Empirically evaluating systemic risks in CCPs: Evidence from two CDS CCPs*

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Abstract

We empirically evaluate the systemic stability of two large CDS CCPs. We show that positive correlations between the exposures of large dealers could lead to substantially larger combined stress losses to a CCP than if we consider dealers in isolation. These results highlight crowded trade concerns. We then study the risk faced by a set of CCPs from the clearing activities of their common dealers. We that the high positive correlations in exposures of dealers across CCPs can lead to dealers experiencing large losses to both CCP simultaneously. Our study illustrates the potential for contagion of stress through CCPs.

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1 Introduction

While there is a growing body of theoretical research analyzing how systemic risk could arise in the context of central clearing (see, e.g., Duffie (2010), Duffie and Zhu (2011)), as well as optimal CCP design (Duffie (2014); Biais, Heider, and Hoerova (2016)) empirically we know little about the extent to which central clearing contributes to systemic fragility.[1] Understanding this question is important to both regulators and academics as central clearing is concentrated – only a small number of CCPs typically clear the same or similar products, while the set of significant clearing dealers is largely limited to a collection of ten to twenty large financial institutions.[2] In this setting, stresses that impact one CCP are likely to impact another CCP, either directly through the default of a common member or indirectly through a non-trivial correlation with other cleared products.

Using a supervisory data set of the weekly CDS positions of the major CDS clearing dealers, we empirically evaluate the systemic stability of two large CCPs. Using market shocks as severe as those during the most recent U.S. and the European financial crises, we show that the stress losses of large dealers could be substantial even if the total net exposure of a dealer appears small. This suggests that the riskiness and the co-movement between different reference entities may play a substantial role in overall clearing member vulnerability in times of stress. Next, we compare the risk a single CCP faces from the clearing activity of each individual clearing member with that from the simultaneous activity of all large members. This is useful in understanding the empirical relevance of the commonality in clearing member portfolios in setting margin requirements. While existing margin requirements typically treat each dealer in isolation, Menkveld (2016) shows theoretically that crowded trades of dealers could amplify CCP stress losses beyond previously-posted margins. Consistent with that idea we show that (persistent) positive correlations between

[1] See Benoit et al. (2016) for a review of the systemic risk literature. See also Zawadowski (2013); Biais, Heider, and Hoerova (2016); Menkveld (2016); Lin and Surti (2015)); Amini, Filipovic, and Minca (2015); Koeppl, Monnet, and Temzelides (2012).

[2] See Ali, Vause, and Zikes (2016) and Getmansky, Girardi, and Lewis (2016).

the exposure of large members of a CCP could lead to substantially larger combined stress losses than if we were to consider clearing members in isolation.

We then study the risk faced by a set of CCPs from the clearing activities of their common dealers. This analysis is helpful in illustrating the potential for contagion of financial stress as the major clearing members of CCP1 are the exact same institutions that are also clearing members of CCP2. To the extent that total net profits of a clearing member are positively correlated across the two CCPs, then the combined losses of a clearing member in a stress scenario would be more likely to result in a situation in which the clearing member is unable to meet its margin calls to both CCPs. We find that the combined losses of a clearing member across CCPs could be substantially larger than the stress losses to each CCP due to high positive correlation in the economic exposures of the clearing member across CCPs.

We rely on the weekly CDS position data from the DTCC trade repository from January 2010 through August of 2015 for all cleared CDS trades – trades between either CCP1 or CCP2 and each of six large clearing members.[3] Our data include positions for which one of these six clearing members is a counterparty. In other words, our data include CDS transactions in which any of the members are either trading directly or engaging in client clearing. Even though our data allows us to study smaller clear members to CCP1 and CCP2, we focus on the six largest dealers as these clear the vast majority of CDS trades in our data set.

We first show that there is substantial variation in the time series evolution of clearing member net exposures to each CCP by netting each clearing member's notional exposures to all cleared reference entities. Moreover, most clearing members we examine exhibit substantial and persistent deviations from a fully hedged portfolio with the estimated half-life of a shock to net exposure that ranges from 10 to 40 weeks. This persistence suggests that dealers exhibiting elevated net exposures are likely to present increased risk to the clearing system for a significant period of time into the future.

[3]The DTCC trade repository also contains information on non-cleared trades but these data is not being considered for this analysis since we are focusing on stress testing of CCP's and thus on cleared trades.

While the netted exposure across all reference entities provides a simple representation of the risks clearing members pose to CCPs, it nevertheless ignores the riskiness of the different underlying CDS positions as well as the correlation structure between the different types of CDS positions. To account for this source of heterogeneity, we employ a simple market model for the changes in CDS spreads. We then rely on a simulated distribution of market shocks, as well as the estimated coefficients and fitted residuals from the market model to arrive at simulated weekly changes of CDS spreads for each reference entity. We simulate the market shocks from the actual joint distribution of CDS index changes during 2008-2012 because this period is more likely to produce "extreme but plausible" stress conditions than if we relied on a lengthier sample including a long period of benign financial conditions. Last, for each clearing member we then define "stress losses" as the 1^{st} percentile of the simulated distribution of total net profit. These stress losses represent the total dollar amount of variation margin calls that an individual clearing member would face in conditions of market stress when its CDS positions with the CCP are marked-to-market.

We find that even though stress losses are a function of the exposure of each clearing member with a given CCP, the stress losses do not appear to directly mirror clearing member net exposures. For example, the total net exposures of a number of clearing members to CCP1 in late 2010 and late 2011 appears small but nevertheless stress losses are substantially larger. This suggests that the riskiness and the co-movement between different reference entities may play a substantial role in overall clearing member vulnerability in times of stress. It also suggests that "simple and transparent" risk metrics may be generally inadequate for measuring systemic risk in the clearing system. In addition, while stress losses have decreased over time for some clearing members potentially due to the declining CDS activity that has occurred in recent years, most clearing members continue to exhibit economically large stress losses at the end of the sample period. Similar to net exposures, our results indicate that stress losses are highly persistent – an unexpected rise in a clearing member's stress losses is likely to persist for one or several months into the future.

Another potential source of risk to the clearing system stems from one set of clearing members exhibiting significant directional positions or being engaged in crowded trades (see, e.g., Menkveld (2016), Huang and Menkveld (2016)) in which case a market event could require large variation margins to be transferred to another set of clearing members. In such cases there is a heightened risk that the required margin flows will not materialize if one or more clearing members facing a significant margin call is unable to obtain the required liquidity. To this end, we examine the simultaneous stress losses of all clearing members to each CCP. Simultaneous stress losses to CCP1 are typically several times larger than individual stress losses for most of the early part of the sample, decline substantially in 2013 and 2014 before increasing again in 2015. A similar pattern is observed in the simultaneous losses to CCP2, although the magnitudes are approximately half as large as those for CCP1. These simultaneous losses are substantially larger than the maximum point-in-time losses of individual clearing members, suggesting that clearing members may be engaging in crowded trades.

