

Heterogeneity and Netting Efficiency under Central Clearing: A Stochastic Network Analysis

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Abstract

This paper examines the effect of heterogeneity in clearing members' exposure management practices on system-wide expected exposure under central clearing. Our network model specifies the dynamics of pre-netted interbank exposure as a joint stochastic process that shapes interdependent bank-to-bank exposure distributions beyond normality. Employing over-the-counter derivatives market data provided by the U.S. Office of the Comptroller of the Currency, our simulation results indicate that heterogeneity in bank-to-bank exposure dynamics and size is systemically desirable in general, while the entire system benefits more from central clearing in a more homogeneous environment. Furthermore, policymakers should incentivize individual clearing members to enhance resiliency and stability in counterparty exposure management to maximize netting efficiency under central clearing.

Keywords: Central Clearing; Exposure Distribution; Netting Efficiency; Heterogeneity; Simulation; Stochastic Network Model

JEL Codes: C15, C46, G17, G21

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1 Introduction

The 2007-08 global financial crisis underscored the need for structural changes in over-the-counter (OTC) derivatives markets to mitigate systemic risk. One of the reforms' major dimensions is mandatory central clearing of standardized OTC derivatives contracts through central counterparties (CCPs) to offset bilateral obligations between participants and result in a single net position per participant. The CCPs, in turn, provide a multilateral netting channel to (i) reduce the expected exposure in the entire financial system and (ii) wedge a bulkhead in OTC markets by isolating individual entities from the systemic propagation of counterparty credit risk.; see Duffie, Li & Lubke (2010), Jones & Pérignon (2013) and Pirrong (2011) for extensive review on central clearing counterparty, and Bae, Karolyi & Stulz (2003), Elliott, Golub & Jackson (2014) and Glasserman & Young (2015) for propagation mechanism of financial contagion.¹

However, as illustrated by Duffie & Zhu (2011), a central clearing scheme that is limited to parts of asset classes may deprive clearing members of bilateral netting opportunities across different asset classes. They conclude that introducing CCPs does not always reduce the total expected counterparty exposure. This is because only the payments implied by the novated contracts are netted within the CCPs under central clearing, otherwise the remaining payments could be netted with other contracts of different asset classes. Cont & Kokholm (2014) extend the work of Duffie & Zhu (2011) by introducing the concept of heterogeneity in asset classes in terms of riskiness as well as the inter-market exposure correlation.²

¹Title VII of the Dodd-Frank Wall Street Reform, the Basel Committee on Banking Supervision's document on post-crisis reform BCBS (2017), the 2010 Consumer Protection Act, the G20's 2009 movement, and the European Market Infrastructure Regulation (EMIR) are well known examples; see BCBS (2019*b*), BCBS (2017), BCBS (2019*a*), BCBS-IOSCO (2015) and European Commission (2012).

²Under the assumption of homogeneity regarding asset class riskiness, improving system-wide netting efficiency via CCP requires an unrealistically large number of central clearing members (461 in Duffie & Zhu, 2011). Meanwhile, under the heterogeneity assumption and using the fat-tailed exposure distribution model generates a more down-to-earth number of clearing members (14 in Cont & Kokholm, 2014) for the CCP to improve the system-wide netting efficiency.

In this study, we examine the system-wide benefit of central clearing by gauging the reduction in total expected counterparty exposure through introducing a CCP into the system. Our networked exposure model specifies the dynamics of pre-netted inter-bank exposure as a joint stochastic process that shapes interdependent bank-to-bank exposure distributions beyond normality by extending specifications in the existing literature; e.g., see Duffie & Zhu (2011), Cont & Kokholm (2014) among many others. In reality, asymmetric dominance is often observed between the exposure of two counterparties, as the larger or more creditworthy bank tends to be more exposed to its counterparty, and vice versa. Consequently, taking post-netted exposures as a model primitive may fail to describe the realistic aspects of the sum of the interbank exposures between heterogeneous counterparties. To circumvent these drawbacks, we assume that pre-netted exposure, after being aggregated according to asset class between two counterparties, are modeled by stochastic processes generating skewed and fat-tailed exposure distributions at the end of risk horizons. The advantage of our modeling approach resides in its economic realism, which stems from its flexibility in revealing higher-order moments, and thereby enabling holistic analyses of systemic risk based on more realistic characteristics of interbank exposures in the network.³

Employing OTC derivatives market data provided by the U.S. Office of the Comptroller of the Currency, from a supervisory point of view, we explore how heterogeneity in bank-to-bank exposure management practices and exposure size affect netting efficiency under central clearing. In addition, by perturbing the pre-netted exposure model parameters, we delve into the effect of bank-specific resiliency and stability in the management of interbank exposure on multilateral netting efficiency. Regardless of clearing

³The benefit of a prudent exposure model goes beyond netting efficiency. Duffie, Scheicher & Vuillemeys (2015) document the relationship between central clearing schemes and system-wide collateral demand with party-to-party bilateral CDS exposure data. As the netting efficiency affects the initial margin requirement, the trade-off between bi- and multilateral netting plays a key role in changing collateral demand with the addition of CCPs. This finding highlights the importance of a sensible and realistic exposure model.

schemes, we find that heterogeneous interbank exposures are systemically beneficial to mitigate the amount of potential losses in the OTC derivatives market in a time of stress. This is because the strong positive correlation in exposure distributions coincides with bank tendencies to engage in more homogeneous asset management practices that may make their exposure networks more systemically vulnerable (Acharya 2009). Most importantly, our findings indicate that the systemic benefit of central clearing becomes more pronounced, as the co-movement between individual exposures becomes stronger. In other words, the multilateral netting benefit under central clearing outweighs the bilateral reduction of expected exposures within an environment of systemically homogeneous exposure dynamics between clearing members.

We further find a negative relationship between the CCP benefit and the dispersion in clearing members' size, measured by their notional outstanding OTC derivatives. We can derive a policy-oriented implication from this result. From the perspective of system-wide netting efficiency, regulations are supposed to prevent large clearing members from taking new positions that increase their exposures. Our proposed approach extends the scope of the systemic implication of heterogeneity between clearing members as illustrated by Choi (2014) in that homogeneous management of interbank exposure can improve aggregate netting efficiency under central clearing.

Moreover, our simulation results indicate that the CCP benefit is sensitive to the variation of resiliency and stability parameters of pre-netted exposure processes. Specifically, the CCP benefit is unduly responsive to changes in bank-specific volatilities of exposure processes. Our findings demonstrate that regulators should allocate less central clearing operation costs to clearing members with more positions on resilient and less volatile assets than to those with inelastic and volatile assets.

Prior research such as Duffie & Zhu (2011) and Cont & Kokholm (2014) has viewed greater netting efficiency as a benefit of central clearing. Our study inherits the same

point of view, while our model specification employs a pre-netted version of interbank exposure dynamics in the stochastic network. By doing so, we provide the unique insight in bank-specific and system-wide dimensions under the unified model framework. In this regard, Garratt & Zimmerman (2018) explore the trade-off between the mean and variance of net exposure under the generalized network structure, which does not require a full specification of interconnectedness between participants. They show that the set of multilateral networks, in which less net exposure is totalized, provides a smaller variance of net exposures. Loon & Zhong (2014) examine how the CCP can mitigate counterparty risk between clearing members based on an event study of the CDS market. They find that the prudent role of the CCP increases settlement CDS spreads, leading to the reduction of counterparty risk under central clearing. Ghamami & Glasserman (2017) compare collateral costs and capital requirements from different clearing schemes and conclude that cost incentive to shift central clearing is not sufficient. These empirical studies provide thought-provoking lessons, but they lack to provide the further responses of target quantities with respect to possible environmental changes.

Our work is related to strands of literature that has further investigated the implications of central clearing. Amini, Filipović & Minca (2017) identify the optimal design of central clearing by setting the capital requirement of clearing members to circumvent systemic risk. In another vein, Bignon & Vuillemeys (2019) focus on the history of the 1974 central clearing house failure in the derivatives market. They report that both the inability of the central clearing house to manage members with large positions and the risk-shifting tendency of delaying the liquidation of defaulted positions were the main causes of the central counterparty's default. De Genaro (2016) proposes an alternative to existing robust optimization methods for calculating margin requirement under central clearing to address uncertainty sets beyond elliptical distributions to capture fat-tailness, volatility clustering and tail-dependency for stress tests. The idea is consistent with the methods that mitigate the procyclicality of margin rules based on

long historical data for estimating price volatility. Menkveld (2017) supports the notion of central counterparties' systemic failure by measuring CCP exposure based on the tail risk in traders' portfolios. The simulation results reveal that crowded positions on the CCP may aggravate its exposure during downturns.

The rest of this paper is organized as follows. Section 2 introduces the framework of our analyses and specifies the exposure models. Section 3 describes our methodology and the data we employed. Section 4 provides the main results and discusses heterogeneity in clearing members and their exposure characteristics. Section 5 concludes the paper.

