^k = \sum_{j=1}^{B} s^k N_{ij}^k = -W_{(B+1)i}^k$.

To provide an upper bound, and to isolate the stability implications of CCP clearing, we also consider a scenario where all bilateral trades are centrally cleared i.e. $s^k = 1$. We consider the case of separate CCPs – or segregated services – for each product (Scenario 3), as well as a single CCP or fully integrated services for the five products (Scenario 4) under this assumption.

Table 2: Clearing Structure Scenarios

Scenario	CCP Service	Per cent centrally cleared, by product class
Scenario 1	Product specific	75 per cent interest rate; 50 per cent credit; 20 per cent commodity; 15 per cent equity; 15 per cent currency
Scenario 2	Single	As in Scenario 1
Scenario 3	Product specific	100 per cent of each product class
Scenario 4	Single	100 per cent of each product class

3.3 Expected Exposures and Collateral Demand

The focus of our analysis is future exposures.It is already common practice for variation margin to be exchanged, not only on centrally cleared OTC derivative positions, but also on non-centrally cleared positions – at least for transactions between large banks (ISDA 2014). Accordingly, the starting assumption is that all current exposures arising from already observed price changes are already fully collateralized by the exchange of variation margin.

Participant j's expected future exposure to participant i (either a bank or a CCP) is the expected value of j's losses in the event of i's default, after accounting for initial margin.[5] This can be written as $R_{ij} = \mathbb{E}[\max(V_{ij} - C_{ij}, 0)]$,where:

- V_{ij} is equivalent to the variation margin that would have been paid by participant i to participant j, had

5 That is, j's exposure to i is equal to the variation margin owed by i to j less the initial margin posted by i on its position with j.

participant i not defaulted. If we define Δp^k as the change in the price of product k since the last variation margin payment (assumed to be normally distributed around zero), then the next variation margin payment is given by $V_{ij}^k = W_{ij}^k \Delta p^k$, with $V_{ij} = \sum_{k=1}^{5} V_{ij}^k$. $V_{ij} > 0$denotes that participant j expects to receive a variation margin payment from participant i, while $V_{ij} < 0$ denotes that participant j is expected to pay variation margin to participant i. For participants$i$ and j, the random variable for variation margin obligations over the margining period is $V_{ij} \sim N(0, \sigma_{w_{ij}}^2 W_{ij}^2)$, where $W_{ij} = \sum_k |W_{ij}^k|$ and the per-unit portfolio standard deviation$\sigma_{w_{ij}}^2 = \mathbf{w}'\boldsymbol{\Omega}\mathbf{w}$, where $\mathbf{w}$is a 5×1 vector of portfolio weights such that $\mathbf{w}' = \left(\frac{W_{ij}^1}{W_{ij}}, \ldots, \frac{W_{ij}^5}{W_{ij}}\right)and\boldsymbol{\Omega}$is a 5×5 covariance matrix for price changes across the five derivative product classes.[6] We use the price volatility estimates from the MAGD exercise (Table 3). The covariance between price changes across products is assumed to be zero.[7]

- $C_{ij}$is the collateral posted by participant i as initial margin against its derivative positions with participant j. Initial margin is calculated to cover with a high probability any variation margin that participant j would fail to receive in the event of the default of participant i between the time of default and the time of close-out of the outstanding derivative exposure.[8] We scale up daily derivative price volatilities to cover close-out periods of five and ten days. Five days is the typical close-out period assumed in practice by CCPs to calibrate initial margin on OTC derivative products. The future regulatory minimum in non-centrally cleared settings is ten days, reflecting the likelihood that it will be more difficult to close out positions in a decentralized setting than via a CCP's coordinated default management process. Assuming that the distribution of expected price changes for a given product has a mean of zero, collateral to cover initial margin is calculated as $C_{ij} = m\sigma_{w_{ij}} W_{ij}$, where m is the number of standard deviations of the portfolio variance covered. Note that in the case of product specific CCPs, the price volatility of the portfolio is equivalent to the price volatility of the relevant product class.

We assume any failure to receive variation margin owed by a counterparty (either a bilateral counterparty or a CCP) on a derivative position that is not covered by initial margin is not merely an opportunity loss, but rather a realized loss. This is equivalent to assuming that OTC derivative positions are not speculative, but rather are

6 The zero mean implies that derivatives are fairly priced, valued at zero at the time they are written, with a symmetric distribution of potential price movements such that both long and short sides of the position are as likely to pay as to receive variation margin.

7 The assumption of zero covariance between price changes across products is not expected to have a significant qualitative effect on our results. The effect of covariance between price changes across product classes will depend on correlations in derivative positions held across these product classes. It should be noted that, to the extent that our estimates of net open interest are derived from current exposures arising from an unknown price history, the correspondence between signs and directions for a given product is essentially arbitrary; we can determine whether positions are directional and whether they are offsetting, but cannot determine whether directional positions are long or short. The direction of any assumed correlations between product classes would therefore likewise be arbitrary.

8 Collateral posted by a bank to a CCP as initial margin is intended to cover any variation margin that the CCP would fail to receive in the event that the bank defaulted since the CCP retains an obligation to pay variation margin to non-defaulted banks with mark-to-market gains.

entered into to hedge other balance sheet exposures.

Table 3: Derivative Price Volatilities

Product Class	Daily Volatility	5-day Volatility	10-day Volatility
Interest Rates	0.068	0.152	0.215
Credit	0.119	0.266	0.376
Equity	0.635	1.420	2.008
Currency	0.068	0.152	0.215
Commodity	0.387	0.865	1.224

Note: Derivative price volatilities over close-out periods of longer than a day are estimated by multiplying the daily volatility by the square root of the number of days in the close-out period.

As an indication of the magnitude of exposure if no initial margin is collected ($m = 0$ with $C_{ij} = 0$ for all $i$and j), Table 4 presents uncollateralized expected exposure over various margining periods. Several observations can be made. First, exposures increase at a decreasing rate as the assumed time between default and close-out increases. This is as would be expected, given the assumption that price changes are a random walk. Also, as expected, exposures decrease as netting opportunities increase. Clearing all OTC derivative products through a single CCP service lowers exposures relative to the case of using separate CCP services for each product (Scenarios 2 and 4, relative to Scenarios 1 and 3, respectively). Centrally clearing a larger share of the OTC derivative portfolio also lowers exposures (Scenarios 3 and 4, relative to Scenarios 1 and 2).

Table 4: Expected Exposures with Zero Collateral Coverage

($US billion)

	1-day	5-day	10-day
Scenario 1	64.13	128.65	176.99
Scenario 2	60.35	123.74	171.25
Scenario 3	38.89	50.43	59.09
Scenario 4	25.78	33.43	39.17

The collateral required for initial margin, assuming 99 per cent coverage of one-tailed price movements ($m = 2.33$) is presented in Table 5. Each participant holds initial margin against one direction of possible price movements, because a counterparty default only gives rise to a replacement cost loss if the default coincides with an adverse price movement. If the default coincides with a favourable price movement, there is no loss. Note that banks post margin against outstanding positions with CCPs, but that CCPs do not post margin with banks. Initial margin again increases with the assumed closeout period, and decreases as the scope for netting increases. In the case of a single CCP, the decline in initial margin requirements is substantial.[9]

When the level of initial margin coverage is high, the remaining uncollateralized exposure is substantially reduced. Should there, nevertheless, be a shortfall between a crystallized exposure and initial margin, this would

[9] For the single CCP service, it is assumed that margin is calculated on a portfolio basis across the five product classes. This may be seen as an upper bound to the scope for offsets. As noted in Section 2.2, in practice, CCPs will typically only allow margin offsets between products where there is a significant clear and reliable correlation between prices across the products.

in the case of a bank have to be absorbed by bank capital. In the case of a CCP, a shortfall would be absorbed by its prefunded default fund, which is typically funded primarily by participant contributions.[10]

Table 5: Initial Margin at 99 Percent Coverage

($US billion)

	Total	Bank-to-bank	Bank-to-CCP	CCP-to-bank
Scenario 1	942.10	892.88	49.22	0.00
Scenario 2	930.25	892.88	37.37	0.00
Scenario 3	121.82	0.00	121.82	0.00
Scenario 4	80.76	0.00	80.76	0.00

Note: A 10-day closeout period is assumed for bank-to-bank margin; a 5-day closeout period is assumed for bank-to-CCP margin

We calibrate the CCP's default fund to *Cover 2*, as described in Section 2.1. In defining extreme but plausible market conditionsfor product-specific CCPs, we assume a single product price change at 99.987 per cent (one-tailed) of the price distribution (equivalent to a once-in-30-years event). For a multi-product CCP, we assume a portfolio price change at 99.987 per cent (one-tailed) of the joint price distribution, with zero covariance between price changes across products.Banks are assumed to make contributions to the default fund in proportion to their respective shares of each CCP's overall initial margin.