We next analyze the potential of clearing members to experience stress losses simultaneously to both CCPs. We show that there are substantial fluctuations in the correlation between the net profit of clearing members across the two CCPs switching from highly positive to highly negative. Moreover, for several clearing members the correlations are highly positive – in the range of 0.75 to 0.80 for extended periods of time, suggesting these clearing members are entering into very similar economic exposures with both CCPs. To the extent that stress losses are large, these large and positive correlations could increase the probability that clearing members face large and significant simultaneous margin calls from both CCPs and eventual default. Consistent with these ideas, combined stress losses for clearing members tend to be significantly larger than the maximum of stress losses across CCPs, especially when individual clearing member stress losses to each CCP are high. Importantly, there is a high degree of similarity in economic exposures of individual clearing members across CCPs when economic exposures are large.[4]

Our methodology bears resemblance to that in Ali, Vause, and Zikes (2016) that uses network and VaR analysis to arrive at measures of systemic importance of CDS dealers. Although the authors find a high degree of concentration of CDS trading among market participants, due to data limitations the study relies on single-name CDS only typically representing a minority of activity in the CDS market and as a result finds stress losses that are inconsequential. In contrast, we observe all cleared CDS positions of the major dealers investigated in this paper.

In a recent paper, Menkveld (2016) develops a theory of the systemic risk implications for central clearing. He provides an empirical illustration supportive of his theory using an equity CCP clearing Scandinavian stocks. However, the author notes that in contrast with derivatives markets counterparty risk in equities clearing is limited and short-lived. Specifically, equities settlement only takes 2-3 days after which dealers are no longer exposed to the traded positions. Our study builds off his theory to demonstrate that crowded trades also represents a concern in credit derivatives markets such as the CDS market.

Additionally, a recent paper by Paddrik, Rajan, and Young (2016) also estimates the variation margin payments of CCP clearing members in a time of stress. While the authors also investigate the extent to which individual clearing members contribute to stress amplification at a single CCP, they only consider stress losses to one CCP given their focus on how the CM-CCP network structure translates to sytemic fragility. A general disadvantage of their methodology is that it relies on a scenario-based approach – scenarios that could be stressful for one configuration of dealer positions and exposures may not be stressful for another configuration. This is especially important when a dealer's position moves from being net long to net short: a scenario that would be stressful for a portfolio that is net long would likely not be stressful for a net short portfolio. In contrast, we model stress more flexibly relying on market shocks from the most recent financial crises. We also show that

[4]This could be due to clearing members spreading large exposures across CCPs to potentially reduce collateral or margin requirements.

it is essential to take into account the exposure of clearing members across CCPs given that stress losses of large clearing members exhibit either large positive or large negative correlations across CCPs. Lastly, our study demonstrates substantial time series variation in stress losses of clearing members to a single CCP, to both CCPs, as well as in the correlation of these losses across CCPs. These findings strengthen arguments for continuous monitoring of the clearing system.

Our paper is closely related to the literature that theoretically examines the potential for systemic risk concentration in CCPs as well as optimal CCP design (see, e.g., Bignon and Vuillemey (2017), Cruz Lopez et al. (2017), Huang and Menkveld (2016)). While Biais, Heider, and Hoerova (2016) show that with central clearing margin calls after bad news are crucial for the reduction of moral hazard of protection sellers, in line with theory in Amini, Filipovic, and Minca (2015) and the discussion in Stulz (2010) our study illustrates the importance of default management resources (guarantee funds, default funds, initial margin requirements) for CCP resiliency in addition to variation margins.

Finally, we contribute to the literature analyzing the effect of central clearing on counterparty risk and collateral demand. Even though prior research has shown that the main benefits of central clearing include the potential for reduction in counterparty risk (see, Acharya and Bisin (2014), Loon and Zhong (2014)) and collateral demand to the extent that central clearing is not too fragmented (see, Duffie, Scheicher, and Vuillemey (2015), Duffie and Zhu (2011)), our paper empirically highlights that a substantial cost of large CCPs is the potential for the accumulation of systemic risk.

2 Evaluating Systemic Risk in CCPs

Before proceeding with the empirical analysis, we describe a general approach to systemic risk across a set of CCPs. Specifically, the approach adopted here involves identifying a set of shock scenarios that are intended to be "extreme but plausible," and then using granular data on CCP-member positions to re-value the derivative portfolio of each CCP's clearing member under each scenario. The net mark-to-market position of each clearing member under each scenario is recorded. In the event that a member is in a net negative position (e.g. would be required to post collateral to the CCP), the size of the required margin call can be compared with the post-stress value of their posted initial margin collateral. Importantly, initial margin collateral should be re-valued under the stress scenario and may also be subject to an additional haircut to reflect any close out discount that may be required to quickly liquidate non-cash collateral.

Finally, the result of the stress scenario is aggregated across all CCPs to assess the extent to which one or more clearing members receive compounding or offsetting margin calls that may either attenuate or exacerbate the collateral demand shock emanating from a single CCP. Consider the following hypothetical example of two CCPs clearing CDS. Suppose each CCP has five clearing members and that four clearing members are members of both CCPs.

Table 1 provides some insight into the resiliency of each CCP with the same stress scenario is used to generate stress losses across both CCPs. In particular, we see that under the common stress scenario CCP1 has one member with a margin call above and beyond the posted IM (member 5) while CCP2 has four members that exhibit a loss in excess of the post-stress value of their posted initial margin collateral (members # 1, 5, 6, 7). In addition, the table shows that one clearing member, member 5, experiences a significant stress loss at both CCPs in the stress event. Accordingly, member 5 may be a source of contagion during a stress event as both CCPs will be exposed to a shortfall emanating from a single clearing member. It should also be noted that the stress scenario may have offsetting impacts that reduce the scope for spillovers and contagion. For example, note that member 1 experiences a loss in excess of the post-stress value of its collateral at CCP2 but, at the same time, experiences a significant gain on its CDS portfolio at CCP 1. Accordingly, it is natural to expect that member 1 will not pose a significant risk to CCP 2 since gains that are earned on the portfolio with CCP 1 will generally be available to offset losses on the portfolio with

CCP 2. As this example demonstrates, an interesting empirical question with direct bearing on the size and extent of systemic risk with the combined CCP network is the extent to which member positions exhibit positive or negative correlation during a stress event. We examine this question in detail in the empirical analysis that follows.

Importantly, the illustration in the table is limited to the losses that would be incurred under the stress scenario. It is not directly informative about whether a given clearing member would default on its obligations to post additional collateral since the broader financial resources of the member are not modeled or monitored as a part of the stress test.[5] Clearing members may access financial resources from a variety of sources in addition to the collateral posted to them on their own derivative portfolios. Accordingly, without a fuller and more complete picture of each member's financial resources and the demands that would be placed upon these resources in the stress event it is not possible to make definitive statements about the likelihood of default in all but the most extreme cases. Despite these limitations, however, this illustration is useful and informative as significant stress losses at one or more CCPs is a pre-condition to the crystallization of systemic risk.

Finally, the example provided in the above table makes clear that in order to conduct a meaningful CCP stress test, one must have an operational approach to identifying stress scenarios and must also have enough granular information on each member's derivative portfolio to assess the implications of the stress scenario on the portfolio's valuation. We now turn to a discussion of the empirical data and methods that will be used in the remainder of this paper to estimate the required stress losses.

