Measuring Interbank Exposures in Derivatives and Systemic Risk*

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Abstract

This paper presents a comprehensive analysis of interbank exposures in derivatives markets, including both bilateral and centrally cleared contracts. Using confidential supervisory data for large U.S. banks and public disclosures from central counterparties (CCPs), we develop a novel approach for measuring the interconnectedness among large U.S. banks through both bilateral and centrally cleared derivatives. We examine the top 6 U.S. banks and 9 major global CCPs, investigating potential contagion effects through a theoretical model of triple contagion that incorporates bilateral, centrally-cleared, and collateral price contagion channels. Empirical simulations of contagion under various extreme but plausible stress scenarios, including fire sale amplification, suggest that initial defaults of banks could lead to additional bank failures. We also propose a novel measure of systemic risk arising from interbank exposures in derivatives.

Keywords: Central counterparty, Credit Risk, Counterparty Risk, Derivative, Interconnectedness, Systemic Risk
JEL classification: G00, G10, G20

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1 Introduction

To what extent are banks interconnected and vulnerable to each other's insolvency? Can interbank counterparty exposures in derivatives cause a systemic stress event? Banks engage in various derivative transactions with other banks, either directly via bilateral transactions or indirectly through central counterparties, exposing themselves to counterparty default risk—the risk that their counterparties fail to fulfill their contractual obligations. This paper provides comprehensive measures of large banks' counterparty exposures in derivatives and presents scenario analyses to assess the degree of systemic risk that they pose.

Over-the-counter (OTC) derivative trading continues to be a significant activity for large global banks. According to BIS, the total notional amount of the global non-centrally-cleared OTC derivatives market is about $260 trillion as of end-December 2024.[1] Therefore, the largest 6 U.S. banks accounts for around 23% of the total notional amount of bilateral OTC derivatives outstanding globally. These banks act as major dealers and market makers in various OTC derivative instruments, including interest rate swaps, foreign exchange derivatives, credit default swaps, and equity derivatives (Duffie, 2010; Lu and Wallen, 2024). The largest banks typically maintain substantial trading books, generating counterparty exposures to a wide range of clients, from corporations hedging risks to institutional investors seeking complex investment strategies (Ellul and Kim, 2022; Chang, Kimble, Paligorova, and Zikes, 2025).

Following the derivative market reform spurred by the G20 in 2010, the majority of derivative contracts are now standardized and centrally cleared by a central counterparty (CCP) (Menkveld and Vuillemey, 2021). According to BIS, about 63% of the OTC derivatives are centrally cleared.[2] Major global banks participate as clearing members in multiple CCPs across different jurisdictions, clearing a significant portion of their interest rate swaps, credit default swaps, and other standardized derivatives (Faruqui, Huang, and Takáts, 2018).

[1] See https://www.bis.org/publ/otc_hy2411.htm and https://data.bis.org/topics/OTC_DER/tables-and-dashboards/BIS,DER_D5_1,1.0.

[2] See https://data.bis.org/topics/OTC_DER/tables-and-dashboards/BIS,DER_D5_1,1.0.

This shift to central clearing has altered banks' risk profiles, reducing bilateral counterparty exposures but increasing concentrated exposures to CCPs. For centrally cleared contracts, a CCP becomes a counterparty to every derivative transaction, and any losses associated with a clearing member default may be mutualized through the CCP's prefunded resources provided by all clearing member. Therefore, banks as clearing members are exposed to one another indirectly through centrally cleared transactions.

Despite the regulatory efforts to increase central clearing of OTC derivatives, however, a significant portion of derivatives are still non-centrally cleared bilateral contracts, as the bilateral nature allows for more customized and bespoke derivative contracts. Through these bilateral derivative contracts, banks are also directly exposed to each other's counterparty default risk. Thus, a comprehensive view of interbank counterparty exposures in derivatives encompasses both direct exposures through bilateral contracts as well as indirect exposures through centrally cleared transaction. Only by considering both sets of exposures can one measure the systemic risk from interbank counterparty exposures in derivative markets.

In this paper, we provide a comprehensive view of the interbank counterparty exposures through both direct bilateral exposure and indirect exposure through CCPs. We focus on the top 6 U.S. banks, which account for the majority of OTC derivatives trading among all U.S. banks, and on 9 large global derivatives CCPs, which handle large transaction volumes across multiple asset classes. First, we develop a novel approach to measure interbank exposures from centrally cleared derivatives by utilizing previously unused confidential supervisory data, FR Y-14Q Schedule L.5, along with publicly available CCP data, Public Quantitative Disclosure (PQD) data. We measure direct bilateral exposures between large banks as well as indirect exposures through CCPs.[3]

Second, we develop a novel model of triple contagion to analyze the potential systemic risk from interbank derivative exposures. The model incorporates three different contagion

[3]Banks are also interconnected through various other channels such as interbank lending, common asset holdings, and even common (nonbank) derivative counterparties. These additional sources of interconnectedness could either offset or add to the counterparty exposures we measure.

channels: direct bilateral channel, indirect centrally-cleared channel, and collateral price channel. The collateral price channel incorporates potential price declines due to fire sales of collateral, leading to amplifications of derivative exposures. Such fire sale amplifications could be important given the recent trend of increasing usage of non-cash collateral, including non-cash variation margin or VM, as highlighted in the September 2025 Senior Credit Officer Opinion Survey on Dealer Financing Terms.[4] Our model allows for multiple CCPs and a loss mutualization channel instead of CCP defaults, and is the first attempt to incorporate endogenous collateral price as a contagion channel alongside the other two.

Third, using our theoretical framework, we conduct simulations to examine how initial bank defaults propagate through the interbank derivatives network. The simulations consider various initial default scenarios and assess whether they trigger additional defaults. In the baseline scenario without fire sale effects, no additional defaults occur across different exposure measures. However, when fire sale amplification is incorporated, the results show that interbank derivatives exposures can trigger additional defaults.

Finally, based on these simulation results, we develop a novel systemic risk index. This index is derived from a reverse stress test, which determines the level of fire-sale amplification needed to trigger either an additional bank default or defaults of all remaining banks following an initial bank default. The systemic risk index provides a measure of the likelihood of network amplification triggered by the initial default, offering insights into the overall stability of the interbank derivatives network under different initial default scenarios.

Our paper contributes to the literature by quantifying the interbank derivative counterparty credit exposures in the holistic perspective, which encompasses exposures from both bilateral contracts and centrally cleared contracts. A strand of literature provides theoretical background on the benefits and costs of CCPs. Duffie and Zhu (2011) show that CCPs can mitigate counterparty risk tremendously through netting counterparty exposures and mutualizing losses. Acharya and Bisin (2014) find that transparency provided by CCPs can

[4]See https://www.federalreserve.gov/data/scoos/files/scoos_202509.pdf.

mitigate counterparty risk externality. However, Antinolfi et al. (2022) show that CCPs can weaken incentives to acquire information, necessitating some degree of mutualization of losses to make the information acquisition incentive-compatible (Kuong and Maurin, 2024). Biais et al. (2012), Menkveld (2017), Capponi, Cheng, and Sethuraman (2017), Chang (2019), Wang, Capponi, and Zhang (2022), and Ghamami, Paddrik, and Zhang (2023) show that CCPs can become a new conduit for systemic risk through indirect counterparty exposures. We contribute to this literature by providing empirical evidence on the possible risk propagation through CCPs. Moreover, we contribute to this literature by developing a new theoretical model to incorporate triple contagion channels—bilateral counterparty contagion, centrally-cleared contagion, and collateral price contagion—by incorporating the collateral price contagion in Chang and Chuan (2024).

Another strand of literature provides empirical evidence on the possible spillovers from CCPs' default. Cox and Steigerwald (2018) emphasize how the nature of exposures through CCPs is different from that of bilateral contracts. Faruqui, Huang, and Takáts (2018) analyze the highly concentrated centrally cleared markets and show the importance of considering banks and CCPs jointly to understand systemic risk stemming from destabilizing feedback loop under stress. Bignon and Vuillemey (2020) look into a failure of a CCP in Paris in 1974 and inefficiency in the resolution of the failed CCP. Paddrik, Rajan, and Young (2020) estimate the total amount of contagion through chain of payment defaults through a CCP in the U.S. CDS market. Huang, Menkveld, and Yu (2021) propose a way to monitor intraday exposure for CCPs and claim that extreme levels of acute stress can lead to elevated concentration of positions, which could have negative implications on financial stability.

The papers most closely related to out paper are Arnsdorf (2012), Arnsdorf (2014), Arnsdorf (2019), and Berndsen (2023). Arnsdorf (2012) highlights that the losses shared through the CCP loss mutualization process can arise without a default of a CCP and suggests a practical way of estimating such losses stemming from having a CCP membership. Therefore, Arnsdorf (2014) emphasizes that capturing the total risk a bank faces should include

both credit exposures to other clearing members through bilateral transactions and credit exposures due to CCP membership. We directly contribute to this literature by combining publicly available data and confidential supervisory data. The addition of confidential supervisory data enables us to estimate the centrally-cleared exposures more precisely and it also allows us to measure interbank bilateral exposures.

Another strand of literature that is relevant to our paper is the literature on bilateral counterparty risk. Arora, Gandhi, and Longstaff (2012) find that bilateral counterparty credit risk is priced, but its effect is small when there is collateral. Du, Gadgil, Gordy, and Vega (2023) find that counterparty risk has a modest impact on the pricing of CDS contracts but a large impact on the choice of counterparties. Ellul and Kim (2022) utilize FR Y-14Q Schedule L data, the same data we use in this paper, and show that banks are more likely to either establish or maintain a relationship with non-bank counterparties that are already heavily connected and exposed to other banks, implying financial stability concerns. Chang, Kimble, Paligorova, and Zikes (2025) also utilize FR Y-14Q data and find that the bilateral counterparty exposures of large banks have been increasing, but both the concentration of large banks' counterparty exposures and similarity between large banks' counterparty exposures have been decreasing, implying decrease in systemic risk through bilateral counterparty exposures.

The remainder of the paper is structured as follows. Section 2 presents a concise overview of Global Systemically Important Banks' (GSIBs) derivative trading through both bilateral and centrally cleared channels, followed by an introduction to the sample data in Section 3. Section 4 introduces our novel framework for measuring GSIBs' counterparty exposures from derivative trading and discusses the estimation outcomes. Section 4.4 discusses a panel regression analysis, evaluating the factors contributing to the exposures. Section 5 presents a contagion model, stress testing framework and simulation analysis, and systemic risk indices, followed by the conclusion with a summary of key findings and directions for future research.

2 Bilateral and centrally cleared derivatives exposures

2.1 Bilateral exposures

Large banks act as major dealers in various OTC products, including interest rate swaps, foreign exchange derivatives, credit default swaps, and equity derivatives. The largest banks typically maintain substantial trading books, serving as market makers and providing liquidity to a wide range of clients, from corporations hedging risks to institutional investors seeking complex investment strategies (Falato, Iercosan, and Zikes, forthcoming). While post-2008 regulations like the Dodd-Frank Act in the U.S. have mandated central clearing for certain products, a significant portion of OTC derivatives still trades bilaterally.

For bilaterally traded derivative contracts, each counterparty is directly exposed to counterparty credit risk, which is the risk that the counterparty fails to fulfill their obligated payments. The contractual payment obligations could be (partially) covered by the collateral posted.[5] Any remaining exposure not covered by collateral would be borne as losses by the non-defaulting counterparty.

2.2 Central clearing and mutualization of losses

To understand interbank counterparty exposures stemming from centrally cleared derivatives, we must first describe how central clearing works. Unlike in bilateral transactions where banks directly face each other, in centrally cleared transactions all participants face a single central counterparty (CCP): a CCP steps in between the original buyer and seller after the trade has been executed and agreed upon, and the original agreement between the buyer and seller is legally replaced with two new, separate agreements: one between the buyer and the CCP, and another between the seller and the CCP. By inserting itself into the transaction, the CCP assumes the counterparty risk from both parties and guarantees the

[5]Following the standards for margin requirements for non-centrally cleared derivatives set by the Basel Committee on Banking Supervision (BCBS) and the International Organization of Securities Commissions (IOSCO), the banks in our sample use the Standard Initial Margin Model (SIMM) for IM calculation.

performance of the trade.

To safeguard the CCP and its members from potential defaults of a clearing member, the CCP puts in place a multi-layered risk management framework typically called the default waterfall, illustrated in Figure 1. This default waterfall begins with prefunded resources, which include, sequentially, the defaulting member's initial margins (IMs) and variation margins (VMs) posted to the CCP, the defaulting member's default fund contribution, the CCP's own dedicated resources (capital, or commonly termed "skin-in-the-game"), and the non-defaulting members' default fund contributions. If the prefunded resources are exhausted, the CCP may make additional assessments on surviving members and, ultimately, resort to predefined recovery and resolution protocols.

Thus, when a clearing member defaults and the associated losses exceed the defaulting member's pre-funded resources, the excess losses will be mutualized across all surviving members. Consequently, even banks that have never directly traded with each other develop indirect exposures through their common CCP memberships. Since the CCP capital is very small in practice, the default fund plays a key role in mutualizing the losses across surviving members and thus largely determines the indirect interbank exposures through the CCP. The size of the default fund is typically calculated based on stress tests that simulate extreme but plausible market conditions, and the contributions to the default fund are usually proportional to each member's risk exposure or trading volume. This structure creates powerful incentives for members to monitor and manage their own risks, as well as those of their peers, since all members share in the potential losses associated with a clearing member default.[6]

2.3 Example

Figure 2 depicts an example of both bilateral exposures and centrally-cleared exposures. The example illustrates how a default of a clearing member bank can generate losses to other

[6]Note that the losses through a CCP does not require the default of the CCP itself.

banks through these two types of exposures.

There are four banks, A, B, C, and D, represented by circular nodes. A CCP is represented by a square node in the center. The CCPs has a pool of default funds, represented by the square "DF" node. Finally, other clearing members are represented by a larger circular node, "Other CMs". Solid arrows represent payment obligations net of collateral (IMs and VMs), and the numbers next to solid arrows represent the payment obligation amounts (net current exposure amounts). Dashed arrows represent default fund contributions from clearing members, with blue numbers indicating the contributed amounts.

In the example of Figure 2, bank C defaults due to an exogenous shock, leading to losses for its bilateral counterparties and the CCP. First, we focus on the losses due to bilateral exposures. Banks B and D have in-the-money derivative positions with bank C, as depicted by the solid arrows from bank C. Hence, bank C's default leads to losses for banks B and D in the amounts of 5 and 1, respectively. Therefore, the total amount of losses due to bilateral exposures to the defaulting bank, C, is 6.

Next, we discuss the losses due to centrally-cleared exposures to bank C. First, we examine the total amount of default funds from the dashed arrows of Figure 2: banks A, B, C, and D have contributed to the default fund in the amounts of 4, 1, 3, and 5, respectively. Other clearing members of the CCP have also contributed to the default fund in the amount of 7, resulting in a total default fund amount of 20. Note that the default fund contribution amount may not necessarily be proportional to a clearing member's derivative positions against the CCP. For example, bank D is in-the-money but still contributed 5, possibly due to a large total notional amount, while bank A is out-of-the-money but contributed only 4.

Bank C defaults on its payment to the CCP in the amount of 10 (depicted by the red number next to the solid arrow from bank C to CCP). However, the actual amount of losses transmitted to all other clearing members is 7, as bank C's default fund contribution of 3 is used to cover the default amount first. The loss in the amount of 7 is covered by all other clearing members on a pro rata basis following the share of the remaining default fund.

Finally, we examine the total losses due to bank C's default. Bank A, which does not have any direct bilateral exposure to the defaulting bank, still suffers a loss in the amount of $7 \times (4/17) \approx 1.65$. Although bank B has a large bilateral exposure to bank C, bank B's loss due to CCP membership is the smallest, amounting to $7 \times (1/17) \approx 0.41$. Bank D has a smaller bilateral exposure to bank C, in the amount of 1, but bank D's loss due to CCP membership is the largest, amounting to $7 \times (5/17) \approx 2.05$, which exceeds its bilateral exposure loss of 1.

This simple example in Figure 2 illustrates that the counterparty credit risk due to centrally-cleared exposures can exceed that due to direct bilateral exposures. The example also highlights that banks with no direct exposure to a defaulting bank (bank A in the example) can still suffer losses due to CCP membership. Finally, the example shows that the ranking of loss amounts can change when both types of exposures are considered simultaneously.