Since CCPs are not permitted to draw on the initial margin of one participant to cover losses arising from the default of another participant, the only prefunded pooled resources available to absorb uncollateralized losses to the CCP in the event of counterparty default are those in the default fund and the defaultedparticipant's initial margin. Should these prefunded resources be insufficient, the CCP would allocate any remaining uncovered losses in accordance with its recovery plan. In Sections 4 and 5, we assume that this is done via VMGH.

Table 6: Default Fund Size

($US billion)

	Scenario 1	Scenario 3
CCP1 (Interest Rates)	3.86	5.14
CCP2 (Foreign Exchange)	0.45	3.00
CCP3 (Equity)	1.63	10.83
CCP4 (Credit)	0.84	1.63
CCP5 (Commodity)	0.17	0.87
Total	**6.95**	**21.47**
Total encumbrance (default fund and initial margin)	**949.05**	**143.29**
	Scenario 2	Scenario 4
CCP (Combined)	4.14	11.86
Total encumbrance (default fund and initial margin)	**934.39**	**92.62**

Table 6 sets out the size of each CCP's default fund in each scenario. In the case of Scenario 4, for instance, a

10 We assume that a bank's contribution to the CCP's default fund is fully deducted from its available capital. This represents a conservative application of international bank capital requirements for exposures to CCPs, which were revised in 2014 and will take effect from January 2017 (BCBS 2014).

default fund of \$11.9 billion is available to the CCP to cover any shortfall between a crystallized loss and the defaulted participant's initial margin. This compares with total default fund resources across the five CCPs of \$21.5 billion in Scenario 3, reflecting the reduced netting of exposures when positions across products are fragmented. Since participants' prefunded default fund contributions, like initial margin requirements, represent a call on banks' liquid assets, they contribute to encumbrance. This encumbrance is important in the analysis in Sections 4 and 5. Table 6, therefore, also summarizes the total system encumbrance arising from initial margin and default fund contributions.

3.4 Realized Exposures

For stability analysis, the tail of the distribution is more relevant than expected outcomes. In Sections 4 and 5, therefore, we consider single extreme realizations of OTC derivative price changes and associated *ex post* exposures.

For each of the five products, let v_k be the realized price change for product k in numbers of standard deviations of product k's price movements (σ_k). The variation margin flows from i to j will be:

$$V_{ij} = \sum_k v_k \sigma_k W_{ij}^k \quad (1)$$

The realized exposure of participant j to participant i will equal the positive variation margin obligation from participant i to participant j, less the initial margin on the position. We denote this as M_{ij}:

$$M_{ij} = \max\left(V_{ij} - C_{ij}, 0\right) \quad (2)$$

In what follows, we consider an 'expected tail realization', which is the expected price change conditional on that price change being larger than the price change on which initial margin was calibrated. This 'conditional expected future exposure' is one way to define a 'large' price change that isnot simply an arbitrary large number of standard deviations. Of course, since these calculations are based on a normal distribution, the expected tail realization is only a fraction of a standard deviation above the point at which initial margin is set. Accordingly, we also consider market outcomes further into the tail.[11]

Initial margin is set on the basis of m standard deviations, which corresponds to a realized price change of $\bar{v} = \mathbb{E}[v|v > m] = \frac{\phi(m)}{1-\Phi(m)}$. For example, a one-tailed coverage level of 99 per cent would have a value of m of approximately 2.33 and a value of $\bar{v}$ of approximately 2.67. In this case, the 'realized exposure' for a single-

[11] An alternative approach, which we leave to future research, would be to use alternative price change distributions that exhibit 'fat tails'. Such distributions, such as Generalized Extreme Value Distributions, are common in the finance literature (see Markose and Alentorn (2011)).

product portfolio would be about 0.34 times the portfolio standard deviation (over the exposure period).[12]

As an illustration of the magnitudes involved, Table 7 presents realized exposures based on the conditional expectation of a price movement that is beyond the 99th percentile of the price distribution(for an assumed combination of positive and negative price changes across the product classes).Again, since banks post margin against outstanding positions with CCPs, but CCPs do not post margin with banks, there is an asymmetry between the uncollateralized exposures of banks and CCPs. In interpreting Table 7, it is important to note that the data take no account of the probability of default.

Table 7: Realized Exposure

($US billion)

	Total	Bank-to-bank	Bank-to-CCP	CCP-to-bank
Scenario 1	148.52	93.38	39.87	15.26
Scenario 2	132.83	93.38	28.18	11.27
Scenario 3	136.46	0.00	98.69	37.78
Scenario 4	76.64	0.00	53.28	23.36

Note: Based on the conditional expectation beyond 99 per cent initial margin coverage; assumes price changes of 2.67 standard deviations: positive for interest rates, currency and credit; negative for equities and commodities

4. Financial Network Stability

Efforts by academics and policymakers to evaluate the systemic risk within financial networks have intensified since the global financial crisis highlighted that some financial institutions were 'too interconnected to fail' (Haldane, 2009; Yellen 2013;Acemoglou et. al., 2015). It has been recognized that the failure of certain highly connected financial institutions could trigger the failure of other similarly connected institutions in a network topology with a prominent core-periphery structure (Craig and von Peter, 2012; Markose, 2012).

Markose (2012) uses the insights from May (1972, 1974) that the stability of a network system should be considered within a spectral framework for dynamical systems and that the topology of the network plays a crucial role in the vulnerability of that system to failure.[13] Markose (2012) adapts the epidemiology framework in Wang *et al*(2003) to show that a weighted graph can provide an appropriate dynamic characterisation of a financial network system, and the likelihood of contagion spreading through the system. Stability conditions are governed by a 'cure' rate, defined as a threshold of equity capital that provides a permissible buffer against contagion losses, and 'infection' rates, defined as the exposures of financial institutions to their counterparties. This provides the basis for the so-called eigen-pair method which simultaneously determines the maximum

[12] A price change of $+\bar{v}$ standard deviations would represent a large positive price change (to the benefit of banks with net long positions and to the cost of banks with net short positions), and a price change of $-\bar{v}$ standard deviations would represent a large negative price change (to the benefit of banks with net short positions, and to the cost of banks with net long positions). For a positive W_{ij}^{k}(representing$i$ being short and j being long), this upward movement in prices results in a variation margin payment from $i$to j.

[13] In financial networks, nodes represent financial agents and the edges or connective links represent directed inflows ('in degrees') of liquidity or receivables, and directed outflows ('out degrees') of liabilities or payables. May (1972, 1974) showed that network stability in terms of the maximum eigenvalue involves a trade-off between connectivity and heterogeneity of (weighted) degrees. Networks with high heterogeneity of weighted degrees (where some nodes have a large number of highly weighted links while most have very few) have to have low connectivity to remain stable.

eigenvalue of the network of liabilities (adjusted for Tier 1 capital), to indicate the stability of the overall system, along with eigenvector centrality measures.[14] The right eigenvector gives the ranking of systemic importance of institutions in contributing to instability arising from their liabilities, while the left eigenvector provides a ranking of the vulnerability of financial institutions to contagion.In this section, we extend this methodology to analyse how the introduction of central clearing and collateralization of non-centrally cleared derivatives affects the network structure of OTC derivative exposures between financial institutionsand the stability of the system.Stability conditions are defined in terms of thresholds both of equity capital and liquid assets.

4.1 Network topology

Figures 1 to 4, below, illustrate the network topology associated with each of the alternative scenarios for the clearing structure detailed in Section 3.2 (Table 2).