2 Model Framework

2.1 Pre- and Post-netted Exposures

The aim of this paper is to examine how system-wide expected exposure and the netting efficiency of central clearing vary in response to heterogeneity in the exposure management practices between clearing members in the system. Following Duffie & Zhu (2011), for simplicity, we do not consider the implications of jointly determined defaults in a given network by restricting our scope to the total expected counterparty exposure. In the exposure model specified by Duffie & Zhu (2011), the fundamental unit base for system-wide exposure analysis is *post-netted* exposure, which is denoted by X_{ij}^k , the exposure of bank i to its counterparty j in particular asset group k after netting. It is assessed after the netting of all payments arising from ongoing contracts between the two parties. By assuming normality in the post-netted exposure distribution, Duffie & Zhu (2011) provide inspiring implications regarding netting efficiency under central clearing according to various characteristics, such as the number of central clearing members or the central clearing rates for each asset class.

However, the network model based on the post-netted exposure is limited in order to represent the realistic dynamics of system-wide exposure as it cannot fully accommodate bank-specific risk characteristics or exposure management behaviors by the nature of netting across different originators. For example, when a systemically important bank adjusts its exposure to a counterparty through signing a new contract, gauging its impact on the vulnerability of the entire system is essential from a macro-prudential perspective.

Viewed in this light, we define *pre-netted* exposure, denoted by δ_{ij}^k , by separating and aggregating exposures attributed to each obligor. Specifically, the pre-netted exposure δ_{ij}^k indicates that dealer i adds all exposures from its ongoing contracts with counterparty j in asset class k . The pre-netted exposure is the total ongoing liability of counterparty j to its lender i and corresponds to the gross settlement scheme. Note that pre-netted exposure should be nonnegative by definition. It follows that $X_{ij}^k := \delta_{ij}^k - \delta_{ji}^k$ represents the post-netted exposure of i to its counterparty j in asset class k .

2.2 Stochastic Exposure Model Specification

In turn, we need specific assumptions regarding the distributions of future exposures in the presence of uncertainty. A straightforward example stems from the Normal distribution. Duffie & Zhu (2011) propose an exposure model with a joint Normal distribution to drive the closed-form expression of the total expected counterparty exposure in the system. Cont & Kokholm (2014) extend the model by adopting the Student's t -distribution to reflect the fat-tailed nature of the return distribution implied by non-equity derivatives. These elliptical exposure distribution models are limited to be symmetric around their means. In reality, two counterparties do not have the same or similar position sizes over contracts. Rather, one party typically has dominance in exposure to its counterparty, which in turn leads to an asymmetric distribution model. To account for

this realistic property, we specify the model for exposures at a more primitive level of pre-netted exposure δ_{ij}^k .

To impose interdependency in the bank-to-bank exposures, we presume that each pre-netted exposure process $\delta_{ij}^k(t)$ consists of a systematic component $Y(t)$ and an idiosyncratic component $\varepsilon_{ij}^k(t)$, taking the form of

$$\delta_{ij}^k(t) = \eta_{ij}^k Y(t) + \varepsilon_{ij}^k(t) \quad (1)$$

$$\eta_{ij}^k := w_{ij}^k S_{ij}^k, \quad (2)$$

where η_{ij}^k is the exposure-specific stochastic factor loading on the systematic factor. We assume that S_{ij}^k is an exposure-specific size related constant and w_{ij}^k is a uniformly distributed quantity that is linked through market and bank dimensions. The assumption that factor loadings are uniformly distributed is reasonable if there is a sufficiently large number of market participants. By combining with Gaussian copula, our model specification has an advantage in describing the interactions of agents in a network; for instance, Li (2000) and Embrechts (2009) document general properties of Gaussian copula and their financial applications.

Specifically, the interbank exposure dependency is specified by an adjusted Gaussian copula taking the form

$$\Phi^{-1}(w_{ij}^k) = -\rho_\delta \Phi^{-1}(u_{ij}^k) + \sqrt{1 - \rho_\delta^2} \Phi^{-1}(u_{ji}^k), \quad (3)$$

where Φ^{-1} is the inverse cumulative density function of the Normal distribution. We impose intermarket exposure dependency via the one factor Gaussian copula model to connect each u_{ij}^k .

Note that we intentionally set the copula parameter ρ_δ multiplied on the first term in the right hand side of equation (3) to take the negative its original sign. If

$S_{ij}^k = S_{ji}^k$ holds, the probability density function of β_{ij}^k varies from the delta function (when $\rho_\delta = -1$) to a uniform distribution over the support $[-S_{ij}^k, S_{ij}^k]$ (when $\rho_\delta = 1$). The density of β_{ij}^k disperses over the support as ρ_δ increases from -1 to 1 . Thus $\rho_\delta = -1$ implies that the factor loading β_{ij}^k on $Y(t)$ in $X_{ij}^k(t)$ is zero almost surely, representing the case where the exposure of all participants is totally independent with a systematic factor. Notice that $\rho_\delta = 1$ induces the maximum likelihood of β_{ij}^k taking large absolute values over the support, minimizing the likelihood of β_{ij}^k being zero at the same time. This case can be interpreted as the strongest dependency of the exposure X_{ij}^k on the systematic factor.

To ensure realistic flexibility in the higher-order moments of future exposures along with their tractability, we adopt a mean-reverting square root process, which is also adopted by Cox, Ingersoll Jr & Ross (1985) for modeling $\delta_{ij}^k(t)$. As a result, the pre-netted exposure model can exhibit desirable statistical properties such as stationarity, non-negativity and parsimony while retaining both flexibility and tractability. Intuitively, this feature guides us to an in-depth exploration of the system-wide exposure and the total CCP benefit in various scenarios based on varying model parameters.

Moreover, the post-netted exposure X_{ij}^k based on the Gaussian or t -distribution cannot provide a term-structure perspective; therefore, one should assume that defaults certainly occur at some prefixed future time. By contrast, our proposed stochastic processes for pre-netted exposures are free from such horizon-specific constraint. The mean-reverting property of our pre-netted exposure processes ensures stationarity under mild parametric conditions, reflecting the target-oriented exposure dynamics in reality. The mean-reverting nature of the pre-netted exposure dynamics can be intuitively understood as a bank's tendency to approach the counterparty-specific target exposure level, which is often observed in practice. Specifically, the process level at a prefixed time follows a well-known non-central χ^2 distribution, which provides an exact and ef-

efficient simulation method to generate $\delta_{ij}^k(T)$ for a given $T > 0$ so that one can avoid producing biases within a reasonable computational budget in simulation under the continuous-time model framework.

Each of the factor processes is assumed to be strong solutions of the stochastic differential equations given by

$$d\varepsilon_{ij}^k(t) = \kappa_{ij}^k(\theta_{ij}^k - \varepsilon_{ij}^k(t))dt + \sigma_{ij}^k\sqrt{\varepsilon_{ij}^k(t)}dZ_{ij}^k(t) \quad (4)$$

$$dY(t) = \kappa_Y(\theta_Y - Y(t))dt + \sigma_Y\sqrt{Y(t)}dZ_Y(t), \quad (5)$$

where the pre-netted and post-netted exposure processes take the form of

$$\delta_{ij}^k(t) = w_{ij}^k S_{ij}^k Y(t) + \varepsilon_{ij}^k(t) \quad (6)$$

$$X_{ij}^k(t) = \delta_{ij}^k(t) - \delta_{ji}^k(t) \quad (7)$$

$$= \underbrace{(w_{ij}^k S_{ij}^k - w_{ji}^k S_{ji}^k)}_{:=\beta_{ij}^k} Y(t) + (\varepsilon_{ij}^k(t) - \varepsilon_{ji}^k(t)), \quad (8)$$

where Z_{ij}^k and Z_Y are $(N^2K + 1)$ dimensional standard Brownian motions, respectively. We let S_{ij}^k represent the notional outstanding of dealer i to its counterparty j in asset class k . As desired, the fundamental parity of $X_{ij}^k = -X_{ji}^k$ is respected by design.

2.3 Netting Efficiency under Central Clearing

Motivated by Duffie & Zhu (2011), we explore how the total expected counterparty exposure changes before and after the inauguration of CCP(s) in order to analyze the netting efficiency of central clearing in the OTC derivatives markets. Although the expected counterparty exposure simply measures the expected dollar amount losing upon counterparties' default, neglecting any cost or risk quantities, it provides an intuitive frame for analyzing whether a CCP is mechanically beneficial at the aggregate level.

Suppose an OTC derivatives market with N participants and K asset classes. Let C be a subset of K in which each asset class is at least partially cleared through CCP. Let α_k be the fraction of asset class k that is cleared through the CCP. If all the centrally cleared asset classes have their own dedicated CCPs, entity i 's expected exposure to each k -devoted CCP is expressed by

$$\gamma_i^k = E \left[\max \left(\sum_{j \neq i} \alpha_k X_{ij}^k, 0 \right) \right]. \quad (9)$$

Therefore, the expected exposure of i to CCPs is the sum given by⁴

$$\gamma_i^C = \sum_{k \in C} E \left[\max \left(\sum_{j \neq i} \alpha_k X_{ij}^k, 0 \right) \right]. \quad (10)$$

The sum of i 's expected exposures to other participants over $K \setminus C$ is⁵

$$\phi_i^{K \setminus C} = \sum_{j \neq i} E \left[\max \left(\sum_{k \in K \setminus C} (1 - \alpha_k) X_{ij}^k, 0 \right) \right]. \quad (11)$$

The total expected counterparty exposure of i to all other participants regardless of clearing channel is $\phi + \gamma$. We compute the percentage change in total expected counterparty exposure with the intervention of CCP(s) by defining the CCP benefit given by

$$\text{CCP Benefit (\%)} := 1 - \frac{\text{Total Expected Exposure with CCP}}{\text{Total Expected Exposure without CCP}} \quad (12)$$

$$= 1 - \frac{\sum_i \phi_i^{K \setminus C} + \sum_i \gamma_i^C}{\sum_i \phi_i^K}. \quad (13)$$

Intuitively, the CCP benefit measures the proportion of the total expected exposure

⁴In the simplest case, if there is only one CCP handling all centrally cleared asset classes, typical participant i 's total expected exposure to the CCP is $\gamma_i^{C,*} = E \left[\max \left(\sum_{k \in C} \sum_{j \neq i} \alpha_k X_{ij}^k, 0 \right) \right]$.