3 Data and sample selection

We use the FR Y-14Q, Schedule L.1a confidential supervisory data to measure bank-to-bank counterparty exposures arising from bilateral derivative trading. The FR Y-14Q is part of the Federal Reserve's Comprehensive Capital Analysis and Review (CCAR) and Dodd-Frank Act Stress Test (DFAST) reporting requirements for large bank holding companies and intermediate holding companies. Schedule L of FR Y-14Q specifically focuses on counterparty credit risk, requiring banks to report detailed information about their top 95% of counterparties by CVA and aggregated exposures for the remaining 5% of counterparties. Similar to Chang et al. (2025), we focus on top 6 US global systemically important banks (G-SIBS)— J.P. Morgan, Morgan Stanley, Goldman Sachs, Bank of America, Citigroup, and Wells Fargo—as they account for the vast majority of OTC derivatives trading among U.S. banks.

Specifically, large banks report their exposures to other counterparties, including banks, using four different measures. Among these measures, gross current exposure (gross CE) and net current exposure (net CE) are the most relevant for our purpose. Gross CE is the market value of a derivative contract if that value is positive, after bilateral netting (if there is a legally binding netting agreement). Gross CE thus measures the amount of value lost if a counterparty defaults. However, gross CE does not take into account collateral and is only relevant for a scenario in which no collateral was posted or the value of the posted collateral goes to zero. In contrast, net CE equals gross CE less the value of collateral posted, and it is relevant for a scenario in which the collateral posted maintains its value in case of counterparty default. The schedule also captures data on CVA, total gross notional amounts, and information on collateral, netting agreements, and other risk mitigants, such as single-name CDS hedges. See Chang et al. (2025) for a comprehensive description of the data and stylized facts.

Every quarter, banks are required to report the so-called *unstressed* gross and net CE, which are calculated based on the current market valuations. Additionally, in the fourth quarter of every year, banks are also required to report *stressed* gross and net CE, which are calculated under the assumption of significant market stress. Specifically, banks report gross and net CE under 1) the Federal Reserve's Severely Adverse Scenario (SADV) that underlies the annual supervisory stress test conducted by the Federal Reserve (FRB, 2024) and 2) banks' own stress scenarios (BHC) that are supposed to reflect banks' unique business models and risks.

We also rely on FR Y-14Q, Schedule L.5 for data on banks' default funds contributions to CCPs. Specifically, banks are required to report the amount contributed to the default fund of a CCP, and this amount, if positive, must be reported even if the bank has no outstanding trades with the CCP. Banks also report initial margin (IM) posted to CCPs on Schedule L.5, but only the portion of the IM, if any, that is not held in a bankruptcy remote account. Since this is typically a small fraction of the total amount of IM posted by banks to CCPs,

we do not use this information in our analysis.

In addition to the supervisory data for bank default fund contributions to CCPs, we use the CCPs' Public Quantitative Disclosure data (PQD) available quarterly on their website.[7] PQD provides statistical information that CCPs are required to publish to promote transparency and risk assessment. These disclosures, guided by regulatory bodies like the Committee on Payments and Market Infrastructures (CPMI) and IOSCO, cover various aspects of CCP operations and risk management. Key areas include credit risk metrics (such as initial margin requirements and prefunded resources), liquidity risk data, collateral information, default management statistics, operational risk indicators, clearing activity volumes, segregation and portability details, financial information, risk model performance, and governance practices. For this study, we use three key variables reported in the PQD: the hypothetical capital requirement of the Central Counterparty (K^{CCP}), total initial margin, and total default fund size, which are described in detail in the next section.

Our sample period is from 2018Q1 through 2024Q1, and our analysis includes 9 major CCPs, which cover most of the derivative clearing business globally: two CCPs of Chicago Mercantile Exchange (CME): one for futures & options (F&O) and one for Interest Rate Swaps (IRS); the IRS CCP at the London Clearing House Limited (LCH Ltd SwapClear); the Banque Centrale de Compensation SA (LCH SA); three CCPs from the Intercontinental Exchange, Inc (ICE Clear): ICE Clear Credit, ICE Clear Europe, and ICE Clear US; the Options Clearing Corporation (OCC); and the Eurex Clearing AG (Eurex). LCH SwapClear is known for its dominance in interest rate swaps (IRS) clearing: as of 2025Q2, LCH SwapClear clears over 85% of IRS volume based on data provided by Clarus CCPView (Figure 3, Panel A). Similarly, ICE Clear Credit dominates the clearing on OTC CDS contracts, taking over 80% market share (Figure 3, Panel B). LCH SA and ICE clear Europe are the other two CCPs clearing CDS contract in European market. CME Clearing, a division of CME Group, is a leader in futures and options clearing; Eurex, owned by Deutsche Börse, is

[7] We access the historical data from Clarus CCPView (Clarus Financial Technology Ltd., 2025).

prominent in European exchanged traded derivatives; ICE Clear US and Europe are strong in energy derivatives; OCC is the world's largest equity derivatives clearing organization and the only CCP clearing equity options in the U.S..

Not only is derivative clearing concentrated in several CCPs, but the clearing activity within these CCPs is also highly concentrated among top clearing members, which are predominantly large international banks. Figure 4 illustrates the concentration of clearing members (CMs) across these CCPs, showing the percentage of clearing activity handled by the top 5 and top 10 CMs for each CCP. CME exhibits the highest concentration, with the top 10 CMs accounting for 80% of clearing activity and the top 5 handling 58%. Even the CCP with the lowest concentration level, Eurex, also has 42% activity from the top 10 CMs. This notable member concentration in the clearing industry underscores the importance of understanding the interconnectedness between these top clearing members through the CCPs, which is the primary focus of this paper.

4 Measuring interbank exposures through derivatives

4.1 Bilateral exposures

Table 1 reports summary statistics for the net bilateral interbank exposures (net CEs), pooled across banks and time. On average, the net unstressed exposures, shown in the left panel, are small: the average exposure equals $65 million, or only around 0.05% of Common Equity Tier 1 (CET1) capital. However, they exhibit considerable variation, with a standard deviation of $145 million and the unconditional 90th percentile exceeding $142 million, or 0.1% of CET1. Unsurprisingly, the stressed exposures, shown in the middle panels, are significantly larger: the average exposure equals around 0.5% and 0.4% of CET1 capital under the BHC and SADV scenarios, respectively, and the 90th percentile exceeds $1.37 billion and $1.15 billion, or roughly 1.3% and 0.9% of CET1, respectively.

Figure 5 presents the bilateral exposure over time. Specifically, for each quarter (year)

in the sample, we plot the cross-sectional (across $6 \times 5 = 30$ bank-to-bank pairs) average and 90th percentile of the unstressed (stressed) net CE, in dollar terms (left panels) and as percentage of CET1 capital (right panels). We find that both the average and 90th percentile exhibit a decreasing trend throughout the sample period, both in dollar terms and as a fraction of bank capital. The unstressed exposures declined by around 50% while the stressed exposures declined by around 30% during the sample period. This decline in both metrics suggests a systematic reduction in bilateral counterparty exposures across the banking sector, potentially reflecting increased central clearing, improved bilateral netting arrangements, or enhanced risk management practices.

4.2 Indirect exposures through CCPs

4.2.1 Methodology

To estimate the interbank exposures stemming from centrally cleared derivatives, we must calculate the potentially mutualized loss imposed on member i by the default of member j for each pair of banks i, j. This requires knowing, for each CCP: (1) the hypothetical losses in excess of its own pre-funded resources that a clearing member's default would impose on the surviving members; (2) the surviving members' pro-rata share of the default fund exclusive of the defaulting member's contribution. Such information is not available in the CCPs' Public Quantitative Disclosures or in the FR Y-14Q, Schedule L.5. However, under plausible assumptions, we can leverage the information available in these sources to approximate the potential mutualized losses and the pro rata share to allocate the mutualized losses to non- defaulting clearing members. Andersen and Dickinson (2019) provides the mathematic foundation and a general framework to estimate the pro rata share for allocating risk exposure among clearing members. We adopt their approach in our estimation.

Specifically, CCPs report in the PQD the size of their default fund, and the banks in our sample report their default fund contributions to each individual CCP in FR Y-14Q, Schedule L.5. Denoting the former by DF_k for CCP k and the latter by DF_{ik} for bank i's

contribution to the default fund of CCP k, the share of bank i in the default fund of CCP k is given by

$$S_{ik} = \frac{DF_{ik}}{DF_k}, \tag{1}$$

and the share of bank i in the remaining default fund resources of CCP k following the default of bank j is given by

$$S_{ik}^{-j} = \frac{DF_{ik}}{DF_k - DF_{jk}}. \tag{2}$$

We propose two different approaches to estimate the potential mutualized losses from a defaulting member. First approach utilizes the K^{CCP} in the PQD. CCPs report a hypothetical capital requirement of the CCP for its counterparty credit risk exposures to its clearing members, the so-called K^{CCP}, which represents the amount of capital that a CCP would be required to hold if it were a bank.[8] For a CCP k, it is given by

$$K_k^{CCP} = \sum_i EAD_{ik} \times RW \times \text{capital ratio}, \tag{3}$$

where EAD_{ik} is the exposure amount of the CCP to clearing member i at the time of i's default, RW is a constant risk weight set to 20%, and capital ratio is also constant and set to 8%. The exposure at default is calculated using either the Current Exposure Method (CEM) or the Standardized Approach to Counterparty Risk Method (SA-CCR).[9] Collateral posted by the defaulting clearing member (IM and VM) as well as the defaulting clearing member's default fund contribution are used to offset the CCP's exposure to that clearing member. That is, EAD_{ik} is calculated net of collateral and default fund contribution posted by i, and captures the potential loss to the CCP from the clearing member default in excess of the clearing member's prefunded resources.[10]

[8] See details in the Basel's Capital requirements for bank exposures to central counterparties: https://www.bis.org/publ/bcbs282.pdf.

[9] SA-CCR method is a new approach for banks to estimate their counterparty credit risk exposure. CCPs have adopted the SA-CCR methods when estimating K^{CCP}; see https://www.bis.org/basel_framework/chapter/CRE/52.htm.

[10] A limitation of the SA-CCR calculation is that the framework may not update market volatility and potential future exposures properly in the midst of a crisis, while the IM demand immediately increases.

Equation (3) can be inverted to obtain the total exposure at default EAD across all clearing members:

$$EAD_k = \sum_i EAD_{ik} = \frac{K_k^{CCP}}{RW \times \text{capital ratio}}. \tag{4}$$

Alternatively, we can estimate EAD_k using CCPs' total initial margin IM_k reported in their PQD reports, assuming that changes in clearing members' portfolio values follow a Student's t-distribution with 4 degrees of freedom (df).[11] CPMI regulations require CCPs' IM to cover 99% of the clearing portfolio's risk, and most CCPs set their IM based on 99% Value at Risk (VaR) with additional add-ons. The expected loss over the IM can be represented by the 99% expected shortfall (ES), and EAD_k can be estimated as:[12]

$$\text{EAD}_k = \text{IM}_k \cdot \frac{\text{ES}_{99\%}}{\text{VaR}_{99\%}} - \text{DF}_k \approx 1.394 \cdot \text{IM}_k - \text{DF}_k \tag{5}$$

We employ these two distinct approaches to estimate the total exposure at default (EAD_k) and analyze the interbank exposure from centrally cleared derivatives. While these approaches utilize different inputs and assumptions, resulting in expected variations in outcomes, the discrepancies are not substantial and do not alter the main conclusions of our study. For the remainder of this paper, we focus on the findings derived from the first approach. For comparison, results from the second approach are presented in Appendix C.

Now, to allocate the total EAD_k to individual clearing members and thereby estimate the potential losses shared by surviving member in case of a member default, we assume that the CCP's exposure to clearing member i is proportional to that clearing member's

This gap between the two updating timings could artificially increase the IM coverage, while the exposure numbers remain stale, reducing our estimated losses from exposures. The alternative approach to calculate EAD based on IM can resolve this issue. Therefore, the first approach serves as an underestimated version of interbank exposures.

[11] We can also use alternative distributions, such as a Pareto distribution, which is used by Arnsdorf (2014).

[12] This method is similar to the approach in Arnsdorf (2012). Appendix C provides detailed calculations. Some CCPs use ES to set margin; in that case, estimating expected exposure at default from IM using the ES/VaR ratio is more conservative.

contribution to the default fund:

$$EAD_{ik} = S_{ik} EAD_k. \tag{6}$$

This assumption is grounded in the fact that CCPs generally require members to make default fund contributions commensurate with the riskiness of their positions. The proportionality assumption is also supported mathematically by Andersen and Dickinson (2019), who show that the default fund contributions of the largest clearing members are proportional to their expected exposures at default, under reasonable distributional assumptions.

Having estimated the loss that needs to be mutualized in case of the default of a clearing member i in CCP k, it follows that the loss to a surviving member j is given by

$$Loss_{jik} = S_{jk}^{-i} EAD_{ik}, \tag{7}$$

and the total exposure via centrally cleared derivatives of bank j to the default of bank i is simply given by the sum of losses across all CCPs where these banks are members:

$$Exposure_{ji}^{CCP} = \sum_k Loss_{jik}. \tag{8}$$

In the following subsection, we implement this methodology and describe the evolution of the interbank exposures and its various inputs over time using the first EAD_k estimation approach.

4.2.2 Results

Figures 6 and 7 summarize the key inputs into our calculations of centrally cleared exposures: the EAD and default fund (DF) at the CCP level and the shares of our banks in the CCPs' default funds. Starting with the EAD in Panel A of Figure 6, there is a noticeable increasing trend in EAD for most CCPs and in the aggregate post-COVID. The largest EAD is con-

sistently reported by LCH Ltd, followed by OCC, whose share has grown over time, almost reaching that of LCH Ltd. The remaining 7 CCPs report relatively small EAD during our sample period. Turning to the DF, Panel C shows that OCC has by far the largest default fund of all the CCPs, followed by LCH Ltd, Eurex, and CME.

Turning to the third key input into our calculations—the default fund contributions of the clearing member banks—Figure 7 shows the average default-fund share of top 6 US banks. For confidentiality reasons, we can only report statistics for the aggregate share of the top 6 banks in the CCP default funds and not the individual bank shares. The figure shows that the banks collectively accounted for around 40% throughout the sample period. The relatively large share of the top 6 US banks is hardly surprising, as these banks serve as major dealers in the centrally cleared derivative markets (Duffie, 2010).

With all the inputs at hand, we can now present our estimates of the interbank counterparty exposures from centrally cleared derivatives. Table 1, Panel D, summarizes these exposures, pooled across bank pairs and over time. The mean exposure equals around $643 million, or 0.55% of CET1, with a standard deviation of $530 million, or 0.54% of CET1. However, the 90th percentile equals around $1.3 billion, or 1.3% of CET1. These statistics are quite similar to those for the bilateral stress exposures under the BHC scenario (Panel B) and slightly larger than those for the severely adverse (SADV) Fed scenario (Panel C).

Turning to the evolution of these exposures over time, Figure 8 shows that, on average, the centrally cleared exposures have been growing over time, both in dollar terms and in terms of percent of CET1, with most of the growth occurring post-COVID. Recall that this growth coincides with the decline in bilateral interbank derivative exposures shown in Figure 5, suggesting that the shift from bilateral to centrally cleared derivatives that began with the post-GFC derivatives reforms accelerated post-COVID. Looking at the extremes of these exposures, the 90th percentile shown in orange reaches 2% of CET1 towards the beginning and end of the sample, which are levels similar to those reached by the stressed bilateral exposures in the beginning of the sample.

4.3 Comparing the bilateral and centrally cleared exposures

Two sets of exposures defined above—bilateral and centrally cleared—are not exactly equivalent and cannot be readily added up to obtain the total interbank exposures through both cleared and uncleared derivatives. However, there are similarities between these exposures in several aspects, and it is worth comparing them in more detail. To do so, we closely adhere to the regulatory definitions of the various components of those exposures (BCBS, 2025).