Figure 1: Scenario 1

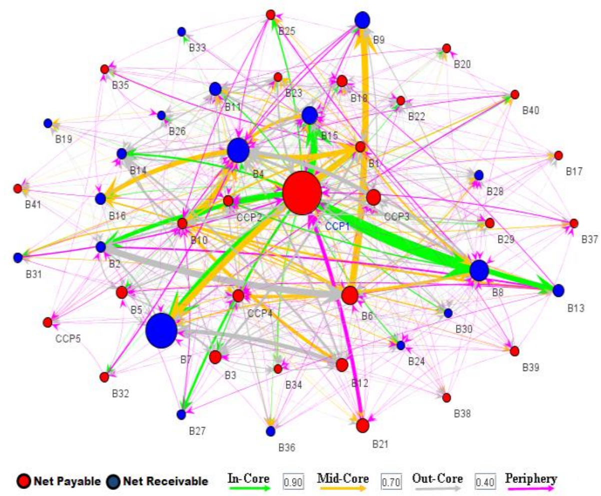


Figure 2: Scenario 2

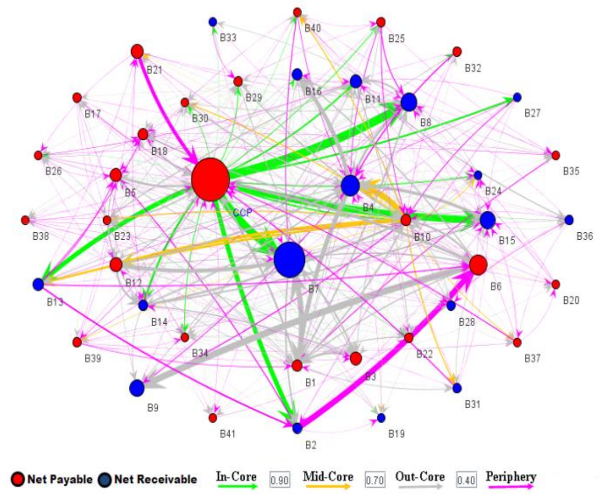


Figure 3: Scenario 3

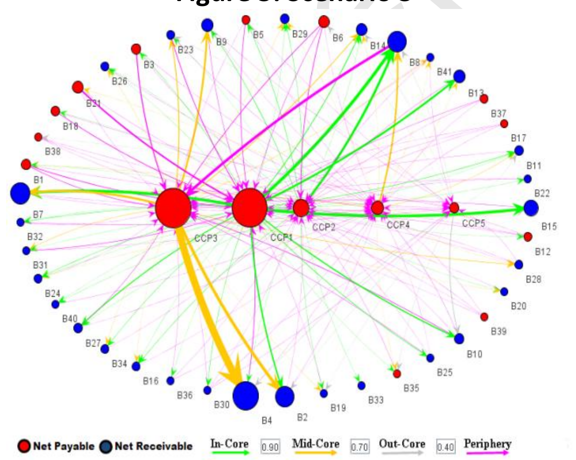
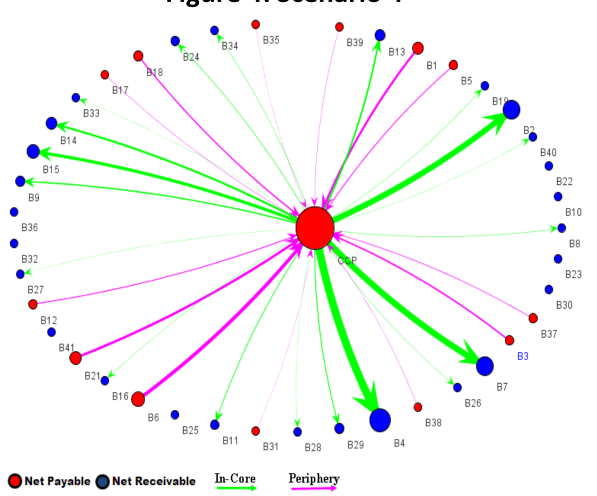


Figure 4: Scenario 4



[14] Despite, considerable ongoing work on the use of the network approach for systemic risk analysis, there is as yet no consensus on a metric to quantify systemic risk or system instability in a financial network. Acemoglou et. al. (2015) study stability of regular networks which have no heterogeneity in degrees (or weighted degrees) and hence eschews the connectivity-heterogeneity trade off that is key to the spectral method given in this paper to quantify potential instability. As will be seen, even with considerable reduction in the connectivity of the network, the extreme heterogeneity of degrees with the star network in Figure 4, which has a single CCP clearing all derivatives products, the maximum eigenvalue of the network in Scenario 4 is higher than other network configurations.

Note: The networks in Scenarios 1 and 2 display 'rich tiering' based on each financial institution's percentile of in and out degrees. Those institutions above the 90th percentile are deemed to be in the inner core; those between the 70th and 90th percentiles are in the mid core; those between the 40th and 70th percentiles are in the outer core; and those below the 40th percentile are in the periphery. Networks were all transactions are novated through a CCP (Scenarios 3 and 4) show a single tiering, with CCPs in the core and all other institutions in the periphery.

The exposures in the graphs capture the uncollateralized exposure (i.e., in excess of initial margin coverage (99 per cent)) for the realized price change of 2.67 standard deviations for each class of derivatives, as discussed in Section 3.4.

The colours of the nodes denote whether the financial institution is a net payer (red) or a net receiver (blue) of variation margin, while the size of the arrows linking the nodes is proportional to the size of the exposure between them. The networks in Scenarios 1 and 2 (Figures 1 and 2) display 'rich tiering', where institutions are arranged in concentric circles based on how connected they are to other institutionsin terms of their in and out degrees. The most connected institutions are in the inner core, followed by two other tiers, the mid and outer cores. The least connected institutions are in the periphery. The network in which all transactions are novated through a single CCP (Scenario 4) displays single tiering, with the CCP in the core and all other institutions in the periphery.

Table 8 summarizes the information in the topology graphs using a series of metrics commonly applied in network analysis. Scenarios 1 and 2 have network connectivity of about 20 per cent and a clustering coefficient of over 26 per cent. These metrics characterize a large central core of highly interconnected financial institutions (nodes with green arrows emanating from them in Figures 1 and 2). The continued presence of non-central clearingresults in negative-to-low kurtosis and low skewness of both in degrees and out degrees, indicating that there are many similarly connected institutions.

Table 8: Network Topology Under Alternative Clearing Arrangements

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Nodes	46	42	46	41
Edges	464	348	172	32
Connectivity	0.224	0.202	0.083	0.032
Clustering Coefficient	0.286	0.265	0.022	0
Mean in degrees	10.087	8.286	3.739	1
Std* in degrees	5.189	4.346	5.114	2.45
Skew in degrees	0.562	0.717	2.60	2.70
Kurtosisin degrees	-0.699	-0.407	5.754	20.45
Mean out degrees	10.087	8.286	3.739	1
Std* out degrees	4.130	3.815	5.009	3.182
Skew out degrees	0.721	1.200	2.726	3.5
Kurtosis out degrees	0.874	2.857	7.059	39

Note:*Std: Standard Deviation. Connectivity of a directed network with N nodes is estimated in terms of the ratio of total number of connected links, K, to the total number of all possible links given by $N(N-1)$,that is,$\frac{K}{N(N-1)}$. The formula for the clustering coefficient is given by $\frac{\sum_i \Delta_i}{N}$, where $\Delta_i = \frac{E_i}{k_i(k_i-1)}$ and $k_i$denotes i's neighbors,the total number of all possible directed links between them is given by $k_i(k_i$-1), and E_i denotes the actual number of links between agent i's k_i neighbors (namely, those of i's $k_i$neighbors who are also mutual neighbors).

When all positions are centrally cleared, the number of network edges, connectivity and clustering all fall sharply. At the same time, skewness and kurtosis of both in degrees and out degrees increase sharply.In particular, with all positions centrally cleared, network connectivity falls to 8 per cent and 3 per cent, in Scenarios 3 and 4, respectively; and the 'star' network in Scenario 4 (Figure 4) exhibits zero clustering. Later in this section, we examine the implications of the observed increase in the heterogeneity in degree distribution in Scenarios 3 and 4 for the stability of the system.

4.2 Methodology for network stability analysis

In this section we extend and adapt the Markose (2012) framework to reflect the institutional details of CCP risk management.In the case of the CCP, the relevant metric is not capital, but rather the pooled financial resources in the CCP's default fund (Table 6). Further, while we assume that a bank can only use a portionof its capital to absorb derivative-related losses, a CCP can use its entire default fund to mitigate losses from clearing members once a defaulted participant's initial margin is exhausted. This heterogeneity in the capital loss thresholds or the cure rates is a new feature introduced in this study. Finally, CCPs can also reduce their potential to transmit stress (and therefore their systemic importance) by allocating widely any uncovered losses that may remain in the event of a participant default.