⁵If all of the positions are bilaterally cleared, bank i 's exposure to its counterparties becomes $\phi_i^K = \sum_{j \neq i} E \left[\max \left(\sum_k X_{ij}^k, 0 \right) \right]$.

that is eliminated by the intervention of the CCP under central clearing. For example, a CCP benefit of 5.13 percent implies that the total expected counterparty exposure is reduced by 5.13 percent under central clearing compared to a case in which all contracts are bilaterally cleared.

3 Methodology

3.1 Simulation Setup

Our model specification beyond the Gaussian distribution gives rise to the absence of closed-form expressions of ϕ and γ . This motivates us to take advantage of Monte Carlo simulation to compute the total expected counterparty exposures to estimate 1-year ahead exposure distributions. Notably, our proposed stochastic models of pre-netted exposures provide well-known transition density functions in closed-form expressions, facilitating the exact simulation algorithm without causing bias in sampling future quantities.⁶

For each iteration, we generate a systematic factor $Y(T)$ and a set of i.i.d. idiosyncratic factors of the pre-netted exposures $\varepsilon_{ij}^k(T)$ from the non-central χ^2 distributions for a given $T > 0$. We estimate the volatility σ_{ij}^k of ε_{ij}^k as the expression given by

$$\sigma_{ij}^k = m_k \frac{S_i^k S_j^k}{\sum_{l \neq i} S_l^k}, \quad (14)$$

where m_k is the risk-weight of asset class k and S_i^k is the notional outstanding of dealer i in asset class k .⁷ The initial value $\varepsilon_{ij}^k(0)$ and the long-term mean level θ_{ij}^k are set

⁶All of the analyses in this paper are based on the programming code implemented in Julia v.1.0.0.

⁷Duffie & Zhu (2011) estimate m_k by the ratio of total market value over total outstanding for each asset class and set $(m_{\text{IRS}}, m_{\text{CDS}}, m_{\text{Forwards}}, m_{\text{Options}}) = (1, 3, 3, 3)$. We adopt their suggested method and obtain almost the same results from the BIS Statistics as of Dec, 2017 (BIS, 2018). We set $(m_{\text{IRS}}, m_{\text{CDS}}, m_{\text{FX}}, m_{\text{Others}}) = (1, 3, 3, 3)$.

to the same as σ_{ij}^k . The mean-reversion speed κ_{ij}^k is set to one for all combinations of (i, j, k) ; see equations (4) and (5). The parameters and initial value of the systematic factor, $\kappa_Y, \theta_Y, \sigma_Y$, and $Y(0)$ are all set to one.

We draw a set of independent factor loadings u_{ij}^k from the uniform distribution on $[-1, 1]$ and link each to the other using the one-factor Gaussian copula model to obtain the set of w_{ij}^k s. Based on the randomly generated sample, we compute and save each $\delta_{ij}^k(T)$ and $X_{ij}^k(T)$. In the subsequent analyses, we draw 100,000 replications in each simulation and obtain 99 percent confidence intervals from 1,000 bootstrapped samples with replacements.

3.2 Data and Sample

We estimate the volatility of pre-netted exposure processes by the notional outstanding of OTC derivatives contracts as of Dec. 2017, reported by the Office of the Comptroller of the Currency (Table1; OCC, 2018). The report categorizes asset classes into Interest Rate Swap (IRS), Credit Default Swap (CDS), foreign exchange derivatives (FX), and commodity/equity-linked derivatives (Other) by providing notional outstanding figures of the top 25 banks and saving associations for each category. While the report encompasses the top 25 major financial institutions, we employ the top 12 holding companies, which account for over 99 percent of the total notional outstanding of OTC derivatives contracts.⁸

The scenarios are drawn to examine how netting efficiency changes depending on the level of central clearing of IRS and/or CDS. Table 2 provides scenarios with different central clearing rates for each asset class and estimated CCP benefit in each scenario.

⁸The analysis results provided by employing the entire dataset ($N = 25$) are almost identical to the results reported here. Therefore, we limit our analysis to the top 12 major financial institutions to save computational resources.

The nonzero central clearing rates are excerpted from the BIS Statistics (BIS, 2018).⁹ For each of the scenarios except for Case 5, a single CCP handles all of the asset classes that are centrally cleared.

In Case 1, we examine whether central clearing of FX and Other has a significant effect on netting efficiency. It should be noted that the current FX and Others central clearings do not have a significant impact on system-wide netting efficiency. From Case 2, we verify that the introduction of CDS CCP leads to a slightly negative total CCP benefit. From Case 2 through 4, we verify that CDS central clearing can contribute to exposure reduction in the presence of IRS central clearing. As IRS CCP is introduced into a system to facilitate the central clearing of the largest derivatives class, CCP starts to improve the netting efficiency. From Case 4 and 5, it can be seen that the versatility of CCP enhances the magnitude of this benefit.

These results generally coincide with the findings of Duffie & Zhu (2011), implying that our selected exposure model is reasonable in estimating the total expected counterparty exposures. Interestingly, median size banks (banks 5 and 9) appear to be the greatest beneficiaries of the central clearing in Case 3 through 5. Notice that they have most of their positions in the IRS market. For example, bank 5's proportion of IRS contracts out of its total outstanding contracts is 90.21% and that of dealer 9 is 91.62%.

4 Main Analysis

This section provides our baseline case along with its parameters. Using our baseline case, we first explore the relationship between total expected exposure and homogeneity in the exposure management practices of clearing members as well as the multilateral

⁹According to the BIS Statistics as of Dec. 2017 (BIS, 2018), the central clearing rates for IRS, CDS, FX, and Others are 75%, 55%, 2%, and 1%, respectively.

Table 1: The Notional Amount of OTC Derivatives Outstanding Held by Major U.S. Banks and Savings Associations

(Unit: million USD)

Bank Name	Interest Rates	Credits	FX	Other	Total
JPMORGAN CHASE BANK NA	30,809,359	1,498,479	10,195,259	2,325,235	44,828,332
CITIBANK NATIONAL ASSN	29,219,795	1,664,568	9,712,379	909,244	41,505,986
GOLDMAN SACHS BANK USA	30,184,570	148,354	1,834,244	32,180	32,199,347
BANK OF AMERICA NA	11,892,152	709,484	3,986,574	337,845	16,926,055
WELLS FARGO BANK NA	6,411,960	27,536	418,943	248,526	7,106,965
HSBC NA	3,413,173	90,290	927,985	99,589	4,531,036
STATE STREET BANK&TRUST CO	5,077	0	1,660,276	27,079	1,692,432
BANK OF NEW YORK MELLON	300,522	180	690,309	992	992,003
PNC BANK NATIONAL ASSN	339,413	6,316	18,137	7,033	370,899
US BANK NATIONAL ASSN	273,096	5,337	54,019	1,334	333,786
NORTHERN TRUST CO	13,499	0	315,417	329	329,245
SUNTRUST BANK	168,212	3,970	5,910	33,769	211,860
MORGAN STANLEY BANK NA	3,956	10,328	205,258	220	219,761
TD BANK NATIONAL ASSN	176,374	365	6,410	0	183,150
CAPITAL ONE NATIONAL ASSN	121,593	3,042	1,069	7,884	133,588
MUFG UNION BANK NA	115,452	76	6,345	2,488	124,361
CITIZENS BANK NATIONAL ASSN	83,195	2,484	9,838	0	95,518
KEYBANK NATIONAL ASSN	81,436	330	8,243	634	90,643
REGIONS BANK	74,597	3,193	1,601	800	80,191
FIFTH THIRD BANK	58,182	3,426	12,194	5,978	79,780
BRANCH BANKING&TRUST CO	62,517	0	441	0	62,958
CAPITAL ONE BANK USA NA	38,827	0	9,107	0	47,934
MANUFACTURERS&TRADERS TR CO	47,038	0	475	0	47,513
COMPASS BANK	42,214	61	802	1,484	44,562
BOKF NATIONAL ASSN	36,762	1	238	2,575	39,576
Total	113,972,972	4,177,820	30,081,472	4,045,216	0

Note. This table provides the notional outstanding of OTC derivatives for the top 25 U.S. commercial banks and saving associations based on a report from the Office of the Comptroller of the Currency in the 4th quarter of 2017. We define the asset classes in four categories: IRS, CDS, FX and Other. We employ the top 12 dealers who account for over 99 percent of the total notional outstanding of OTC contracts for our analysis.

