Central Counterparty Exposure in Stressed Markets

Wenqian Huang†  Albert J. Menkveld‡  Shihao Yu§

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†Wenqian Huang, Bank for International Settlements, Centralbahnplatz 2, 4051 Basel, Switzerland, tel +41 612 808 000, wenchuan.huang@bis.org.

‡Albert J. Menkveld, Vrije Universiteit Amsterdam, School of Business and Economics, De Boelelaan 1105, 1081 HV, Amsterdam, Netherlands, tel +31 20 598 6130, albertjmenkveld@gmail.com and Tinbergen Institute.

§Shihao Yu, Vrije Universiteit Amsterdam, School of Business and Economics, De Boelelaan 1105, 1081 HV, Amsterdam, Netherlands, tel +31 20 598 4722, s.yu@vu.nl.
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Abstract

Time is valuable, particularly in stressed markets. As central counterparties (CCPs) have become systemically important, we need to understand the dynamics of their exposure towards clearing members at high frequencies. We track such exposure and decompose it which leads to the following insights. The composition of CCP exposure is fundamentally different in the tails. At extreme levels or during rapid increases, there is elevated crowding. This is the result of clearing members all concentrating their positions on a single security or a particular portfolio, desirable if motivated by hedging, worrying if due to speculation.
1 Introduction

Regulators are worried about central counterparties (CCPs) risk management in fast markets. Sudden extreme price dislocations (“Flash Crashes”)\(^1\) coupled with super-human trading speeds could have systemic consequences. If traders are unable to deliver on their trades, then CCPs become liable for their losses because a CCP effectively insures the counterparties in these trades. The margins posted by these defaulting traders might not be sufficient to cover these losses. A recent example is the 2018 failure of a Nasdaq clearing member where losses swallowed up two-thirds of the default fund.\(^2\) Such mutualized loss might itself trigger further defaults in which case the event becomes potentially systemic.

State-of-the-art risk management at CCPs therefore becomes of first order importance. CPMI-IOSCO (2017) emphasizes the need for monitoring intraday CCP exposure (p. 32):

> Adverse price movements, as well as participants building larger positions through new trading (and settlement of maturing trades), can rapidly increase a CCP’s exposures to its participants. This exposure can relate to intraday changes in both prices and positions. For the purposes of addressing these and other forms of risk that may arise intraday, a CCP should address and monitor on an ongoing basis...

In this paper we propose a way for CCPs to monitor their exposure intradaily with a focus on stressed markets. In such markets, trading is likely to be fast-paced and data therefore streams at extreme speeds. The approach should be able to cope with such “big data” challenges. More importantly, the monitoring should yield valuable economic insights that generate an understanding of “what just happened,” and potentially guide interventions.

We turn to the academic literature to formulate hypotheses to guide our high-frequency analysis of CCP exposure. Several studies have identified a fire-sale channel as the root cause of price dislocations. The narrative is as follows. During normal times, arbitrageurs smooth prices by trading against pricing errors (thereby essentially engaging in market making). Suppose that at some point a critical mass of them crowds on a single risk factor. That is, their portfolio positions are very similar, say long a book-to-market or

\(^1\)On February 5, 2018, VIX futures jumped 20 points, which is the largest daily increase since the 1987 stock market crash. On October 7, 2016, the British pound dropped by almost ten percent in just eight minutes. On January 15, 2015, the Swiss franc rose by about 20% against the euro within five minutes after the Swiss central bank announced that it abandoned its peg against the euro as per immediately.

\(^2\)On September 10, 2018, the Nordic-German power spread increased by more than 17 times the average daily change which triggered the trader’s default.
size-based portfolio.\footnote{Wagner (2011) clarifies that these arbitrageurs could hold diversified portfolios, yet be exposed to the fire-sale channel. It is position diversity that is the driving force here, not the level of diversification.} If these positions suddenly experience a significant loss then arbitrageurs face high variation margin calls (to mark-to-market their positions). If these arbitrageurs are capital constrained then they might be forced to free up capital by selling some of their positions. This sell pressure might trigger trades at fire-sale prices, thus leading to more losses, triggering further selling, etc. (Shleifer and Vishny 1997, Gromb and Vayanos 2002, Brunnermeier and Pedersen 2009). Perhaps the most prominent example of such dynamic is the “Quant Meltdown” where the arbitrageurs were hedge funds and the portfolios were indeed factor-based portfolios (Khandani and Lo 2007, 2011).

With these motivations let us now discuss in more detail what we do in the remainder of the paper. We develop an approach for tracking and decomposing CCP exposure intraday. The exposure measure is based on the tail risk of losses in an oncoming period, aggregated across all clearing members (Duffie and Zhu 2011, Menkveld 2017).\footnote{Menkveld (2017) extends Duffie and Zhu (2011) to focus on the tail risk in losses as opposed to mean losses.} The measure relies on analytic results that are all straightforward to compute. It further allows for decomposition across clearing members or securities.

We implement the approach on a sample of high-frequency CCP data to test three hypotheses on CCP exposure in stressed markets. We define such markets for a CCP as ones where either its exposure is at the highest levels or where exposure changes are extremely high.\footnote{One could argue that the tails are not riskier to a CCP because higher exposures against clearing members are insured by the latter posting higher margins with the CCP. While this is true, it is also true that if there are losses that exceed the margin, they exceed by a larger amount in the tail (i.e., loss given default is likely to be larger). A deeper analysis of risk net of margin and other forms of collateralization (e.g., the default fund) are beyond the scope of this study.} The three hypotheses pertain to the following questions:

1. Are sudden extreme increases in CCP exposure driven by the same factors as regular exposure changes? Or does one see, for example, elevated crowding?

2. Is the same true for extreme levels as opposed to extreme changes? Again, is crowding a larger part of it?

3. Finally, at these extreme levels is the relative contribution of clearing-member house accounts (i.e., principal trades) larger than their client accounts (i.e., agency trades)? If so, then this is worrisome as clearing members are typically highly leveraged financial intermediaries and therefore less able to absorb large shocks.
The empirical analysis that we do to address these questions is based on a high-frequency 2009-2010 sample of a European CCP: European Multilateral Clearing Facility (EMCF). This CCP was the largest equity CCP in Europe and later merged with DTCC in the US to become the world’s largest equity CCP. Counterparty risk arises in equity trading because the settlement of a trade typically occurs three days after it is concluded. A trade therefore is like a three-day forward contract between a buyer and a seller. Counterparty risk then pertains to one side defaulting in this period. Admittedly, analysis of a CCP that insures credit default swaps or interest rate swaps would have been more relevant in terms of systemic risk, but disaggregated CCP data is extremely hard to come by (see literature review below). The application to actual CCP data could therefore in and of itself be considered a contribution.\(^6\)

The key findings are several. First, CCP exposure changes, on average, are almost entirely driven by changes in the positions of clearing members due to their trading. However, if one zooms in on extreme exposure increases then security volatility and position crowding start to contribute substantially. For the top 100 increases they collectively contribute 30% where volatility contributes 13% and crowding 17%.

Second, we find a similar result when comparing the full sample with the subsample of high exposure levels — more crowding in the latter. More specifically, CCP exposure concentrates on a few clearing members and a smaller set of risk factors. For example, comparing the full sample with the top 1% subsample, the contribution of the largest five members increases from 28% to 47%. The contribution of the largest principal component across all risk factors.

Third, it is not true that at high exposure levels the CCP is relatively more exposed to house accounts. There is only a modest increase from 67% to 70% when comparing the full sample to the top 1%. However, we do find stronger concentration within the set of house accounts. A large share of the total house-account exposure originates from just a few clearing members.

In sum, the findings collectively suggest that stronger concentration/crowding characterizes CCP exposure both for large exposure increases and at extremely high exposure levels. There is, however, only a minor increase in the contribution of house accounts at these high levels.

One additional finding worth emphasizing is that idiosyncratic events can severely impact CCP exposure. For example, a disappointing earnings announcement by Nokia at noon on April 22, 2010 caused its share price to fall by about 15% in the minutes after, leading to an exposure increase of almost 16 times its average

\(^6\)Although we cannot claim that any of our findings carry over to credit default swap or interest rate swap for lack of evidence, the market-microstructure invariance principle suggests that they might (Kyle and Obizhaeva 2016). This invariance principle states that trading in all securities is similar in a fundamental sense but might differ in terms of speed.
The decomposition of the exposure change shows that volatility is the largest component causing the jump. The exposure jump, however, was only a relatively small part of the extremely large CCP exposure increase that day. Most of it appears to be caused by clearing members increasing their Nokia position, either long or short, during heavy trading in the afternoon. (Note that this is a non-trivial finding as the strong volume could have been due to traders reducing their positions after observing elevated volatility.)

The exposure-change decompositions further reveal a substantial contribution of the crowding component that day. Members tilted their portfolio towards Nokia. Altogether the Nokia example neatly illustrates the paper’s main finding that volatility and crowding become important components of CCP exposure in the tails.

Our paper contributes to a rapidly expanding empirical literature on central clearing. CCP trade data disaggregated across members are scarce. Proprietary daily data have been used to compare CCP exposure to the margins collected (Jones and Perignon 2013, Menkveld 2017, Lopez et al. 2017). Duffie et al. (2015) analyze a snapshot of bilateral exposures on uncleared credit default swaps to assess the netting efficiency potential of central clearing. Event studies on CCP introductions yield insight in how trading is affected (Loon and Zhong 2014, 2016, Menkveld et al. 2015, Benos et al. 2016). We contribute to this literature by proposing an approach to monitor CCP exposure intradaily along with economically meaningful decompositions.

The paper contributes to a nascent literature on CCP systemic risk. Capponi et al. (2015) analyze the endogenous build-up of asset concentration due to central clearing. Amini et al. (2015) investigate partial netting for a subset of liabilities in a network setting that accounts for knock-on effects and asset liquidation effects. Glasserman et al. (2015) compare margining in dealer markets and a centrally cleared market. Menkveld (2016) endogenizes the fire-sale premium that a CCP will have to pay in the catastrophic state that a critical mass of members default and liquidity supply is thus impaired.

The rest of the paper is organized as follows. Section 2 formalizes and motivates the three overriding hypotheses. Section 3 presents the approach to monitoring and decomposing CCP exposure. Section 4 describes the data and discusses implementation issues. Section 5 presents the empirical results of testing the three hypotheses. Section 6 concludes.

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7Bignon and Vuillemey (2019, Fig. 3 and A1) do a forensic analysis on the Paris commodity futures CCP that failed in 1974. They, for example, find that there was elevated activity (in terms of transactions) in the half year before failure, but open positions declined (measured in 1000 tons sugar).