While Markose (2012) considers only solvency stress,this analysis also considers the possibility that liquidity stress can arise from the encumbrance of liquid assets to meet prefunded initial margin requirements and default fund contributions.To measure liquidity stress, we use a simple metric of the share of a bank's liquid assets that are encumbered. This metric is assumed to be independent of counterparty default. We show that while more collateral reduces systemic risk from a solvency perspective, it increasesthe risk that a liquidity shortfallwill trigger contagion. Indeed, we find that the stability or tipping point for the system can be specified in terms of the sum of the liquidity and solvency thresholds.

4.2.1 Populating the stability matrix

We assume that there are $B + c$ financial institutions, where B is the number of banks and c is the number of CCPs, either one in Scenarios 2 and 4,or five in Scenarios 1 and 3.[15]The 'stability matrix' $\mathbf{\Theta}$ isa$(B + c) \times (B + c)$ matrix where the (i, j)-th element represents the positive residual obligation M_{ij} from participant i to

15 In Scenarios 1 and 3, CCP1 clears interest rate derivatives; CCP2clears currency derivatives; CCP3 clears credit derivatives; CCP4 clears equity derivatives and CCP5 clears commodity derivatives.

participant j (as discussed in Section 3.4) as a share of participant j's resources. Bank j's resources, K_j, include bank$j$'s Tier 1 capital adjusted for bank j's contributions to any CCP default funds. In the case of a CCP, K_j represents the CCP's default fund. The elements of $\mathbf{\Theta}$, $\theta_{ij} = M_{ij}/K_j$,are positive for pairs of financial institutions that have a direct financial link, and are zero otherwise. Finally, the exposures of clearing participants to their CCPs are adjusted for the CCP'sloss allocation process, which we assume is VMGH. The haircut isassumed to be set according to the ratio of the CCP's own aggregate uncollateralized exposure to that acrossits participants.[16]

In the hybrid case where derivatives are cleared both bilaterally and centrally (with separate CCPs), the matrix $\mathbf{\Theta}$ is given as follows:

$$\mathbf{\Theta} = \begin{bmatrix} 0 & \frac{M_{12}}{K_2} & \cdots & \frac{M_{1B}}{K_B} & \frac{M_{1CCP_1}}{K_{CCP_1}} & \cdots & \frac{M_{1CCP_5}}{K_{CCP_5}} \\ \frac{M_{21}}{K_1} & 0 & \cdots & \frac{M_{2B}}{K_B} & \frac{M_{2CCP_1}}{K_{CCP_1}} & \cdots & \frac{M_{2CCP_5}}{K_{CCP_5}} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \frac{M_{B1}}{K_1} & \frac{M_{B2}}{K_2} & \cdots & 0 & \frac{M_{BCCP_1}}{K_{CCP_1}} & \cdots & \frac{M_{BCCP_5}}{K_{CCP_5}} \\ \frac{M_{CCP_1 1}}{K_1} & \frac{M_{CCP_1 2}}{K_2} & \cdots & \frac{M_{CCP_1 B}}{K_B} & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \frac{M_{CCP_5 1}}{K_1} & \frac{M_{CCP_5 2}}{K_2} & \cdots & \frac{M_{CCP_5 B}}{K_B} & 0 & \cdots & 0 \end{bmatrix} \quad (3)$$

When banks' derivative positions are all centrally cleared,the $B \times B$ top left side block of $\mathbf{\Theta}$is null. In Scenario 4, with a single multi-product CCP, the $\mathbf{\Theta}$ matrix becomes a single star-like network with zeroseverywhere except in the $(B + 1)$-th row and column.

The dynamics of systemic stressare determined by the following factors.

i) Liquidity stress can ariseat each point in time from the encumbrance of banks' liquid assets to fund initial margin and default fund contributions. Let L_i denote bank i's liquid assets, defined as in Section 3.1. Let C_i be bank i's total initial margin and F_i be bank i's contributions to the default fund. Then the proportion of encumbered liquid assets, given by $\frac{C_i+F_i}{L_i}$, is a metric for each bank's vulnerability to liquidity stress.At the level of each bank, the size of the prefunded initial margin works to reduce one-for-one the maximum loss given default that it can imposeon other counterparties, including the CCPs, as reflectedin the numerator of elements ofthe $\mathbf{\Theta}$ matrix. Note, since the CCP does not pay initial margin or contribute to a default fund, its encumbered liquidity ratio term is zero.

16 Since CCPs only novate positions and therefore hold a balanced book, a CCP's aggregate uncovered exposure to its variation-margin-paying participants represents the maximum loss that CCP would need to allocate to its variation-margin-receiving participants. For a given CCP, the ratio of the CCP's exposure to participants and participants' exposures to the CCP represents the maximum haircut that a CCP would apply to participants' variation margin gains if default fund resources were exhausted. We adjust participant exposures to CCPs according to this 'upper bound' variation margin gains haircut.

ii) The solvency of an institution is defined in terms of a threshold, $1 \leq \rho^i \leq 0$, which determines the share of resources that can be used to deal with counterparty losses before the financial entity is deemed to have failed. For a bank, we assume that only 10 per cent of Tier 1 capital ($\rho^{Bank} = 0.1$) can be absorbed to deal with potential derivative losses before the bank is deemed to be in stress. Since a CCP can use all of its default fund to protect against losses, ρ^{CCP}=1.

iii) The way in which interconnectedness with counterparties can transmit stress to an institution,i, is given by $\sum_j \frac{M_{ji}}{K_i} = \sum_j \theta_{ji}$; that is,the sum of realized exposures of financial institution i to counterparties j, given as a share of bank i's adjusted Tier 1 capital (or CCP c's default fund).

iv) Finally, even if an institution has sufficient capital to avert solvency stress, it can only meet its own variation margin obligations to the extent that it has unencumbered liquidity.Hence, while capital can mitigate the likelihood that an institution falls victim to stress, lower encumbrance can mitigate the likelihood that an institution itself becomes a trigger for stress.Thus, both capital and encumbrancecharacterize the so-called contagion stress rates below.

Incorporating the factors above, the dynamics characterizing the transmission of contagion in a financial network for a bank can be given by:

$$u_{iq+1} = \left[\frac{(C_i + F_i)}{L_i} - \rho^{Bank}\right] u_{iq} + \sum_j \frac{M_{ji}}{K_{i0}} u_{jq} \ . \qquad (4)$$

Here, q+1 is a time step. A financial institution's own rate of contagion stress at stage q is given by $u_{iq} = \left(1 - K_{iq}/K_{i0}\right)$ for q>0,where K_{iq}/K_{i0} is the ratio of resources at q and resources at the initial date[17], and u_{jq}denotes the contagion stress rateof thecounterparty$j$ to which$i$ is exposed.In matrix notation, the dynamics of the system can be characterized in the following way:

$$\mathbf{U}_{q+1} = \left[\mathbf{D}^{\mathbf{Liq}} - \boldsymbol{D}^{Sol} + \boldsymbol{\Theta}'\right]\mathbf{U}_q = \mathbf{Q}\mathbf{U}_q \ . \qquad (5)$$

Here,$\mathbf{U}_q$is a vector where each element is the rate of failure $u_{iq}$of an institution in the system at time q; $\mathbf{D}^{\mathbf{Liq}}$ is the diagonal matrix where the elements in the diagonal are encumbered liquidity ratiosof each institution, $\frac{(C_i+F_i)}{L_i}$(noting that this will be zero for a CCP); $\mathbf{D}^{\mathbf{Sol}}$is thediagonal matrix where the elements in the diagonal arethe capital loss thresholds for each institution ρ(noting that this will also be 1 for CCPs); and $\boldsymbol{\Theta}'$ is the transpose of the matrix in (3) that gives the exposures of each institution to other participants' unfunded variation margins relative to Tier 1 capital or default fund resources.

[17]Note, with the inclusion of the liquidity encumbrance ratio, we have a more generalized contagion stress rate for banks than the one in Markose (2012) with each i's rate of contagion stress constrained as follows: $u_{iq} < 1 - \left(\frac{(C_i+F_i)}{L_i} - \rho^{Bank}\right)$. This captures the conditions that cumulated losses at any $q$do not exceed the capital buffer, and that the liquidity encumbrance ratio be less than 1.