3 Data and Sample

In this section we describe the data sets that we employ in our analysis. We obtain weekly CDS position data from the DTCC trade repository from January 2010 through August of

[5]A more thorough discussion of the complexities associated with modeling the probability of default for members whose margin call exceeds posted collateral can be found in the Bank of England's 2014 financial stability paper, Murphy and Nahai-Williamson (2014).

2015 for all cleared CDS trades – trades between either CCP1 or CCP2 and each of six large clearing members.[6] Our data include positions for which one of these six clearing members is a counterparty. In other words, our data include CDS transactions in which any of the members are either trading directly or engaging in client clearing.[7] Even though our data allows us to study smaller clear members to CCP1 and CCP2, we focus on the six largest dealers as these clear the vast majority of CDS trades in our data set. All weekly positions are reported in the data set as of the end of the day every Friday.

Our CDS position data contain the following characteristics of each CDS position: notional amount, buyer/seller, reference entity, maturity and currency. We round maturity (in days) to the nearest year to define 11 maturity classes – less than 1 year, 1 year, 2 years, ..., and greater than 10 years. Further, we translate the notional value of each CDS position to U.S. dollar terms (if necessary) so that all subsequent analyses are expressed in U.S. dollar terms.

The data used in this study are confidential. The analyses presented in this study have been anonymized to ensure that no firm or CCP specific information is revealed in a manner that would allow a reader to identify the identity of any firm or CCP that is considered in this analysis. More specifically, we show anonymized results pertaining to each CCP and each clearing member. The CCPs included in this study are drawn from the set of CCPs that engage in CDS clearing. The clearing members are drawn from the set of bank holding companies that are regulated by the Federal Reserve. Whenever we show results pertaining to a specific clearing member or a specific CCP, the results are normalized so that the specific monetary value of the data being presented is not revealed. This normalization procedure ensures that the data presented in this study can not be used to identify the identity of any specific firm or CCP. When we show results that aggregate data from both CCPs the monetary value of the data series being presented is provided since the aggregation precludes

[6]The DTCC trade repository also contains information on non-cleared trades but these data is not being considered for this analysis since we are focusing on stress testing of CCP's and thus on cleared trades.

[7]Beginning in 2015 our DTCC trade repository data differentiates between client and house positions.

any identification of a single CCP.

We obtain CDS spread data from Markit Group for the period from January 2005 through the present. Our CDS data are most aptly described as "indicative quotes" rather than "transaction prices". Accordingly, when deciding which quote data to use it is important to consider the liquidity characteristics of the CDS underlying the indicative quotes. To ensure that the indicative quotes are based on the most liquid segment of the CDS market we restrict our attention to those quotes that relate to the most highly traded and liquid segment of the market in each major trading area. In particular, we select the quote associated with the 'MR' restructuring clause in North America and an 'MM' restructuring clause outside of North America. We also restrict our attention to the quoted 5-year CDS spread as this is the most liquid maturity in the CDS market.[8]

In the subsample of CDS index contracts, we restrict attention to the CDS spreads of "on-the run" indexes. Index contracts frequently rebalance their constituents to exclude members that no longer meet the index criteria and substitute these constituents with new members. While both the rebalanced ("on-the-run") and the old ("off-the-run") contracts trade simultaneously, the "on-the-run" index is the most liquid contract at any point in time. Accordingly, we simply use the "on-the-run" spread and assume that the change in spread on any "off-the-run" index is identical to that of the "on-the-run" spread.

4 Risk Management Model

In this section we describe the methodology that is used to model the mark-to-market losses on each clearing member's derivative portfolio with each CCP.

[8]Our analysis considers mark-to-market changes in the value of CDS with maturities besides 5 years. In the analysis to follow we assume that the CDS spread term structure is flat.

4.1 Exposure Measurement

The CDS portfolios that each clearing member maintains with each CCP is complex as it consists of a large number (typically several hundred) bought and sold CDS positions, each with its own maturity. Consider for example, the portfolio that clearing member # 3 (CM3) maintained with CCP1 as of one of the dates during our sample period. Table 2 describes the CM3 cleared portfolio in terms of the bought and sold CDS positions within each of the 11 specified maturity ranges that were described earlier. Also, for convenience and ease of presentation, all bought and sold positions are aggregated across all reference entities.

Table 2 shows that the bulk of the exposure for both protection sold and purchased is concentrated in the shorter remaining maturity categories – from less than 1 year to 5 years in maturity. In addition, the gross notional amounts are larger just below the 5-year remaining maturity consistent with the institutional regularity in the CDS market that the 5-year tenor is the most utilized and liquid segment of the market. Finally, note that the portfolio is comprised of several hundred underlying CDS contracts. Moreover, the CDS exposures are spread over a large number of different reference entities. In what follows, we develop a risk management model that effectively deals with the granular and complex nature of these clearing member CDS portfolios.

In what follows, we aggregate CDS exposures from sales and purchases by reference entity and maturity range to facilitate the stress testing exercise that follows. In particular, in each week τ and for each given reference-entity i and maturity range α we calculate the net exposure that the clearing member m has to each CCP j as follows:

$$Net\ Exposure_{i\alpha jm\tau} = \sum_{k} Notional\ Bought_{i\alpha jm\tau} - \sum_{l} Notional\ Sold_{i\alpha jm\tau} \tag{1}$$

so that the resulting exposure reflects the net amount of credit protection bought on a reference entity i within a given maturity range α. In Equation 1, k indexes different purchases on a reference entity i and maturity range α, while in a similar manner l indexes sales. As a normalization, a positive amount reflects a net protection bought position and a negative amount reflects a net sold protection position. The exposure calculation is made with respect to the reference-entity and maturity range of the CDS position but ignores all other trade characteristics such as document clause so that all positions within a reference entity-maturity range pairing are converted in US dollars (if necessary) and then aggregated together into a single net exposure amount. In particular, in what follows we abstract from the distinction between different "versions" of the same index. Exposures to any version of an index are aggregated into a single net exposure amount to that index. For example exposures to versions 3 and 4 of the CDX.NA.IG are aggregated into a single exposure amount to the CDX.NA.IG.

In the context of the cleared portfolio of CM3 described above the exposure calculation would correspond to the net amounts that are recorded in Table 2. Unlike the table, however, the exposure amounts would be calculated separately for each of the approximately 400 reference entities to which CM3 had a position with CCP1.

In Figure 1, we present plots of the overall net exposure that each clearing member has to each CCP aggregated across all positions and remaining maturity ranges. The plots in Figure 1 provide an overall sense for the time-variation in exposures that clearing members have to both CCPs. Due to confidentiality concerns we normalize all exposures by the maximum exposure amount over our sample period. To the extent that each clearing member is acting in a dealer capacity we would expect net exposures to hover around zero (i.e. maintain a hedged portfolio with the CCP) with deviations above and below zero reflecting temporary imbalances that are effectively soaked up by the dealer's position. Figure 1 shows that, generally, speaking all clearing members except CM4 exhibit substantial and persistent deviations from a completely hedged portfolio with the CCPs. It should be noted, as discussed earlier, that these data reflect both "house" and client positions that each clearing member has. Even if part of the exposure of CMs is coming from client positions, the CMs are ultimately responsible for client positions. A stress scenario has to incorporate the inability of clients to cover their margin calls and is motivated by crowded trades (see, e.g., Menkveld (2016)).