8A related set of papers does not focus on concentration and systemic risk but rather on incentives and economic efficiency Koeppel et al. (2012), Fontaine et al. (2014), Acharya and Bisin (2014), Biais et al. (2016), Huang (2019).
2 Hypotheses

This section develops three hypotheses that will be taken to the data. Each hypothesis is stated formally and then followed by a motivation.

**Hypothesis 1.** *The drivers of CCP exposure changes are different in the (right) tail.*

CCP exposure changes can be driven by a variety of factors that are either price-related (e.g., volatility or correlation) or trade-related (i.e., trade causes member positions to change). We expect the latter to dominate CCP exposure changes in normal times. However, we conjecture that turbulent periods are characterized by elevated volatility and lots of trading. The strong positive correlation of volatility and transaction rate is a well-known stylized fact in the microstructure literature (e.g., Jones et al. 1994).

The intense trading at times of extremely high volatility does *not* necessarily imply that CCP exposure increases rapidly. A sudden volatility increase might actually trigger traders to *reduce* their recently established positions to contain risk. Such trading benefits a CCP as it reduces its exposure.

On the other hand, a volatility shock might lead to (more) speculation in which case traders increase their positions. A heterogeneity in beliefs or in signals might generate such stronger position taking (e.g., Kim and Verrecchia 1994). Or, in a more recent paper, Crego (2019) proposes a channel by which risk-averse informed traders strategically wait to trade on their (idiosyncratic) signal until the arrival of a public signal which removes significant uncertainty. Either way, member positions would increase in magnitude and CCP exposure rises as a result.

An even more worrisome channel that could cause high volatility and fast trading is what, in the literature, is often called a self-reinforcing fire-sale channel. For example, financially constrained arbitrageurs (hedge funds, sell-side banks, high-frequency traders, etc.) hit by adverse price shocks might have to quickly liquidate their large positions and thereby cause transitory price shocks (Shleifer and Vishny 1997, Gromb and Vayanos 2002, Brunnermeier and Pedersen 2009).

Such liquidations would not be a concern if these arbitrageurs had diverse positions (Wagner 2011). This is not the case however if these traders followed similar trading strategies and their portfolios thus crowd on a small set of risk factors/portfolios (Stein 2009). In such scenario there might not be enough cash-in-the-market to liquidate these positions and markets have to clear at fire-sale prices. A prominent example is the “Quant Meltdown” of 2007 when quantitative equity market-neutral hedge funds crowded on similar
trading strategies and made record losses (Khandani and Lo 2007, 2011). The risk that a CCP finds itself in such scenario is particularly high when there is substantial crowding in its members’ portfolios.

To test for such crowding in stressed markets, one needs to be able to decompose changes in CCP exposure into price- and trade-related components. One of the trade-related components should then be crowding across clearing members.

**Hypothesis 2.** The structure of CCP exposure levels is different in the (right) tail.

Hypothesis 2 restates Hypothesis 1 but this time in terms of levels instead of changes. The reason to also study whether there is, for example, elevated crowding for extreme exposure levels is derived from studies on historical CCP failures. Bignon and Vuillemey (2019) study the 1974 failure of the Paris Commodity Clearing House. They show that in a year starting from November 1973 the position of the largest clearing member rose from 9% of the total open position in sugar futures to 56% of it. Another example is the 1987 failure of the Hong Kong Futures Guarantee Corporation where at the point of failure the largest four members had accumulated 80% of the short position in all contracts (Cox 2015).

If there is crowding then understanding what causes the crowding requires one to be able to decompose the exposure level across clearing members and across risk factors. The reason is that strong crowding could occur because outstanding positions are held by only a few clearing members. The CCP failures in Paris and Hong Kong are examples of such crowding. There is, however, a more opaque way for there to be elevated crowding. In the extreme case, all clearing members contribute equally to CCP exposure but they crowd on a single risk factor, for example a particular security or portfolio. The 2007 Quant Crisis is an example of such “risk-factor crowding.” Let us turn to a simple example to make this distinction between the two types of crowding as clear as possible.

Suppose there are four clearing members and two assets with independently distributed payoffs. First consider the baseline case of member 1 and member 2 having traded one unit of asset A and therefore having open and opposite positions in this asset. Suppose the same holds for member 3 and 4 in asset B. In this baseline case there is no crowding. Let us now consider the two polar cases of crowding. An example of perfect member crowding is one where member 1 and 2 trade as in the baseline case, but member 3 and 4 refrain from trading. The reason is that there is concentration in CCP exposure as only two members contribute. For an example of perfect risk-factor crowding consider again the baseline case but now with member 3 and 4 also trading one unit of asset A. Note that in this case all clearing members contribute
equally to CCP exposure, yet there is perfect crowding. In both cases there is a strong correlation in portfolio
returns across clearing members which increases the expected aggregate loss and therefore CCP exposure
(Menkveld 2017, Section 1.5).

When testing the second hypothesis it is desirable to measure how much crowding contributes to CCP
exposure and whether such crowding is member or risk-factor crowding. It turns out that there are ways to
do this with the proposed CCP exposure measure. We will return to this issue in Section 3.3.

**Hypothesis 3.** *The relative contribution of house accounts to CCP exposure increases in the (right) tail.*

The third hypothesis focuses on the two types of clearing-member accounts: house accounts and client
accounts. House accounts capture the trading that clearing members do for their own books whereas in client
accounts they register their trading on behalf of clients. It is worth decomposing CCP exposure across these
two types of accounts as one could argue that CCP exposure to house accounts carries more risk. Clearing
members are often highly leveraged financial intermediaries whose trading is unlikely to be pure hedging.
For example, they often engage in market making to absorb temporary order imbalances. Therefore more
exposure to house accounts at times of high CCP exposure is worrisome. Testing the third hypothesis will
show whether or not this is the case.

3 Approach

This section presents an approach to monitoring CCP exposure intraday. It is based on the framework
proposed by Duffie and Zhu (2011) and extended by Menkveld (2017) to include tail risk and crowding.
CCP exposure is essentially a measure that is based on the distribution of losses in clearing member accounts
for the oncoming period. We study the Value at Risk (VaR) for these losses following Menkveld (2017).\(^9\)
We first present the exposure measure in detail, then show how one could decompose exposure change
needed for testing the first hypothesis, and finally present exposure level decompositions needed for testing
the second and third hypotheses.

3.1 The CCP exposure measure: A VaR of aggregate loss

Consider the case of a single CCP, \(I\) securities, and \(J\) clearing members (or traders, the two terms will be
used interchangeably). \(P_t\) is an \(I \times 1\) vector consisting of current security prices. \(R_t\) is an \(I \times 1\) vector that

\(^9\)Duffie and Zhu (2011) study the *mean* loss which is invariant to the level of crowding — the VaR loss is not.
contains next period’s security returns. \( R_t \) is assumed to be normally distributed: \( R_t \sim \mathcal{N}(0, \Omega_t) \) where \( \Omega_t \) is the \( I \times I \) covariance matrix of security returns. Let \( n_{j,t} \) be the \( I \times 1 \) vector of member \( j \)'s current positions expressed in euro. The portfolio return in euro for the member in the next period is then a scalar \( X_{j,t} \) where
\[
X_{j,t} = n_{j,t}' R_t.
\]

Collect all \( n_{j,t} \) into an \( I \times J \) matrix \( N_t \) which thus becomes the (euro) position matrix of all members. Collect all \( X_{j,t} \) into the \( J \times 1 \) vector \( X_t \) which thus becomes the future return vector for all members, where \( X_t = N_t' R_t \). Since \( X_t \) is linear in \( R_t \), \( X_t \) is normally distributed: \( X_t \sim \mathcal{N}(0, \Sigma_t) \) where \( \Sigma_t = N_t' \Omega_t N_t \) is the \( J \times J \) covariance matrix of (euro) portfolio returns.

As a CCP is exposed to losses, define
\[
L_{j,t} = -\min(0, X_{j,t})
\]
as the loss in member \( j \)'s portfolio. Then aggregate loss \( A_t \) is:
\[
A_t = \sum_j L_{j,t}.
\]

Duffie and Zhu (2011) propose to base CCP exposure on the mean aggregate loss:
\[
E(A_t)
\]
and derive an analytical expression for it which suffices for their analysis of netting efficiency. Menkveld (2017) considers the VaR of aggregate loss a more appropriate measure for CCP exposure and refers to it as \( \text{ExpCCP} \). Following standard practice and maintaining tractability, Menkveld (2017) uses the delta-normal method to compute the VaR:
\[
\text{ExpCCP}_t \equiv \text{VaR}(A_t) = E(A_t) + \alpha \text{var}(A_t)^{\frac{1}{2}},
\]
where \( \alpha \) is a parameter that needs to be calibrated. We follow Menkveld (2017) and use \( \text{ExpCCP} \) as our exposure measure. In Appendix A we list all the results needed to compute \( \text{ExpCCP} \).

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The normality assumption yields analytic results for CCP exposure along with natural decompositions. To stay close to normality in the data, the sample clock will run in transaction time (for details see Section 4.2.)
3.2 Decomposition of CCP exposure change

The first hypothesis states that the drivers of CCP exposure change are different in the tail. As discussed in the hypothesis section, sudden extreme CCP exposure increases might be driven by volatility shocks and crowding in addition to position changes. To test such hypothesis one needs to decompose exposure changes and verify to what extent volatility and crowding contribute a larger part in the tail.

We propose to decompose exposure changes based on a relatively straightforward one-factor-at-a-time (OFAT) approach (Daniel 1973). The underlying factors will consist of price-related factors and trade-related factors. Examples of price-related factors are security return volatility, correlation, and price level. Trade-related factors are member positions and crowding across members. The remainder of this subsection describes the approach in detail.

Let us start by writing $\text{ExpCCP}_t$ as defined in (4) as a function of the underlying variables:

$$\text{ExpCCP}_t = f (\Sigma_t).$$

(5)

To arrive at a meaningful decomposition across factors we use the following two insights:

1. Following the financial econometrics literature we decompose covariance matrices into their diagonal and off-diagonal components (Bollerslev 1990, Engle 2002):

$$\Psi_t = D\Psi_t R\Psi_t D\Psi_t,$$

(6)

where $D\Psi_t$ is a diagonal matrix with $\psi_{ii,t}$ as the $i$-th diagonal element and $R\Psi_t$ is the correlation matrix associated with the covariance matrix $\Psi_t$. This decomposition will turn out to be useful to identify correlation effects in security returns and crowding across members.