The system stability of (4) will be evaluated on the basis of the power iteration:

$$\mathbf{U}_q = \mathbf{Q}^q \mathbf{U}_1. \qquad (6)$$

Following Markose (2012), the system can shown to be stable as q tends to infinity if the maximum eigenvalue of Q, $\lambda_{max}(\mathbf{Q})$, is less than 1.The following condition can also be seen to be the tipping point for the system:

$$\lambda_{max}(\mathbf{Q}) = \lambda_{max}(\mathbf{D^{Liq}}) - \lambda_{max}(\mathbf{D^{Sol}}) + \lambda_{max}(\mathbf{\Theta}') < 1. \qquad (7)$$

The maximum eigenvalues of the diagonal matrices $\mathbf{D^{Liq}}$and $\mathbf{D^{Sol}}$ are trivially given by the maximum element along the diagonal. In other words, the bank with the highest encumbered liquidity ratio or the smallest capital loss thresholds will make the largest direct contribution to system instability. This stability condition captures an insight, explored further in the following section, that increasing collateralization involves a trade-off for system stability:it can mitigate second round solvency stress by reducing the instability from interconnectedness, determined by $\lambda_{max}(\mathbf{\Theta}')$, only by first increasing the likelihood of liquidity stress. Further, $\lambda_{max}(\mathbf{\Theta}')$ is not just influenced by the size of the financial flows, but also by the topology of the network.

The right and left eigenvectors associated with the maximum eigenvalue of the matrix $\mathbf{\Theta}$ contain information, respectively, about the systemic importance and vulnerability of individual institutions.

The right eigenvector centrality score, $\widetilde{v_i}$, for the i^{th} node for matrix Θ, is proportional to the sum of the centrality scores of all nodes to which it is connected, weighted by the ratio of its liabilities to theTier 1 capital or default fund resources of the counterparty. Hence,

$$\widetilde{v_i} = \frac{1}{\lambda_{max}(\mathbf{\Theta}')} \sum_j \theta_{ij} \widetilde{v_j} \,. \qquad (8)$$

Using vector notation, the eigenvalue equation for$\mathbf{\Theta}$ for the eigen-pair $(\lambda_{max}(\Theta), \widetilde{\boldsymbol{v_1}})$ is given as:

$$\mathbf{\Theta}\widetilde{\boldsymbol{v}} = \lambda_{max}(\mathbf{\Theta}')\widetilde{\boldsymbol{v}}\,. \qquad (9)$$

Hence, financial institutions with high eigenvector centrality that reflects their connections to a large number of similarly highly connected counterparties can contribute greatly to the instability of the system.Using the eigenvalue equation, and noting that a matrix and its transpose have the same maximum eigenvalue, the left eigenvector, $\boldsymbol{v}$, is defined as

$$\mathbf{\Theta}'\boldsymbol{v} = \lambda_{max}(\mathbf{\Theta}')\boldsymbol{v}. \qquad (10)$$

Using the power iteration algorithm, (6), and also (10), we can estimate the steady state percentage capital loss for i as the product of $\lambda_{max}(\mathbf{\Theta}')$ and i's vulnerability index, using the infinity norm, denoted as $v_{i\infty}$[18],

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[18] For this analysis, it is important to make sure that the right and left eigenvectors associated with the largest eigenvalue are given using the infinity norm. The infinity norm of a vector **x** denoted as $\|\mathbf{x}\|_\infty$is the largest number in the vector.Hence, the highest ranked financial institution will have an index of 1 in terms of its eigenvector centrality. There is a simple conversion from the eigenvector produced

$$u_{i\#} \cong \lambda_{max}(\mathbf{\Theta}')\boldsymbol{v}_{i\infty}\ . \qquad (11)$$

Thus,the most vulnerable institution, which has a left eigenvector index of 1, can lose an amount proportionate to $\lambda_{max}(\mathbf{\Theta}')$ of its buffers earmarked to safeguard its solvency in the worst case. Likewise, at tipping points, the most systemically important institution can inflict capital or default fund losses proportional to $\lambda_{max}(\mathbf{\Theta}')$.

For all other scenarios than the single star network associated with Scenario 4, the maximum eigenvalue can be obtained using the power iteration in(6).In the case of Scenario 4, the extreme sparseness of the $\mathbf{\Theta}$ matrix requires an alternative approach. We apply a direct calculation based on the Rayleigh Quotient:

$$\lambda_{max}^{star} = \frac{\boldsymbol{x}'\mathbf{\Theta}'\boldsymbol{x}}{\boldsymbol{x}'\boldsymbol{x}}\ . \qquad (12)$$

Here, the vector $\mathbf{x}$ is set to be the row sum of the matrix $\mathbf{\Theta}$.

4.3 Results of stability analysis

Table 9 provides information about the stability properties of the financial system described by our data on the OTC derivativesmarket, assuming that CCPs hold prefunded resources to *Cover 2* and manage realized uncovered losses using VMGH. More specifically, Table 9 includes information on the risk of a systemic problem arising from a liquidity event in our system, as summarized by the Liquidity Systemic Risk Index (LSRI, $\boldsymbol{\lambda_{max}}(\mathbf{D^{Liq}})$), and the probability of a solvency problem arising from second-round stress, as summarized by the Solvency Systemic Risk Index (SSRI, $\boldsymbol{\lambda_{max}}(\mathbf{\Theta}')$). From the stability condition above, we know that the system will be stable when:

LSRI+SSRI<1+ρ = 1.1.

In Scenarios 1 and 2, in which a significant portion of positions remain non-centrally cleared, the limited scope for netting combined with the need to prefundinitial margin gives rise to high encumbrance levels (as observed in Table 6). At least one bank has about 83 per cent of its liquid assets encumbered. Hence, the LSRI is very high.For Scenarios 3 and 4, in which all positions are cleared via a CCP and netting efficiency is correspondingly higher, liquidity risk is significantly reduced.

The SSRIs, by contrast, are relatively low, at 0.16under Scenario 1 and 0.12 for Scenario 2, where the price change is 2.67 standard deviations. This is consistent with the observed trade-off between liquidity risk and solvency risk in Heath, Kelly and Manning (2013):to the extent that high encumbrance reflects collateralization, the risk of solvency stress declines as liquidity risk increases. The low SSRIs also reflect the still largely

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using the Euclidean norm to one using the infinity norm (see, Markose,2012). For the result in (11), note for any real non-negative vector $\mathbf{U_1}$ in (6), the qth power of the matrix, denoted as $\boldsymbol{\Theta}'^{q}$,can be solved iteratively using the infinitynorm of the vector $\boldsymbol{\Theta}'^{q}\boldsymbol{U_q}$, denoted as $||\boldsymbol{\Theta}'^{q}\boldsymbol{U_q}||_\infty$ to normalize the vector as in the equation:$\boldsymbol{U_{q+1}} = \frac{\boldsymbol{\Theta}'\boldsymbol{U_q}}{||\boldsymbol{\Theta}'\boldsymbol{U_q}||_\infty} = \frac{\boldsymbol{\Theta}'^{q}\boldsymbol{U_1}}{||\boldsymbol{\Theta}'^{q}\boldsymbol{U_1}||_\infty}$. The iteration is said to have converged at q when $\boldsymbol{U_{q+1}} = \boldsymbol{U_q} = \boldsymbol{v}$ with an epsilon margin of error. The vector $\boldsymbol{v}$is the left eigenvector of the matrix and $||\boldsymbol{\Theta}'\boldsymbol{v}||_\infty = \lambda_{max}(\mathbf{\Theta}')$. Multiplying through by $\lambda_{max}(\mathbf{\Theta}')$ in the power iteration equation, we have the eigenvalue equation given in (10) $\boldsymbol{\Theta}'\mathbf{v} = \lambda_{max}\mathbf{v} \equiv \boldsymbol{\Theta}'^{q}\boldsymbol{U_1} \equiv \boldsymbol{U_\#}$, at the point of convergence of the power iteration algorithm. This yields the result in (11).

decentralized topology in these scenarios and correspondingly dispersed exposures. However, the LSRI and SSRI outcomes in combination exceed 1.1 when price volatility is 3.89 standard deviations, thereby violating the stability condition for the system. This implies a need for some institutions to increase capital in these scenarios, and for the system to increase liquidity to relieve the constraints of encumbrance. Recall, however, that these results are based on banks' observed liquid asset holdings at a point in time under a different collateralization regime and network structure. It can reasonably be assumed that banks would naturally alter their liquid asset holdings in response to a new regime.