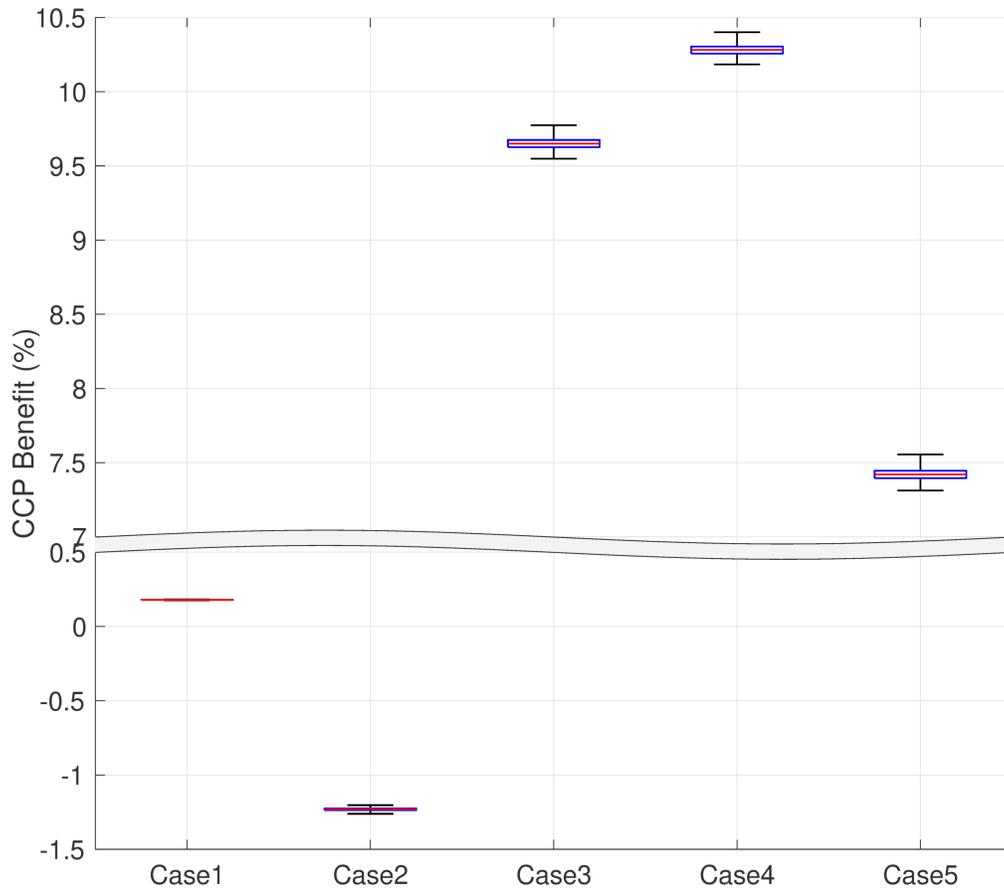
Table 2: Estimated CCP Benefit across Various Clearing Scenarios

Panel A. Clearing Scenarios					
	Case 1	Case 2	Case 3	Case 4	Case 5
IRS	0	0	0.75	0.75	0.75
CDS	0	0.55	0	0.55	0.55
FX	0.02	0.02	0.02	0.02	0.02
Others	0.01	0.01	0.01	0.01	0.01
Number of CCPs	1	1	1	1	4

Panel B. CCP Benefit (%) for Selected Clearing Scenarios					
	Case 1	Case 2	Case 3	Case 4	Case 5
Bank 1	0.15 (0.15, 0.16)	-1.07 (-1.1, -1.05)	4.10 (3.98, 4.24)	4.70 (4.58, 4.84)	2.05 (1.92, 2.19)
Bank 2	0.22 (0.21, 0.22)	-1.59 (-1.62, -1.55)	5.25 (5.08, 5.41)	6.00 (5.83, 6.17)	2.49 (2.32, 2.66)
Bank 3	-0.13 (-0.13, -0.13)	-0.72 (-0.73, -0.72)	26.02 (25.75, 26.29)	26.35 (26.07, 26.62)	25.17 (24.89, 25.43)
Bank 4	0.44 (0.43, 0.45)	-3.08 (-3.16, -3.01)	9.97 (9.66, 10.25)	11.45 (11.12, 11.75)	4.67 (4.36, 4.98)
Bank 5	-0.10 (-0.11, -0.1)	-0.62 (-0.63, -0.61)	43.09 (42.71, 43.47)	43.28 (42.91, 43.65)	42.10 (41.72, 42.48)
Bank 6	0.45 (0.44, 0.46)	-1.60 (-1.64, -1.56)	19.00 (18.65, 19.32)	19.52 (19.17, 19.84)	15.36 (15, 15.69)
Bank 7	1.38 (1.37, 1.39)	1.38 (1.37, 1.39)	1.37 (1.36, 1.38)	1.37 (1.36, 1.38)	1.30 (1.29, 1.31)
Bank 8	1.43 (1.42, 1.44)	1.43 (1.42, 1.43)	-2.40 (-2.5, -2.29)	-2.40 (-2.51, -2.3)	-3.58 (-3.69, -3.46)
Bank 9	-0.11 (-0.12, -0.11)	-2.57 (-2.62, -2.53)	51.82 (51.45, 52.15)	53.02 (52.67, 53.34)	50.08 (49.69, 50.41)
Bank 10	0.23 (0.22, 0.24)	-1.56 (-1.6, -1.53)	28.90 (28.58, 29.21)	29.17 (28.85, 29.47)	26.06 (25.71, 26.38)
Bank 11	1.47 (1.46, 1.48)	1.47 (1.46, 1.48)	1.10 (1.08, 1.11)	1.10 (1.08, 1.11)	0.66 (0.65, 0.67)
Bank 12	0.09 (0.09, 0.09)	-2.21 (-2.27, -2.16)	30.93 (30.52, 31.31)	31.81 (31.43, 32.18)	27.64 (27.23, 28.02)
Total	0.18	-1.23	9.65	10.28	7.42
CCP Benefit	(0.18, 0.18)	(-1.25, -1.21)	(9.56, 9.74)	(10.19, 10.38)	(7.33, 7.52)

Note. This table reports the estimated CCP benefit specific to the selected scenarios of central clearing rates along with the number of CCPs. Panel A reports the clearing scenarios along with the central clearing rates for each asset class. The central clearing fractions are excerpt from “Statistical Release: OTC derivatives statistics at end December 2017” (BIS, 2018). The central clearing rates of FX and Other are set to 0.02 and 0.01 for all scenarios, respectively. Panel B illustrates the scenario-specific CCP benefits and the numbers in parentheses indicate 99% confidence intervals obtained by bootstrapping 1,000 sample sets with replacement.

Figure 1: Estimated CCP Benefit for Each Clearing Scenario



Note. These box plots depict the estimated CCP benefit, namely, the fraction of the expected total exposure under central clearing over that under an all-bilateral arrangement. The central line indicates the median CCP benefit, while the bottom and top edges of the box depict the first and third quartiles, respectively. The whiskers extend to the most extreme data points that are not considered outliers. The case number in this figure coincides with those in Panel A of Table 1. We draw 100,000 replications for each simulation. As shown, the simulation setting provides sufficiently small standard deviations, implying a significant degree of accuracy in the simulation results.

netting benefit. In our stochastic network model, each exposure process has factor loadings on the systematic term that are connected with the cross-exposure parameter (ρ_δ) and the cross-asset parameter (ρ_{Mkt}). By varying the copula parameters, we explore how heterogeneity in exposure management practice affects the efficiency of central clearing.

We next investigate how the total expected counterparty exposure of a system responds to changes in macro-level regulatory parameters. Specifically, our experiment is based on heterogeneity in counterparty exposure sizes measured by the standard deviation of their notional outstanding distribution. If there is any systematic relationship between the heterogeneity in exposure sizes and the entire CCP benefit, regulators are incentivized to drive clearing members in the direction of improving system-wide welfare.¹⁰ For example, a negative relationship between the two prompts regulators to prevent clearing members from taking overly large positions that create increased size variations.

Our experiment goes on to investigate the policy-oriented implications in the model parameters specific to individual interbank exposures with respect to the overall CCP benefit under central clearing. The parameter κ_{ij}^k controls the mean-reversion speed of a stochastic process ε_{ij}^k . The speed of adjustment to its long-term mean, as the stabilized state of the exposure level, can be interpreted as the resiliency of exposure. If greater resiliency of exposure enhances the central clearing benefit, clearing members who have fewer positions on contracts with resilient exposures should assume more of the cost of running the central clearing system.

We also investigate the sensitivity of the CCP benefit with respect to exposure stability. This stability is demonstrated by the volatility σ_{ij}^k of the pre-netted exposure

¹⁰Acharya (2009) evokes the necessity of collective correlation regulation as well as the importance of individuals participating in the system. The externalities of other members' payoffs affect individuals so that the response analysis of individuals with respect to micro level regulatory variable changes does not serve as an optimal regulation solution.

processes such that it can be interpreted as the uncertainty of the level of exposure in the future. The relationship between stability in interbank exposure and the system-wide CCP benefit suggests that regulators should levy more of the central clearing operation costs to clearing members who are aggravating in terms of exposure volatilities.