2. $\Sigma_t$ is itself a function of “deeper” variables:

$$\text{ExpCCP}_t = f (\Sigma_t)$$

$$= f (N_t \Omega_t N_t')$$

(7)

$$= f (\Omega_t, P_t, \tilde{N}_t),$$

where the variables are: the covariance matrix of security returns $\Omega_t$, the price level $P_t$, and the
member portfolio matrix $\tilde{N}_t$ expressed in terms of the number of securities (as opposed to $N_t$ which is expressed in euro). The reason for using $\tilde{N}_t$ instead of $N_t$ is to be able to pull out a price-level effect when considering the change from $N_{t-1}$ to $N_t$.

Combining (6) and (7) yields:

$$\text{ExpCCP}_t = f(\Sigma_t)$$

$$= f(D_{\Sigma} R_{\Sigma} D_{\Sigma})$$

$$= f\left( D_{\Sigma} \left( D_{\Omega}, R_{\Omega}, P_t, \tilde{N}_t \right), R_{\Sigma} \left( D_{\Omega}, R_{\Omega}, P_t, \tilde{N}_t \right) \right)$$

which expresses $\text{ExpCCP}_t$ in terms of price-related variables ($D_{\Omega}, R_{\Omega}, P_t$) and trade-related variables ($\tilde{N}_t$).

The OFAT decomposition changes these variables sequentially from their value at $t - 1$ to their value at $t$. The sequencing matters and we pick the baseline sequencing motivated by the following principles:

- We first change price variables and then change trade variables. The reason for this sequencing is that it identifies a pure price effect. In other words, the price components communicate what CCP exposure change would have been had members’ portfolios not changed.

- Changes in idiosyncratic volatilities precede changes in correlations. In other words, we first consider changes in the diagonal and then changes in the off-diagonal of a covariance matrix. This approach makes interpretation of the components straightforward: Changes in variances become pure in the sense that they are evaluated keeping correlations constant.

These principles therefore suggest the following baseline OFAT decomposition:

$$\Delta\text{ExpCCP}_t = f\left( D_{\Sigma} \left( D_{\Omega,1}, R_{\Omega,1}, P_{t-1}, \tilde{N}_{t-1} \right), R_{\Sigma} \left( D_{\Omega,1}, R_{\Omega,1}, P_{t-1}, \tilde{N}_{t-1} \right) \right)$$

where the sequencing is illustrated by the (red) numbers on top of the various variables.\(^{11}\) The decomposition

\(^{11}\)To study how robust the insights are from the decomposition based on this particular sequencing, one could redo the decomposition based on all alternative sequences (see Section 5.1 and Appendix E.1).
yields five components. For example, the first component $\text{RetVol}_{t}$ is computed as:

$$
\text{RetVol}_{t} = f \left( D_{\Sigma} \left( D_{\Omega_{t-1}}, R_{\Omega_{t-1}}, P_{t-1}, \tilde{N}_{t-1} \right), R_{\Sigma} \left( D_{\Omega_{t-1}}, R_{\Omega_{t-1}}, P_{t-1}, \tilde{N}_{t-1} \right) \right)
- f \left( D_{\Sigma} \left( D_{\Omega_{t-1}}, R_{\Omega_{t-1}}, P_{t-1}, \tilde{N}_{t-1} \right), R_{\Sigma} \left( D_{\Omega_{t-1}}, R_{\Omega_{t-1}}, P_{t-1}, \tilde{N}_{t-1} \right) \right).
$$

(10)

which captures the contribution of volatility change.

We list the five components below and discuss each of them in detail. Note that the numbering corresponds to the red numbers in (9):

**Price components.**

1. $\text{RetVol}_{a}$: The impact of a change in return volatility on CCP exposure change. This effect captures the well-known empirical fact that volatility is time-varying (commonly referred to as GARCH or stochastic volatility in the financial econometrics literature).

2. $\text{RetCorr}_{a}$: The additional impact of a change in the correlations of security returns on CCP exposure change. The time-varying nature of such correlations is another well-known empirical fact and can be identified, for instance, through a dynamic conditional correlation (DCC) model (Engle 2002).

3. $\text{PrLevel}_{a}$: The additional impact of a change in the price level of securities. This effect is entirely due to covariance matrices being defined in relative terms (i.e., they are based on relative returns as opposed to euro returns). For example, a covariance matrix might not have changed in the interval, but if price levels dropped, then CCP exposure dropped because the latter is defined in terms of euro. Such effect is picked up by $\text{PrLevel}_{a}$.

**Trade components.**

4. $\text{TrPosition}_{a}$: The additional impact of trades in the interval. These trades might expand or reduce members’ legacy positions. CCP exposure therefore does not necessarily increase after new trades. It declines if their overriding effect was to reduce members’ outstanding positions.

5. $\text{TrCrowding}_{a}$: The additional impact due to changes in the correlations of member’s portfolio returns. If such correlations increase (in magnitude) then CCP exposure increases.

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12 We include explicit formulas for all five components in Appendix B for completeness.
In Appendix C we illustrate the decomposition of exposure changes by presenting a simple example. We
discuss how the various components change when changing either price- or trade-related variables.

### 3.3 Decomposition of CCP exposure level

Testing the second and third hypotheses requires a decomposition of CCP exposure level (as opposed to
exposure change). For example, to test whether there is more crowding at higher exposure levels, it is
desirable to decompose CCP exposure across members and across securities. If one finds more concentration
either across members (member crowding) or across securities (risk-factor crowding), then there is elevated
crowding as discussed in Section 2.

\( ExpCCP \) being homogeneous of degree one in member portfolio volatility and in security votility sug-
gests a natural decomposition. Let us focus on the decomposition across members to clarify (Menkveld
2017, Section 1.5). As \( ExpCCP \) is homogeneous of degree one in member portfolio risk \( \sigma_j \), applying
Euler’s homogeneous function theorem yields: \(^{14}\)

\[
ExpCCP = \sum_j \sigma_j \left( \frac{\partial}{\partial \sigma_j} ExpCCP \right).
\]

(11)

The contribution of member \( j \) therefore is: \(^{15}\)

\[
ExpCCP_j = \sigma_j \left( \frac{\partial}{\partial \sigma_j} ExpCCP \right) = \sqrt{\frac{1}{2\pi}} \sigma_j + \sum_{i \in \{j\}} \frac{\alpha}{\sigma_A} \left( \frac{\pi - 1}{2\pi} \right) \sigma_i \sigma_j M(\rho_{ij}),
\]

(12)

where \( \sigma_A \) is the standard deviation of aggregate loss and \( M \) is defined in (15) in Appendix A. Verbally this
result suggests that member \( j \)’s contribution to \( ExpCCP \) is equal to its portfolio risk \( \sigma_j \) times the (marginal)
price of such risk in terms of CCP exposure \( \frac{\partial}{\partial \sigma_j} ExpCCP \). This type of decomposition is used when test-
ing for elevated member-crowding on high exposure levels (H2) and for verifying whether house accounts
contribute more to \( ExpCCP \) in these conditions (H3).

A decomposition across securities is derived analogously where the risk units are \( \omega_k \) instead of \( \sigma_j \).

\(^{13}\) \( \sigma_j \) is the square root of the \( j \)-th diagonal element of the portfolio return covariance matrix \( \Sigma \).

\(^{14}\) Time subscripts are suppressed here for the sake of brevity.

\(^{15}\) This equation corresponds to Menkveld (2017, equation (27)). Note that there is typo in (27) as \( \sqrt{1/(2\pi)} \) should have been
multiplied by \( \sigma_j \) instead of \( \sigma_j^2 \). This typo has been corrected in (12) below.

\(^{16}\) \( \omega_k \) is the square root of the \( k \)-th diagonal element of the security return covariance matrix \( \Omega \).
A detailed derivation is included as Appendix D. This decomposition is used to test for elevated risk-factor crowding at high exposure levels (H2).

4 Application

This intermezzo section presents the data and discusses various implementation issues. These issues include normality of returns (needed for ExpCCP), estimation of the return covariance matrix, and setting the parameter $\alpha$ in the delta-normal VaR.

The data sample used for testing the hypotheses was made available by the European Multilateral Clearing Facility (EMCF). EMCF, now merged with DTCC in the US to become EuroCCP, is an equity CCP for Nordic equity markets, including Denmark, Finland, and Sweden. The sample consists of trade records with time stamp, transaction size, transaction price, an (anonymized) counterparty ID, and information on whether it was a house- or client-account trade. A trade done on a house account is for a clearing member’s own book whereas a client-account trade is done on behalf of its customers.\textsuperscript{17} The sample runs from October 19, 2009, through September 10, 2010, and includes trades on almost all exchanges: NASDAQ-OMX, Chi-X, Bats, Burgundy, and Quote MTF. The only exchange with Nordic trades that it did not clear was Turquoise. Turquoise, however, had a market share of less than 1\% at the time.

An equity CCP insures counterparty risk for equity trades in the period that starts when a trade is concluded and ends when it settles. When an exchange concludes a trade, the money and the securities are not immediately transferred. Such transfer happens three days later in our sample. Should one side to the trade defaults in this period, the CCP inherits its position and the trade will follow through all the way to settlement.

A three-day deferred settlement is conceptually similar to a three-day forward contract between the two sides of the trade. To fix language, we therefore refer to yet-to-settle trades as “positions.” Note that these positions change overnight absent any trade. This change is simply due to settlement of legacy trades and these trades are therefore removed from member positions. In other words, if a member does not trade for three consecutive days, his position in all equities becomes zero as all his earlier trades settled. Finally, we refer to a member’s set of open positions at any point in time as his portfolio. We emphasize that this should not be confused with a member’s portfolio in terms of its equity holdings. It simply refers to the \textsuperscript{17}The post-crisis EMIR regulation in Europe requires a CCP to segregate trades on house accounts from those on client accounts as of 2013. Our data sample precedes this date but EMCF had already implemented such segregation.
Table 1: Summary statistics. This table presents various summary statistics for the CCP data sample. Trades on house accounts are done for a clearing member’s own book. Trades on client accounts are done for clients.