The EAD_{ik} in equation (3) is calculated according to the formula

$$EAD_{ik} = \alpha(RC_{ik} + PFE_{ik}), \tag{9}$$

where α—a conservative scaling factor to account for potential underestimation of exposure, model risk, and general wrong-way risk—is set to 1.4; RC_{ik} is the replacement cost to CCP k from a default of clearing member i and it is defined as the difference between market value and any collateral posted—subject to applicable thresholds and minimum transfer amounts—and thus closely resembles the bilateral unstressed net CE discussed in Section 4.1; and PFE_{ik} is the potential future exposure associated with CCP's positions with clearing member i, calculated assuming a 10-day margin period of risk. The PFE_{ik} therefore accounts for any adverse market movements against the CCP as it tries to replace the contracts with the defaulting clearing member. In summary, the EAD_{ik} is approximately equal to

$$EAD_{ik} = \alpha(netCE_{ik} + PFE_{ik}). \tag{10}$$

Thus, the centrally cleared exposures based on EAD_{ik} are not directly comparable to the unstressed bilateral net CE because they contain an add-on for potential future losses as well as a multiplier to account for model risk and wrong-way risk. The bilateral stressed net CE is perhaps a more appropriate counterpart because it is based on a revaluation of the current net CE assuming significant market stress, effectively adding a potential future

exposure to a counterparty over the course of a severely adverse stress scenario. However, it is difficult to directly map the scenario parameters, and the associated revaluation of the net CE, to the PFE in the EAD formula above.[13] In the rest of the paper, we will consider either the unstressed or stressed bilateral exposures together with the centrally cleared ones, noting that the results based on unstressed bilateral net CE likely provide a lower bound.

4.4 Determinants of derivative exposures

To explore what determines the interbank derivative exposures we measure, we regress quarterly unstressed bilateral or centrally cleared exposures of bank i to bank j, denoted by y_{ijt}, on bank j's lagged assets, capital ratio (CET1), and a liquidity ratio (HQLA). We control for lagged macro variables that include the federal funds rate (FF) and the VIX index, and include bank and time fixed effects (in regressions without macro variables):

$$y_{ijt} = \mu_i + \mu_j + \mu_t + \beta_1 \text{assets}_{j,t-1} + \beta_2 \text{CET1}_{j,t-1} + \beta_3 \text{HQLA}_{j,t-1} + \beta_4 FF_{t-1} + \beta_5 VIX_{t-1} + \epsilon_{ijt}. \tag{11}$$

There are 30 (6 by 5) bank-to-bank pairs for both bilateral and centrally-cleared exposures, and 24 different quarters of observation from the sample period 2018Q1–2024Q1. We consider OLS standard errors and standard errors clustered at the quarter level; the number of banks in our sample is too small to consider standard errors clustered at the bank level. We do not consider stressed bilateral exposures because they are only observed annually, making the sample size too small and statistical power too weak.

Tables 2 and 3 report the results. We find that once we account for bank fixed effects, the bilateral exposures tend to be higher for counterparties that are better capitalized, while centrally cleared exposures correlate negatively with counterparty capital; counterparty liquidity, proxied by the HQLA ratio, does not seem to robustly affect either set of exposures.

[13] Banks calculate stressed CE based on a set of scenarios defined either by their own internal models or by CCAR exercises, while CCPs estimate PFE from clearing member defaults following predefined formulas and parameters set by capital regulations.

The bilateral exposures tend to decrease with the federal funds rate and increase with the VIX index, although the latter effect is not statistically significant. In contrast, the centrally cleared exposures exhibit positive but insignificant correlation with the fed funds rate and negative and highly significant correlation with the VIX index. The negative correlation with the VIX index is expected as CCPs tend to increase their initial margin and other prefunded collateral requirements when market volatility increases, potentially reducing exposures from member defaults and the mutualized losses.

5 Default and contagion scenarios

5.1 A model of triple contagion

We develop a novel model of contagion to analyze the potential systemic risk from these interbank derivative exposures. The financial network model has three different contagion channels: direct bilateral channel, indirect centrally-cleared channel, and collateral price channel. The model is based on the typical payment equilibrium models pioneered by Eisenberg and Noe (2001) and combines the collateral price channel developed by Chang and Chuan (2024). While the core structure of the model is similar to those in Paddrik et al. (2020) and Ghamami et al. (2023), our model allows for multiple CCPs and a loss mutualization channel instead of CCP defaults. Moreover, the model is the first attempt to incorporate endogenous collateral price as a contagion channel in addition to the other two.

Banks and CCPs. There are n different banks indexed by i and j, where $i, j \in \mathcal{B} \equiv \{1, 2, \ldots, n\}$, and m different CCPs indexed by k, where $k \in \mathcal{C} \equiv \{1, 2, \ldots, m\}$. Banks and CCPs manage their payments using liquidity buffers, such as cash reserves and short-term lines of credit, denoted as b_i for bank i and b_k for CCP k. Banks are exposed to each other through derivative contracts, which specify the VM payment obligations to each other. Banks not only have VM obligations to pay to CCPs but also have committed assessment amounts for loss mutualization mechanism after CCPs' prefunded resources are depleted.

Banks have also posted collateral as IM, a combination of cash and securities collateral.

VM payment obligations and IM collateral. Let d_{ij} denote the VM payment obligation from bank i to bank j that is exogenously given. Similarly, let d_{ik} and d_{ki} denote the VM payment obligation from bank i to CCP k and vice versa. Note that if d_{ik} is positive, then d_{ki} is zero, and vice versa. Trivially, $d_{ii} = d_{kk} = 0$ for any $i \in \mathcal{B}$ and $k \in \mathcal{C}$. Let c_{ij} denote the IM collateral posted from bank i to bank j that is also exogenously given. Similarly, let c_{ik} denote the IM collateral posted by bank i to CCP k. Denote the average price of the collateral c_{ik} as p_{ik}. For example, if c_{ik} is purely cash collateral, $p_{ik} = 1$ and there will be no impact from a fire sale, which is discussed later.

Default fund contribution and assessment. For each CCP $k \in \mathcal{C}$, each bank i has posted a separate cash collateral, g_{ik}, which is the default (guarantee) fund contribution. Moreover, in addition to their derivative VM payment obligations, banks also have committed to assessment obligations, which are proportional to their default fund contribution amount by a factor γ_k: thus, each member bank i is obligated to pay up to $\gamma_k g_{ik}$, when CCP k's losses have to be mutualized. However, this payment is required only when CCP k has exhausted all its prefunded resources in its default waterfall.

Total liability. Let $d_i = \sum_{j \in \mathcal{B}} d_{ij} + \sum_{k \in \mathcal{C}} d_{ik}$ denote the total VM payment obligation of bank i to all other banks and CCPs, $d_k = \sum_{i \in \mathcal{B}} d_{ki}$ denote the total VM payment obligations of CCP k to all member banks, and $\gamma g_i = \sum_{k \in \mathcal{C}} \gamma_k g_{ik}$ denote the total assessment payment obligations of i to all CCPs.

Actual payment and default. Denote the actual payment made by bank j to bank i as $x_{ji} \leq d_{ji}$, which could be less than the payment obligation due to a shock. If $x_{ji} < d_{ji}$, the difference will be covered by the IM amount if $d_{ji} - x_{ji} \leq c_{ji} p_{ji}$. Otherwise, the difference $d_{ji} - x_{ji} - c_{ji} p_{ji}$, i.e., the payment obligations less the actual payment and the collateral amount times its price, is the loss amount to bank i.

Similarly, denote the actual payment made by bank i to CCP k as $x_{ik} \leq d_{ik}$. If $x_{ik} < d_{ik}$, the difference will be covered by the IM and the default fund contribution amount if

$d_{ik} - x_{ik} \leq c_{ik}p_{ik} + g_{ik}$. Otherwise, the difference $d_{ik} - x_{ik} - c_{ik}p_{ik} - g_{ik}$, i.e., the payment obligation less the actual payment, collateral amount times its price, and the default fund contribution by the defaulting bank i, is the loss amount to CCP k.

We assume that, when bank i defaults, it pays nothing to its counterparties, i.e., $x_{ik} = x_{ij} = 0$ for all $k \in \mathcal{C}$ and $j \in \mathcal{B}$ for each $i \in \mathcal{B}$. In other words, if $x_{ik} < d_{ik}$, it will pay nothing to CCP k and cause losses to the CCP in the amount of $d_{ik} - c_{ik}p_{ik} - g_{ik} > 0$. This assumption corresponds to a *hard default* option, i.e., a defaulting bank cannot make even a partial payment from its remaining assets due to frictions (other than its prefunded IM and default fund contribution amount). This model of default is indeed the most conservative but could also be the case when a shock big enough to make a large bank default hits the financial system (Paddrik et al., 2020).[14] Furthermore, we assume that CCPs always pay their full VM payment obligations at the end. If a CCP cannot fulfill its payment obligations even after receiving the full amount of assessments from their clearing member banks, the government intervenes and provides funds to make the CCP solvent. This assumption is also in line with reality, as CCPs are almost impossible to default,[15] and policymakers can intervene to support CCPs to prevent their failure.

Net wealth. We define the net wealth (excluding assessment) of CCP k as

$$w_k \equiv \sum_{i \in \mathcal{B}} \underbrace{((x_{ik} + c_{ik}p_{ik} + g_{ik}) \wedge d_{ik})}_{\text{payment from bank } i} + b_k + \sum_{i \in \mathcal{B} \setminus \mathcal{D}} g_{ik} - \sum_{i \in \mathcal{B}} d_{ki}, \tag{12}$$

where $\mathcal{D}$ is the set of defaulting banks, and $\wedge$ is the meet operator to choose the minimum between the two elements. The net wealth of CCP k in (12) consists of: each bank's actual payment plus prefunded resources up to the promised VM payment, the CCP's liquidity buffer, the default fund contributions from non-defaulting member banks, subtracted by the CCP's payment obligations to all member banks. If $w_k \geq 0$, CCP k has enough prefunded

[14] We can further consider the possibility that non-defaulting banks cannot recover their IM from the defaulting banks in full. If such failures to return collateral occur, the contagion dynamics in our model would be further exacerbated. See Chang (2021) for further discussion on this topic.

[15] We also find that this is the case with our data.

resources to cover all of its obligations. However, if $w_k < 0$, CCP k has to require assessments from the non-defaulting member banks proportional to their default fund contribution amount, i.e.,

$$s_{ik}(\mathcal{D}) \equiv \frac{g_{ik}}{g_k - \sum_{j \in \mathcal{D}} g_{jk}}, \tag{13}$$

which corresponds to (2). Hence, non-defaulting member bank i's additional assessment payment to CCP k is $s_{ik}(\mathcal{D}) \left[-w_k\right]^+$, where $[\cdot]^+ \equiv \max\{\cdot, 0\}$.

Then, we can define the net wealth of bank i as

$$w_i \equiv \sum_{j \in \mathcal{B}} \underbrace{\left((x_{ji} + c_{ji} p_{ji}) \wedge d_{ji}\right)}_{\text{payment from bank } j} + \sum_{k \in \mathcal{C}} d_{ki} + b_i - \sum_{j \in \mathcal{B}} d_{ij} - \sum_{k \in \mathcal{C}} \Big(d_{ik} + \underbrace{s_{ik}\left(\mathcal{D}\right)\left[-w_k\right]^+ \wedge \gamma_k g_{ik}}_{\substack{\text{loss mutualization} \\ \text{through assessments}}}\Big), \tag{14}$$

i.e., actual payments and collateral value from other banks up to the promised VM payments, payments from CCPs, and liquidity buffer, subtracted by i's payment obligations to other banks, i's payment obligations to CCPs, and i's obligations to pay additional assessment amount if a CCP has to mutualize losses. Bank i defaults if its net wealth is negative, i.e., $w_i < 0$, resulting in zero actual payments to others, i.e., $x_{ij} = x_{ik} = 0$ for all $j \in \mathcal{B}$ and $k \in \mathcal{C}$. Otherwise, bank i is solvent and pays its full promised payment amounts $x_{ij} = d_{ij}$ and $x_{ik} = d_{ik}$ for each $j \in \mathcal{B}$ and $k \in \mathcal{C}$.

Fire sales and market price effect. Defaulting banks' collateral could be on fire sales, which create downward pressure on the market price of the collateral. Surviving banks can participate in the market for collateral and support the current price if needed. However, if the surviving banks have limited liquidity buffers, then the price of the collateral assets may decrease, increasing the counterparty exposures of all banks. We formalize this feedback between fire sales and collateral price by the market price function: $\phi(W) : \mathbb{R}^+ \to \mathbb{R}^+$, which is (weakly) increasing in W and upper semicontinuous, where $W \equiv \sum_{i \in \mathcal{B}} \left[w_i\right]^+$ is

the sum of positive net wealth of all solvent banks. For expositional simplicity, we assume that one collateral price p can represent the average price of the average composition of all different collateral assets for each c_{ij}, c_{ik} and their prices p_{ij}, p_{ik}. This reduced-form representation of the interaction between fire sales and market clearing price is consistent with a microfoundation with explicit models of fire sales and market clearing, as shown by Lemma 6 in Chang and Chuan (2024).

Payment equilibrium and full equilibrium. For a fixed collateral price $p = p_{ij} = p_{ik}$ for all $i, j \in \mathcal{B}$ and $k \in \mathcal{C}$, a payment equilibrium is a triple $(X, w, \mathcal{D})$, where $X \equiv (x_{ij})_{i\in\mathcal{B}\cup\mathcal{C}, j\in\mathcal{B}\cup\mathcal{C}}$ is the matrix of actual payments, $w \equiv [(w_i)_{i\in\mathcal{B}}, (w_k)_{k\in\mathcal{C}}]$ is the vector of net wealth, and $\mathcal{D} \subset \mathcal{B}$ is the set of defaulting banks, satisfying the hard default payment rule, the net wealth equations (12) and (14), and the definition of default $w_i < 0$ for each $i \in \mathcal{B}$.

A quadruple $(X, w, \mathcal{D}, p)$ is a full equilibrium if $(X, w, \mathcal{D})$ is a payment equilibrium for the given price p, and the price p satisfies the market clearing condition

$$p = \phi(W), \tag{15}$$

where $W = \sum_{i\in\mathcal{B}} [w_i]^+$ as defined earlier.

Recursive sequence of contagion. Let $\Psi(w, p)$ be the function of updated wealth such that

$$\Psi(w, p) : \mathbb{R}^{n+m} \times \mathbb{R}_+ \longrightarrow \mathbb{R}^{n+m}, \tag{16}$$

where the matrix of actual payments is determined by the hard default rule on the the vector of wealth in the input, and the resulting updated vector of wealth is determined by the actual payments. Then, the first n elements of the vector $\Psi(w, p)$ determine the updated vector for the market clearing condition, i.e., $\phi\left((\Psi(w, p)_i)_{1\le i\le n}\right)$. Then, we can use the updated price to update the wealth vector again. This process can be repeated as the following recursive sequence:

$$
\begin{aligned}
w^1 &= \Psi(w^0, p^0), \qquad & p^1 &= \phi\left(\left(w_i^1\right)_{1\le i\le n}\right), \\
w^2 &= \Psi(w^1, p^1), \qquad & p^2 &= \phi\left(\left(w_i^2\right)_{1\le i\le n}\right), \\
w^3 &= \Psi(w^2, p^2), \qquad & p^3 &= \phi\left(\left(w_i^3\right)_{1\le i\le n}\right), \\
&\vdots & &\vdots.
\end{aligned}
\tag{17}
$$

Proposition 1. *There exists a full equilibrium. Furthermore, the sequence in* (17) *converges to the full equilibrium with the maximum wealth vector and price.*

Proof. See Appendix B ■

Proposition 1 implies that we can find the full equilibrium under the best-case scenario for any given starting wealth vector w. More concretely, we can use the following algorithm to find the best full equilibrium:

1. Assume an initial defaulting set $\mathcal{D}^0$ and set $\mathcal{D} = \mathcal{D}^0$.
2. Set the actual payments from the banks in the defaulting set $i \in \mathcal{D}$ as zero, i.e., $x_{ij} = x_{ik} = 0$ for all $j \in \mathcal{B}$ and $k \in \mathcal{C}$.
3. Calculate the wealth vector for every bank and CCP.
4. If a CCP k has a negative wealth, then subtract the corresponding assessment amount from each solvent bank i in the amount of $s_{ik}(\mathcal{D})(-w_k) \wedge \gamma_k g_{ik}$.
5. Calculate the updated wealth vector for every bank.
6. Update the collateral price with $\phi(W)$.
7. Return to step 3 and proceed to update the collateral price. If the collateral price reaches a fixed point, then proceed to the next step.
8. Define a new defaulting set $\mathcal{D}'$ with the updated wealth vector. If $\mathcal{D}' \neq \mathcal{D}$, then update the defaulting set $\mathcal{D}$ as $\mathcal{D}'$ and return to step 2. If $\mathcal{D}' = \mathcal{D}$, then we have found the best full equilibrium.