Interestingly, most clearing members not only exhibit significant swings in the net exposure of their positions with the CCP but these deviations can also be highly persistent. As a specific example, the net exposure of CM6 to CCP1 becomes positive in 2012 and continues to grow until 2014. Similarly, CM3's exposure to CCP2 becomes significantly negative in early 2010 and continues to grow until early 2011. Panel A of Table 3 presents the first five autocorrelations (correlogram) of each dealer's net exposure to both CCPs. The autocorrelations presented in Table 3 suggest that net exposures are highly persistent with a first order autocorrelation across dealers and CCPs that ranges from 0.93 to 0.97. The estimated half-life of a shock to net exposure, reported in the final row of Panel A ranges from 10 to 40 weeks. Accordingly, these large and persistent net exposures will have natural implications for the stress tests to follow as clearing members with a significant one-way net exposure to a CCP are in a position to present measurable risk to the CCP. Moreover, as shown in Table 3, the net exposures are highly persistent so that dealers exhibiting elevated net exposures are likely to present increased risk for a significant period of time into the future.

4.2 Modeling CDS Spreads

While the netted exposure across all reference entities provides a simple representation of the risks clearing members present to CCPs, it nevertheless ignores the riskiness of the different underlying CDS positions as well as the correlation structure between the different types of CDS positions.

To account for this source of heterogeneity, we employ a relatively standard market model for the changes in CDS spreads. We focus on CDS spread changes rather than levels as mark-to-market valuation changes are driven by CDS spread changes. We then use the coefficients estimates from the market model to simulate the distribution of CDS spread changes for each reference entity and ultimately the entire portfolio in a way that incorporates information regarding the correlation between positions.

We estimate the following model for each reference entity in our sample of cleared CDS positions:

$$\Delta CDS_{it} = \alpha_0 + \beta_{IGi\tau}\Delta IG_{it} + \beta_{HYi\tau}\Delta HY_{it} + \epsilon_{it} \tag{2}$$

where ΔCDS_{it} is the weekly change in CDS spreads for references entity i in week t. For US names ΔIG_{it} and ΔHY_{it} correspond to $\Delta CDXIG_{it}$ and $\Delta CDXHY_{it}$ – the weekly changes in the Markit's North America Investment Grade and High Yield Indexes. For European names ΔIG_{it} and ΔHY_{it} correspond to $\Delta iTraxxEU_{it}$ and $\Delta iTraxxCrossover_{it}$ – the weekly changes in the Markit's iTraxx Europe and Crossover Indexes.

For each week from January 2010 through August 2015 and for each reference entity, we estimate the market model using weekly data from the previous 5 years. This gives us a weekly time-series of estimated coefficients $(\alpha, \beta_{IG}, \beta_{HY})$ on the market indexes. The estimated model is also used to form an estimate of the residual CDS spread change for each reference entity in each week (ϵ).

Figure 2 presents a time series of the estimated beta coefficients and resulting R-Squared for the model. The time series plot of the beta estimates is the average beta coefficient estimated across all reference entities. The R-squared is the average R-squared across all reference entities. The figure presents the results for North American CDS reference entities in the top panel and the European reference entities in the bottom panel. The average R-squared presented in the figure is roughly constant over the sample period and is roughly 40 percent in the case of US reference entities and 50 percent in the case of European reference entities. The model's predictive power is generally consistent with the behavior of the market model in related contexts. As an example, Campbell et al. (2001) finds that a simple CAPM model for US stocks exhibits an R-squared between 30 and 40 percent.

Through 2014, the average beta coefficients are relatively stable and sum to roughly unity across the investment grade and high yield indexes which is consistent with the notion that the "average" CDS reference entity exhibits a beta of 1.0 to the market. In 2014, however, both the North American and European coefficient estimates exhibit an abrupt change in behavior. The European coefficient estimates ultimately return to their pre-2014 level while the US coefficient estimates first rise and then fall and never quite return to their pre-2014 level. This change in estimated coefficients could be driven by changes in the sample as reference entities enter the sample as more and more names are cleared or could be related to the behavior of the CDS indexes that are used in the model's estimation.

4.3 Portfolio Simulations

Once we have estimated the market model coefficients and the associated CDS spread residuals we can use the realized distribution of market shocks and the fitted residuals to arrive at simulated weekly changes of CDS spreads for each name. We use historical simulation to simulate the joint distribution of weekly CDS spread changes for all CDS reference entities at every point in time τ from 2010w1 through 2015w34. More specifically, we first simulate the actual joint distribution of weekly market shocks, the changes in spreads for the IG and HY indexes, from January 2008 through December 2012 to generate a simulated distribution of 50,000 market shocks.

We simulate the market shocks from the actual distribution of CDS index changes during 2008-2012 because this period is associated with a period of significant stress in financial markets (it includes both the U.S. financial crisis as well as a large part of the European crisis). Thus, using data from this period is more likely to produce "extreme but plausible" stress scenarios than would be the case if we relied on a lengthier sample including a long period of benign financial conditions. To compare the CDS spread changes during 2008-2012 with those in "normal" times, Figure 4 presents the time series distribution of weekly changes in market shocks for each week τ from January 2010 through August 2015. Panel A presents the distribution of changes in CDXNAIG and CDXNAHY while Panel B plots the time series distribution of changes in iTraxxEU and iTraxxCrossover. Intuitively, these plots show that the largest weekly changes in index CDS spreads occur during the US financial crisis of 2008/2009 and during the European crisis of 2011/2012.

Figure 5 presents a histogram of simulated changes in CDXNAIG and CDXNAHY spreads, while Figure 6 plots the histogram of changes in the iTraxxEurope and iTraxxCrossover spreads. The histograms reveal, as expected,that the high yield indexes are significantly more volatile than the investment grade indexes. For instance, the 1^{st} and the 99^{th} percentiles of the high yield indexes are between 1% and 2% in absolute magnitude, while the same percentiles of the investment grade index spread changes are roughly 30 basis points which is substantially smaller. Accordingly, dealer portfolios with a higher concentration in high-yield single-names and high-yield indexes should, all else equal, be expected to exhibit more risk.

In each week from January 2010 through August of 2015 and for each reference entity we use the estimated coefficients, the fitted residuals, and the simulated market shocks to arrive at a distribution of simulated CDS spread changes. More specifically, we plug in the simulated (ΔIG, ΔHY) and idiosyncratic shocks to obtain a distribution of weekly $\Delta CDS_{ir\tau}$, where r is the simulation replica and i denotes the reference-entity:

$$\Delta CDS_{ir\tau} = \widehat{\alpha_{i\tau}} + \widehat{\beta_{IGi\tau}} \Delta IG_{ir\tau} + \widehat{\beta_{HYi\tau}} \Delta HY_{ir\tau} + \widehat{\epsilon_{in\tau}} \quad (3)$$

Importantly, when simulating the model we include the residual component of the CDS spread change. In the context of large and well-diversified portfolios it should not be necessary to consider the residual component of CDS spread changes since such idiosyncratic shocks should "wash out" over the entire portfolio. In these data, however, we find it not uncommon for clearing members to hold large and concentrated positions, especially in certain index positions. Accordingly, we retain and simulate the residual component of the CDS spread change along with the market index components. This feature of the data also suggests another avenue through which systemic risks may arise. In particular, a clearing member holding a large and concentrated position in a single (or small number of) CDS contract(s) may bear significant losses attributable to a single market event which could impair its ability to perform on its obligations with the CCP in question and potentially other CCPs with which it is engaged in a trading relationship.