Panel A: General information

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of trading days</td>
<td></td>
<td></td>
<td>228</td>
</tr>
<tr>
<td>Number of stocks</td>
<td></td>
<td></td>
<td>242</td>
</tr>
<tr>
<td>Number of accounts</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>House accounts</td>
<td></td>
<td></td>
<td>87</td>
</tr>
<tr>
<td>Client accounts</td>
<td></td>
<td></td>
<td>139</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td>226</td>
</tr>
</tbody>
</table>

Panel B: Trade information across stocks

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean of daily number of trades</td>
<td>590</td>
<td>1,056</td>
<td>102</td>
</tr>
<tr>
<td>Mean of daily volume (shares)</td>
<td>398,922</td>
<td>1,074,108</td>
<td>33,143</td>
</tr>
<tr>
<td>Mean of daily volume (euro)</td>
<td>4,521,293</td>
<td>9,767,987</td>
<td>371,674</td>
</tr>
</tbody>
</table>

Panel C: Trade information across clearing members (by account type)

<table>
<thead>
<tr>
<th></th>
<th>All accounts</th>
<th>House accounts</th>
<th>Client accounts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean of end-of-day position (euro)</td>
<td>0</td>
<td>-11,237</td>
<td>11,567</td>
</tr>
<tr>
<td>Standard deviation of end-of-day position (euro)</td>
<td>1,535,067</td>
<td>1,880,137</td>
<td>1,069,244</td>
</tr>
<tr>
<td>Within-member standard deviation end-of-day position (euro)</td>
<td>619,105</td>
<td>988,685</td>
<td>387,785</td>
</tr>
</tbody>
</table>

yet-to-settle trades as these are relevant for CCP exposure since it is for these open positions that the CCP insures counterparty risk.

4.1 Data

Summary statistics. Table 1 introduces the sample by presenting various summary statistics. The sample captures trading in 242 stocks on 228 days. It contains 226 trading accounts, 87 of which are house accounts and the remaining 139 are client accounts.

The table shows that Nordic stocks are reasonably actively traded leading to substantial variation in account positions. On average a stock trades 590 times per day generating an average volume of €4.5 million. The standard deviation in account positions is €1.5 million. The corresponding within-account standard deviation is relatively modest: €0.6 million. In other words, most variation in positions is across accounts. Separating between house and client accounts shows that house-account positions tend to be larger in magnitude. Their standard deviation is €1.9 million whereas it is €1.1 million for client accounts. By the way, it is not surprising that we find an average position of zero as for every buyer there is a seller.
4.2 Implementation issues

Volume clock to recover normally distributed returns. It is well known that financial returns are not normally distributed when sampled using the wall clock. Returns exhibit negative skewness and excess kurtosis especially at high frequencies. However, the financial econometrics/microstructure literature has shown that normality of security returns can be recovered when time is measured on a volume-clock as opposed to the wall-clock (Clark (1973), Ané and Geman (2000), Easley et al. (2012)). When using a volume clock, security prices are sampled each time a pre-specified amount of volume has been traded. It turns out returns based on such prices are much closer to being normally distributed with less negative skewness and less excess kurtosis.

As normally distributed portfolio returns are needed for computing $ExpCCP$, we will use a volume clock in our empirical analysis inspired by Easley et al. (2012). We pick the average number of volume bins per day to be equal to 34. This corresponds to a 15-minute frequency on the wall clock as the market is open from 9:00 to 17:30. The bin size therefore is picked to be the average daily euro volume divided by 34. The choice for a 15-minute frequency is common in the microstructure literature as it strikes a balance between sample size and microstructure noise (Hansen and Lunde 2006). As a robustness check, we consider other frequencies as well (see Section 5.1 and Appendix E.3).

Our implementation follows the volume-clock literature except for two notable differences. First, instead of creating the clock security by security based on security-specific volume, we group all securities together and implement the clock based on group volume. Suppose the clock starts now, then the latest prices known now are stacked into a vector. If the volume bin is one million euros, then we wait until one million euros were traded across all securities, and at that moment we again stack the latest prices of all securities into a vector. Returns are then computed based standard log differencing. The benefit of this approach is that we have a unified (market) volume clock. Second, the wall clock is not completely ignored as we reset the volume clock at market open. This way the analysis avoids mixing in overnight effects and thus remains cleanly focused on intraday exposures only.

To assess whether volume-clock returns are indeed closer to normal than wall-clock returns we compute both for various member portfolios. Wall-clock returns are based on 15-minute intervals. Table 2 presents skewness of returns, their excess kurtosis, and the Jarque-Bera statistic which includes both skewness and

---

18 More specifically, the conversion of portfolio-return correlations to portfolio-loss correlations is done with the $M$ function in (15) which relies on normality.
Table 2: Statistics on member portfolio returns: Wall- versus volume-clock. This table presents various statistics based on realized euro returns for member portfolios. These statistics are presented for wall-clock and volume-clock returns to assess to what extent the returns are normally distributed. The statistics include skewness, excess kurtosis, and the Jarque-Bera statistic. The latter combines the former to and is computed as \((S^2 + K^2/4)/6\), where \(S\) is skewness and \(K\) is excess kurtosis. The clock runs in 15-minute intervals for the wall-clock and for a bin size that, on average, makes a volume bin last 15 minutes. Statistics are presented for the largest five members in terms of volume, for all five pooled, and for all members pooled.

<table>
<thead>
<tr>
<th>Member</th>
<th>Skewness Wall-clock</th>
<th>Skewness Volume-clock</th>
<th>Kurtosis Wall-clock</th>
<th>Kurtosis Volume-clock</th>
<th>Jarque-Bera Wall-clock</th>
<th>Jarque-Bera Volume-clock</th>
</tr>
</thead>
<tbody>
<tr>
<td>Largest</td>
<td>-0.29</td>
<td>-0.24</td>
<td>8.69</td>
<td>3.42</td>
<td>3.16</td>
<td>0.50</td>
</tr>
<tr>
<td>2nd largest</td>
<td>1.50</td>
<td>0.01</td>
<td>30.66</td>
<td>3.16</td>
<td>39.54</td>
<td>0.42</td>
</tr>
<tr>
<td>3rd largest</td>
<td>1.96</td>
<td>0.37</td>
<td>109.55</td>
<td>3.96</td>
<td>500.69</td>
<td>0.66</td>
</tr>
<tr>
<td>4th largest</td>
<td>-0.47</td>
<td>-0.05</td>
<td>15.51</td>
<td>1.97</td>
<td>10.06</td>
<td>0.16</td>
</tr>
<tr>
<td>5th largest</td>
<td>1.96</td>
<td>0.19</td>
<td>46.60</td>
<td>3.15</td>
<td>91.12</td>
<td>0.42</td>
</tr>
<tr>
<td>Largest 5 pooled</td>
<td>1.01</td>
<td>0.03</td>
<td>46.79</td>
<td>3.20</td>
<td>91.38</td>
<td>0.43</td>
</tr>
<tr>
<td>All pooled</td>
<td>-0.62</td>
<td>-0.19</td>
<td>205.47</td>
<td>18.46</td>
<td>1759.19</td>
<td>14.20</td>
</tr>
</tbody>
</table>

Kurtosis. Under the null of normality, these statistics are all zero in expectation. Return statistics are presented individually for the largest five clearing members, for all five pooled, and for all members pooled.

The results show strong evidence in favor of the volume-clock when returns are required to be normal. All three statistics are substantially smaller in magnitude for the five largest members. When pooled, skewness drops from 0.96 to 0.19, kurtosis drops from 46.60 to 3.15, and the Jarque-Bera statistic drops from 91.12 to 0.42. When considering all members instead of the largest five only, skewness decreases in magnitude from -0.61 to -0.19, kurtosis drops from 205.47 to 18.46, and Jarque-Bera drops from 1759.19 to 14.20. These statistics suggest that non-normality is indeed much less of an issue for volume-clock returns consistent with the literature.19

Estimation of time-varying return covariance. To account for time-varying volatility in returns, we estimate \(\Omega_t\) as the exponentially weighted moving average (EWMA) of the outer product of returns. This approach is in line with standard practice (e.g., RiskMetrics and EMCF) and corresponds to estimating an IGARCH(1,1).

What remains is to pick the EWMA decay parameter. RiskMetrics uses 0.94 for their highest frequency: daily returns. As round-the-clock variance is 38 times larger than the intraday 15-minute variance we pick

19Easley et al. (2012) sample E-mini future returns based on volume-clock and find similar evidence of partial recovery of normality.
the decay parameter to be 0.9984 (because 0.9984^{38} \approx 0.94). \( \Omega_t \) is therefore calculated recursively as:

\[
\Omega_t = (1 - 0.9984)R_{t-1}R'_{t-1} + 0.9984\Omega_{t-1}.
\]

(13)

The sample used for our analysis starts on December 7, 2009, but we use data as of October 19, 2009, to have a burn-in period for \( \Omega_t \). We start off the recursion with the zero matrix but given that 0.94 corresponds to a half-life of 11 days, the effect of this choice is negligible by the time we arrive at December 7, 2009.

Pick \( \alpha \) to make \( \text{ExpCCP} \) a 99% VaR. CPMI-IOSCO (2012) recommends that a CCP use a 99% VaR to set margins. We follow this lead and calibrate the alpha parameter in our delta-normal VaR to 2.5 to achieve an exceedance rate of 1%.21

5 Results

In this section we first present the time series of CCP exposure. Several salient spikes will be discussed. In the three subsequent subsections we test the three hypotheses of Section 2.

Figure 1 plots the time series of CCP exposure: \( \text{ExpCCP}_t \). Panel (a) plots exposure levels and shows one particularly strong spike in May 2010. This turns out to be the peak month of the Greek sovereign debt crisis.22 \( \text{ExpCCP} \) reached €5 million that month. That is, the 99% VaR of losses across all members in the oncoming volume bin is €5 million. Although such level is about triple the average level, it is still a relatively moderate amount and will not cause a systemic crisis in and of itself. As stated in the introduction, equity CCPs are unlikely to be systemic but as CCP data is extremely scarce we are privileged to have access to such data. We believe that it is interesting to study \( \text{ExpCCP} \) dynamics (which is what we do in the remainder of the section) to test several hypotheses.

Elevated levels of CCP exposure in Nordic equity markets during the Greek sovereign debt crisis might sound surprising. It is, however, not that surprising given the literature on this crisis. For example, Mink 20

Given that overnight return variance is about four times the variance of an intraday 15-minute period, we update the covariance matrix after an overnight return \( R_{t-1} \) by:

\[
\Omega_t = (1 - 0.9984^4)R_{t-1}R'_{t-1} + 0.9984^4\Omega_{t-1} \text{ where } R_{t-1} = R_{t-1}/\sqrt{4}.
\]

Note that aggregate loss is not normal since it is the sum of truncated normals.