5.2 Empirical simulation results

Based on the theoretical model of triple contagion, we develop a simulation model that can utilize the empirical data.

For the baseline case, we assume that fire sale effects don't exist, i.e., the collateral price is constant as $\phi(W) = p^0$ for any $W \geq 0$. This is because we do not have information about the actual amount of IM posted by banks as well as the exact composition of the collateral posted. As discussed in Section 4.3, the EAD calculation already accounts for potential declines in collateral prices by multiplying exposures by a parameter. Along the lines of the EAD calculation, we later experiment with multiplying the exposure amounts to account for potential fire sale effects.

We also assume that banks suffer losses even on their prefunded default fund contributions, g_{ik}. In other words, banks' default fund contributions are considered to be a part of the banks' available liquidity buffer. Relatedly, we assume that each CCP's assessment factor γ_k is not binding. This assumption is in line with reality, as default fund amounts are supposed to cover defaults of the top 2 clearing members of a CCP, and γ_k typically range from 2 to infinity (no cap on assessments when multiple defaults occur) (CPMI–IOSCO, 2016). So, the sum of assessments and default funds can cover exposures to top 6 or more clearing members' default. Thus, we are assuming the most conservative scenario for centrally-cleared exposures, as we don't assign an upper bound for exposures to CCPs.

Further, we assume that banks have balanced derivative positions, i.e., they do not have market risk or directional exposures in derivatives. Therefore, their net wealth does not depend on the realization of interbank derivative exposures as long as they get paid in full on all contracts. In other words, we focus on counterparty risks, while abstracting away from market risks. This is in line with reality, as large banks primarily use derivatives for market-making rather than for their own hedging purposes, so their counterparty risk dominates their market risk. For example, Falato et al. (forthcoming) find that banks have virtually no market risk after the Volcker Rule implementation, Lu and Wallen (2024) find that bank

trading desks bear little to no market risk, and McPhail et al. (2023) find that many large banks rely minimally on interest rate derivatives to hedge their own interest rate risk.

For the banks' liquidity buffer, we use each bank's HQLA amount and liquidity coverage ratio to calculate available liquidity. The liquidity buffer of bank i at time t is calculated as

$$b_{i,t} \equiv HQLA_{i,t} \times (LCR_{i,t} - 1), \tag{18}$$

where $LCR_{i,t}$ is the liquidity coverage ratio, i.e., $HQLA_{i,t}$ divided by the net cash outflows of bank i over a 30-day period. This measure corresponds to the actual free liquidity to be used to cover any potential losses from interbank derivative exposures. In reality, banks have many other sources of liquidity, including the discount window, the Standing Repo Facility, and other possible emergency facilities. Thus, our measure of liquidity buffer is an extremely conservative estimate of banks' actual liquidity resources.

Under these assumptions, contagion of losses through a bank's default is the sum of bilateral exposures (directly measured from FR Y-14Q) and the indirect centrally cleared exposures we derive as in equation (8). Therefore, the algorithm in Section 5.1 can be simplified as the following:

1. Assume an initial defaulting set $\mathcal{D}^0$ and set $\mathcal{D} = \mathcal{D}^0$.

2. Each surviving bank j suffers losses from each $i \in \mathcal{D}$, which is the sum of direct exposure measured by net CE and the indirect exposure derived by (8).

3. For each surviving bank j, if the total loss exceeds the liquidity buffer of bank j, b_j, then bank j also defaults and is included in the new defaulting set $\mathcal{D}'$. If $\mathcal{D}' \neq \mathcal{D}$, then update the defaulting set $\mathcal{D}$ as $\mathcal{D}'$ and return to step 2. If $\mathcal{D}' = \mathcal{D}$, then we have found the best full equilibrium.

Moreover, we also incorporate the possible collateral price contagion by simply assuming that all exposures are amplified due to potential fire sales. For the second set of simulations,

we multiply both the bilateral and centrally cleared exposures by 10. This represents a plausible yet extreme case of the fire-sale contagion effect, as typical IM covers roughly about 99% of the exposures and a collateral price decline of 10% leads to the updated IM only covering about 90% of the exposures, amplifying them by 10. Considering that a substantial portion of the IM consists of cash, U.S. Treasuries, or other safe assets, a 10% decline in value is a considerably large drop.

Figures 9, 10, and 11 show the simulation results of the baseline model. For the initial defaulting set of banks, we vary the number of defaulting banks from 1 to 3 and consider all different combinations of banks. For each time period and each number of initial defaults (1,2, and 3, represented by blue, green, and red, respectively), we plot the maximum average losses (the total losses to the surviving banks divided by the number of surviving banks) across different combinations of the initial defaulting set of banks and the maximum number of additional defaults.

Figure 9 shows the quarterly time-series chart using unstressed bilateral exposures for the direct interbank exposures. Figure 10 shows the annual time-series chart using stressed bilateral exposures under SADV scenario. Figure 11 shows the annual time-series chart using stressed bilateral exposures under BHC scenario. Even though the average losses are a bit higher under the stressed scenarios, there are no additional defaults in all scenarios across the three figures.

We now examine contagion patterns under fire sale amplification. Figure 12 shows the simulation results using unstressed bilateral exposures when there is fire sale amplification. Only the worst scenario of 3 initial defaults generates one additional default of a bank prior to 2020. Even though there are fluctuations in the average losses, there are no additional defaults afterwards. Figure 13 shows the simulation results using bilateral exposures under the SADV scenario when there is fire sale amplification. Strikingly, the worst scenario of 3 initial defaults leads to default of all the remaining banks up to 2020, partially due to high exposures among the banks. However, there are no additional defaults afterwards. Figure 14

shows the simulation results using bilateral exposures under the BHC scenario when there is fire sale amplification. Even though there are no cases in which all banks default, the worst scenario of 3 initial defaults generates 2 additional defaults until 2022. Moreover, the worst scenario of 2 initial defaults also generates an additional default until 2020.

Overall, Figures 12, 13, and 14 highlight that interbank exposures in derivatives can trigger an additional default when there is fire sale amplification, and the extent of contagion differs across different measures of bilateral exposures (unstressed, SADV scenario, and BHC scenario). These results are in line with the literature, which finds that direct bilateral exposures alone cannot trigger additional defaults (Upper, 2011), while our analysis extends this analysis by including centrally cleared exposures and fire sale amplification.

5.3 Systemic risk index

Based on the empirical simulations of contagion with fire sale amplification, we find that interbank contagion through derivative exposures can cause an additional bank to default or all remaining banks to default. This implies, if we flip the perspective, we can perform *reverse stress tests*—finding the threshold extent of amplification needed to trigger an additional default or all banks to default. Once we know these thresholds, we can map them into a distribution of exposure amplification and calculate the likelihood of exceeding the thresholds. Hence, using the results of the reverse stress tests, we develop a systemic risk index.

First, we discuss the probability of initial shock scenarios. Following our previous simulations, we consider all possible combinations of 1 through 3 initial defaulting banks. The probability of each scenario is based on each bank's probability of default. For each bank's probability of default, we use Bloomberg's 1-year probability of default (market-implied probability of default) based on 1-year CDS spreads for the corresponding bank. We use the observations from the last month of each quarter.

Second, we discuss our setting of the exposure amplification channel. We assume that

our estimated exposures can be amplified up to 100 times, following a certain probability distribution. The source of this amplification can be wrong-way risk, increased market volatility, drying up of liquidity sources, and others. Although our results do not depend on the ultimate sources of the exposure amplification, we provide an example of fire sale amplification in the following.

Following the empirical simulation model, we assume that the distribution of the collateral value (IM + VM) is uncorrelated with the extent of contagion. This assumption works as a downward bias, as correlation between collateral price and extent of contagion would exacerbate fire sale amplification. Instead, we assume that the (total average) collateral value $\tilde{p}$ is a random variable with the cumulative distribution function of the collateral price $F(\tilde{p})$. Recall the assumption that collateral value covers 99% of a given gross current exposure in expected sense, i.e.,

$$\text{Net CE} \equiv d_{ji} - c_{ji}p = 0.01d_{ji}, \tag{19}$$

when the collateral price remains at the unstressed price of the collateral $\tilde{p} = p$. However, if the collateral price declines (possibly due to fire sales), the net CE is amplified from $0.01d_{ji}$ to

$$\widetilde{\text{Net CE}} \equiv d_{ji} - c_{ji}\tilde{p} \in [0.01d_{ji}, d_{ji}]. \tag{20}$$

In other words, depending on the realized collateral price $\tilde{p}$, the amplified net CE can be up to 100 times the net CE without amplification, and the distribution of such amplification is determined by the distribution of the price, $F(\tilde{p})$. Although the exposures we measure are greater than the net CE as we discussed in Section 4.3, the degree of amplification of exposure measures is monotonically increasing in the degree of amplification of net CEs.

Third, for each realized combination of initial defaulting banks $\mathcal{D}^0$, we compute the minimum amplification of exposures that triggers either an additional default or all banks'

default. This reverse stress test provides us with an idea of how resilient the banking system is by showing how much of an amplification of derivative exposures it can withstand. For the corresponding threshold exposure amplification, which can be represented as $p^*(\mathcal{D}^0)$ and $p_*(\mathcal{D}^0)$ for an additional default and all banks' default, respectively, we compute the cumulative distributions $F(p^*(\mathcal{D}^0))$ and $F(p_*(\mathcal{D}^0))$ to derive the likelihood of either of the stress events (conditional on the given realization of initial defaulting banks). Note that these thresholds depend on the structure of the two contagion channels—direct bilateral exposures channel and the indirect centrally-cleared exposures channel.

Finally, we define our systemic risk index for each stress event: an additional bank default or all the remaining banks defaulting. For each initial default set $\mathcal{D}^0$ from the set of possible initial default sets, i.e., $\mathcal{D}^0 \in \mathbb{D}$, we compute the probability of that initial default by multiplying the probability of default of each bank in $i \in \mathcal{D}^0$, denoted as PD_i. Then, for each $\mathcal{D}^0$, we multiply this by the probability of $\tilde{p}$ being less than or equal to the required threshold for the corresponding stress event, i.e., $F(p^*(\mathcal{D}^0))$ and $F(p_*(\mathcal{D}^0))$. Then, the ultimate probabilities of stress events happening due to a initial default set $\mathcal{D}^0$ is

$$G^*(\mathcal{D}^0) \equiv \left(\prod_{i\in\mathcal{D}^0} PD_i\right)\left(\prod_{i\in\mathcal{B}\setminus\mathcal{D}^0} (1-PD_i)\right) F(p^*(\mathcal{D}^0)) \tag{21}$$

$$G_*(\mathcal{D}^0) \equiv \left(\prod_{i\in\mathcal{D}^0} PD_i\right)\left(\prod_{i\in\mathcal{B}\setminus\mathcal{D}^0} (1-PD_i)\right) F(p_*(\mathcal{D}^0)), \tag{22}$$

for an additional default and all banks default, respectively. We are assuming that PD_i is not correlated with PD_j for $i, j \in \mathcal{B}$. However, if the probabilities of default are correlated, the probabilities of systemic events in (21) and (22) could be higher.

The systemic risk index for each stress event is derived by summing all the ultimate probabilities in (21) and (22) across different sets of initial defaulting banks, i.e., the systemic

risk index for each stress event is

$$SR^* \equiv \sum_{\mathcal{D}^0 \in \mathbb{D}} G^*(\mathcal{D}^0) = \sum_{\mathcal{D}^0 \in \mathbb{D}} \left(\prod_{i \in \mathcal{D}^0} PD_i \right) \left(\prod_{i \in \mathcal{B} \setminus \mathcal{D}^0} (1 - PD_i) \right) F(p^*(\mathcal{D}^0)) \tag{23}$$

$$SR_* \equiv \sum_{\mathcal{D}^0 \in \mathbb{D}} G_*(\mathcal{D}^0) = \sum_{\mathcal{D}^0 \in \mathbb{D}} \left(\prod_{i \in \mathcal{D}^0} PD_i \right) \left(\prod_{i \in \mathcal{B} \setminus \mathcal{D}^0} (1 - PD_i) \right) F(p_*(\mathcal{D}^0)), \tag{24}$$

for an additional default and all banks default, respectively.

For the baseline case, we assume that $F(\tilde{p})$ follows a uniform distribution with support $[0, d/c]$, i.e., the amplification of the exposures can range from 100 times to 0 times (if the collateral price increases and covers the entire exposure as $d - c(d/c) = 0$), where we assume a common collateral ratio as $d/c = d_{ji}/c_{ji}$ for all $i, j \in \mathcal{B} \cup \mathcal{C}$. This is equivalent to having the degree of exposures uniformly distributed in $[0, 100]$.[16]

Figures 15 and 16 show the time series charts of the systemic risk indices using unstressed bilateral exposures and stressed bilateral exposures, respectively.

Figure 15 indicates that the systemic risk index spiked during the COVID-19 period around the first quarter of 2020, partly due to heightened probability of default of banks. Although the probability of an additional bank default is at a small but non-negligible level (around 0.4% probability at its peak), the probability of all banks defaulting is close to negligible. Interestingly, the probability of all banks defaulting ticks up slightly around the end of 2021 and beginning of 2022, while the probability of any default remains relatively subdued.

Figure 16 also indicates that the systemic risk index spiked during the COVID-19 period, although the effect only appears in the observation at the end of 2020 because the stressed exposures are only reported in the fourth quarter of each year. The probability of an additional bank default is much greater than that for the unstressed exposures, peaking around 0.65%. Also, the probability of all banks defaulting is non-negligible, especially for

[16] As $\tilde{p}$ goes from 0 to d/c, $\widetilde{\text{Net CE}}$ goes from d to 0, which is equivalent to going from 100-times amplification to 0-time amplification of the measured exposures $0.01d$.

the bilateral exposures under the BHC scenarios. Interestingly, the probability of all banks defaulting in 2022Q4 is greater than that of 2020Q4, even though the probability of default of each bank is lower in 2022. This implies that the intricate interaction across different contagion channels plays an important role in determining the true systemic risk due to contagion in interbank derivative exposures. Thus, our measure captures underappreciated potential systemic risks that are not captured by aggregate market variables.

6 Conclusion

This study provides a comprehensive analysis of interbank exposures in derivatives markets, focusing on the top 6 U.S. banks and 9 major global CCPs, incorporating both bilateral and centrally cleared contracts. Our novel approach offers a more comprehensive representation of the interconnectedness among large U.S. banks through derivatives. For example, we observe shifts from bilateral to centrally cleared exposures over the past several years.

We also develop a new model of contagion that incorporates amplification of counterparty exposures through fire sales. The scenario analysis reveals that, under extreme but plausible stressed scenarios with fire sale amplification, the default of up to three large banks can lead to additional bank failures.

Based on these findings, we develop a new measure of systemic risk by incorporating the probability of realization of each scenario and the likelihood of exposure amplification through fire sales, using reverse stress tests. Our systemic risk index can be informative in monitoring changes in the potential systemic risk from interbank derivative exposures.

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A Figures and Tables

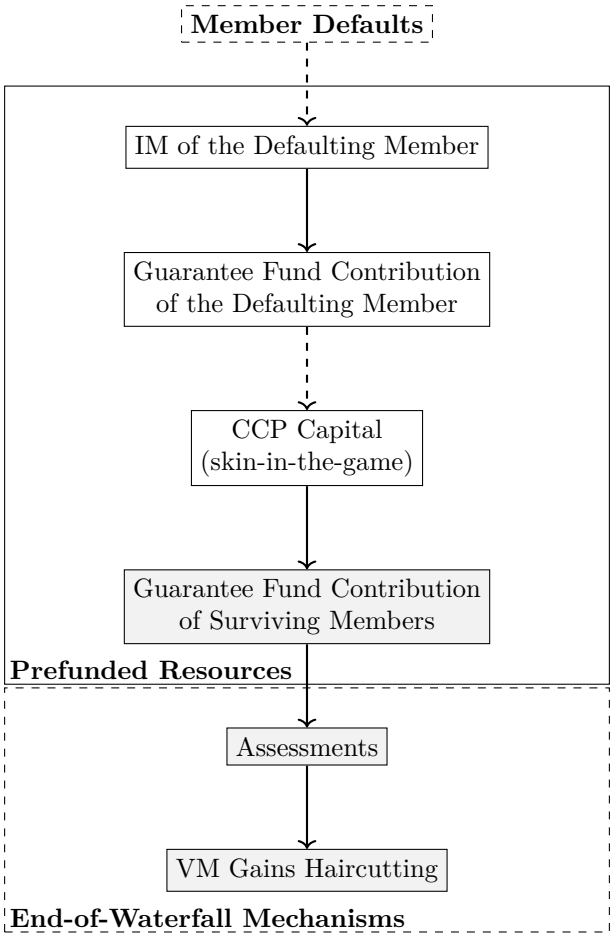


Figure 1: Typical CCP default waterfall mechanism

Note: Each solid node represents a mechanism along the CCP default waterfall. Gray nodes represent mechanisms that incur losses to non-defaulting members.