Another advantage of our approach is that the correlation structure across reference-entities is preserved. First, the market index shocks are bootstrapped from the joint distribution of market shocks so the correlation structure that is present in the market index shocks is then used in the market model. In addition, the sensitivities of each reference entity to the market shocks are estimated with historical data from the same 5-year period resulting in betas that preserve the cross-correlation between reference entities.

It is important to recognize that the approach considered here is not the only possible approach to defining stress scenarios. Importantly, the degree of severity and time-horizon considered here could be adjusted to either be more or less severe. In comparing this approach to the approach taken in bank stress tests conducted by the Federal Reserve, these stress scenarios are relatively modest as we only consider a one week horizon rather than the six month horizon considered by the bank stress tests of trading book assets. Of course, CCPs are different from banks in the sense that they require daily margining of all positions. Accordingly, it may be reasonable to expect that if a clearing member failed to provide the required margin collateral for a full five day period that the CCP would take steps to deal with any losses resulting from the clearing member's positions.

Aside from varying the overall level of severity, the stress scenarios could also be specified using a scenario-based approach as is done in the context of the bank stress tests. For example, a recent paper by Paddrik, Rajan, and Young (2016) also estimates the variation margin payments of CCP clearing members using the scenario-based approach. Such an approach is not without merit, however, the simulation based approach used here automatically adjusts to the specific positions and exposures of the clearing members. Put differently, a scenario based approach would specify some number of distinct scenarios that could be stressful for one configuration of dealer positions and exposures but not stressful for another configuration of dealer positions and exposures. This point is especially important in cases where a dealer's position moves from being net long to net short: a scenario that would be stressful for a portfolio that is net long would likely not be stressful for a portfolio that is positioned to be net short. The approach adopted here ensures that the identified stress scenarios are relevant to the specific positions and exposures of the clearing members.

4.4 Portfolio Valuation Changes

In estimating portfolio valuation changes, we assume a flat term structure of CDS spreads at all maturities. We employ this assumption to keep the analysis as simple and straightforward as possible.[9] Accordingly, we apply the same CDS spread shock to each reference-entity regardless of its maturity. We adjust the price response of each CDS position to the change in CDS spread by accounting for the duration of each CDS position. More specifically, we round the maturity of each CDS position to the nearest year.[10] We then assume that the mark-to-market change in the value of a CDS contract can be well approximated by the standard, linear, duration-based approximation. In other words, if the remaining maturity of a position on reference entity i, at time τ, and simulation replica r is one year, we assume that the CDS spread change is exactly equal to $\Delta CDS_{ir\tau}$ in Equation 3, while if the maturity of a position on the same reference entity i, at time τ, and simulation replica r is 10 years we assume the CDS spread change is equal to $10 * \Delta CDS_{ir\tau}$. More formally, we have the

[9] In general, there are two broad considerations that should inform the specification of the underlying pricing model. First, it is important to ensure that the pricing model is appropriately realistic and captures the most salient pricing features of the CDS market. At the same time, it is important to consider how precisely such pricing features can be observed. As previously discussed, the 5 year tenor is the most liquid and often traded tenor for most CDS contract. Accordingly, we are most confident in the 5 year CDS quotes in our data. Variation in the CDS spreads of other tenors may be relevant but are harder to measure with confidence.

[10] In the case of the final maturity range which is 10 years or more we simply assume a maturity of 10 years.

following expression for the maturity-adjusted CDS-spread changes:

$$\Delta\widetilde{CDS}_{ir\tau} = maturity * \Delta CDS_{ir\tau} \tag{4}$$

Next, at every point in time τ, we multiply the net notional exposure of each CM m to each name i with CCP j by the 50,000 simulated $\Delta CDS_{ir\tau}$. Then sum up the total loss or gain for the CM for each simulation replica:

$$Total\ Net\ Profit_{rjm\tau} = \sum_{i=1}^{N}(\Delta\widetilde{CDS}_{ir\tau} \times Net\ Exposure_{ijm\tau}) \tag{5}$$

Equation 5 describes the total profit, $Total\ Net\ Profit_{rjm\tau}$, in simulation replica (scenario) r of clearing member m to CCP j at time τ. Figure 7 presents the simulated distribution of total net profit of one of the clearing members in our sample, CM3, to one of the CCPs (CCP1) and one of the weeks we study. In other words, this histogram depicts the total net profit that results under each of the 50,000 simulation replicas. The figure shows that the distribution of weekly total net profit is fairly symmetric around zero with a few large outliers. In addition, the tails of the simulated distribution of weekly net profit reveal that net profit could be quite large in absolute magnitude. For example, the 1^{st} percentile of weekly net profit is approximately $-\$1$ billion while the 99^{th} percentile is approximately \$2 billion. It should also be noted that this simulated distribution of portfolio valuation changes results from both the specific positions of the clearing member and the assumed distribution of CDS spread shocks that are applied to the portfolio. In the case of this portfolio at this point in time the stress loss would be associated with the 1^{st} percentile of the simulated total net profit distribution. In what follows this general procedure is employed to compute stress losses that serve as the basis for the micro and macro-prudential stress tests that we consider.

5 CCP Stress Tests

In this section we discuss our analysis of CCP member exposures and describe the specific analyses that could be used to evaluate risk in the clearing system. Our analysis focuses on potential losses resulting in collateral (variation margin) calls as well as an analysis of the liquid resources that members would be able to access to satisfy the resulting collateral calls. Our analysis is confined to an analysis of potential losses as our data do not contain specific information on the size and type of available liquid resources for each member. Nor do our data contain information on the amount of initial margin and default fund contributions that have been posted with each CCP by each member. Given that initial margins are typically based on VaR estimates holding each dealer in isolation, our results still sheds lights on the optimal design of these requirements.

5.1 Stress Losses of an Individual Dealer Losses to a CCP

We next investigate the potential for individual clearing members to incur large losses on their CDS positions at each CCP independently. For each clearing member m we define the "stress scenario" as the simulation replica r that results in the 1^{st} percentile of total net profit as defined in Equation 5. Due to confidentiality concerns all total net profit numbers are normalized by the maximum of net notional exposures over our sample period. Figure 8 presents the weekly stress losses of each clearing member to CCP1 (Panel A) and CCP2 (Panel B) over time – from January 2010 through August of 2015. These stress losses represent the dollar amount each clearing member would be required to post with a given CCP in a given week if the stress scenario were realized. In other words, this is the total amount of variation margin calls that a clearing member would face in a stress scenario when its CDS positions with the CCP are marked-to-market.