A review of the main events in this month is as follows. On May 5 mass protests erupted in Greece against the imposed austerity measures, with three deaths reported. This social unrest led to concerns that it could jeopardize the rescue package proposed by the European Union and the International Monetary Fund on May 2. To fund this intervention and future ones, the European Commission created the European Financial Stabilisation Mechanism on May 9 (EC 2010). On May 10, the European Central Bank announced the Securities Markets Program to address “dysfunctional” securities markets (ECB 2010).
Figure 1: CCP exposures, both levels and changes. This figure plots CCP exposure $Exp_{CCP}$. Panel (a) plots exposure levels and Panel (b) plots exposure changes. Each shaded area corresponds to one month (wider areas indicate a higher monthly volume as the clock runs in volume time).
Table 3: Decomposition of changes in CCP exposure. This table presents the composition of CCP exposure change for all changes and separately for the top 100 and top 10 increases. Panel A presents the decomposition in euro. Panel B presents the same decomposition but in percentages. The five components capture changes in security return volatilities (\(\text{RetVola}\)), security return correlations (\(\text{RetCorr}\)), the pricing level (\(\text{PrLevel}\)), outstanding member positions (\(\text{TrPosition}\)), and the extent of overlap in member positions (\(\text{TrCrowding}\)).

<table>
<thead>
<tr>
<th></th>
<th>Full sample</th>
<th>Top 100 (\Delta E_{xpCCP})</th>
<th>Top 10 (\Delta E_{xpCCP})</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: CCP exposure change decomposition in euro</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\text{RetVola})</td>
<td>272</td>
<td>10,949</td>
<td>69,311</td>
</tr>
<tr>
<td>(\text{RetCorr})</td>
<td>113</td>
<td>3,555</td>
<td>-89</td>
</tr>
<tr>
<td>(\text{PrLevel})</td>
<td>-133</td>
<td>3,195</td>
<td>-5,324</td>
</tr>
<tr>
<td>(\text{TrPosition})</td>
<td>14,255</td>
<td>38,002</td>
<td>39,445</td>
</tr>
<tr>
<td>(\text{TrCrowding})</td>
<td>443</td>
<td>8,186</td>
<td>15,571</td>
</tr>
<tr>
<td>(\Delta E_{xpCCP})</td>
<td>14,949</td>
<td>63,887</td>
<td>118,914</td>
</tr>
<tr>
<td><strong>Panel B: CCP exposure change decomposition in percentage</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\text{RetVola})</td>
<td>1.8%</td>
<td>17.1%</td>
<td>58.3%</td>
</tr>
<tr>
<td>(\text{RetCorr})</td>
<td>0.8%</td>
<td>5.6%</td>
<td>-0.1%</td>
</tr>
<tr>
<td>(\text{PrLevel})</td>
<td>-0.9%</td>
<td>5.0%</td>
<td>-4.5%</td>
</tr>
<tr>
<td>(\text{TrPosition})</td>
<td>95.4%</td>
<td>59.5%</td>
<td>33.2%</td>
</tr>
<tr>
<td>(\text{TrCrowding})</td>
<td>3.0%</td>
<td>12.8%</td>
<td>13.1%</td>
</tr>
<tr>
<td>(\Delta E_{xpCCP})</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

and De Haan (2013) find that news about the Greek bailout generally led to abnormal stock returns for European (including Nordic) banks: Positive returns for regulatory initiatives that favor banks, negative returns otherwise. Bhanot et al. (2014) find that Greek yield spread increases are associated with negative abnormal returns on financial stocks throughout Europe. Beetsma et al. (2013) document spillover effects from the Greek yield spread to those of other European countries and Candelon et al. (2011) find similar evidence when studying CDS on sovereign debt. We will revisit the Greek crisis when decomposing \(E_{xpCCP}\) in Section 5.2.

Panel (b) of Figure 1 plots exposure changes instead of levels. It shows that periods with high levels do not necessarily correspond to periods with disproportionate intraday increases. It is the latter that CPMI-IOSCO (2017) is particularly worried about when presenting its latest guidance on CCP risk management. The largest peak corresponds to the idiosyncratic event when Nokia announced earnings that were far below analyst expectations at noon on April 22, 2010. Its share price dropped by about 15% in subsequent minutes. Volume jumped and remained high throughout the afternoon, 400% above what volume was in the morning of that day. We revisit the Nokia event when decomposing \(\Delta E_{xpCCP}\) in Section 5.1.
5.1 H1: The drivers of CCP exposure changes are different in the (right) tail

Hypothesis 5.1 essentially states that extremely large sudden increases in CCP exposure are different in nature than regular changes. As discussed in the hypothesis development section (Section 2), they are likely to reflect a jump in volatility and elevated trading. There might also be crowding if members all tilt their portfolio to the single risk factor at the heart of the turbulence (in the later part of the section, we explore the Nokia event to illustrate). These stand in contrast to “average” changes in CCP exposure that we conjecture to mostly reflect member position changes due to trade.

To test the first hypothesis, we decompose CCP exposure changes into various components for three samples: the full sample and subsamples with the largest 100 and the largest 10 increases (see Section 3.2 for the change decomposition approach). Table 3 presents the decomposition results and yields the following insights. First, for the full sample exposure changes seem indeed driven only by member position changes: $TrPosition$ dominates all other components.

Second, when zooming in on the top-100 and top-10 increases, a different picture emerges. While $TrPosition$ drops to 59.5% and 33.2% respectively, two other components, volatility and crowding, grow much more important. While the volatility component makes up only 1.8% of exposure changes for the full sample, it jumps to 17.1% and 58.3% for the top-100 and top-10 increases, respectively. The crowding component is only 3.0% of exposure changes for the full sample but jumps to 12.8% and to 13.1% for the top-100 and top-10 increases, respectively.

Third, the price and correlation components remain small in the two subsamples. Overall, all of these findings support the hypothesis that extreme increases in CCP exposure are different in nature than overall changes. Specifically, while CCP exposure changes on average are close to completely driven by member position changes, extreme ones exhibit substantial contributions from volatility changes and changes in crowding.

In Appendix E we show that these findings are robust to changing the component sequencing, changing the estimate of the time-varying return covariance, and changing the sampling frequency. One notable result worth mentioning here is that for lower frequencies the difference between the full sample and the top-10 subsample gets attenuated. This highlights the importance of monitoring changes in CCP exposure at high

\[23\text{Note that percentages in this analysis can turn negative since they simply represent a component’s contribution scaled by total changes in CCP exposure.}\]
(a) Decomposition of $\Delta ExpCCP$ for bin 23 on April 22, 2010, 12:02:18 - 12:05:05

(b) Decomposition of $\Delta ExpCCP$ for all volume bins on April 22, 2010

Figure 2: Decomposition of the largest CCP exposure increase: The Nokia event. At noon on April 22, Nokia announced disappointing earnings which caused the stock price to drop by 15% in a few minutes on increase volume. CCP exposure rose steeply in the volume bin subsequent to the announcement. Panel (a) decomposes this exposure change into five components: security return volatility ($RetVola$), security return correlation ($RetCorr$), price level ($PrLevel$), position changes ($TrPosition$), and the extent of crowding in member positions ($TrCrowding$). Panel (b) zooms out and cumulates these components for the full day.

To illustrate these general findings, Figure 2 zooms in on the Nokia event. Panel (a) decomposes the exposure jump of €0.24 million immediately following Nokia’s disappointing announcement. A couple of features stand out. First, return volatility is by far the largest component: €0.30 million. Its effect is moderated by the price-level component being negative: €-0.06 million. In other words, Nokia volatility

24 For completeness we also did these robustness analyses for the empirical results on the second and third hypothesis. Again, the results do not change qualitatively. To conserve space we decided to only provide those robustness results upon request.
spikes due to a large negative return of about -15%, but relative volatility applies at a lower price level because of the negative return. It is the latter effect that is subsumed by the price-level component. Finally, the trade components are both positive implying that on average traders expand their positions in a way that leads to more crowding. These trade components are however dwarfed by the volatility component.

Panel (b) zooms out and shows how exposure built up throughout the day. Its most salient feature is that while the volatility spike dominates exposure change in the volume bin just after the event, it is only about a fifth of that day’s exposure increase. The reason is that volatility is only a major component in the bin just after the event, trade components dominate subsequent bins. The high volume in the afternoon therefore turns out to be due to traders expanding their positions, not reducing them. There is also elevated crowding but its contribution is only about 20% of the total contribution of trade components. Finally, traders do not seem to take substantial positions ahead of the Nokia announcement as all components only start to contribute substantially in the afternoon.

Perhaps the most important message of these Nokia results is that firm-specific shocks can have systemic impact through heightened CCP exposure. News that strikes like lightning causes volatility to spike and, more importantly, makes traders expand their positions in ways that lead to more concentration in their portfolios (i.e., crowding).

5.2 **H2: The structure of CCP exposure levels is different in the (right) tail**

The second hypothesis focuses on the highest exposure *levels* as opposed to the largest changes. Does one see evidence of elevated exposure concentration (i.e., crowding) either across members, across (a combination of) stocks, or across both? Such finding would raise concerns about market conditions that are potentially prone to fire-sale dynamics.

To verify whether the structure of CCP exposure is different in the tail, we decompose exposure for the full sample and for the subsamples of the top 10% and the top 1% CCP exposure levels (see Section 3.3 for details on the decomposition).\(^{25}\) The decomposition is done both across members and across stocks. We then compute the Herfindahl-Hirschman Index (HHI) along with shares of the largest 1, 5, and 10 contributors to measure the concentration level.

\(^{25}\)The reason for picking the top 10% here instead of the top 100 used in the previous subsection is that CCP exposure levels are very persistent as compared to exposure changes. The top 100 subsample is smaller than the top 10% sample and, therefore, when used in the level analysis it would essentially point to the same period of time. The same argument applies to picking the top 1% instead of the top 10.
Table 4: Decomposition of CCP exposure across members and across stocks. This table presents the results of decomposing CCP exposures across members and across stocks for the full sample and for subsamples with high levels. Various concentration measures are reported: the share of the member/stock with the largest contribution, the five largest contributors, and the 10 largest contributors. The table further reports the Herfindahl-Hirschman Index.