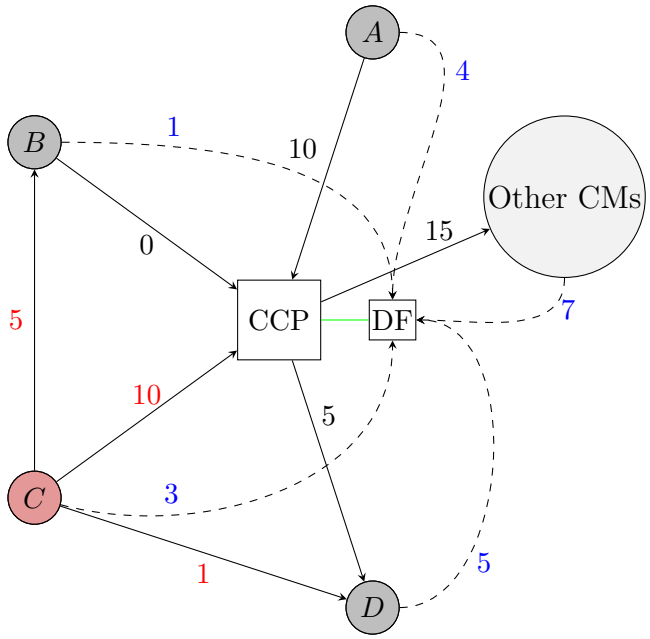


Figure 2: Example of a clearing member default without spillovers

Note: Each circular node in the figure represents a clearing member and a set of clearing members for "Other CMs". Red nodes represent defaulting members. The square "CCP" node represents the CCP, which clears all the centrally cleared transactions, and the square "DF" node represents the CCP's default fund, which collects contributions from all the clearing members. Solid arrows represent payment obligations net of collateral, and the numbers next to solid arrows represent the payment amounts (net current exposures). Dashed arrows represent default fund contributions from clearing members, and the blue numbers next to the dashed arrows represent the contribution amount.

In this example, bank C defaults, resulting in losses for banks B and D in the amount of 5 and 1, respectively. Bank C also defaults on its payment of 10 to the CCP. Bank C's default fund contribution 3 is used first, and then the remaining loss of 7 is distributed to all the other clearing members on pro rata basis according to their default fund contributions. The total default fund amount can cover the losses from the default of bank C in this case.

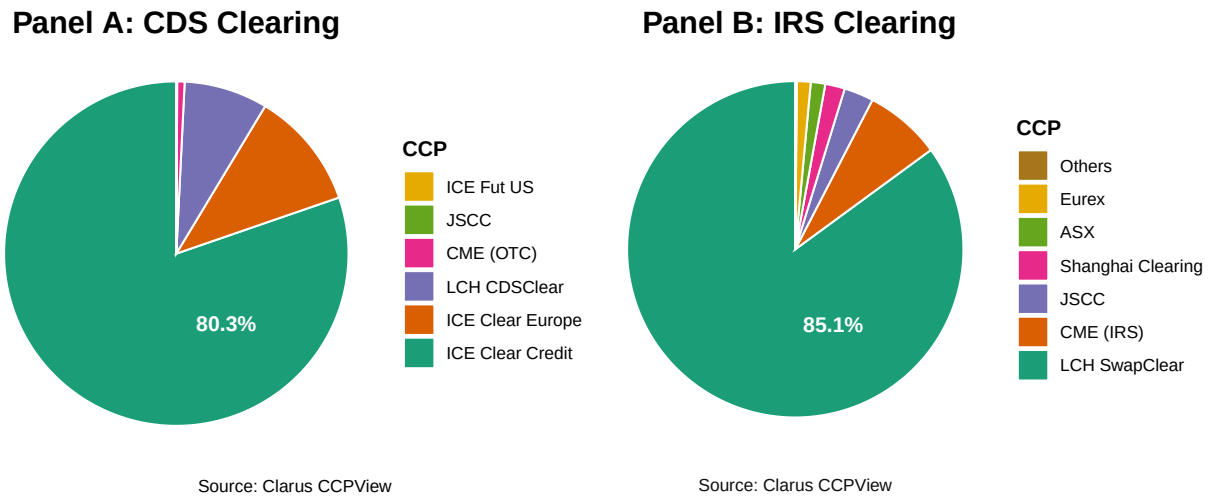


Figure 3: CCPs' market share for OTC derivative clearing

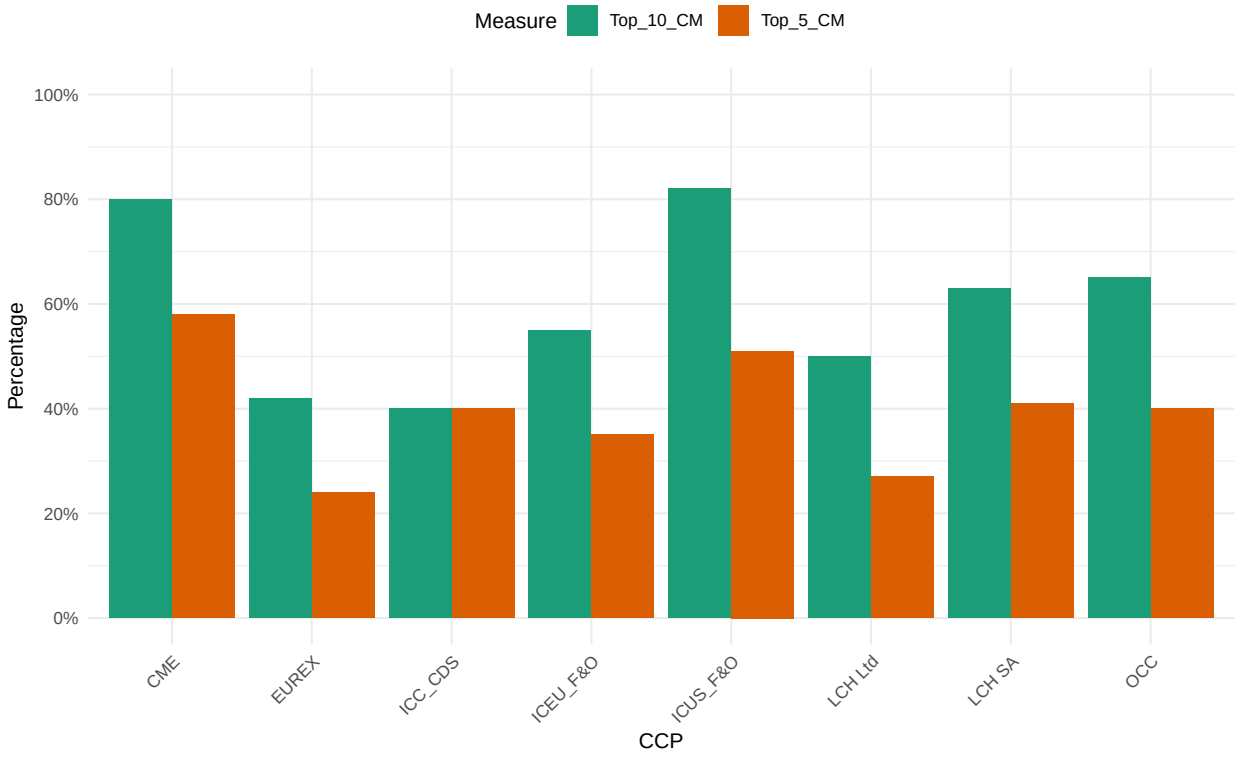


Figure 4: Clearing member concentration in CCPs

Source: Public Quantitative Disclosures via Clarus CCPView.

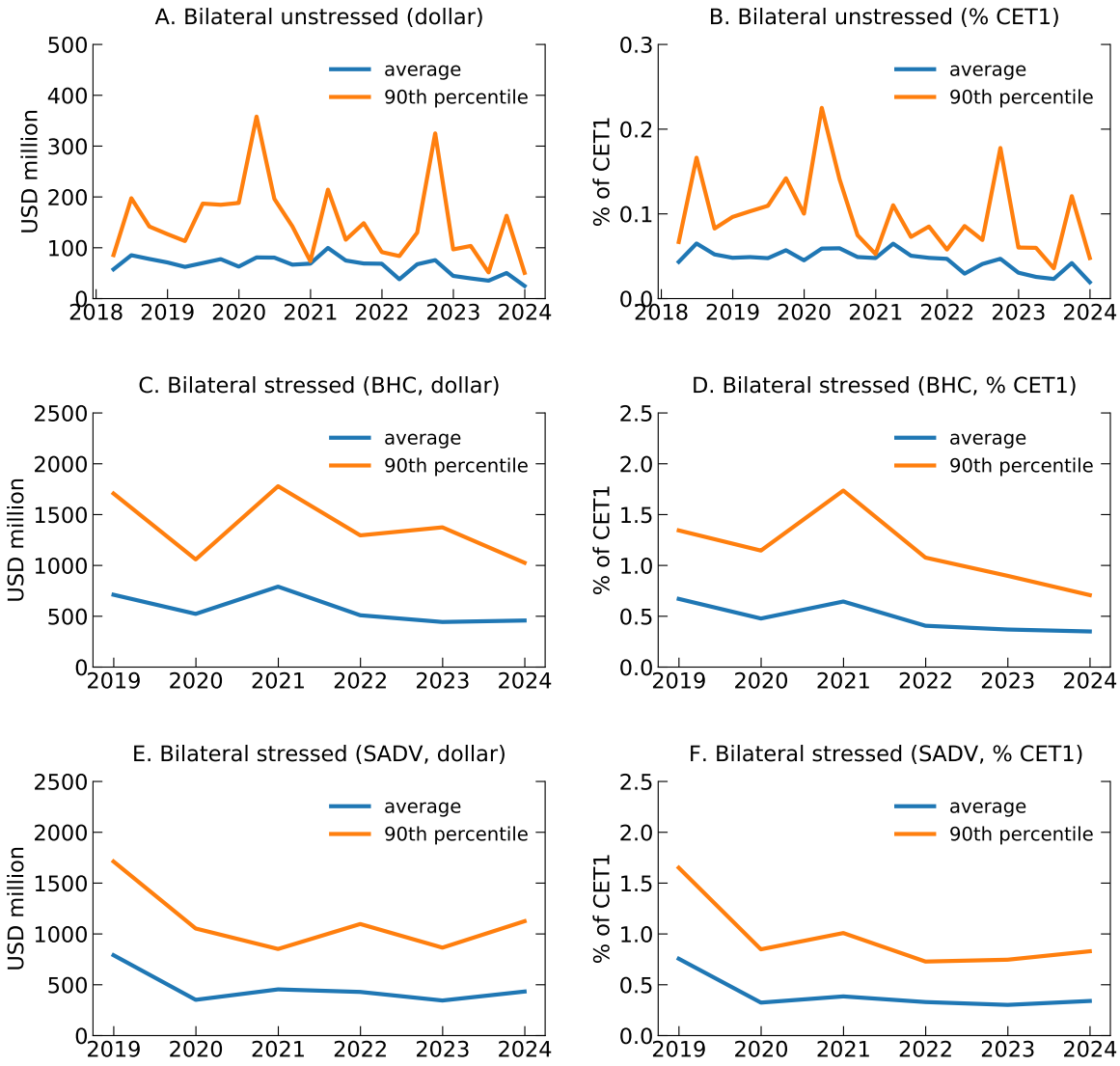


Figure 5: Interbank exposures through bilateral derivatives

Note: The top panel show the average and 90th percentile of the unstressed net bilateral exposures in dollars (left chart) and as percent of CET1 capital (right chart). The middle and bottom panels show analogous time series for stressed bilateral exposures under the BHC scenarios (middle panel) and the Federal Reserve's severely adverse scenario. Source: FR Y-14, Schedule L.1.a.

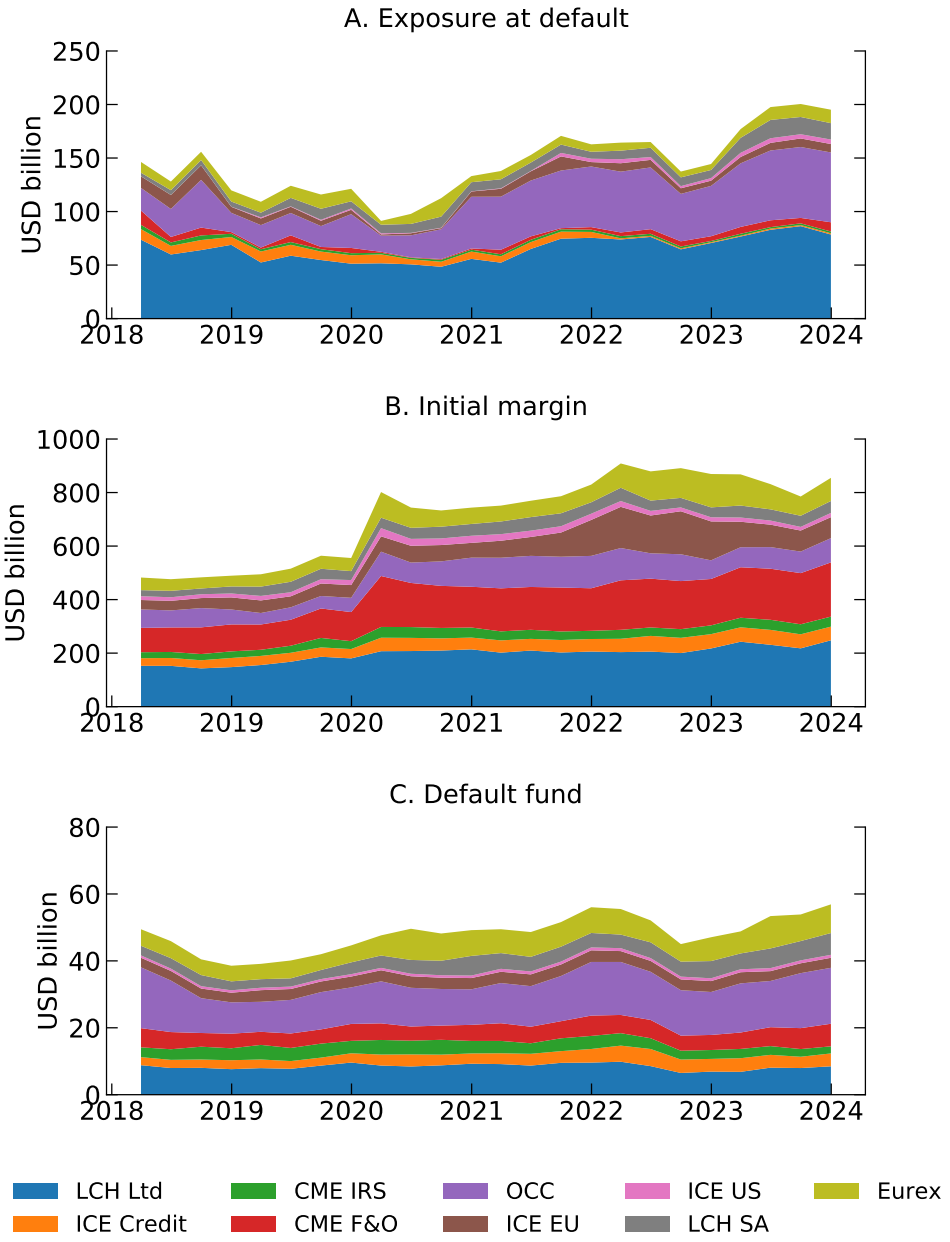


Figure 6: Exposure at default, initial margin, and default fund size at the CCPs in our sample

Source: Public Quantitative Disclosures via Clarus CCPView.