The nature of this analysis is uniquely micro-prudential. Importantly, the stress scenario that pertains to each clearing member's exposure to each CCP varies across clearing members and across CCPs. As an example if one clearing member has a large "net long" exposure at CCP1 and another clearing member has a large "net short" CDS position at CCP2 the stress scenario for the first clearing member would likely be drawn from the positive tail of the CDS spread distribution (declining spreads) while the stress scenario that would be relevant to the second clearing member would likely be drawn from the negative tail of the CDS spread distribution (rising spreads). Moreover, the exact constellation of CDS spread changes that constitutes the stress scenario for each member and CCP at each point in time evolves with the member's portfolio. The same holds true for a member's portfolio across two CCP's. A member that is "net long" at CCP1 and "net short" at CCP2 would exhibit stress losses at each CCP that are generated by a different stress scenario.

The analysis presented in Figure 8 is useful for identifying situations in which a clearing member may pose a heightened degree of risk to a CCP. The analysis is similar in spirit to the analysis of net exposure that is presented in Figure 1 but it should be noted that this stress loss analysis is considerably more granular and sophisticated as it accounts for the behavior of all instruments in each member's cleared portfolio with the CCP. In particular, note that that even though stress losses are a function of the exposure of each clearing member with a given CCP, the stress losses do not appear to directly mirror clearing member net exposures. For example, the total net exposure of CM5 to CCP1 in late 2011 appears small but nevertheless the stress loss looks larger. Similarly, the total net exposure of CM5 with CCP1 in late 2010 is virtually zero while the stress loss is one of the largest over the sample period. This suggests that the riskiness and the comovement between different reference entities may play a substantial role in overall clearing member vulnerability in times of stress.

Panel A of Figure 8 shows that with the exception of CM4 that does not maintain a large overall net exposure to CDS there is substantial variation in the stress losses of clearing members over time. Interestingly, stress losses of some CCP1 clearing members have declined substantially since 2014. For example, CM5 had large weekly stress losses in late 2011, while CM3 experienced weekly stress losses several times in 2012 and in 2010, 2013, and 2015; CM1 has a large weekly stress loss in early 2015. The stress losses of the other clearing members to CCP1 appear substantially smaller for most of the sample period. Panel B of Figure 8 illustrates the stress losses of the clearing members with CCP2. Stress losses of clearing members with CCP2 are substantially smaller than those with CCP1 – the largest losses occur in the first half of the sample period and are roughly 2-3 times smaller than to CCP1.

Panel B of Table 3 reports the correlogram for the stress losses of each clearing member at each CCP. As in the case of net exposures, the results indicate that stress losses are highly persistent as the first order autocorrelation is typically in excess of 0.9 and the half-life of a shock to stress losses, reported in the final row of Panel B, is usually between 6 and 20 weeks. Accordingly, an unexpected rise in a clearing member's stress losses is likely to persist for one or several months into the future.

5.2 Simultaneous Losses of All CMs to a CCP

The stress loss measures that have been discussed so far consider losses that would accrue to a particular clearing member. Such measures are important for identifying potential risks to the clearing system but it is not the only loss measure that is useful for measuring risks to the clearing system. From the perspective of a CCP, a significant risk is the risk associated with large variation margin payments across members that may result in significant financial strains for those members that are required to make large margin payments. Of course, across the entire CCP, variation margin payments are fully offsetting but the distribution of variation margin payments across members can display important time-variation. As an example, a CCP's members may all be managing largely hedged portfolios in which case even a significant market event would result in relatively small variation margin payments from those members experiencing a loss. Alternatively, a CCP's members could exhibit significant directional positions in which case a market event could result in a large amount of variation margin being transferred from one set of clearing members to another set of clearing members. In such cases there is a heightened risk that the required margin flows will not materialize if one or more clearing members facing a significant margin call is unable to find the required liquidity.

To consider this source of risk to a CCP, we examine the potential for several clearing members to simultaneously experience large losses to a CCP and therefore face simultaneous margin calls. Formally, total losses for each week τ to a CCP j are computed as follows:

$$Total\ Loss_{rj\tau} = \sum_{m=1}^{6} min(\sum_{i=1}^{N}(\Delta\widetilde{CDS}_{ir\tau} \times Net\ Exposure_{ijm\tau}), 0) \tag{6}$$

Stress losses for each week τ to a CCP j are defined as the 1^{st} percentile of the simulated $Total\ Loss$ distribution for week τ to a CCP j. Figure 9 presents the simultaneous stress losses of all clearing members to CCP1 (Panel A) and CCP2 (Panel B). Due to confidentiality concerns all total net profit numbers are normalized by the maximum of net notional exposures over our sample period. In particular, a point on the plot can be interpreted as the total margin flow that each CCP would be required to collect from its members that are "out-of-the money" if the identified stress scenario were to materialize. More negative values of the series in the plots indicates that the CCP needs to transfer more variation margin across clearing members. Panel A shows that the simultaneous stress losses to CCP1 are typically several times larger than individual stress losses for most of the early part of the sample, decline substantially in 2013 and 2014 before increasing again in 2015. Simultaneous losses to CCP2 in Panel B are substantially smaller – the magnitudes are approximately half as large as those in Panel A which is also broadly consistent with the smaller notional positions of the members on CCP2.

5.3 Simultaneous Losses of a CM to both CCPs

While the analysis above is informative about the vulnerability of a CCP to the stress losses of a particular clearing member, it does not shed light on the potential of clearing members to experience stress losses simultaneously to both CCPs. This question is important as the major clearing members of CCP2 are largely the same institutions that are also clearing members of CCP1. To the extent that total net profits of a clearing member are positively correlated across the two CCPs, then the combined losses of a clearing member in a stress scenario would be more likely to result in a situation in which the clearing member is unable to meet its margin calls to both CCPs. This is because a high positive correlation would imply that in a stress scenario the clearing member experiences simultaneous margin calls from both CCPs. Alternatively, a negative correlation of the clearing member's total net profit between the two CCPs will provide a diversification offset and alleviate the likelihood of the clearing member defaulting to a CCP in a stress scenario.

Naturally, we analyze the time series of Spearman rank correlations between the total net profit of each clearing member across the two CCPs. More specifically, in each week, this correlation is calculated from the distribution of simulated total net profit of each clearing member at each CCP. Importantly, note that the total net profit at each CCP is generated according to the simulated joint distribution of valuation changes for CDS positions at both CCPs which generates a non-trivial correlation between the net profit at each CCP. We employ the Spearman rank correlation because as Figure 7 indicates the distribution of simulated total net profit exhibits noticeable deviations from the normal distribution making the rank correlation somewhat more appropriate though results using the more standard correlation measure are qualitatively similar.

Figure 10 presents the calculated rank correlation in net profit for each clearing member's portfolio with each CCP. A positive value of the correlation indicates that a large loss (gain) to one CCP would likely be accompanied by a large loss (gain) at the other CCP. Alternatively, a negative value of the correlation indicates that a large loss (gain) at one

CCP would likely be accompanied by a large gain (loss) at the other CCP thereby reducing the overall severity of the total loss as collateral received by one CCP could be used to fund the margin call made by the other CCP.

The results presented in the Figure reveal that there are substantial fluctuations in the correlation between the net profit of clearing members across the two CCPs. Interestingly, the plots indicate that these correlations switch abruptly between highly positive and highly negative values. Panel C of Table 3 also indicates considerable persistence in these correlations as the first order autocorrelation coefficient ranges from 0.8 to 0.9. Moreover, for several clearing members (CM3, CM2, and CM5) the correlations are highly positive at approximately 0.75 to 0.80 for extended periods of time. This implies these clearing members are entering into very similar economic exposures with both CCPs. To the extent that stress losses are large, these large and positive correlations could increase the likelihood that clearing members face large and significant simultaneous margin calls from both CCPs.