<table>
<thead>
<tr>
<th>Panel A: Decomposition of CCP exposure across traders</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full sample</td>
</tr>
<tr>
<td>Top 1 member</td>
</tr>
<tr>
<td>Top 5 members</td>
</tr>
<tr>
<td>Top 5 members</td>
</tr>
<tr>
<td>Herfindahl-Hirschman Index (HHI)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Decomposition of CCP exposure across stocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top 1 stock</td>
</tr>
<tr>
<td>Top 5 stocks</td>
</tr>
<tr>
<td>Top 10 stocks</td>
</tr>
<tr>
<td>Herfindahl-Hirschman Index (HHI)</td>
</tr>
</tbody>
</table>

Table 5: Principal component analysis of member portfolio returns. This table uses principal component analysis to characterize the commonality in member portfolio returns for the full sample and for subsamples where CCP exposure levels are large. It reports the size of the first, the second, and the third principal component along with the sum of these three.

<table>
<thead>
<tr>
<th>Full sample</th>
<th>Top 10% ExpCCP</th>
<th>Top 1% ExpCCP</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC1</td>
<td>7.8%</td>
<td>20.8%</td>
</tr>
<tr>
<td>PC2</td>
<td>5.2%</td>
<td>8.9%</td>
</tr>
<tr>
<td>PC3</td>
<td>2.7%</td>
<td>6.4%</td>
</tr>
<tr>
<td>PC1+PC2+PC3</td>
<td>15.7%</td>
<td>36.0%</td>
</tr>
</tbody>
</table>

Table 4 reveals that indeed concentration seems elevated in the tail but only for members, not for individual stocks. For all three share measures (i.e., share of the top 1, 5, and 10 members) the concentration increases substantially from the full sample to the top 1% sample. For example, the share of the largest five members increases from 27.8% to 34.9% for the top 10% and to 46.8% for the top 1%. The HHI index shows a similar trend and increases from 0.030 to 0.046 and 0.085, respectively. There is no such trend in the corresponding numbers for the decomposition across individual stocks. The share of the top five stocks, for example, stays rather flat. It changes from 43.3% to 48.9% for the top 10% and to 41.1% for the top 1%.

The unchanged concentration for the decomposition across stocks does not preclude crowding in a particular portfolio of stocks. To study whether this is the case, we apply principal component analysis (PCA) on member portfolio returns for the full sample and for both subsamples. Table 5 shows that there does appear to be elevated crowding in the subsamples. It is strongest for the first principal component (PC1) whose share in total variance increases from 7.8% in the full sample to 20.8% for the top 10% sample and to 37.6% for the top 1% sample. As the largest CCP exposures occur mostly in the Greek crisis period, it is likely that this component captures a market effect. To verify, we compute the correlation of PC1 with the
local market index and indeed find the pattern we expect: it is 0.43 for the full sample, 0.86 for the top 10% subsample, and 0.98 for the top 1% subsample.

Finally, to illustrate these results graphically Figure 3 plots the Herfindahl-Hirschman index for both the cross-member and the cross-stock decompositions (see Table 4). Panel (a) plots the cross-member HHI index in solid red and overlays the CCP exposure level in dashed blue (using the second y-axis). It illustrates that highest concentrations occur mostly in the Greek crisis period. Panel (b) plots the cross-stock HHI index and, as expected, shows that it stays rather flat at times where CCP exposure peaks. This does not mean that the cross-stock index is flat throughout. It does show the largest peak around the Nokia event when exposure increase is the largest as analyzed in the previous subsection. Upon further inspection we unsurprisingly find that the concentration occurs in the stock of Nokia.
Table 6: Decompositions CCP exposure across house and client accounts. Panel A decomposes CCP exposure across house and client accounts. Panel B shows the concentration of CCP exposure within each account type by means of the Herfindahl-Hirschman Index (HHI). Both panels consider the full sample and subsamples of the top 10% and the top 1% CCP exposure levels.

<table>
<thead>
<tr>
<th>Panel A: Contribution to CCP exposure by account type</th>
<th>Full sample</th>
<th>Top 10%</th>
<th>Top 1%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contribution by house accounts (%)</td>
<td>66.8%</td>
<td>66.0%</td>
<td>69.7%</td>
</tr>
<tr>
<td>Contribution by client accounts (%)</td>
<td>33.2%</td>
<td>34.0%</td>
<td>30.3%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Hirsch-Herfindahl index (HHI) within account type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Herfindahl-Hirschman Index (HHI) within house accounts</td>
</tr>
<tr>
<td>Herfindahl-Hirschman Index (HHI) within client accounts</td>
</tr>
</tbody>
</table>

5.3 H3: The relative contribution of house accounts increases in the (right) tail

The third hypothesis states that the relative contribution of house accounts is higher for extreme CCP exposure levels. This is potentially worrisome as clearing members are highly leveraged financial institutions.

Table 6 presents evidence largely rejecting the third hypothesis. The decomposition across house and client accounts in Panel A shows that house accounts contribute 66.8% to CCP exposure in the full sample. This contribution however hardly changes when measured for top 10% subsample (66.0%) and increases only mildly to 69.7% in the top 1% subsample.

Panel B shows that in spite of the relative contribution of all house accounts combined being rather flat across subsamples, there is concentration within house accounts. The Herfindahl-Hirschman index computed based on each member’s contribution to the total of house-account contributions increases from 0.051 for the full sample to 0.083 for the top 10% and to 0.160 for the top 1%. The results suggest that in stressed markets the positions in the books of some clearing members expand while the positions of others shrink. This causes their total contribution to CCP exposure to remain unchanged, yet there is more concentration within the set of house accounts.

There appears to be no such pattern for client accounts whose collective contribution remains flat across the three samples but also the within-client concentration remains largely unchanged. The HHI index is 0.068 for the full sample, 0.071 for the top 10% subsample, and 0.081 for the top 1% subsample.

In sum, the significantly higher concentration within house accounts is potentially worrisome. Most clearing members are highly leveraged sell-side banks who, if trading for speculative reasons, might default on their position if they turn out to be on the wrong side of the bet. Given that they seem to crowd on the same (set of) risk factors, there might be multiple members that are heavily under water on their bets at the same time. Admittedly, it is unlikely that they default on their equity trades, but if the pattern carries over to
CCPs that clear interest rate derivatives or credit default swaps, then such pattern does become a systemic worry.

6 Conclusion

In summary, we test three hypotheses about the exposure a CCP has vis-à-vis its clearing members. All three hypotheses focus on tail events and whether or not the nature of CCP exposure changes in such cases. The academic literature has emphasized elevated concentration (i.e., crowding) in such stressed markets with a risk of fire-sale price dynamics.

We develop an approach for monitoring CCP exposure whereby both exposure level and exposure changes can be decomposed to identify the relative contribution of various factors. The empirical results support the hypotheses that the nature of exposure levels or exposure changes is different in the tail: There is indeed more crowding in stressed markets. The hypothesized larger contribution of house accounts to total exposure in such conditions is not supported by the data. However, within house accounts there is more concentration with few clearing members contributing a disproportionate amount to total house-account exposure.

Our findings suggest that CCP executives and regulators should monitor at high frequency with a particular focus on tail events. Whether or not contingency planning is needed and if so, what form it should take, is for future research. We, however, believe that the approach we developed is useful for monitoring CCP exposure at high frequencies. The decompositions allow for immediate diagnostic analysis. As all results are analytic thus avoiding heavy-duty simulations, the approach can be implemented in real-time. This we believe is an asset in today’s extremely fast markets.
Appendix

A Results needed to compute ExpCCP

Let $L_t$ be the $J \times 1$ vector that stacks all $L_{jt}$. Since $A_t = \sum_j L_{jt}$, one needs to compute $E(L_t)$ and $\text{var}(L_t)$ to evaluate (4). Following Menkveld (2017, Proposition 1) yields the following two results:

\[ E(L_t) = \mu_t, \quad \mu_{jt} = \sqrt{\frac{1}{2\pi}} \sigma_{jt}, \]
\[ \text{var}(L_t) = \Psi_t, \quad \psi_{ij,t} = \frac{\pi - 1}{2\pi} \sigma_{i,t} \sigma_{j,t} M(\rho_{ij,t}). \]  

(14)

where $\sigma_{ij,t}$ is the $(i, j)$-th element of the covariance matrix of member portfolio returns $\Sigma_t$, $\sigma_{i,t}$ is short for $\sigma_{ii,t}$, and $\rho_{ij,t} = \sigma_{ij,t}/\sigma_{i,t} \sigma_{j,t}$. The function

\[ M(\rho) = \left[ \left( \frac{1}{2\pi} + \arcsin(\rho) \right) \rho + \sqrt{1 - \rho^2} - 1 \right] / (\pi - 1) \]

maps portfolio return correlations into portfolio loss correlations. Detailed proofs are in Menkveld (2017).

$ExpCCP$ can now be written explicitly as:

\[ ExpCCP_t = \sum_j \sqrt{\frac{1}{2\pi}} \sigma_{jt} + \alpha \left( \sum_i \sum_j \frac{\pi - 1}{2\pi} \sigma_{i,t} \sigma_{j,t} M(\rho_{ij,t}) \right)^{\frac{1}{2}}. \]

(16)

B Decomposition of CCP exposure change

This section presents the various components that add up to CCP exposure change:

\[ \Delta ExpCCP_t = \text{RetVolatility}_t + \text{RetCorrelation}_t + \text{PrLevel}_t + \text{TrPosition}_t + \text{TrCrowding}_t. \]

(17)

Price components. The three price components are:

\[ \text{RetVolatility}_t = f \left( D\left( D_{\Omega_t}, R_{\Omega_{t-1}}, P_{t-1}, \tilde{N}_{t-1} \right), R\left( D_{\Omega_t}, R_{\Omega_{t-1}}, P_{t-1}, \tilde{N}_{t-1} \right) \right) - f \left( D\left( D_{\Omega_{t-1}}, R_{\Omega_{t-1}}, P_{t-1}, \tilde{N}_{t-1} \right), R\left( D_{\Omega_{t-1}}, R_{\Omega_{t-1}}, P_{t-1}, \tilde{N}_{t-1} \right) \right), \]

(18)
\[ \text{RetCorr}_t = f\left(D\left(D_{\Omega t}, R_{\Omega t}, P_{t-1}, \tilde{N}_{t-1}\right), R\left(D_{\Omega t}, R_{\Omega t}, P_{t-1}, \tilde{N}_{t-1}\right)\right) \]
\[ - f\left(D\left(D_{\Omega t}, R_{\Omega t}, P_{t-1}, \tilde{N}_{t-1}\right), R\left(D_{\Omega t}, R_{\Omega t}, P_{t-1}, \tilde{N}_{t-1}\right)\right), \text{ and} \]
\[ \text{PrLevel}_t = f\left(D\left(D_{\Omega t}, R_{\Omega t}, P_t, \tilde{N}_{t-1}\right), R\left(D_{\Omega t}, R_{\Omega t}, P_t, \tilde{N}_{t-1}\right)\right) \]
\[ - f\left(D\left(D_{\Omega t}, R_{\Omega t}, P_{t-1}, \tilde{N}_{t-1}\right), R\left(D_{\Omega t}, R_{\Omega t}, P_{t-1}, \tilde{N}_{t-1}\right)\right). \]