4.1 Baseline Case

To derive meaningful policy-oriented insights based on a battery of sensitivity analyses, we first develop our baseline model by identifying constant parameters of analyses. We set the number of market participants N as 12 and the number of asset classes K as 4 according to our dataset. We set the central clearing rates of IRS, CDS, FX, and Other to 75%, 55%, 2%, and 1% based on the BIS Statistics as of Dec. 2017 (BIS, 2018). In each of the subsequent analyses, we denote Case 4 in Table 2 as “Single CCP” and Case 5 as “Multiple CCPs”. To address the neutral state of the economy, we set the copula parameters $\rho_\delta = 0$ and $\rho_{Mkt} = 0.5$.

4.2 Heterogeneity in Exposure Dynamics

We turn to address the relationship between heterogeneity in interbank exposure among central clearing members and net counterparty exposure. Choi (2014) points out heterogeneous fragilities of banks to systemic panic cause strong entities to run out from market preemptively. In the meanwhile, Barth & Seckinger (2018) argue that tightening the capital adequacy and leverage ratios can promote high-quality banks not to issue new equities, as they are not allowed to absorb the entire supply of debts. Thus, heterogeneity in banking sector increase market share of low-skilled banks and decrease the average capability of banks.

Along with the stochastic network model described in Section 2, we assume that

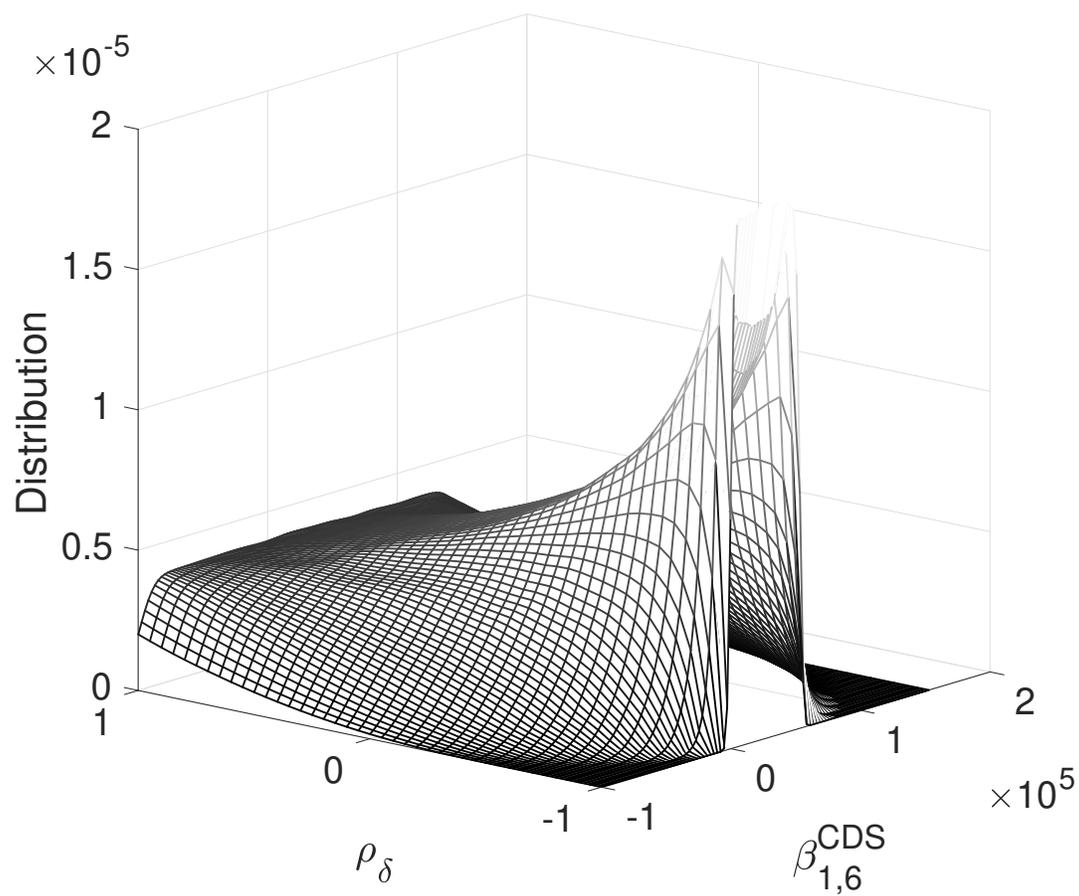
in the real world the systematic factor loadings of individual exposure processes are uniformly distributed. Intermarket dependency is specified by the one-factor Gaussian copula model, and interbank exposure dependency is specified by the adjusted Gaussian copula model connecting factor loadings w_{ij}^k .

Figure 2 provides a graphical illustration of the probability density of systematic factor loading β_{ij}^k . Although the form of each density function shows mild asymmetry, we can observe that the density of β_{ij}^k spreads out from a concentration at zero as ρ_δ increases from -1 to 1 .

Figure 3 shows the effect on the stochastic factor loadings of intermarket and interbank dependency, respectively. Each scatter plot depicts $(\beta_{ij}^k, \beta_{ij}^{k'})$ pair for different combinations of $(\rho_{Mkt}, \rho_\delta)$. We observe that interbank dependency affects the scale of the systematic part in exposure processes and intermarket dependency affects the similarity in values of the systematic part on a fixed scale. When intermarket homogeneity expressed by ρ_{Mkt} is fixed, as the exposure management homogeneity increases, the probability of betas taking on larger values is increased. That is, the scale and probability of the influence of the systematic part are increased thereby resulting in homogeneous exposures. On the other hand, for fixed interbank homogeneity expressed by ρ_δ , when intermarket homogeneity is increased, the probability that exposure in different markets is more likely to take similar values. Exposure homogeneity is obtained by having a similar scale but similar value. In subsequent analyses, we set $\rho_{Mkt} = 0.5$ as a baseline parameter.

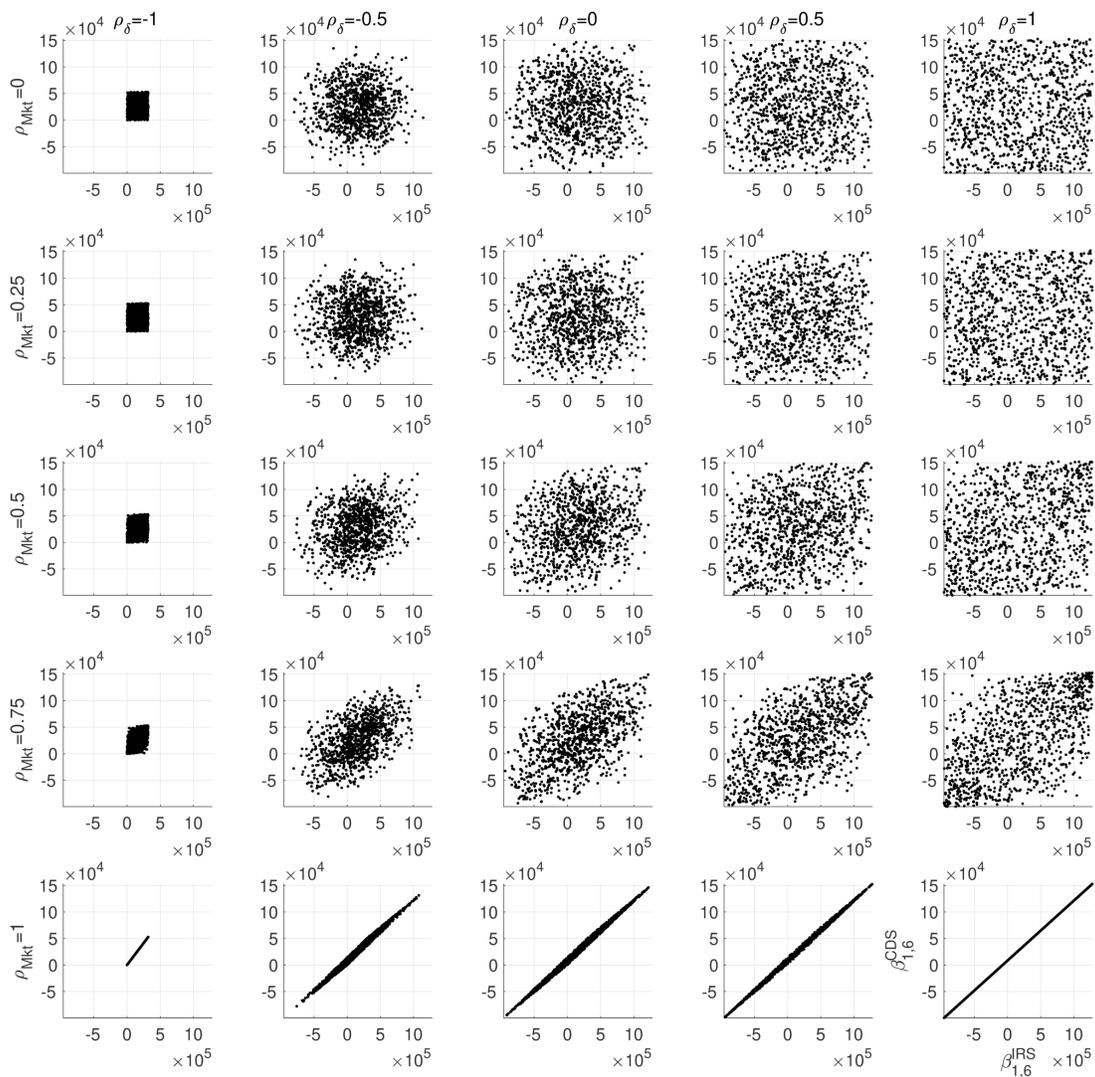
Employing the baseline parameters specified in Section 4.1, we estimate total expected counterparty exposure and netting efficiency across different homogeneity parameters in exposure management for different clearing schemes. The results are shown in Figure 4. Each Panel in Figure 4 depicts the response of system-wide exposure to changes in the copula parameter ρ_δ . The results show that regardless of clear-