We next examine the combined losses of each clearing member to both CCPs. Total Net Profit for each clearing member m, in week τ and simulation replica r to both CCPs is defined as the sum of the previously defined $Total\ Net\ Profit_{rjm\tau}$ in each simulation replica across the two CCPs and is given by the following formula:

$$Total\ Net\ Profit_{rm\tau}^{CCPs} = \sum_{j=1}^{2}\sum_{i=1}^{N}(\Delta\widetilde{CDS}_{ir\tau} \times Net\ Exposure_{ijm\tau}) \tag{7}$$

Stress losses are once again defined as the 1^{st} percentile of the simulated distribution of $Total\ Net\ Profit_{rm\tau}^{CCPs}$. It should be noted, however, that the extreme percentile measured here is qualitatively different from the extreme percentiles that were used to define the micro-prudential stress tests described earlier. Specifically, this analysis considers the distribution of the combined net profit across both CCPs while the previous analysis considered the net profit of each clearing member at each CCP in isolation. Moreover, since these results are aggregated across both CCPs the combined stress losses are reported in dollar amounts and are not normalized as has been done in previous figures. We do so to give the reader a sense of the magnitude of combined stress losses. In particular, Figure 11 presents the combined stress loss of each clearing member to both CCPs simultaneously. These figures automatically account for situations, for example, where the positions at one CCP hedge the positions at the other CCP. The results presented in Figure 11 would be most informative for evaluating whether a particular clearing member poses a heightened risk to the CDS clearing system rather than risk to a particular CCP and would be an important analysis to consider in the context of a macroprudential CCP stress test.

The results in Figure 11 indicate important variation in combined stress losses across clearing members. Some clearing members, such as CM1 and CM6, display combined stress losses that typically hover in a relatively narrow range without displaying any significant trends while other clearing members such as CM5, CM2 and CM3 display considerably more volatile combined stress losses. Moreover, combined stress for some of these members such as CM5 and CM2 display a declining trend (i.e. stress losses that are closer to 0) since the middle of 2014. Other clearing members such as CM6 and CM1 exhibit larger stress losses in the most recent part of the sample. As is the case for the other stress loss measures that are analyzed in Panel D of Table 3, combined stress losses are highly persistent across all clearing members. In particular, the first-order autocorrelation coefficient of combined stress losses ranges from roughly 0.85 to 0.95 with the half-life of a shock to combined stress losses generally ranging from four to sixteen weeks. Accordingly, a clearing member that experience a significant increase in combined stress losses would be expected to present a heightened risk to the central clearing system for a significant period of time.

6 Conclusion

Using the CDS positions of the major CDS clearing dealers, we evaluate the systemic stability of two large CCPs. We show that the stress losses of large dealers could be substantial even if the total net exposure of a dealer appears small, suggesting that the co-movement between different reference entities may play a substantial role in overall clearing member vulnerability in times of stress. We also demonstrate that (persistent) positive correlations between the exposure of large members of a CCP could lead to substantially larger combined stress losses than if we were to consider clearing members in isolation. This highlights the importance of crowded trade concerns.

Finally, we study the risk faced by multiple CCPs from their common clearing dealers. Simultaneously facing large margin calls from multiple CCPs could reduce the ability of a clearing member to meet these obligations. We find that the combined losses of a clearing member across CCPs could be substantially larger than the stress losses to each CCP due to high positive correlation in exposures across CCPs. Overall, highlight the importance of continuous regulatory monitoring of the clearing system.

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Table 1: Coordinated Macroprudential Stress Testing. This table describes an example of coordinated macroprudential stress testing of two CCPs. The seven clearing members have positions with both CCPs.

	CCP 1				*CCP 2*			
	Pre Stress	*Post Stress*			*Pre Stress*	*Post Stress*		
	Collateral Value	*Margin Call*	*Collateral Value*	*Stress Loss*	*Collateral Value*	*Margin Call*	*Collateral Value*	*Stress Loss*
CM 1	110	+60	105	0	60	−60	55	5
CM 2	90	+80	85	0	65	+100	65	0
CM 3	40	−20	30	0	50	−10	45	0
CM 4	60	+20	55	0	0	+160	0	0
CM 5	100	−140	85	55	25	−50	5	45
CM 6	0	0	0	0	50	−100	40	60
CM 7	0	0	0	0	40	−40	35	5

Table 2: CDS Portfolio of CM3 with CCP 1. This table presents the the total dollar notional amount (in billions of US dollars) of outstanding CDS purchases and sales of CM3 with CCP 1. The notional amounts are split between 11 maturity categories (<1 *Year*, 1 *Year*, ..., 10 *Years*). The table also presents the total number of separate entities that the CDS contracts are wirtten on.

	Total Protection Purchases		*Total Protection Sold*	
Rem. Maturity	*Notional Amt*	*N*	*Notional Amt*	*N*
<1 *Year*	34.11	242	27.04	216
1 *Year*	40.47	256	30.78	229
2 *Years*	38.84	250	43.19	222
3 *Years*	39.16	246	40.67	251
4 *Years*	49.88	248	51.05	238
5 *Years*	22.79	136	11.62	171
6 *Years*	1.84	60	3.32	143
7 *Years*	3.41	35	2.03	133
8 *Years*	1.36	13	2.30	10
9 *Years*	2.97	12	0.54	4
10 *Years*	0.27	1	0.35	2

Table 3: Correlogram This table presents correlograms of net exposure CDS of each clearing member of the two CCPs examined in Panel A. Panel B conducts a similar analysis for stress losses of clearing members. Panel C presents a correlogram for the Spearman rank correlations of the simulated profit & loss of a clearing member across the two CCPs. Panel D presents a correlogram of the joint stress losses of each clearing memer to both CCPs.

Panel A: *Net Exposure*

Lag	*CM* 1		*CM* 2		*CM* 3		*CM* 4		*CM* 5		*CM* 6	
	CCP 1	*CCP* 2	*CCP* 1	*CCP* 2	*CCP* 1	*CCP* 2	*CCP* 1	*CCP* 2	*CCP* 1	*CCP* 2	*CCP* 1	*CCP* 2
1	0.964	0.977	0.962	0.967	0.959	0.966	0.932	NA	0.966	0.986	0.981	0.968
2	0.929	0.962	0.909	0.939	0.939	0.944	0.880	NA	0.937	0.973	0.958	0.937
3	0.890	0.951	0.839	0.909	0.910	0.920	0.851	NA	0.907	0.963	0.936	0.905
4	0.845	0.939	0.776	0.874	0.883	0.895	0.812	NA	0.881	0.956	0.910	0.877
5	0.808	0.926	0.724	0.843	0.848	0.867	0.770	NA	0.858	0.946	0.891	0.860
Shock Half Life	18.88	29.37	18.00	20.66	16.41	20.13	9.79	NA	20.11	48.94	35.89	21.41