**Trade components.** The two trade components are:

\[ \text{TrPosition}_t = f\left(D\left(D_{\Omega t}, R_{\Omega t}, P_t, \tilde{N}_{t}\right), R\left(D_{\Omega t}, R_{\Omega t}, P_t, \tilde{N}_{t}\right)\right) \]
\[ - f\left(D\left(D_{\Omega t}, R_{\Omega t}, P_t, \tilde{N}_{t}\right), R\left(D_{\Omega t}, R_{\Omega t}, P_t, \tilde{N}_{t}\right)\right) \text{ and} \]
\[ \text{TrCrowding}_t = f\left(D\left(D_{\Omega t}, R_{\Omega t}, P_t, \tilde{N}_{t}\right), R\left(D_{\Omega t}, R_{\Omega t}, P_t, \tilde{N}_{t}\right)\right) \]
\[ - f\left(D\left(D_{\Omega t}, R_{\Omega t}, P_t, \tilde{N}_{t}\right), R\left(D_{\Omega t}, R_{\Omega t}, P_t, \tilde{N}_{t}\right)\right). \]

**C Example of CCP exposure change analysis**

Table 7 presents a simple example to illustrate the insights that one can get from a decomposition of CCP exposure changes. Suppose there are four agents (A1, A2, A3, A4) and two securities (S1 and S2) that cost \( \varepsilon 1 \) and have returns that are standard normal and mutually independent at least at the beginning of time. All agents start with a zero position in the securities. To illustrate real-time CCP exposure monitoring we consider a particular sequence of events. We compute CCP exposure change after each event and present its decomposition. This controlled setting serves to familiarize with the approach before implementing it on real-world data.

The first two columns of Table 7 describe the sequence of events. CCP exposure is computed after each event based on the loss distribution for the oncoming period. In some cases, events are illustrated by horizontal arrows that correspond to positions in the first security. Arrows that point right denote long positions. Left arrows denote short positions. Vertical arrows correspond to positions in the second security. Up arrows denote long positions. Down arrows denote short positions. The remaining columns show CCP exposure, its change, and the decomposition of this change into the five factors. These changes and decompositions are discussed below.

- **t = 0.** CCP exposure is 0 for the simple reason that none of agents has a position.
Table 7: Simple example to illustrate the decomposition of CCP exposure changes. This example illustrates how the one-factor-at-a-time decomposition approach identifies the different components in CCP exposure changes. There are four agents ($A1, A2, A3, A4$) and two securities ($S1, S2$). Arrows denote positions in these securities. Arrows right and left illustrate long and short positions in $S1$, respectively, arrows up and down illustrate long and short positions in $S2$, respectively. Red dashed arrows correspond to new trades. CCP exposures are computed with $\alpha = 2.5$, which is the calibrated value based on our real-world sample (see Section 4.2).

$$\Delta \text{ExpCCP}_t = \text{RetVol}_t + \text{RetCorr}_t + \text{PrLevel}_t + \text{TrPosition}_t + \text{TrCrowding}_t$$

<table>
<thead>
<tr>
<th>$t$</th>
<th>Trades/changes</th>
<th>$\text{ExpCCP}_t$</th>
<th>$\Delta \text{ExpCCP}_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>$\sigma_1 = \sigma_2 = 1$, $\rho = 0, p_1 = p_2 = 1$.</td>
<td>0.0</td>
<td>0.0 0.0 0.0 0.0 0.0 0.0</td>
</tr>
<tr>
<td>1</td>
<td>$A2 \rightarrow A1$</td>
<td>2.3</td>
<td>2.3 0.0 0.0 0.0 2.9 -0.6</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>3.7</td>
<td>1.4 0.0 0.0 0.0 1.8 -0.4</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
<td>5.7 2.0 2.0 0.0 0.0 0.0 0.0</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>$A4 \rightarrow A3 \rightarrow A1$</td>
<td>6.7</td>
<td>2.8 0.0 0.0 0.0 1.5 1.3</td>
</tr>
<tr>
<td>7</td>
<td>$A4 \rightarrow A2 \rightarrow A3 \rightarrow A1$</td>
<td>4.6</td>
<td>-2.1 0.0 0.0 0.0 -2.0 -0.1</td>
</tr>
</tbody>
</table>
• $t = 1$. $A1$ entered a long position of one unit on $S1$ and $A2$ is on the opposite side of that trade. CCP exposure becomes €2.3. The decomposition shows that €2.9 is due to expanded positions ($TrPosition$) and the crowding component is €-0.6 ($TrCrowding$). The reason for this negative crowding term is simply that in this case the members have taken the opposite side of the same trade and their portfolio returns are therefore perfectly negatively correlated.

• $t = 2$. $A3$ entered a long position of one unit in $S2$ with $A4$ taking the short side. CCP exposure increases by €1.4 to €3.7. The decomposition shows a positive $TrPosition$ of €1.8 and a negative $TrCrowding$ of €-0.4. The positive position risk is due to the new trade leading to larger positions. Furthermore, the new trade between $A3$ and $A4$ is in $S2$ and therefore orthogonal to the positions between $A1$ and $A2$. In other words, the new trade between $A3$ and $A4$ lowers the correlations between member portfolio returns. Hence, there is less crowding now than before.

• $t = 3$. The return volatility of $S1$ increased from 1 to 2. CCP exposure increases by €2.0 to €5.7. The decomposition indeed attributes it to the volatility component ($RetVola$).

• $t = 4$. The correlation between the returns of $S1$ and $S2$ increased from 0 to 0.5. CCP exposure increases by €0.3 to €6.0. The decomposition assigns it to the correlations component ($RetCorr$).

• $t = 5$. The price of $S1$ drops from €1 to €0.5. CCP exposure drops by €2.1 which is completely assigned to the price level ($PrLevel$). This is simply the result of volatility being defined in relative terms. If it does not change, but the price level drops then the VaR which is expressed in euro drops.

• $t = 6$. $A3$ traded again with $A4$ but this time he entered a one-unit long position in $S1$ where $A4$ takes the short side. CCP exposure increases by €2.8 to €6.7. Positions now crowd on the risk factor $S1$. The decomposition assigns €1.3 of the increase to $TrCrowding$ and the remaining €1.5 to $TrPosition$.

• $t = 7$. $A3$ and $A4$ effectively undid their first trade by entering a reverse trade. In this reverse trade $A3$ is long one unit of $S2$ and $A4$ is short one unit. CCP exposure declines by €2.1 to €4.6. The decomposition shows that most of the decrease is due to a reduction in outstanding (net) positions (i.e., the drop is largely assigned to $TrPosition$). This event shows that trade does not necessarily imply more exposure, it could reduce exposure when, after the trade, positions shrink. Note that combining $t = 6$ and $t = 7$ the size of trade positions have not changed — members are long or short the same amount of risk — but CCP exposure has increased due crowding.
In summary, the decompositions of CCP exposure changes generate insight into the drivers of these changes. 

*TrPosition* picks up whether new trades extend or reverse legacy positions. *TrCrowding* captures the correlation of member portfolio returns. *RetVola, RetCorr*, and *PrLevel* identify exposure changes due to changes in the volatility of returns, their correlations, and price levels, respectively.

### D  Decomposition of CCP exposure across securities

*ExpCCP* being homogeneous of degree one in $\omega_k$ yields: \(^{26}\)

$$
\text{ExpCCP} = \sum_i \omega_k \left( \frac{\partial}{\partial \omega_k} \text{ExpCCP} \right).
$$

(23)

The contribution of security $k$ therefore is:

$$
\text{ExpCCP}_k = \sum_{i,j} \omega_k \left( \frac{\partial}{\partial \omega_k} \text{ExpCCP} \right)
= \sum_j \sqrt{\frac{1}{2\pi} \frac{B_{jj}}{2\sigma_j} + 
+ \frac{\alpha}{2\sigma_A} \sum_{i,j} \left( \frac{\pi - 1}{2\pi} \right) \left( M' \left( \rho_{ij} \right) B_{ij} \right)
+ \frac{\sqrt{1 - \rho_{ij}^2}}{\pi - 1} \left( \frac{\sigma_j}{2\sigma_i} B_{ii} + \frac{\sigma_i}{2\sigma_j} B_{jj} \right)},
$$

(24)

where

$$
B_{ij} = n_i' \frac{\partial \Omega}{\partial \omega_k} n_j, \quad M' \left( \rho_{ij} \right) = \frac{\frac{1}{2}\pi + \arcsin \left( \rho_{ij} \right)}{\pi - 1}.
$$

(25)

### E  Robustness checks

#### E.1  Alternative sequencing in exposure change decomposition

The decomposition of CCP exposure change presented in Table 3 and discussed in Section 5.1 critically depends on the sequencing of the various components. To verify how robust the decomposition results are to alternative sequences, we redo the analysis across all possible alternatives inspired by Hasbrouck (1995). As the components belong to two groups (that are preserved in the sequencing) we end up with $2 \times 3! \times 2! = 24$ possible sequences.

---

\(^{26}\)Note that each element $\omega_{ij}$ of the covariance matrix $\Omega$ can be written as $\rho_{ij} \omega_i \omega_j$ where $\rho_{ij}$ denotes the elements of the accompanying correlation matrix. This should clarify what homogeneity or a partial derivative with respect to $\omega_k$ is.
Table 8: Decomposition of exposure change for alternative component sequences. This table presents the mean and, in brackets, the lower and the upper bound of the (relative) share of components across alternative sequences of the various components. It serves as a robustness check for Table 3 which is based on a particular economically motivated sequence. The price and trade variables are kept together as a group so the number of sequences considered is $2 \times 3! \times 2! = 24$.