Figure 2: Distribution of Systematic Factor Loading of Post-netted Exposure $X_{1,6}^{\text{CDS}}$ by Varying ρ_δ



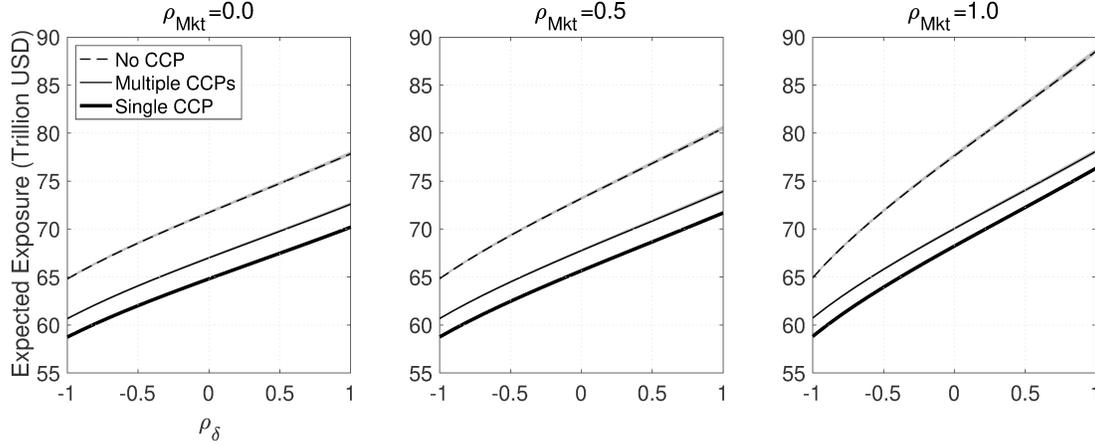
Note. This figure depicts the probability density of systematic factor loading of the post-netted exposure of bank 1 to counterparty 6 in CDS with respect to changes in ρ_δ .

Figure 3: Pairs of Systematic Factor Loadings of Exposures in Different Asset Classes



Note. This figure illustrates sample pairs of the stochastic factor loadings $(\beta_{1,6}^{\text{IRS}}, \beta_{1,6}^{\text{CDS}})$ of exposures in different asset classes.

Figure 4: Cross-Exposure Copula Parameter and Total Counterparty Expected Exposure



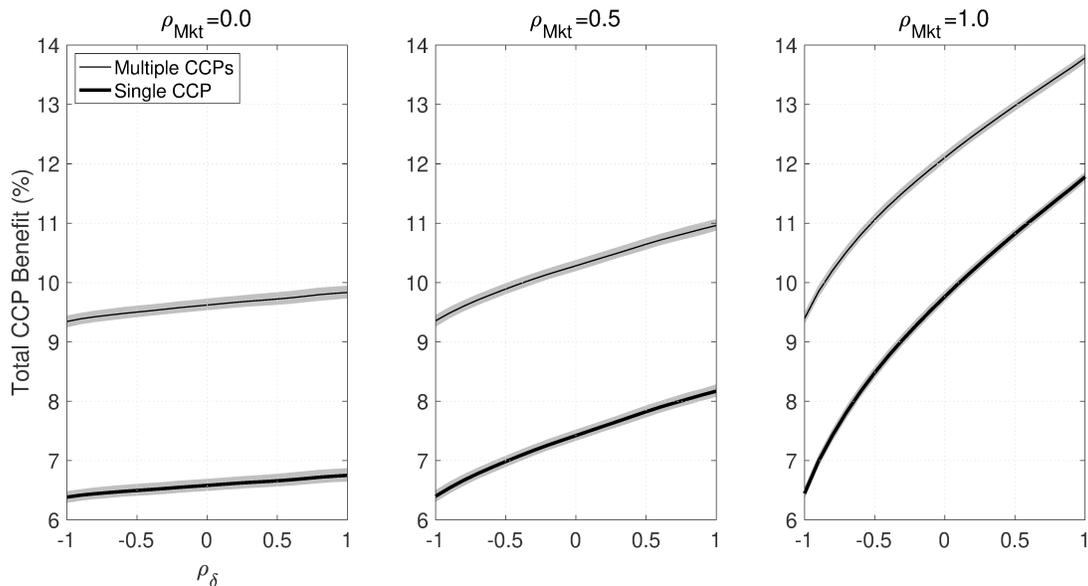
Note. This figure shows the total expected counterparty exposure under different clearing schemes across different $\rho_\delta \in [-1, 1]$ with their 99% confidence interval bands. “Single CCP” and “Multiple CCPs” corresponds to Case 4 and 5 in Table 2, respectively.

ing schemes, heterogeneous clearing members’ exposure management practices provide less system-wide exposure. A smaller amount of exposure is systemically desirable since the total expected exposure measures the amount of potential losses in the OTC derivatives market from a systemic point of view. The difference in exposures under central/bilateral clearing tends to increase as cross-exposure correlation increases, especially when markets move more homogeneously.

Figure 5 illustrates the responses of CCP benefit to changes in copula parameter ρ_δ . We observe that central clearing netting efficiency increases as clearing members manage their exposures in more homogeneous ways. Moreover, when markets are more strongly correlated, the role of central clearing for netting efficiency is accentuated.

In summary, promoting heterogeneity in interbank exposure distributions is desirable as it always reduces the amount of potential losses in the system. This implication coincides with the findings of Acharya (2009) and Choi (2014) that heterogeneity is systemically prudential. In the meantime, the multilateral netting benefit under central

Figure 5: Cross-Exposure Copula Parameter and Estimated CCP Benefit



Note. This figure shows the estimated CCP benefit under different clearing schemes across $\rho_{\delta} \in [-1, 1]$ with their 99% confidence interval bands. “Single CCP” and “Multiple CCPs” corresponds to Case 4 and 5 in Table 2, respectively.

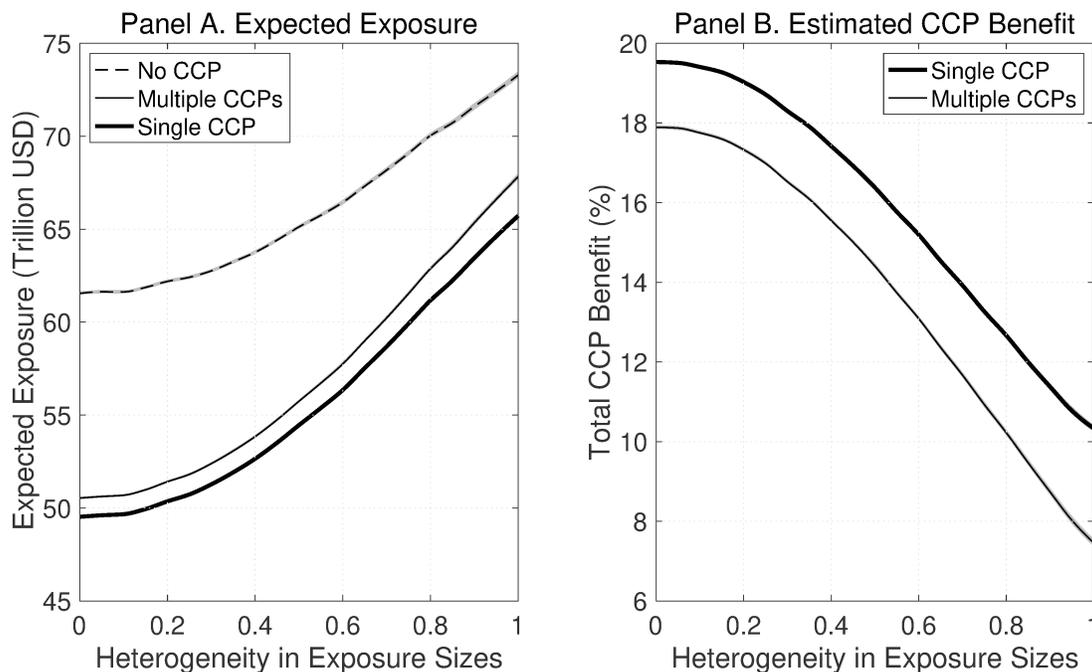
clearing outweighs the bilateral reduction of expected exposure within an environment of systemic homogeneity in the distributions of interbank exposure dynamics.

4.3 Heterogeneity in Exposure Size

Throughout these analyses, we estimate the parameters of exposure distributions based on the notional outstanding of each asset class, which is the key determinant in generating exposure and, in turn, the netting efficiency of central clearing. The notional outstanding of OTC derivatives contracts can be regarded as a proxy candidate for dealer size. To address heterogeneity in outstanding size, we set the baseline as the empirical distribution obtained from OCC (Table 1) and adjust standard deviation while maintaining the mean for each of the asset classes.