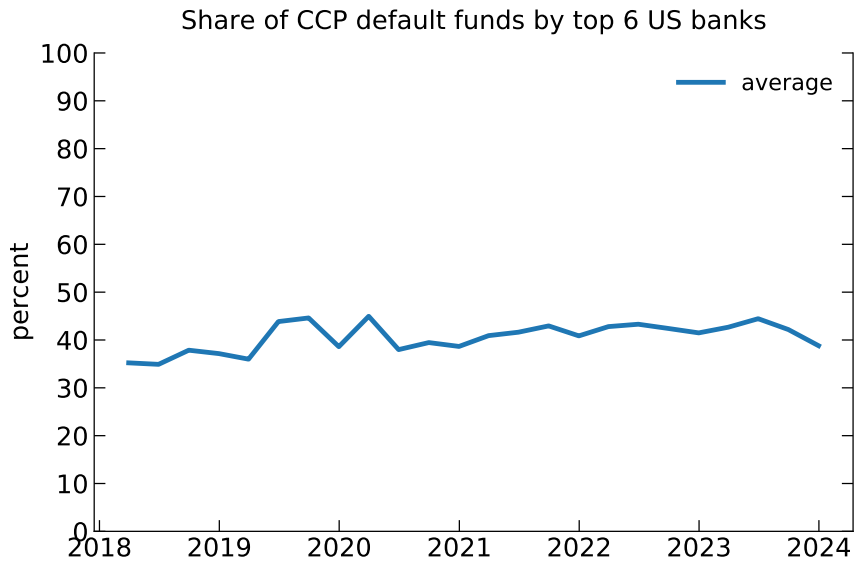


Figure 7: Default fund contributions of top 6 US banks in 9 derivatives CCPs

Note: The panel shows the average share of the top 6 US banks across the CCPs in the sample. Source: FR Y-14Q, Schedule L.5 and Public Quantitative Disclosures via Clarus CCPView.

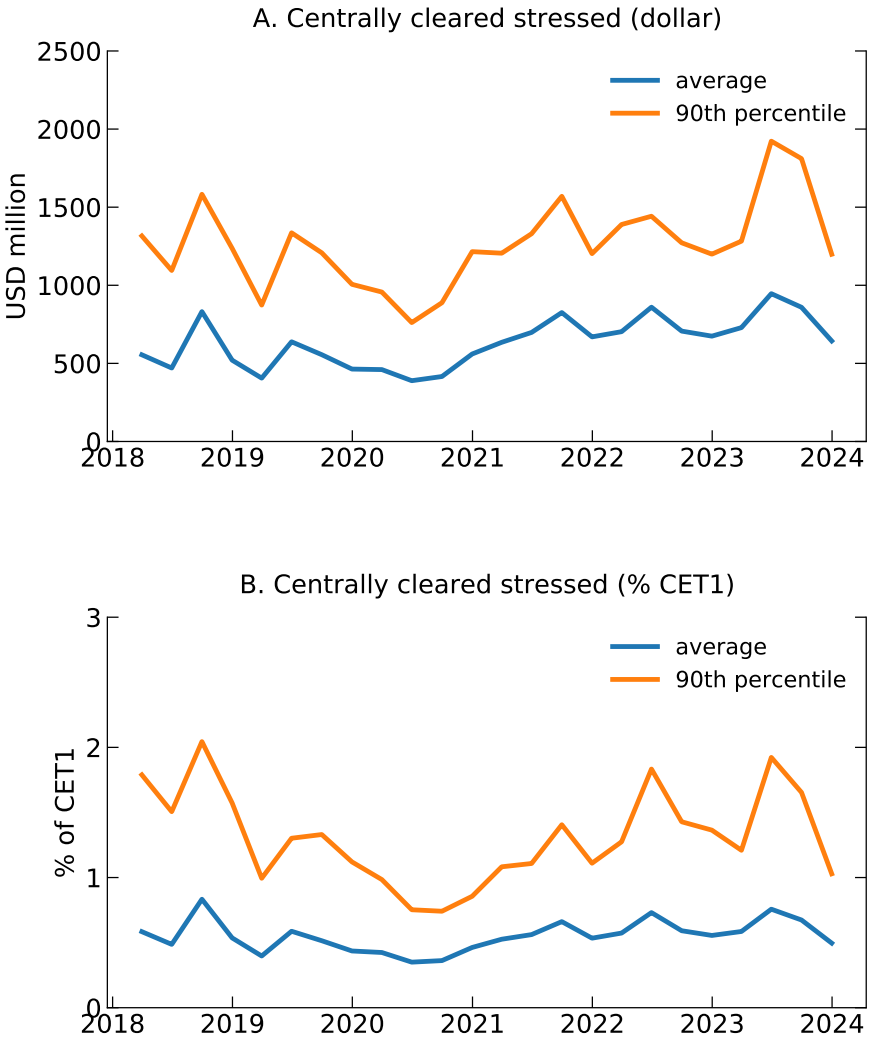


Figure 8: Interbank exposures through centrally cleared derivatives

Note: The top panel show the average and 90th percentile of exposures in dollars and the bottom panels shows the exposures expressed as percent of CET1 capital. Source: FR Y-14Q, Schedule L.5 and Public Quantitative Disclosures via Clarus CCPView.



Figure 9: Simulation results using unstressed bilateral exposures

Note: The left y-axis shows the number of additional defaults, and the right y-axis shows the maximum of average losses to the surviving banks across different combinations of defaulting banks. Source: FR Y-14Q, Schedule L.5, Public Quantitative Disclosures via Clarus CCPView, and author's calculations.

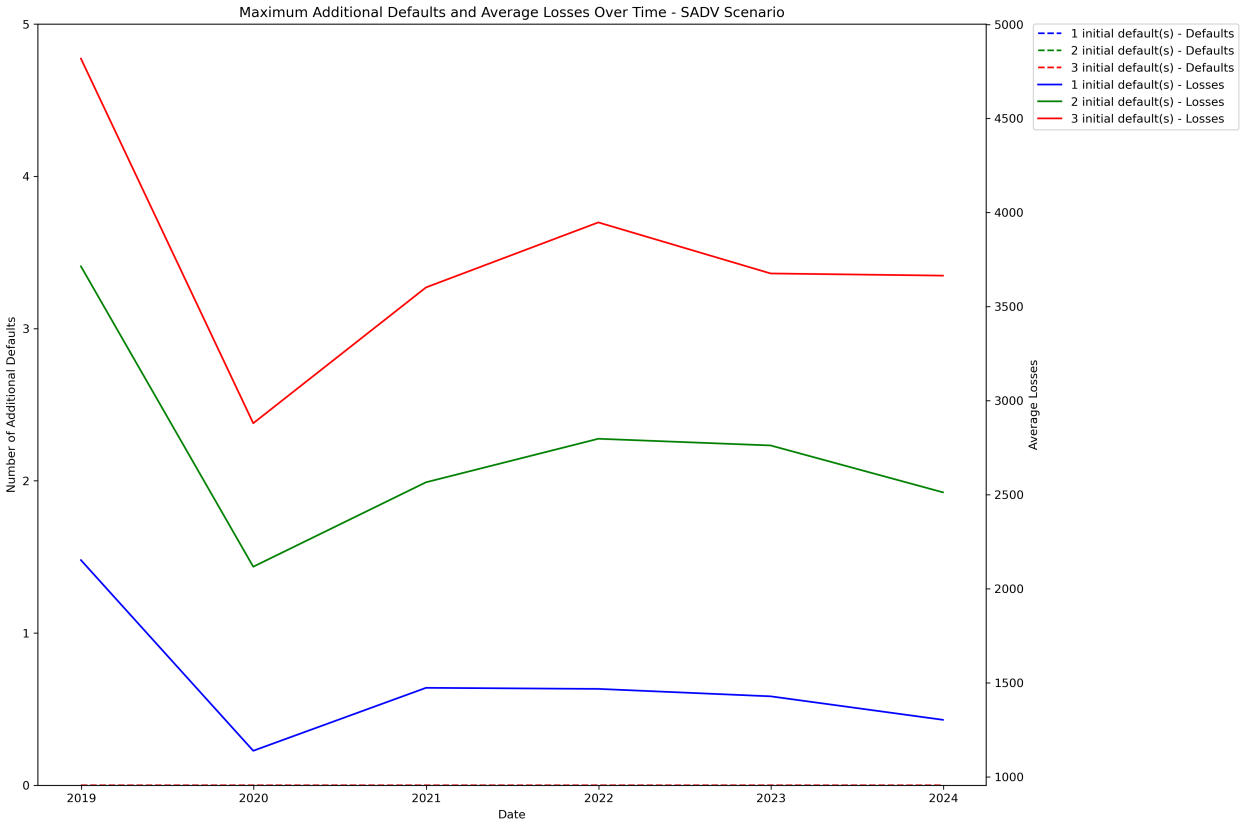


Figure 10: Simulation results using stressed bilateral exposures under SADV scenario

Note: The left y-axis shows the number of additional defaults, and the right y-axis shows the maximum of average losses to the surviving banks across different combinations of defaulting banks. Source: FR Y-14Q, Schedule L.5, Public Quantitative Disclosures via Clarus CCPView, and author's calculations.

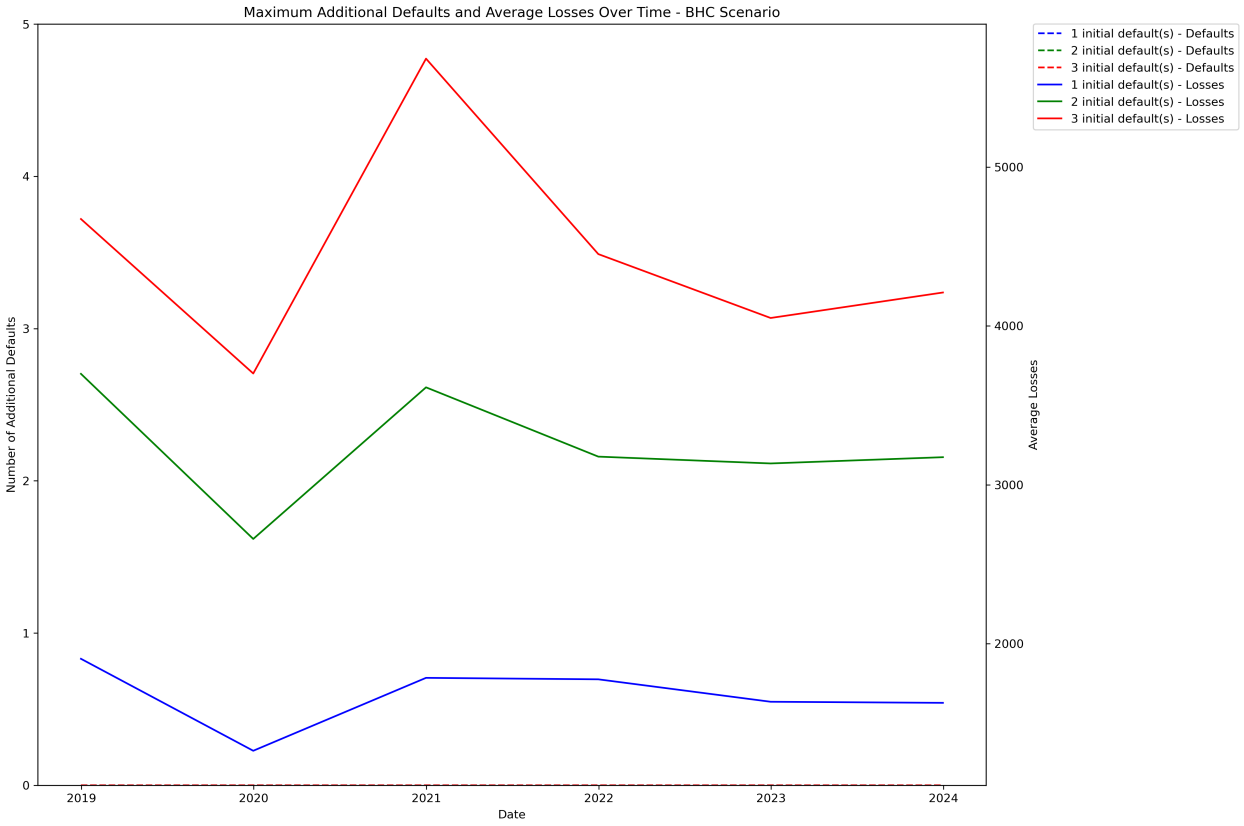


Figure 11: Simulation results using stressed bilateral exposures under BHC scenario

Note: The left y-axis shows the number of additional defaults, and the right y-axis shows the maximum of average losses to the surviving banks across different combinations of defaulting banks. Source: FR Y-14Q, Schedule L.5, Public Quantitative Disclosures via Clarus CCPView, and author's calculations.

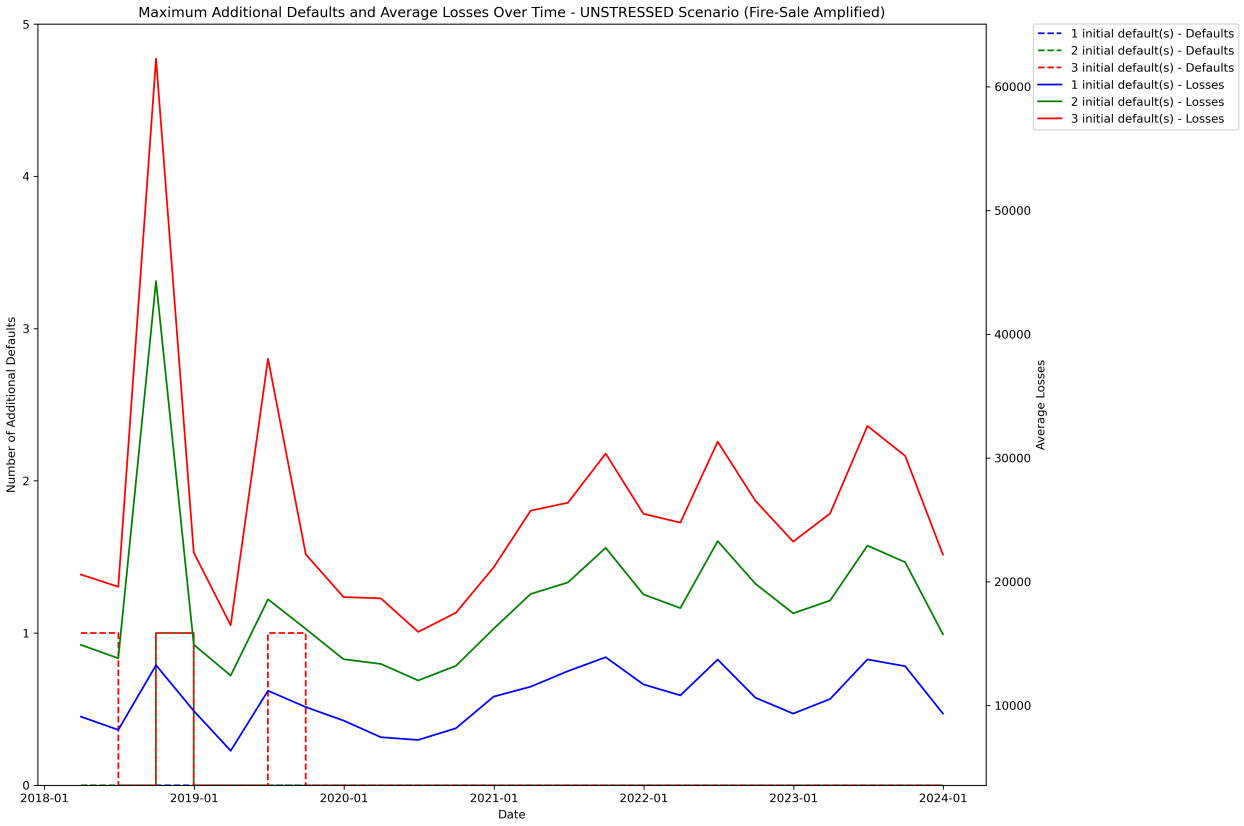


Figure 12: Simulation results using unstressed bilateral exposures with fire sales

Note: The left y-axis shows the number of additional defaults, and the right y-axis shows the maximum of average losses to the surviving banks across different combinations of defaulting banks. Source: FR Y-14Q, Schedule L.5, Public Quantitative Disclosures via Clarus CCPView, and author's calculations.