In the more centralized networks of Scenarios 3 and 4, the SSRI outcomes are somewhat higherthan in Scenarios 1 and 2.This reflects the extreme heterogeneity in link/degree distribution with CCP having a large number of interconnections with banks across the system and the latter having at most one in or out degree. The sumof LSRI and SSRI nevertheless remains comfortably below the threshold for instability in both scenarios and under both realized price volatilities.

Table 9: Systemic Risk Indices (Cover 2, VMGH)

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Liquidity Systemic Risk Index (LSRI)				
	0.83	0.83	0.27	0.15
Solvency Systemic Risk Index (SSRI)				
Realized 2.67 Volatility	0.16	0.12	0.21	0.30
Realized 3.89 Volatility	0.39	0.31	0.45	0.58
Total Systemic Risk (SSRI+LSRI)				
Realized 2.67 Volatility	0.99	0.95	0.48	0.45
Realized 3.89 Volatility	1.22	1.14	0.72	0.73

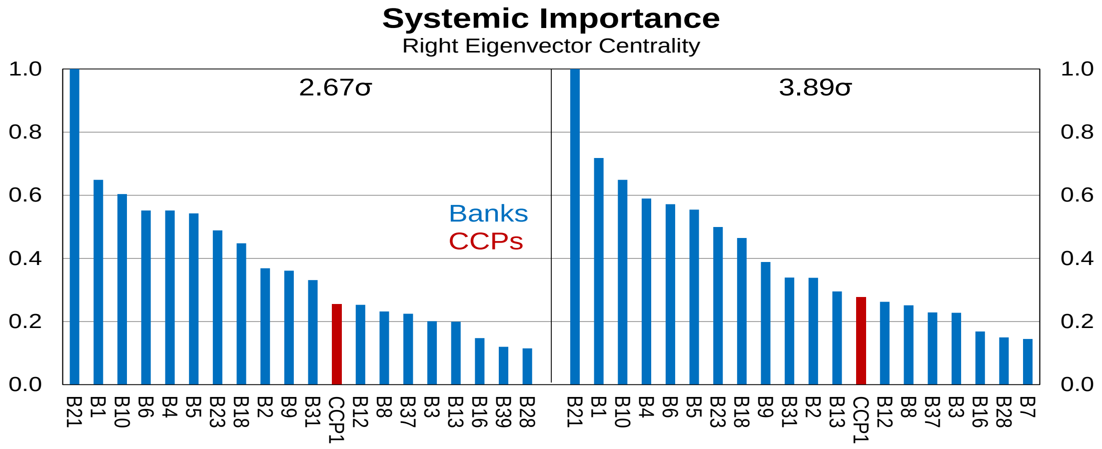
Note: The SSRI from the unfunded obligations is calculated for 2.67 and 3.89 standard deviation price moves.

As discussed in Section 4.2, the eigen-pair methodology also permits institutions to be ranked according to their importance to system stability.These metrics provide a quick assessment of the vulnerabilities in the system.Figure 5(a) orders banks and CCPs according to their contribution to system instability (right eigenvector centrality) under Scenario 1,which is the closest to the extant system structure. The rankings are qualitatively similar for the 2.67 and3.89 standard deviation price shocks, althoughthe precise positions of some institutions in the ranking change. CCPs are not among the most prominent institutions in the network on this metric; since the CCPs maintain balanced positions, the size of their liabilities to banks is small relative to the banks' Tier 1 capital.

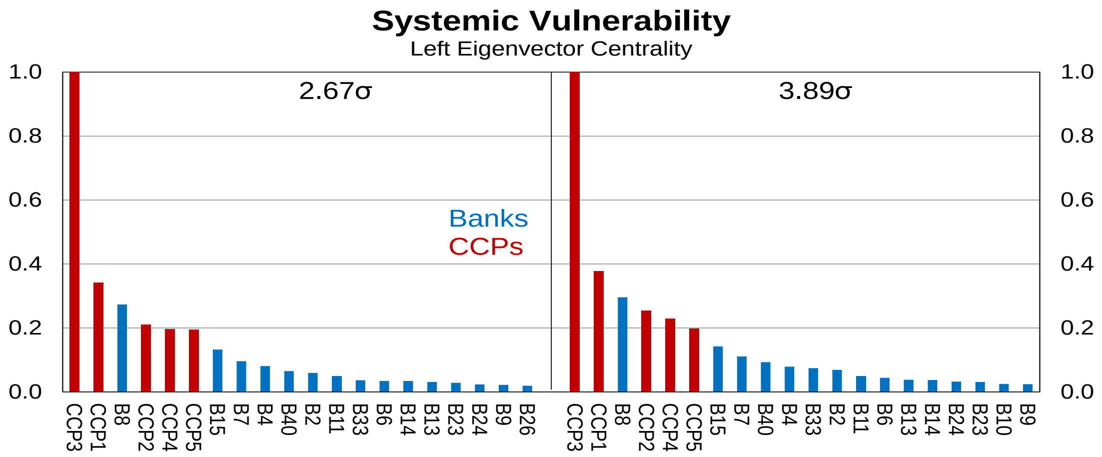
Figure 5(b) gives the rank order of institutions' exposure to stress in other institutions (left eigenvector centrality).Typically, CCPs show up as being systemically vulnerable on this metric, reflecting their large exposuresto banks' unfunded variation margins relative to the size of their own default funds.Based on theseresults – and reflecting the maximum eigenvalue in Table 9 – CCP3, the CCP for credit derivatives, is the most vulnerable financial institution. On this metric, using the calculation in equation (11), CCP3 is exposed to the potential loss of 16 per cent of its default fund in Scenario 1 with aprice shock of2.67 standard deviations. This rises to 39 per cent in the event of an adverse price move of 3.89 standard deviations. CCP1, the CCP for interest rate derivatives, is the second most vulnerable institution in this scenario.

Figure 5: Rank Ordering of Financial Institutions: Top 20(Scenario 1, Cover 2 with VMGHadjustment)

(a)



(b)



Note: Ranking of institutions can differ in the respective 2.67and 3.89 price volatility cases; for example, in Figure 5(a), B6 is ranked fourth for the 2.67 standard deviation case, while B4 is ranked fourth for the 3.89 standard deviation case. Eigenvectors normalized to equate highest centrality rank to 1.

In Figure 5(b), the two banks most vulnerable to contagion have vulnerability indices of 0.29 (B8) and 0.14 (B15), implying that they are exposed to potential losses of Tier 1 capital of approximately 11 per cent and 5 per cent, respectively. Thus, the most vulnerable bank could experience a loss exceeding the 10 per cent threshold. Finally, in the single CCP case of Scenario 4 with price volatility of 3.89, Table 9 gives a maximum eigenvalue of the $\mathbf{\Theta}$ matrix of 0.58. The CCP is the most vulnerable in this scenario; with an index of 1, and using (11), the

CCP can suffer a potential loss of 58 per cent of its default fund in the worst case. In sum, these metrics provide a quick assessment of the threats on the ground.

5. Contagion Analysis

Section 4 revealed that the large exposures of CCPs and their extensive interconnections make them among the most vulnerable institutions in the system. However, given their role and the design of their risk frameworks, CCPs would not be expected to transmit stress widely through the system in the event of a shock.This section builds on the analysis in Section 4, to explore further how awell-designed CCP can be a source of stability, rather than instability. To do this, we simulate the key design features of CCPs and trace directly the channels by which stress could be transmitted through the system in extreme market conditions. The particular focus is on the circumstances in which prefunded financial resourcesare exhausted and unfunded losses are allocated via VMGH.