We define heterogeneity in exposure size as the ratio of standard deviation of

Figure 6: Heterogeneity in Exposure Size and Total Expected Exposure



Note. This figure illustrates the total exposure and estimated CCP benefit across different levels of heterogeneity in bank-to-bank exposure size with their 99% confidence interval bands. Size heterogeneity is measured by the ratio of the standard deviation of outstanding over that of the baseline case.

outstanding over the standard deviation of the baseline case. Thus, as the size heterogeneity parameter changes from 1 to 0, clearing members outstanding in each asset class clusters to their means. For each clearing scheme, we control the size homogeneity parameter and measure the total expected counterparty exposure and corresponding CCP benefit. Figure 6 illustrates the results. We observe that in contrast to the effect of cross-exposure and cross-asset heterogeneity, heterogeneous exposure sizes generate larger system-wide exposure, which is systemically undesirable. On the other hand, we observe that the CCP benefit is more pronounced as exposure size become more homogeneous.

4.4 Term-structure Analysis of Tail Risk Measures

So far, we have limited our focus to the expected value of aggregate counterparty exposure in the system before and after the introduction of CCP. From a macro-prudential perspective, policy-makers should be more concerned about extremely large losses. In this regard, we consider the tail risk of system-wide expected exposures across different risk horizons by taking well-known tail risk measures such as Value-at-Risk (VaR) and Expected Shortfall (ES).

The VaR of total counterparty exposure X at confidence level $\alpha \in (0, 1)$ is the smallest total counterparty exposure y such that the probability that X exceeds y is at least $\alpha > 0$, i.e.,

$$\text{VaR}_\alpha(X) = \inf\{x \geq 0 \mid 1 - F_X(x) < \alpha\}, \quad (15)$$

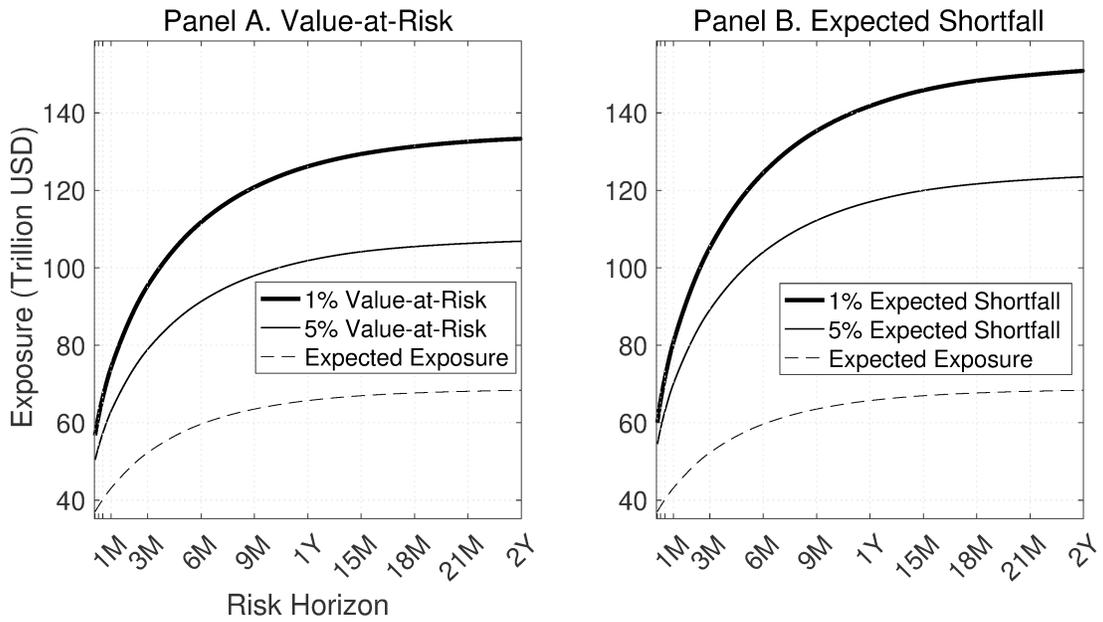
where $F_X(x)$ indicates the cumulative distribution function of total counterparty exposure X . The definition of expected shortfall (ES), the total expected counterparty exposure in the worst $\alpha \times 100\%$ of scenarios, is given by

$$\text{ES}_\alpha(X) = \frac{1}{\alpha} \int_0^\alpha \text{VaR}_\gamma(X) d\gamma. \quad (16)$$

Figure 7 shows the term-structure of VaR and ES of total expected counterparty exposure at the 1% and 5% significance levels alongside the total expected counterparty exposure. Our simulation results indicate that the tail risk level increases as we expand the risk horizon, suggesting that it is desirable to shorten the margin periods of risk for the purpose of systemic risk management.¹¹ To gauge the rate of change in tail risk

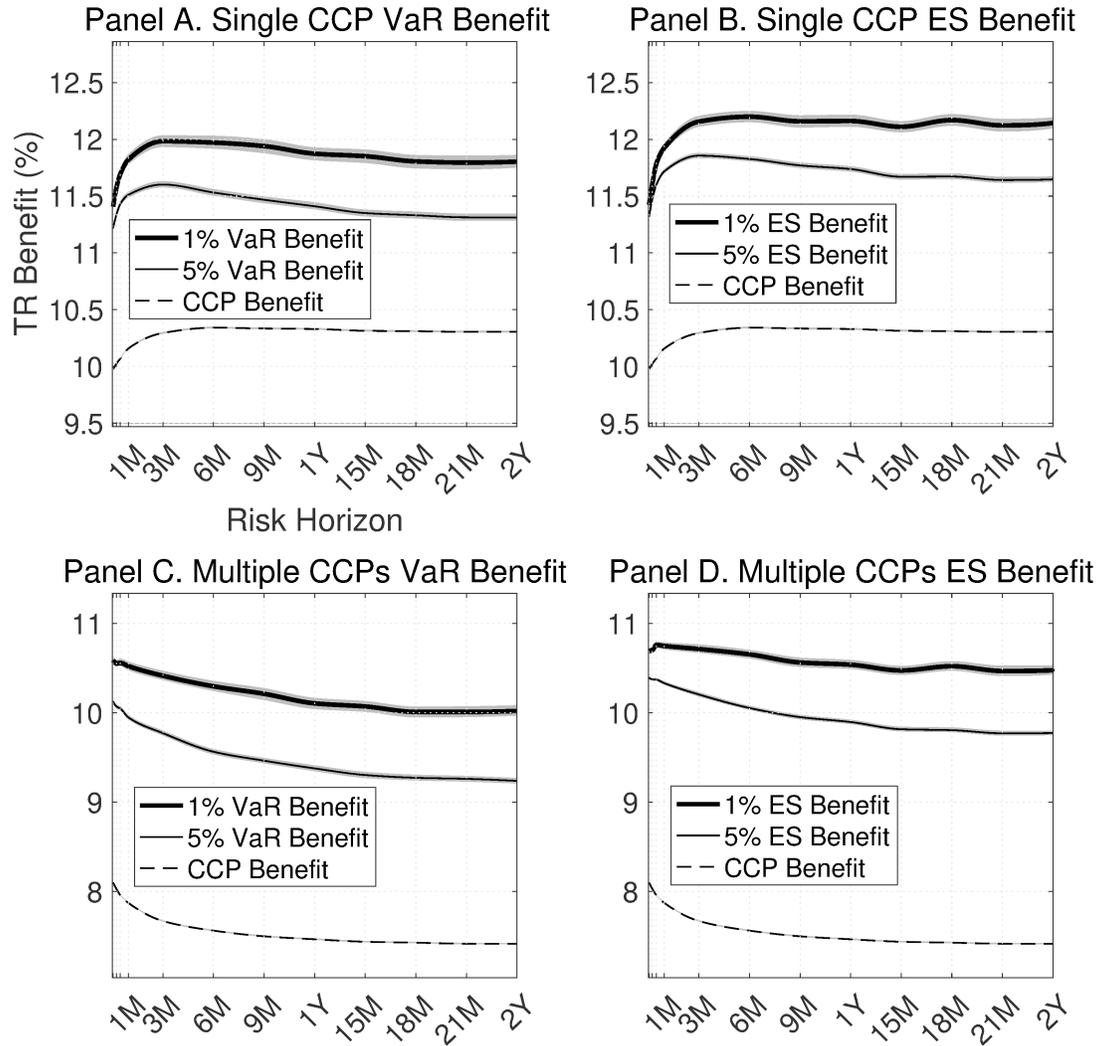
¹¹Margin period of risk is the time from the most recent collateral coverage of the marking-to-market value of a contract with a defaulting counterparty until the time the contract is closed out.

Figure 7: Term-structure of Value-at-Risk (VaR) and Expected Shortfall (ES) of Total Counterparty Exposure



Note. The left panel illustrates the term-structure of Value-at-Risk of total counterparty exposure at the 1% and 5% significance levels alongside total expected counterparty exposure drawn from 10,000,000 samples along with their 99% confidence interval bands obtained by 1,000 bootstrapped samples with replacement. The right panel illustrates the term-structure of Expected Shortfalls of total counterparty exposure at the 1% and 5% level alongside total expected counterparty exposure. The assumption of a single CCP (Case 4 in Table 2) is imposed for the simulations in both panels.