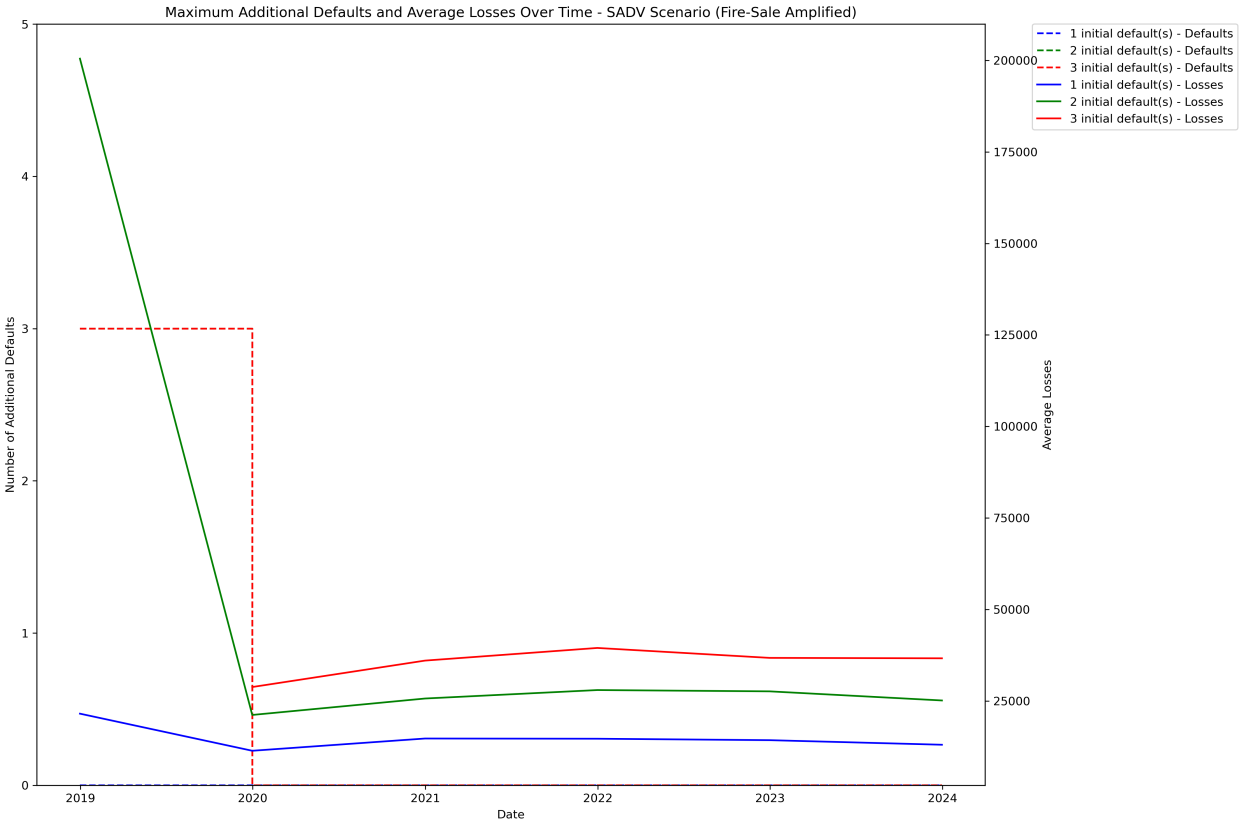


Figure 13: Simulation results using stressed bilateral exposures under SADV scenario with fire sales

Note: The left y-axis shows the number of additional defaults, and the right y-axis shows the maximum of average losses to the surviving banks across different combinations of defaulting banks. Source: FR Y-14Q, Schedule L.5, Public Quantitative Disclosures via Clarus CCPView, and author's calculations.

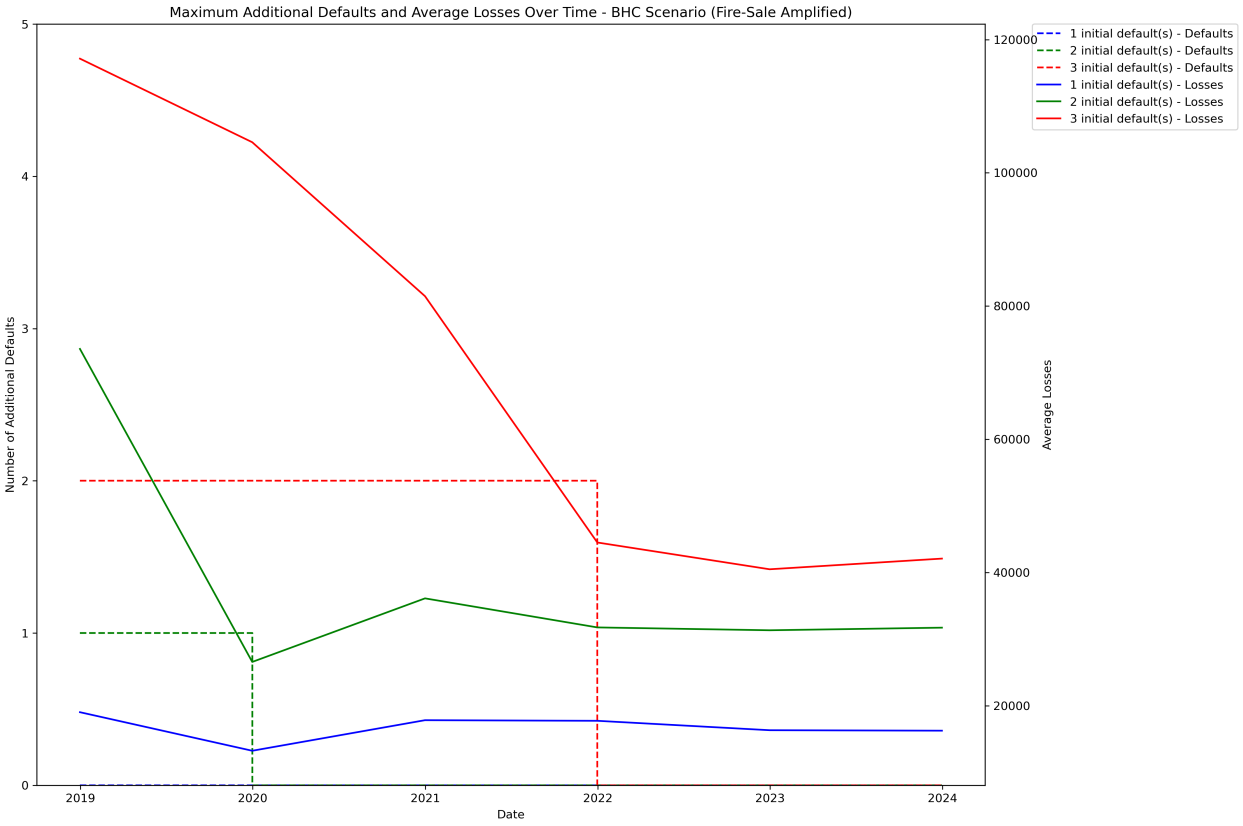


Figure 14: Simulation results using stressed bilateral exposures under BHC scenario with fire sales

Note: The left y-axis shows the number of additional defaults, and the right y-axis shows the maximum of average losses to the surviving banks across different combinations of defaulting banks. Source: FR Y-14Q, Schedule L.5, Public Quantitative Disclosures via Clarus CCPView, and author's calculations.

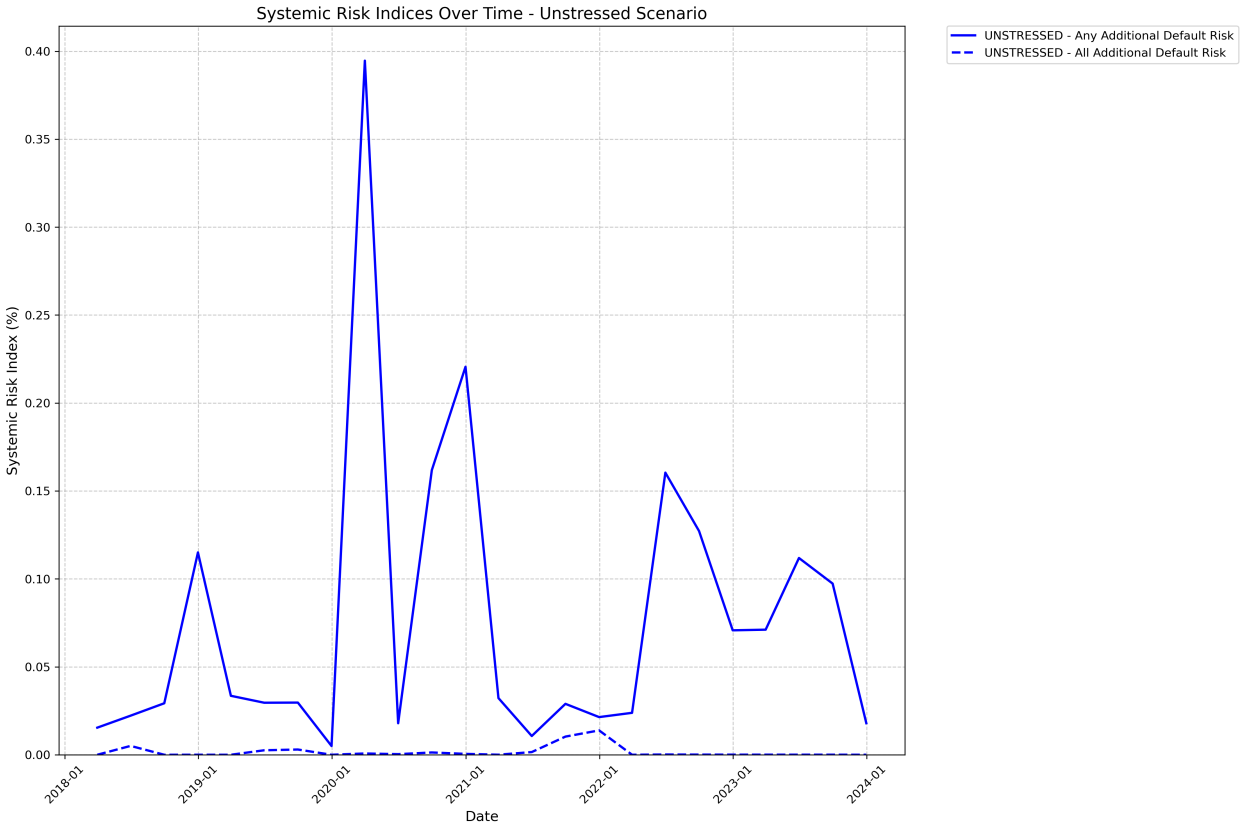


Figure 15: Systemic risk indices using unstressed bilateral exposures

Note: The y-axis shows the systemic risk (probability of a stress event), the solid line indicates the systemic risk index for any additional default due to contagion, and the dashed line indicates the systemic risk index for all other banks default due to contagion. Source: Bloomberg, FR Y-14Q, Schedule L.5, Public Quantitative Disclosures via Clarus CCPView, and author's calculations.

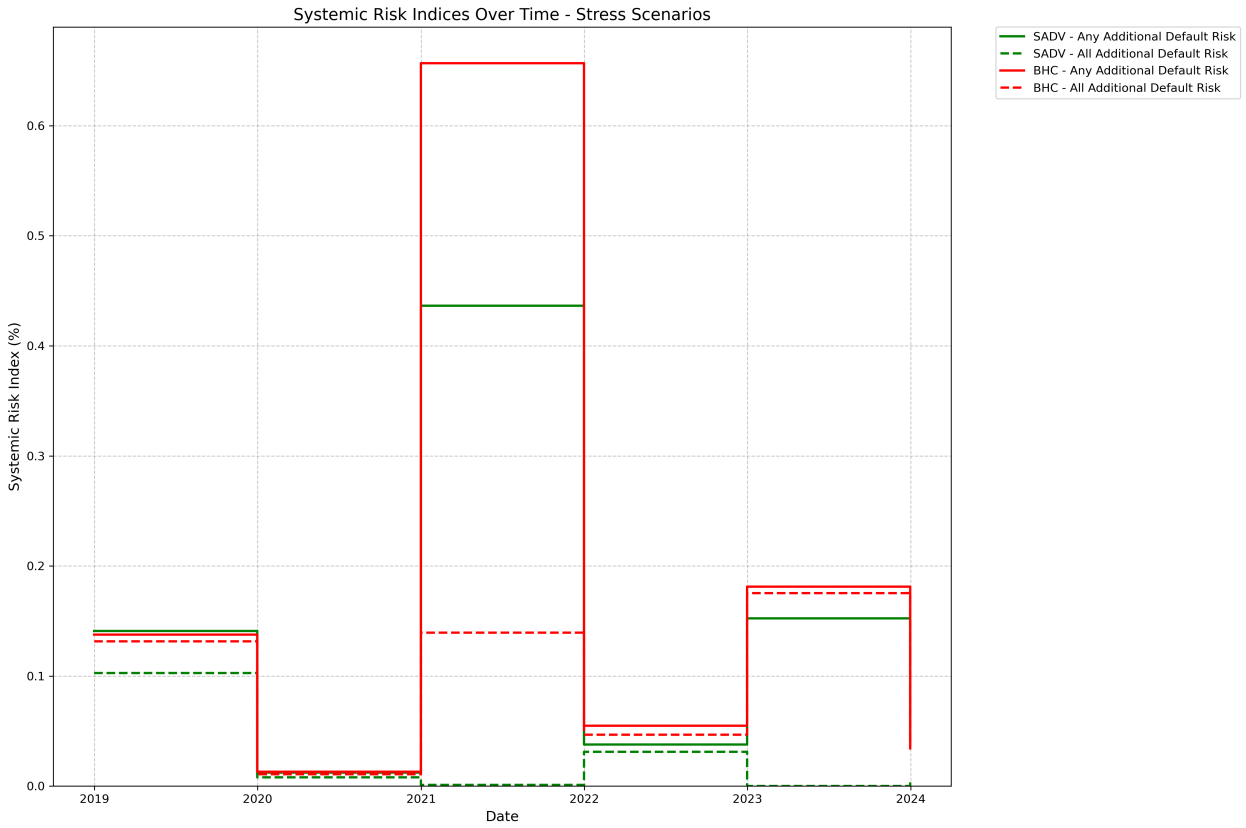


Figure 16: Systemic risk indices using stressed bilateral exposures under BHC and SADV scenarios

Note: The y-axis shows the systemic risk (probability of a stress event), the solid red line indicates the systemic risk index for any additional default due to contagion under BHC scenarios, the dashed red line indicates the systemic risk index for all other banks default due to contagion under BHC scenarios, the solid greeb line indicates the systemic risk index for any additional default due to contagion under SADV scenarios, and the dashed green line indicates the systemic risk index for all other banks default due to contagion under SADV scenarios. Source: Bloomberg, FR Y-14Q, Schedule L.5, Public Quantitative Disclosures via Clarus CCPView, and author's calculations.

Table 1: Summary statistics for interbank derivative exposures through bilateral and centrally cleared derivatives, pooled across bank and time.

	Bilateral unstressed		Bilateral stressed (BHC)		Bilateral stressed (SADV)		Centrally cleared	
	$mn	%CET1	$mn	%CET1	$mn	%CET1	$mn	%CET1
mean	64.6	0.045	573.1	0.487	467.6	0.406	634.0	0.551
std	149.6	0.102	656.5	0.605	522.8	0.562	529.6	0.545
50pct	12.0	0.010	368.6	0.263	330.1	0.227	686.1	0.479
75pct	52.0	0.038	848.9	0.697	668.0	0.638	1027.1	0.814
90pct	141.7	0.098	1369.5	1.293	1158.5	0.934	1317.5	1.320

Table 2: Regressions for unstressed bilateral exposures.

	(1)	(2)	(3)	(4)	(5)	(6)
$\text{assets}_{j,t-1}$	-0.0138	-0.0138***	-0.0455	-0.0455**	-0.0676	-0.0676***
	(0.010)	(0.005)	(0.034)	(0.021)	(0.042)	(0.020)
$\text{cet1}_{j,t-1}$	-12.76***	-12.76***	15.94*	15.94**	21.99**	21.99**
	(3.677)	(1.846)	(8.479)	(5.906)	(10.040)	(9.221)
$\text{hqla}_{j,t-1}$	2.788*	2.788**	0.396	0.396	0.618	0.618
	(1.544)	(1.185)	(2.612)	(1.701)	(3.108)	(2.323)
FF_{t-1}	-4.598	-4.598**	-5.776	-5.776***		
	(3.540)	(2.100)	(3.820)	(1.797)		
VIX_{t-1}	-0.345	-0.345	0.552	0.552*		
	(0.657)	(0.381)	(0.668)	(0.277)		
Constant	207.5***	207.5***	-54.45	-54.45	-89.51	-89.51
	(63.087)	(30.570)	(106.290)	(81.758)	(114.907)	(108.764)
Observations	720	720	720	720	720	720
Adjusted R^2	0.024	0.024	0.133	0.133	0.115	0.115
Bank FE	no	no	yes	yes	yes	yes
Quarter FE	no	no	no	no	yes	yes
Clustering	no	quarter	no	quarter	no	quarter

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Regressions for stressed cleared exposures.