5.1 Methodology

We conduct two experiments:

- *Pure price shock*. In the first instance, we consider an extreme but plausible shock to OTC derivative prices. If these price moves lead to a variation margin requirement that exceeds a threshold level of a bank's unencumbered liquid asset holdings (as defined in Section 4), that bank is deemed to be in 'liquidity stress'. To better illustrate the dynamics at play, we assume conservatively that a bank is in liquidity stress if a variation margin requirement exceeds 10 per cent of its available liquid assets. Depending on the magnitude of the shock, the degree of collateral coverage, and the capital positions of the stressed bank's counterparties, failure to receive variation margin could generate 'secondary solvency stress' for others in the system. We assume a bank will be in secondary solvency stress if the incoming variation margin payments that it fails to receive exceed a given proportion of its available capital; $\rho^{Bank} = 0.1$, as in Section 4. This is how contagion propagates in our model.Conservatively, we do not account for incoming variation margin payments and do not allow for partial payment of variation margin by a bank in stress. These assumptions imply that a CCP's outgoing variation margin obligations cannot be a direct *initial* source of stress because outgoing obligations are always fully funded in the absence of a participant default. As before, $\rho^{CCP} = 1$.
- *Price and solvency shock*.In the spirit of Furfine (2003), we add sequential exogenous solvency shocks to the price shocks considered in the first experiment. Again, the default of a bank will cause a default on its variation margin obligations, which can generate secondary solvency stress for others in the system.

As in Section 4, CCP *c*'s prefunded resources comprise initial margin and its default fund, $K_{c,}$ calibrated to

Cover 2 in extreme but plausible market conditions. Should these prefunded financial resources be insufficient to meet a CCP's obligations to non-defaulted participants, the CCP must proceed to VMGH loss allocation. To the extent that the participants rely on these amounts to fund other obligations, VMGH could be a channel for solvency stress.

5.2 Results

To illustrate the key messages, wesummarize the results from each of the experiments described in Section 5.1. A more detailed presentation of the results is available in Heath *et al*. (2015), including consideration of alternative stress thresholds and loss allocation mechanisms.

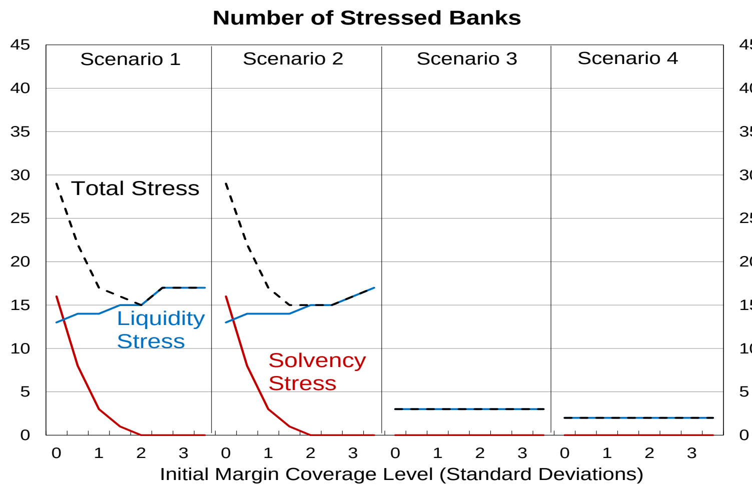
5.2.1 Pure price shocks

In addition to the 2.67 and 3.89 standard deviation price shocks, we also consider an extreme six standard price deviation of the historical price distribution.To test the resilience of the system further, especially where the CCP is a central node, realized exposures are based on 10-day price changes for all clearing arrangements in all scenarios. This is a more conservative closeout assumption than is used in calibrating initial margin and other financial resources of the CCP, increasing the probability that these resources are challenged. In each experiment we allow initial margin coverage on both non-centrally and CCP cleared positions to vary, demonstrating how this affects the stability of the system.

The results for 2.67 standard deviation price shocks are presented in Figure 6. The figure shows the number of banks experiencing solvency stress (red line) and the number experiencing liquidity stress (blue line) under each of the four scenarios. The total number of banks in stress, the sum of the two, is depicted by the dashed line.Some observations may be made. First, under non-central clearing (Scenarios 1 and 2) variation margin inflows and outflows vis-à-vis different counterparties cannot be offset. As a result, a large number of banks do not have sufficient unencumbered liquid assets to meet their variation margin payments. At low levels of initial margin coverage, the counterparties of these banks have large uncollateralized exposures and the non-receipt of variation margin results in a direct charge against capital. With a low solvency threshold, many fall into solvency stress.The scenarios involving universal CCP clearing are generally 'safer' than those without.

Second, as initial margin coverage increases, the source of stress in the system shifts from secondary solvency stress to initial liquidity stress because a larger share of banks' high-quality liquid assets are encumbered. At the same time, however, with higher initial margin coverage levels, the counterparties to these banks are better protected against non-receipt of variation margin. Indeed, at initial margin coverage of 99 per cent and beyond, there is no incidence of solvency stress under any scenario. These results are consistent with the observed trade-off in the LSRI and SSRI outcomes in Section 4.3. They are also consistent with the u-shaped trade-off described in Heath *et al* (2013), where it was shown that as collateral coverage increases in less netting-efficient clearing structures, solvency stress declines substantially but liquidity stress increases.

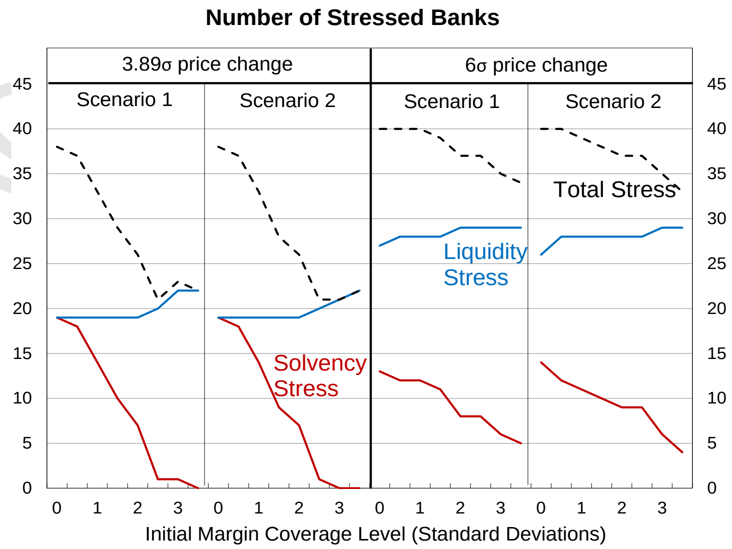
Figure 6: 2.67σ Price Change, 10 Per Cent Stress Threshold



As might be expected, in Scenarios 1 and 2, the level of stress in the system increases as the size of the price movements become more extreme(Figure 7). Indeed, at very low levels of initial margin coverage, almost the entire system falls into stress under these much larger price movements. The incidence of secondary solvency stress again falls sharply as initial margin coverage increases; and there is evidence of the u-shaped trade-off between solvency and liquidity stress at high levels of initial margin coverage.

Even with these more extreme price movements, there is only a modest increase in the incidence of stress under Scenarios 3 and 4 (not shown in Figure 6). This again reflects the effectiveness of netting in a CCP and the wide dispersion under VMGH of any losses in excess of the CCPs' prefunded financial resources.

Figure 6: 3.89σ and 6σPrice Changes, 10 Per Cent Stress Threshold



5.2.1 CCP loss allocation

Table 10 presents the scale of uncovered losses distributed by the CCPs under Scenarios 3 and 4, and the magnitude of the resultant haircut assuming losses are distributed using VMGH. The results reveal that, except in the case of a six standard deviation price move, uncovered losses are absorbed with relatively small haircuts (between 6 and 8 per cent).

Table 10: Uncovered Losses and Variation Margin Gains Haircutting

Parameter combinations (severity of price change, clearing scenario)

Price change (standard deviations)	**2.67**		**3.89**		**6**	
Scenario	**3**	**4**	**3**	**4**	**3**	**4**
Uncovered losses (US$ bn)	0	0	8.9	6.2	44.0	20.5
Variation margin haircut*	0	0	6.2	8.0	19.8	17.1

*Per cent of the CCP's variation margin obligation.

The absence of uncovered losses when prices move by 2.67 standard deviations is to be expected because there is little evidence of initial liquidity stress in either scenario and CCPs' default fund resources are calibrated to withstand large participant defaults in much more extreme market conditions. The incidence of uncovered losses under the assumption that prices move by 3.89 standard deviations is unsurprising, given that this price movement is larger than that used to calibrate the CCPs' prefunded resources. However, the relatively small variation margin haircuts do not challenge any participant's solvency threshold. With extreme tail price changes of six standard deviations the losses that must be allocated increase. In Scenario 3, this is sufficient to trigger solvency stress at one capital-constrained bank, but does not trigger any secondary solvency stress in Scenario 4.