Figure 8: Term-structure of the CCP Benefit based on Value-at-Risk (VaR) and Expected Shortfall (ES) of Total Counterparty Exposure under Different Clearing Schemes



Note. Panel A and B illustrate the term-structures of the CCP Benefit based on VaR and Es computed from 10,000,000 samples along with their 99% confidence interval bands obtained by 1,000 bootstrapped samples with replacement under a single CCP assumption (Case 4 in Table 2), respectively, whereas Panel C and D are drawn under the multiple CCPs assumption (Case 5 in Table 4).

(TR) measures by introducing CCP, we define the $\text{TR} \in \{\text{VaR}, \text{ES}\}$ benefit as

$$\text{TR}_\alpha \text{Benefit (\%)} = 1 - \frac{\text{TR}_\alpha(\text{Exposure Under Multilateral Netting})}{\text{TR}_\alpha(\text{Exposure Under Bilateral Netting})}. \quad (17)$$

Our finding shows a clear benefit from central clearing. That is, the contribution of CCP to system-wide risk reduction is larger at the tail end; i.e., CCP plays a more significant role in more systemically extreme scenarios. Moreover, if there are multiple CCPs in the system, we observe that the CCP benefit becomes more pronounced based on tail risk measures with shorter risk horizons. This confirms that shortening the margin periods of risk is systemically prudential even in the presence of multiple CCPs.

4.5 Allocating Operational Costs of Central Clearing

In general, both macro- and micro-level exposure risks, if properly measured and managed under central clearing, are indeed helpful to stabilize the entire financial system in a complementary manner. Allocating the cost of a central clearing system to its participating members can be justified based on the contribution of a clearing member to total exposure risk. By adjusting the parameter values of our exposure process models, we explore the effect of exposure stability and resiliency on the system-wide expected exposure and the netting efficiency of central clearing.

In our pre-netted exposure model, σ_{ij}^k represents the volatility of the interbank exposure process. That is, the stability of a bank's counterparty exposure management in particular derivatives category can be proxied by σ_{ij}^k . We investigate the variation of the total expected counterparty exposure along with the CCP benefit in response to changes in exposure-specific volatility σ_{ij}^k by varying it from 50% to 150% of the baseline level, as shown in Figure 9.

Panel A and B in Figure 9 show that the system-wide expected exposure increases

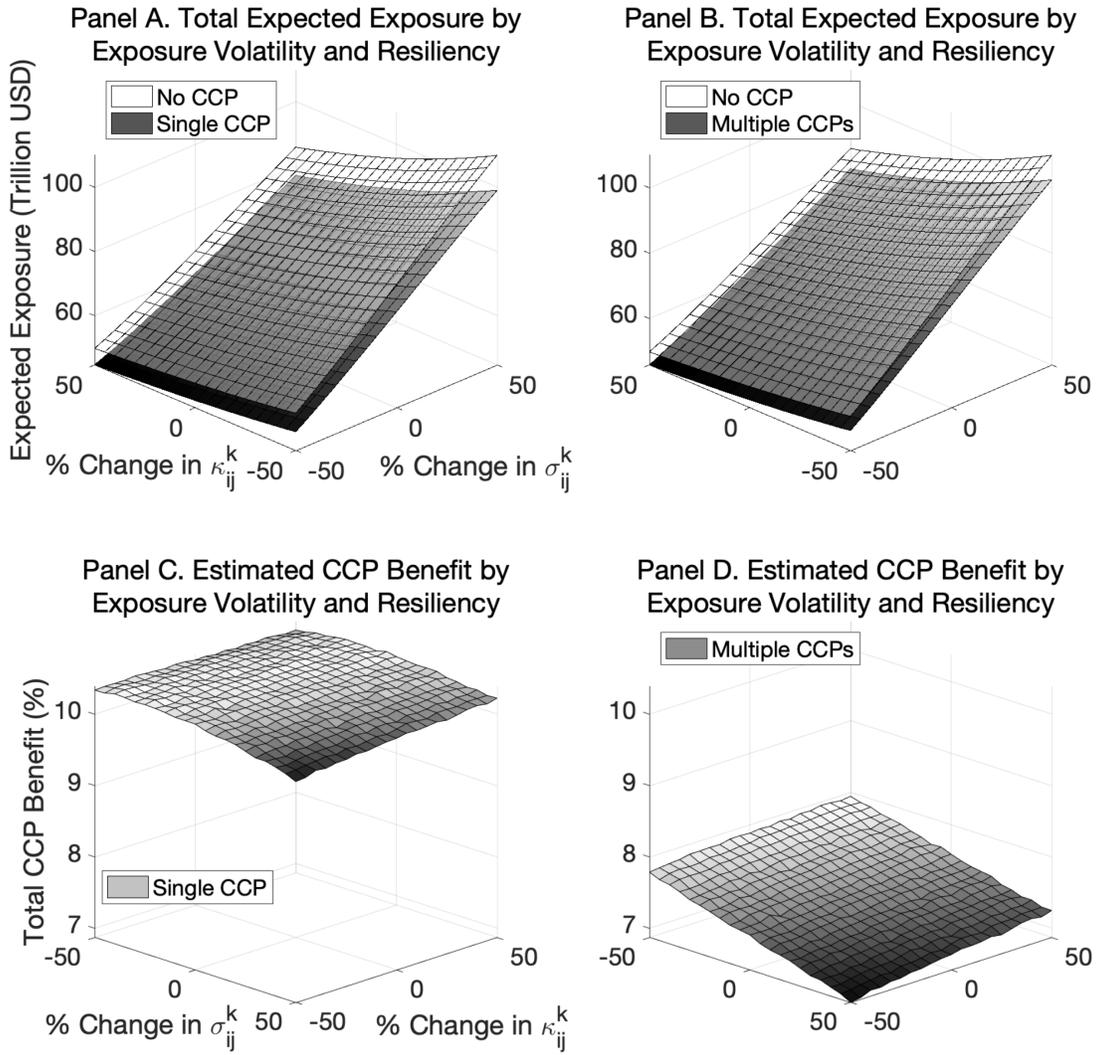
in an economically significant manner as we increase exposure process volatility. We also observe that the less volatile exposure process provides a greater netting efficiency under central clearing as illustrated by Panel C and D in Figure 9. This result can be explained by the positive relationship between exposure volatility and the standard deviation of its distribution in a given risk horizon. Hence, it is reasonable to charge a larger portion of central clearing operational costs to the clearing members that contribute more to the expected exposure of the system by deteriorating netting efficiency under central clearing.

In our pre-netted exposure model, κ_{ij}^k represents the speed of adjustment to the long-term exposure level. The mean-reversion speed parameter κ_{ij}^k can be interpreted as how quickly a bank's counterparty exposure level is adjusted to its target level. Accordingly, we investigate how the total expected counterparty exposure and the CCP benefit vary in response to changes in the bank-specific exposure resiliency parameter κ_{ij}^k . Figure 9 shows that the resilient exposure process generates slightly less total expected exposure. As the exposure process converges more quickly to its long-term target level, it does not fluctuate as much as it did before. However, its effect is seemingly weaker than the volatility effect.

5 Conclusion

We investigate the advantages of multilateral netting in mitigating the magnitude of total expected counterparty exposure over a bilateral netting scheme with a more realistic exposure model specification. Our stochastic model of pre-netted interbank exposure network illustrates bank-to-bank and cross-asset exposure interdependencies in a large financial system. The proposed model explains the relationship between heterogeneity in exposure management practices and multilateral netting benefits under central clear-

Figure 9: Total Expected Exposure and Estimated CCP Benefit by Varying κ and σ



Note. This figure depicts the total expected counterparty exposure and estimated CCP benefit in response to percentage changes in κ_{ij}^k and σ_{ij}^k relative to the baseline setting.

ing. Through Monte Carlo Simulation, we explore patterns of system-wide exposure and netting efficiency under central clearing with respect to exposure heterogeneity.

The simulation results indicate that banks' stronger tendencies to employ more homogeneous asset management practices leads to a expectation of larger system-wide exposure after netting, while netting efficiency under central clearing becomes more pronounced in the more systemically homogeneous environment of interbank exposure dynamics. Thus, regulators, who are responsible for macro-prudential supervision, should be cautious in prompting market participants to choose similar assets even though doing so improves system-wide netting efficiency under a central clearing scheme.

The notional outstanding of OTC derivatives held by banks can be an indicator of their exposure size. Our simulation results show that as exposure size become more homogeneous, system-wide exposure becomes smallerboard and central clearing netting efficiency becomes larger. Since, in practice, it is not feasible to encourage small clearing members to incur larger net exposure by taking new positions, it is desirable that regulatory schemes impose limitations on the ability of large clearing members to increase their net exposures.

We subsequently explore variations in the total expected exposure and CCP benefit in response to bank-specific resiliency and stability parameters. Our findings demonstrate that the CCP benefit is sensitive to changes in bank-specific characteristics, particularly the stability of exposure management practices. As a greater proportion of the costs of joining a system should be allotted to members who contribute more to the deterioration of macro-prudence, clearing members with more volatile and less resilient exposure should bear a larger portion of the central clearing operational costs.

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