<table>
<thead>
<tr>
<th>Component</th>
<th>Full sample</th>
<th>Top 100 $\Delta$ExpCCP</th>
<th>Top 10 $\Delta$ExpCCP</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A</strong>: CCP exposure change decomposition in euro</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RetVola</td>
<td>275</td>
<td>11,003</td>
<td>69,022</td>
</tr>
<tr>
<td></td>
<td>(263, 288)</td>
<td>(1,058, 1,1427)</td>
<td>(65,622, 72,392)</td>
</tr>
<tr>
<td>RetCorr</td>
<td>115</td>
<td>3,612</td>
<td>215</td>
</tr>
<tr>
<td></td>
<td>(112, 118)</td>
<td>(3,555, 3,669)</td>
<td>(-93, 534)</td>
</tr>
<tr>
<td>PrLevel</td>
<td>-132</td>
<td>3,363</td>
<td>-3,619</td>
</tr>
<tr>
<td></td>
<td>(-136, -128)</td>
<td>(3,171, 3,555)</td>
<td>(-5,390, -1,881)</td>
</tr>
<tr>
<td>TrPosition</td>
<td>14,598</td>
<td>38,656</td>
<td>39,875</td>
</tr>
<tr>
<td></td>
<td>(14,245, 14,951)</td>
<td>(37,609, 39,723)</td>
<td>(37,246, 42,661)</td>
</tr>
<tr>
<td>TrCrowding</td>
<td>93</td>
<td>7,253</td>
<td>13,421</td>
</tr>
<tr>
<td></td>
<td>(-253, 439)</td>
<td>(6,347, 8,180)</td>
<td>(11,435, 15,565)</td>
</tr>
<tr>
<td>$\Delta$ExpCCP</td>
<td>14,949</td>
<td>63,887</td>
<td>118,914</td>
</tr>
<tr>
<td><strong>Panel B</strong>: CCP exposure change decomposition in percentage</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RetVola</td>
<td>1.8%</td>
<td>17.2%</td>
<td>58.0%</td>
</tr>
<tr>
<td></td>
<td>(1.8%, 1.9%)</td>
<td>(16.6%, 17.9%)</td>
<td>(55.2%, 60.9%)</td>
</tr>
<tr>
<td>RetCorr</td>
<td>0.8%</td>
<td>5.7%</td>
<td>0.2%</td>
</tr>
<tr>
<td></td>
<td>(0.8%, 0.8%)</td>
<td>(5.6%, 5.7%)</td>
<td>(-0.1%, 0.4%)</td>
</tr>
<tr>
<td>PrLevel</td>
<td>-0.9%</td>
<td>5.3%</td>
<td>-3.0%</td>
</tr>
<tr>
<td></td>
<td>(-0.9%, -0.9%)</td>
<td>(5%, 5.6%)</td>
<td>(-4.5%, -1.6%)</td>
</tr>
<tr>
<td>TrPosition</td>
<td>97.7%</td>
<td>60.5%</td>
<td>33.5%</td>
</tr>
<tr>
<td></td>
<td>(95.3%, 100%)</td>
<td>(58.9%, 62.2%)</td>
<td>(31.3%, 35.9%)</td>
</tr>
<tr>
<td>TrCrowding</td>
<td>0.6%</td>
<td>11.4%</td>
<td>11.3%</td>
</tr>
<tr>
<td></td>
<td>(-1.7%, 2.9%)</td>
<td>(9.9%, 12.8%)</td>
<td>(9.6%, 13.1%)</td>
</tr>
<tr>
<td>$\Delta$ExpCCP</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
</tr>
</tbody>
</table>
Table 9: Decomposition of exposure change for a rolling-window estimate of return covariance. This table repeats the exposure-change decompositions reported in Table 3 and adds decompositions based a 50-day rolling-window estimate of return covariance instead of the EWMA estimate used in the baseline decompositions.

<table>
<thead>
<tr>
<th></th>
<th>EWMA estimate of Cov(R)</th>
<th>Rolling-window estimate of Cov(R)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full sample</td>
<td>Top 100</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Panel A: CCP exposure change decomposition in euro</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RetVola</td>
<td>272</td>
<td>10,949</td>
</tr>
<tr>
<td>RetCorr</td>
<td>113</td>
<td>3,555</td>
</tr>
<tr>
<td>PrLevel</td>
<td>-133</td>
<td>3,195</td>
</tr>
<tr>
<td>TrPosition</td>
<td>14,255</td>
<td>38,002</td>
</tr>
<tr>
<td>TrCrowding</td>
<td>443</td>
<td>8,186</td>
</tr>
<tr>
<td>ΔExpCCP</td>
<td>14,949</td>
<td>63,887</td>
</tr>
<tr>
<td>Panel B: CCP exposure change decomposition in percentage</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RetVola</td>
<td>1.8%</td>
<td>17.1%</td>
</tr>
<tr>
<td>RetCorr</td>
<td>0.8%</td>
<td>5.6%</td>
</tr>
<tr>
<td>PrLevel</td>
<td>-0.9%</td>
<td>5.0%</td>
</tr>
<tr>
<td>TrPosition</td>
<td>95.4%</td>
<td>59.5%</td>
</tr>
<tr>
<td>TrCrowding</td>
<td>3.0%</td>
<td>12.8%</td>
</tr>
<tr>
<td>ΔExpCCP</td>
<td>100.0%</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

The results in Table 8 show that the decomposition results appear robust. The table reports the mean, the lower and the upper bound of each component’s contribution across all 24 sequences. The distance between the lower and upper bounds seems small as it is only a few percentage points for the relative shares reported in Panel B, never exceeding 6%. The key observations in the main text all hold up: The position component dominates all other components for the full sample, but volatility and crowding become much more important when considering only the top-100 and the top-10 exposure changes.

E.2 Moving-window return covariance estimate

The exposure change decomposition analysis presented in Table 3 relies on a EWMA estimate of the covariance matrix of returns. To verify whether the results are robust we redo the analysis with a rolling-window estimate of return covariance. For the length of the window we picked the burn-in period used for EWMA (i.e., 50 days). We have considered other alternatives such as parametric estimation of the time-varying covariance matrix. One natural approach is to estimate a multivariate GARCH but implementation is infeasible given the large dimensions of the covariance matrix that needs to be estimated: 242 × 242. We therefore stick to a parameter-free estimate but this time based it on a rolling window.

Table 9 shows that the decomposition results when using a rolling-window estimate are similar to the ones using an EWMA estimate. Importantly, the key observations in the main text all hold up: The position component dominates all other components for the full sample, but volatility and crowding become much
**Table 10: Decomposition of exposure change for different frequencies.** This table repeats the exposure-change decompositions of Table 3 and adds decompositions based on lower frequencies. The baseline result is based on having, on average, 34 volume bins per day which corresponds to 15-minute intervals. The added frequencies are 17 and 8 and therefore correspond to 30-minute and 1-hour intervals, respectively.

<table>
<thead>
<tr>
<th></th>
<th>Baseline: 34 bins per day (15-minute intervals)</th>
<th>17 bins per day (30-minute intervals)</th>
<th>8 days per day (1-hour intervals)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full sample</td>
<td>Top 10</td>
<td>Full sample</td>
</tr>
</tbody>
</table>

**Panel A: CCP exposure change decomposition in euro**

<table>
<thead>
<tr>
<th></th>
<th>Full sample</th>
<th>Top 10</th>
<th>Full sample</th>
<th>Top 10</th>
<th>Full sample</th>
<th>Top 10</th>
</tr>
</thead>
<tbody>
<tr>
<td>RetVola</td>
<td>272</td>
<td>69,311</td>
<td>984</td>
<td>89,104</td>
<td>3,881</td>
<td>276,342</td>
</tr>
<tr>
<td>RetCorr</td>
<td>113</td>
<td>-89</td>
<td>316</td>
<td>14,133</td>
<td>683</td>
<td>26,155</td>
</tr>
<tr>
<td>PrLevel</td>
<td>-133</td>
<td>-5,324</td>
<td>-351</td>
<td>-20,163</td>
<td>-1,603</td>
<td>-24,318</td>
</tr>
<tr>
<td>TrPosition</td>
<td>14,255</td>
<td>39,445</td>
<td>38,730</td>
<td>101,854</td>
<td>123,654</td>
<td>327,711</td>
</tr>
<tr>
<td>TrCrowding</td>
<td>443</td>
<td>15,571</td>
<td>1,279</td>
<td>22,431</td>
<td>5,052</td>
<td>77,654</td>
</tr>
<tr>
<td>∆ExpCCP</td>
<td>14,949</td>
<td>118,914</td>
<td>40,959</td>
<td>207,359</td>
<td>131,667</td>
<td>683,545</td>
</tr>
</tbody>
</table>

**Panel B: CCP exposure change decomposition in percentage**

<table>
<thead>
<tr>
<th></th>
<th>Full sample</th>
<th>Top 10</th>
<th>Full sample</th>
<th>Top 10</th>
<th>Full sample</th>
<th>Top 10</th>
</tr>
</thead>
<tbody>
<tr>
<td>RetVola</td>
<td>1.8%</td>
<td>58.3%</td>
<td>2.4%</td>
<td>43.0%</td>
<td>2.9%</td>
<td>40.4%</td>
</tr>
<tr>
<td>RetCorr</td>
<td>0.8%</td>
<td>-0.1%</td>
<td>0.8%</td>
<td>6.8%</td>
<td>0.5%</td>
<td>3.8%</td>
</tr>
<tr>
<td>PrLevel</td>
<td>-0.9%</td>
<td>-4.5%</td>
<td>-0.9%</td>
<td>-9.7%</td>
<td>-1.2%</td>
<td>-3.6%</td>
</tr>
<tr>
<td>TrPosition</td>
<td>95.4%</td>
<td>33.2%</td>
<td>94.6%</td>
<td>49.1%</td>
<td>93.9%</td>
<td>47.9%</td>
</tr>
<tr>
<td>TrCrowding</td>
<td>3.0%</td>
<td>13.1%</td>
<td>3.1%</td>
<td>10.8%</td>
<td>3.8%</td>
<td>11.4%</td>
</tr>
<tr>
<td>∆ExpCCP</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

more important when considering only the top-100 and the top-10 exposure changes.

**E.3 Alternative sampling frequencies**

Is high-frequency analysis important for the decomposition results presented in Table 3? Note that the volume bins were chosen such that, on average, they span fifteen minutes. A higher frequency is computationally feasible but economically impossible as “microstructure noise” starts to bias return covariance estimates (Andersen et al. 2003). Lower frequency, however, is possible and in this section we redo the decomposition based on volume bins that, on average, span 30 minutes or a full hour.

Table 10 presents the results but only reports full-sample and top-10 decompositions to save space. The table shows that the main results are unaffected: the position component dominates in the full sample, but volatility and crowding become important in top-10 subsample. These results however become attenuated when the analysis is done at the lower frequency. That is, the contribution of volatility and crowding drops in the top-10 subsample. This result testifies to the importance of high-frequency analysis of CCP exposure changes to diagnose the nature of trading during brief spells of volatility spikes and extreme volume.
References