5.2.3. Price and solvency shocks

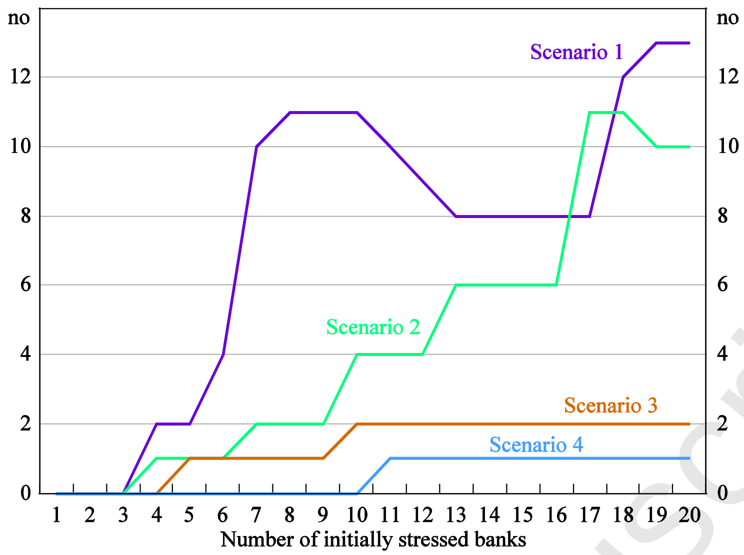
For the case of price changes of 3.89 standard deviations in each product and a solvency stress threshold for banks of 10 per cent, we consider the effects on the financial system of banks defaulting sequentially in order of the size of the CCP's exposure (based on the single CCP service in Scenario 4), beginning with the largest.

In the scenarios in which some non-central clearing persists, stress is well contained until four banks are initially stressed (Figure 7). Prior to this point, initial margin coverage at 99 per cent is sufficient to limit contagion. However, once this point is reached, sizeable uncovered losses on bilateral positions begin to draw down capital and Scenarios 1 and 2 appear much less stable than Scenarios 3 and 4. Stress transmission becomes particularly marked in the least netting-efficient clearing structure of Scenario 1.

In Scenarios 3 and 4, by contrast, the system is more resilient to multiple participant defaults due to the added safeguards of: multilateral netting of variation margin obligations; a mutualized default fund calibrated to 3.65 standard deviations; and wider dispersion of uncovered losses via VMGH. There is nevertheless some incidence of secondary solvency stress in these scenarios, although this occurs only after 11 banks become initially stressed in Scenario 4, and after 10 banks become initially stressed in Scenario 3. In both cases, the extent of subsequent secondary stress is also limited.

Figure 7: Price and Solvency Shocks with VMGH

Number of banks in secondary stress



Note: 3.89σ price change, 10 per cent stress threshold

6. Policy implications and conclusions

The network analysis in this paper confirms how OTC derivative market reforms are fundamentally altering the topology of the financial network, concentrating risk in CCPs. This concentration and CCPs' risk management arrangements are the subject of considerable policy debate. In this paper, we have modelled a series of very extreme 'tail-of-tail' scenarios to examine the circumstances in which CCPs could feasibly be a channel for contagion in the event of stress in the financial system. The analysis demonstrates that there could be circumstances in which, having exhausted its prefunded resources, a CCP transmits stress back to its participants by haircutting their variation margin gains. This is, however, found to occur only in the most extreme of scenarios, and even then contagion is well contained if CCPs maintain financial resources in accordance with international standards. It is nevertheless important that CCP participants and regulators understand the level of stress that CCPs' prefunded financial resources are designed to withstand, and the channels by which losses could be transmitted back into the system in the event an extreme shock depletes these resources.

The analysis in Sections 4 and 5 gives rise to policy messages in three broad areas: (i) the trade-off between liquidity and solvency risk as collateral coverage increases; (ii) the level of a CCP's prefunded and unfunded financial resources; and (iii) network analysis.

Using real data on banks' OTC derivatives positions, the analysis in this paper confirms the finding in Heath, Kelly and Manning (2013) that there is a trade-off between liquidity risk and solvency risk. We present evidence consistent with the u-shaped relationship identified in that paper: the incidence of solvency stress declines as collateral coverage increases, but at the same time the incidence of liquidity stress steadily rises. In the scenario that most closely resembles the near-term topology of the financial network – ie. the scenario in which central clearing and non-central clearing co-exist and central clearing occurs via product-specific CCP services – the interaction between liquidity and solvency risks is particularly important.

Netting efficiency is a critical determinant of the shape of this interaction. From Table 5 we find that the combination of initial margin requirements and CCP default fund contributions encumber almost $1 trillion of banks' liquid assets in situations where less netting-efficient non-central clearing prevails (ie. Scenarios 1 and 2). By contrast, where all OTC derivative positions are centrally cleared, liquid asset encumbrance falls by some 90 per cent (ie. Scenarios 3 and 4).We demonstrate that highly encumbered banks may face difficulties in meeting their variation margin obligations, particularly where there is less scope for netting across products and counterparties (see Table 7). This is the channel for liquidity stress in our analysis. The propensity for such stress to arise increases with collateral coverage – especially in these netting-inefficient arrangements and where at least some market participants have constrained access to liquid assets (see Sections 4.3 and 5.2).

Importantly, we acknowledge in our framework that, while CCP clearing concentrates risk in a single node (or few nodes) in the network, that node cannot generally be a direct source of stress in the system; a CCP maintains a balanced book and does not assume financial risks other than those arising from the positions that it clears for its participants. Accordingly, typically the only circumstance in which the CCP may experience stress is if one or more of its participants defaults. If this arises, the adequacy of the CCP's financial safeguards is critical.

Realized market conditions could, however, be more extreme than thoseassumed by the CCP in calibrating its prefunded financial resources, not only in terms of the magnitude of the price moves across products and the number of defaults, but also in terms of the assumed co-movement between products and the assumed closeout period. In such circumstances, the CCP's prefunded financial resources could be exhausted. To ensure that it did not then become insolvent and cease its provision of critical infrastructure services, the CCP would, in accordance with international standards, allocate any uncovered losses to its participants. The results suggest that, even in very extreme market conditions, losses would be expected to be well contained and the transmission of stress limited. A CCP operating in accordance with international standards can therefore be expected to promote stability in financial networks overall. Nevertheless, to assist participants in modelling and managing their potential obligations in the event of loss allocation, CCPs should provide sufficient transparency about their exposures, stress testing models and risk frameworks.

Since our analysis is focused on 41 large banks, it does not capture the extent to which the allocation of losses via VMGH could impose stress on non-banks, such as investment funds and other end users of derivatives who may have more directional positions. Equally, however, extending the network beyond large banks could, by dispersing uncovered losses more widely, potentially leave the system even better able to absorb stress.

The stability and contagion analysis in this paper emphasizes the importance of understanding how, in the event a shock did arise, stress could be transmitted through the system. However, in the absence of granular level 'big data', especially on the network of bilateral exposures, there is considerable model error in network analysis.This may obscure the true nature of system instability. Once challenges around data access, data aggregation and data quality are overcome, trade repositories for OTC derivatives should be able to deliver more detailed information to support such data-intensive analysis. Methodologies and techniques for analysing these data will also be further refined, perhaps building on the techniques in this paper. Regulators could then consider complementing transparency of CCPs' risk frameworks with regulatory stress tests and system-wide network and contagion analysis. Wendt (2015) makes a similar recommendation. Metrics such as the eigen-pair method described in Section 4 provide a good first approximation of the stability of the network and which particular institutions may warrant closer attention. This could be a useful tool for regulators.

Other subjects of future research may include the implications for end-users who participate indirectly in the market through intermediating banks, as well as possible ways in which OTC derivative activity may change endogenously in response to alternative market structures.

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CCPs and Network Stability in OTC Derivatives Markets

Highlights

● Analyses use of collateral and central clearing in OTC derivatives markets.

● Concentrating risk in CCPs could generate instability if not appropriately managed.

● Quantifies tradeoff between solvency and liquidity stress.

● Network stability analysis identifies thresholds for solvency and liquidity stress.

● CCP stress transmission limited by prefunded resources and dispersed loss allocation.