	(1)	(2)	(3)	(4)	(5)	(6)
$\text{assets}_{j,t-1}$	0.262***	0.262***	0.357***	0.357***	0.308***	0.308***
	(0.035)	(0.015)	(0.057)	(0.084)	(0.064)	(0.067)
$\text{cet1}_{j,t-1}$	91.48***	91.48***	-78.64***	-78.64***	-60.76***	-60.76***
	(12.437)	(12.259)	(14.116)	(17.925)	(15.386)	(15.615)
$\text{hqla}_{j,t-1}$	-13.92***	-13.92**	7.448*	7.448	2.919	2.919
	(5.224)	(6.083)	(4.348)	(4.784)	(4.763)	(4.512)
FF_{t-1}	3.228	3.228	15.97**	15.97		
	(11.976)	(17.950)	(6.359)	(12.460)		
VIX_{t-1}	-4.026*	-4.026*	-8.984***	-8.984***		
	(2.224)	(2.251)	(1.112)	(1.646)		
Constant	-675.7***	-675.7**	887.6***	887.6**	703.6***	703.6***
	(213.407)	(307.183)	(176.945)	(344.455)	(176.092)	(217.296)
Observations	720	720	720	720	720	720
Adjusted R^2	0.109	0.109	0.808	0.808	0.834	0.834
Bank FE	no	no	yes	yes	yes	yes
Quarter FE	no	no	no	no	yes	yes
Clustering	no	quarter	no	quarter	no	quarter

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B Proof of Proposition 1

Define the composition function Φ as $\Phi(w,p) : \mathbb{R}^{n+m} \times \mathbb{R}_+ \longrightarrow \mathbb{R}^{n+m} \times \mathbb{R}_+$, where the first $n+m$ elements are determined by Ψ, and the last element is determined by ϕ, following the sequence in (17). Then, a fixed point of $(w^*, p^*) = \Phi(w^*, p^*)$ is a full equilibrium.

Even if all agents are solvent and $x_{ij} = d_{ij}$ for all $i, j \in \mathcal{B}$, there exists

$$\bar{w} \equiv \sup_{i,X,\mathcal{D},p} |w_i(X, \mathcal{D}, p)|,$$

where $|\cdot|$ denotes the absolute value, i.e., the largest absolute value of wealth possible from all possible combination of actual payments, default set, and the collateral price. Similarly, there exists the least upper bound of the market price $\bar{p} \equiv \phi(n\bar{w})$. Then, the composition function Φ is a function from and on a complete lattice, $L \equiv [-\bar{w}, \bar{w}]^{n+m} \times [0, \bar{p}]$. Finally, Φ is increasing in both entries, as an increase in w (weakly) increases $\Phi(w,p)$ as the increase can prevent a default and increase payments to other banks. Hence, the resulting wealth and market price increase. Similarly, an increase in the collateral price (weakly) increases payments to others, as the value of the IM increases to the solvent banks, which further (weakly) increases the market price. Since Φ is a monotonic (order-preserving) function on a complete lattice L, by the Knaster-Tarski theorem, there exists a set of fixed points, i.e., a set of full equilibria, of Φ on the lattice L, and the set of fixed points is a complete lattice as well. Thus, there exists a full equilibrium with the maximum wealth vector and price, (w^{**}, p^{**}).

Now, we show that the sequence in (17) converges to the full equilibrium with the maximum wealth vector and price (w^*, p^*). Because $(\bar{w}, \bar{p})$ is the largest element in the domain L, $(w^1, p^1) = \Phi((\bar{w}, \bar{p})) \leq (\bar{w}, \bar{p})$. Since Φ is monotone, $(w^l, p^l) = \Phi(w^{l-1}, p^{l-1}) \leq (w^{l-1}, p^{l-1}) = \Phi(w^{l-2}, p^{l-2}) \leq (w^{l-2}, p^{l-2}) \leq \cdots \leq (\bar{w}, \bar{p})$, i.e., the sequence $\{(w^l, p^l)\}$ in (17) is weakly decreasing. Since, $(w,p) \geq (-\bar{w}, 0)$, the sequence $\{(w^l, p^l)\}$ converges to its greatest lower bound, (w^*, p^*), by the monotone convergence theorem.

Because both ϕ and Ψ are upper semicontinuous and monotone, Φ is also upper semicontinuous, i.e., $\lim_{l\to\infty}\Phi(w^l,p^l)\leq\Phi(w^*,p^*)$. Moreover, because Φ is order preserving and $(w^*,p^*)\leq(w^l,p^l)$ for any l, $\Phi(w^*,p^*)\leq\lim_{l\to\infty}\Phi(w^l,p^l)$. Combining the two, we find that $\Phi(w^*,p^*)=\lim_{l\to\infty}\Phi(w^l,p^l)$. Since $(w^l,p^l)=\Phi(w^{l-1},p^{l-1})$, for any l, $\Phi(w^*,p^*)=\lim_{l\to\infty}\Phi(w^l,p^l)=\lim_{l\to\infty}(w^{l+1},p^{l+1})=(w^*,p^*)$. Therefore, (w^*,p^*) is a fixed point of Φ.

Finally, we show that $(w^*,p^*)=(w^{**},p^{**})$. Because $(w^{**},p^{**})\leq(\bar{w},\bar{p})$, we have

$$(w^{**},p^{**})=\Phi((w^{**},p^{**}))\leq\Phi(\bar{w},\bar{p})=(w^1,p^1). \tag{25}$$

Applying Φ to both sides recursively implies

$$\begin{aligned}
(w^{**},p^{**})=\Phi((w^{**},p^{**}))&\leq\Phi(w^1,p^1)=(w^2,p^2)\\
(w^{**},p^{**})=\Phi((w^{**},p^{**}))&\leq\Phi(w^2,p^2)=(w^3,p^3)\\
&\vdots\\
(w^{**},p^{**})=\Phi((w^{**},p^{**}))&\leq\Phi(w^{l-1},p^{l-1})=(w^l,p^l),
\end{aligned}$$

i.e., $(w^{**},p^{**})\leq(w^l,p^l)$ for all l. Therefore, $(w^{**},p^{**})\leq\lim_{l\to\infty}(w^l,p^l)=(w^*,p^*)$. Since (w^{**},p^{**}) is the fixed point with the maximum wealth vector and price and (w^*,p^*) is also a fixed point, $(w^{**},p^{**})=(w^*,p^*)$.

C Alternative approach to estimate interbank exposure from centrally cleared derivative

By assuming 1) the change value of a clearing member's portfolio follows a student t-distribution with 4 degrees of freedom and zero mean; and 2) CCP sets initial margin based on the 99% Value at Risk (VaR) of the clearing portfolio, we can estimate the expected exposure at default for a clearing member using the 99% VaR, the 99% Expected Shortfall (ES), and the ratio between them.[17]

The 99% VaR for a t-distribution with 4 degrees of freedom is the negative of the 1st percentile of the distribution. Let x be the random variable following a t-distribution with $\nu = 4$ degrees of freedom, denoted t_ν. The 1st percentile is given by $t_{0.01,4}$ and this value to be approximately -3.747.

$$\text{VaR}_{99\%} = -t_{0.01,4} \approx -(-3.747) = 3.747 \tag{26}$$

The Expected Shortfall (ES) for a Student's t-distribution with ν degrees of freedom at confidence level α is calculated as:

$$ES_\alpha = -\frac{1}{\alpha}\int_{-\infty}^{q_\alpha} x f_\nu(x) dx \tag{27}$$

where q_α is the α-quantile (VaR) of the distribution and $f_\nu(x)$ is the probability density function of the t-distribution. For the 99% ES with 4 degrees of freedom, this integral is numerically evaluated, resulting in $ES_{99\%} \approx 5.2260$.

The ratio of the 99% Expected Shortfall to the 99% Value at Risk is:

$$\text{Ratio} = \frac{\text{ES}_{99\%}}{\text{VaR}_{99\%}} = \frac{5.226}{3.747} \approx 1.39, \tag{28}$$

[17] Some CCPs use ES for their margin model; in these cases, the expected exposure should be smaller as these CCPs have higher margin requirements. Thus, our approach is more conservative in such cases.

therefore, the ratio between the 99% expected shortfall and the 99% VaR for a random variable following a t-distribution with 4 degrees of freedom is approximately 1.394. Figure 17 displays the relationship between VaR and ES.

The EAD for a clearing member i at CCP k can be expressed as:

$$\mathrm{EAD}_{ik} = \mathrm{IM}_{ik} \cdot \frac{\mathrm{ES}_{99\%}}{\mathrm{VaR}_{99\%}} - \mathrm{DF}_{ik} \approx 1.394 \cdot \mathrm{IM}_{ik} - \mathrm{DF}_{ik}. \tag{29}$$

The total EAD for a CCP k can be expressed as:

$$\begin{aligned} \mathrm{EAD}_k &= \sum_i EAD_{ik} = \sum_i (\mathrm{IM}_{ik} \cdot \frac{\mathrm{ES}_{99\%}}{\mathrm{VaR}_{99\%}} - \mathrm{DF}_{ik}) \approx \sum_i (1.394 \cdot \mathrm{IM}_{ik} - \mathrm{DF}_{ik}) \\ &= 1.394 \cdot \sum_i \mathrm{IM}_{ik} - \sum_i \mathrm{DF}_{ik} = 1.394 \cdot \mathrm{IM}_k - \mathrm{DF}_k. \end{aligned} \tag{30}$$

Then we can estimate EAD_k using the IM_k and DF_k data published in CCPs' PQD and follow the steps in Section 4 to estimate the interbank exposures from centrally cleared derivatives. Figure 18 presents the estimated interbank exposure over time, from 2018 to 2024. It shows the 90th percentile exposure and the average exposure. The numbers are higher than the results based on the first approach specified in Section 4. Both 90th percentile and average exposures show an increasing trend after 2018, with a notable spike in exposure occurring around the end of 2022. After peaking in 2022, both metrics show a general downward trend, suggesting a potential reduction in overall interbank risk from centrally cleared derivatives.

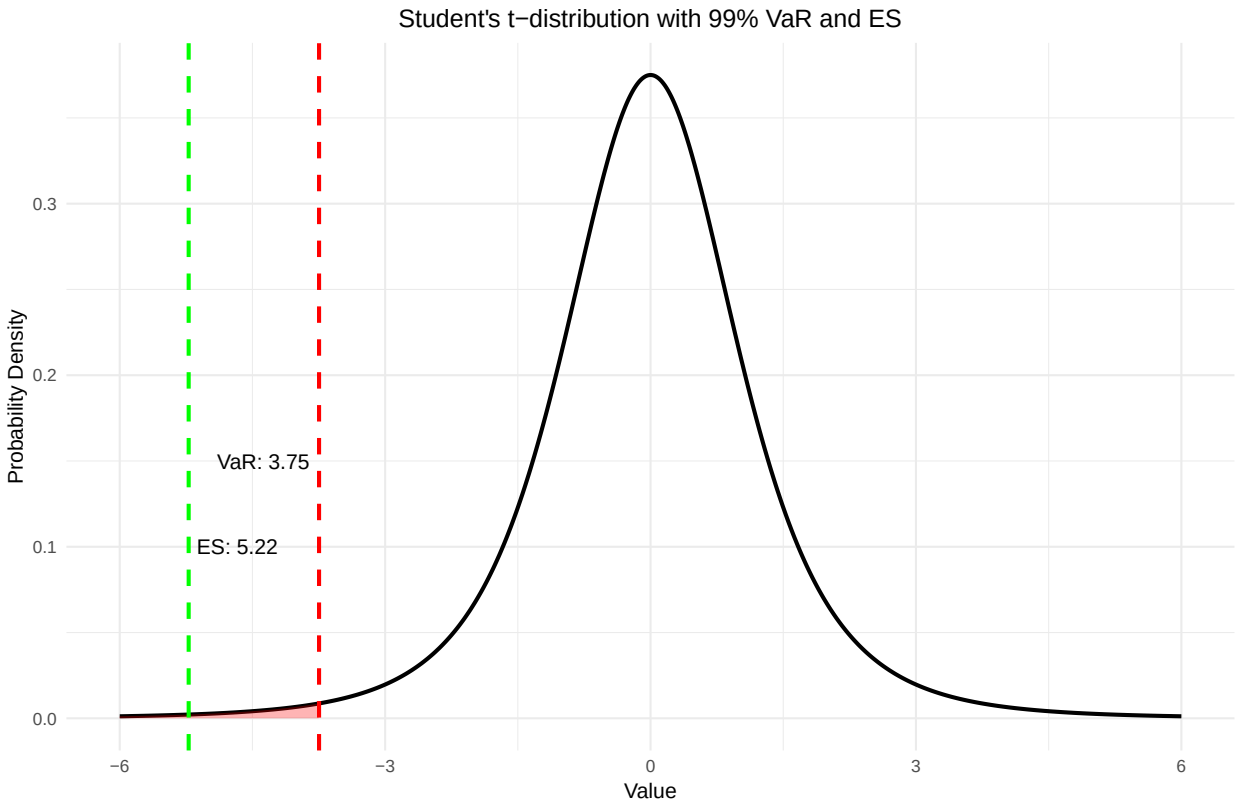


Figure 17: 99% VaR and ES for Student t-distribution

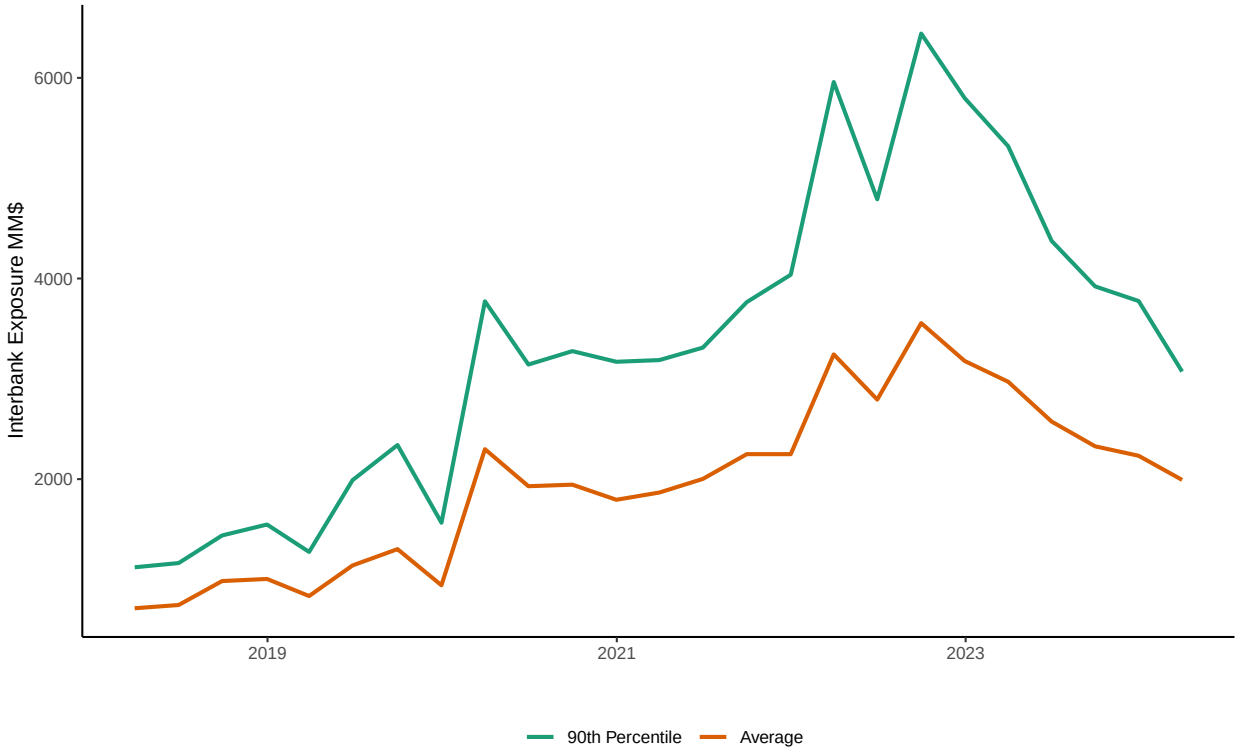


Figure 18: Interbank exposure from centrally cleared derivative estimated by alternative method (in $MMs)