Panel B: *Stress Losses*

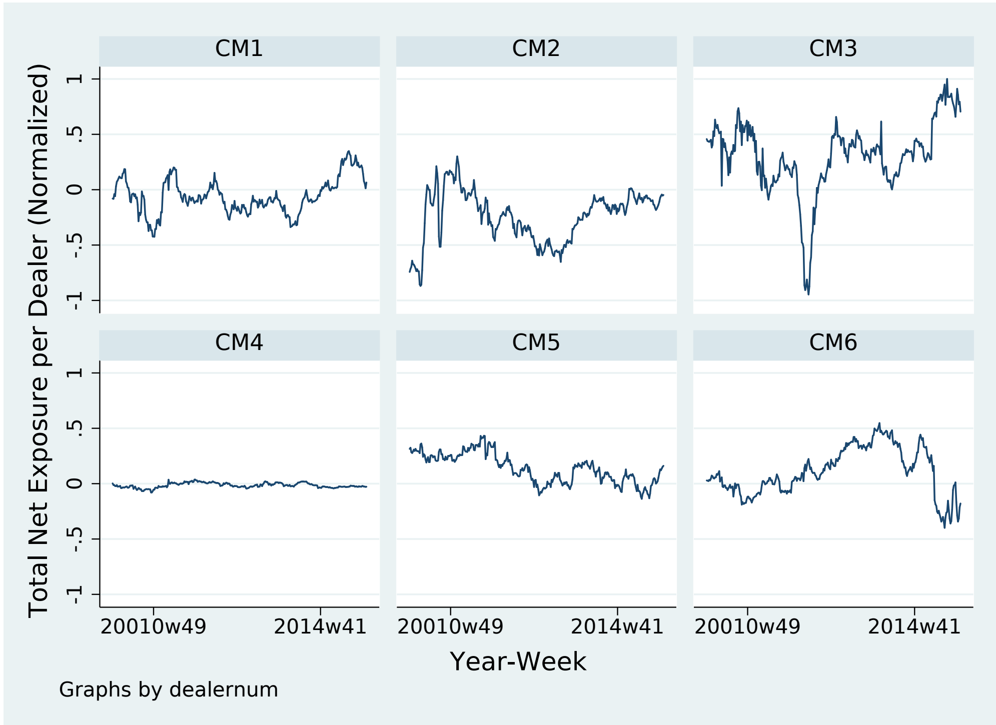
Lag	*CM* 1		*CM* 2		*CM* 3		*CM* 4		*CM* 5		*CM* 6	
	CCP 1	*CCP* 2	*CCP* 1	*CCP* 2	*CCP* 1	*CCP* 2	*CCP* 1	*CCP* 2	*CCP* 1	*CCP* 2	*CCP* 1	*CCP* 2
1	0.977	0.908	0.937	0.944	0.949	0.905	0.858	NA	0.984	0.980	0.963	0.916
2	0.948	0.838	0.869	0.897	0.913	0.862	0.755	NA	0.974	0.962	0.917	0.838
3	0.913	0.784	0.797	0.855	0.883	0.818	0.690	NA	0.963	0.952	0.876	0.783
4	0.874	0.724	0.739	0.813	0.854	0.773	0.626	NA	0.951	0.942	0.841	0.756
5	0.834	0.670	0.691	0.774	0.821	0.727	0.536	NA	0.941	0.929	0.812	0.723
Shock Half Life	29.96	7.21	10.62	12.02	13.19	6.98	4.54	NA	43.88	33.76	18.58	7.89

Panel C: *Correlation in Stress Profit & Loss*

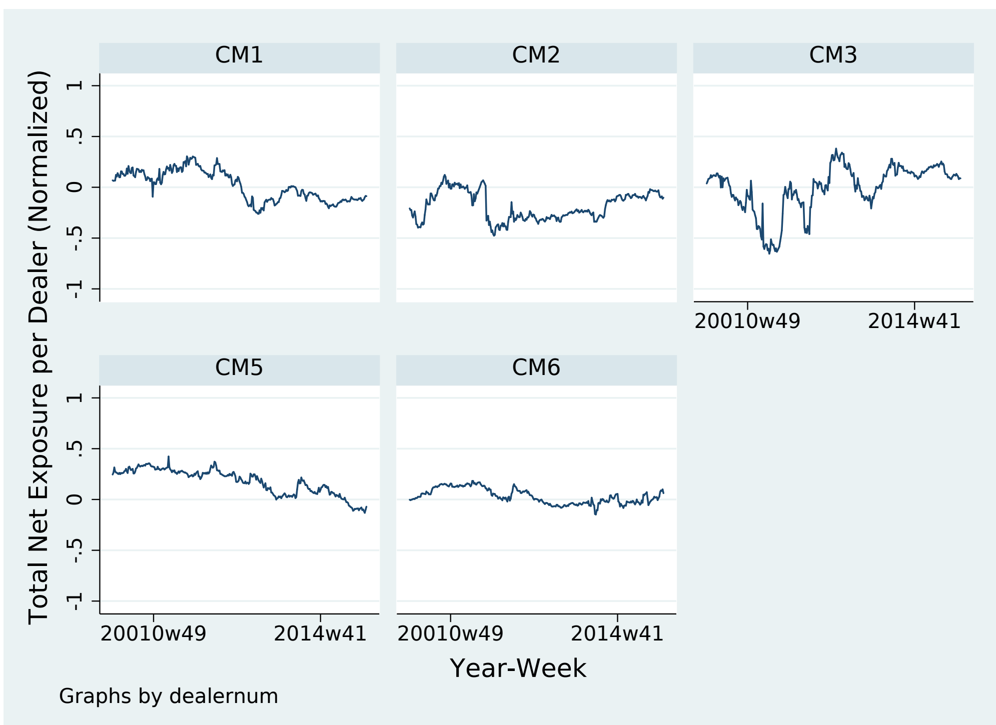
Lag	*CM* 1	*CM* 2	*CM* 3	*CM* 4	*CM* 5	*CM* 6
1	0.929	0.855	0.908	NA	0.920	0.854
2	0.870	0.759	0.851	NA	0.827	0.744
3	0.814	0.633	0.807	NA	0.758	0.648
4	0.770	0.522	0.771	NA	0.679	0.523
5	0.731	0.423	0.732	NA	0.610	0.460
Shock Half Life	9.38	4.41	7.16	NA	8.33	4.38

Panel D: *Joint Stress Losses*

Lag	*CM* 1	*CM* 2	*CM* 3	*CM* 4	*CM* 5	*CM* 6
1	0.961	0.959	0.947	0.914	0.986	0.959
2	0.921	0.919	0.912	0.852	0.977	0.909
3	0.883	0.873	0.881	0.809	0.969	0.862
4	0.843	0.826	0.851	0.771	0.960	0.822
5	0.802	0.781	0.811	0.731	0.952	0.791
Shock Half Life	17.20	16.75	12.75	7.71	50.24	16.66



(a) $CMs\ of\ CCP$ 1



(b) $CMs\ of\ CCP$ 2

Figure 1: Net CDS Exposure of each clearing member (CM) of CCP 1 and CCP 2 This figure plots the total net CDS exposure of each the top clearing members (CMs) of CCP 1 and CCP 2 in terms of single-name and index CDS from January 2010 through December of 2014. The CDS exposure is normalized by the maximum of the weekly net CDS exposures across all clearing members.

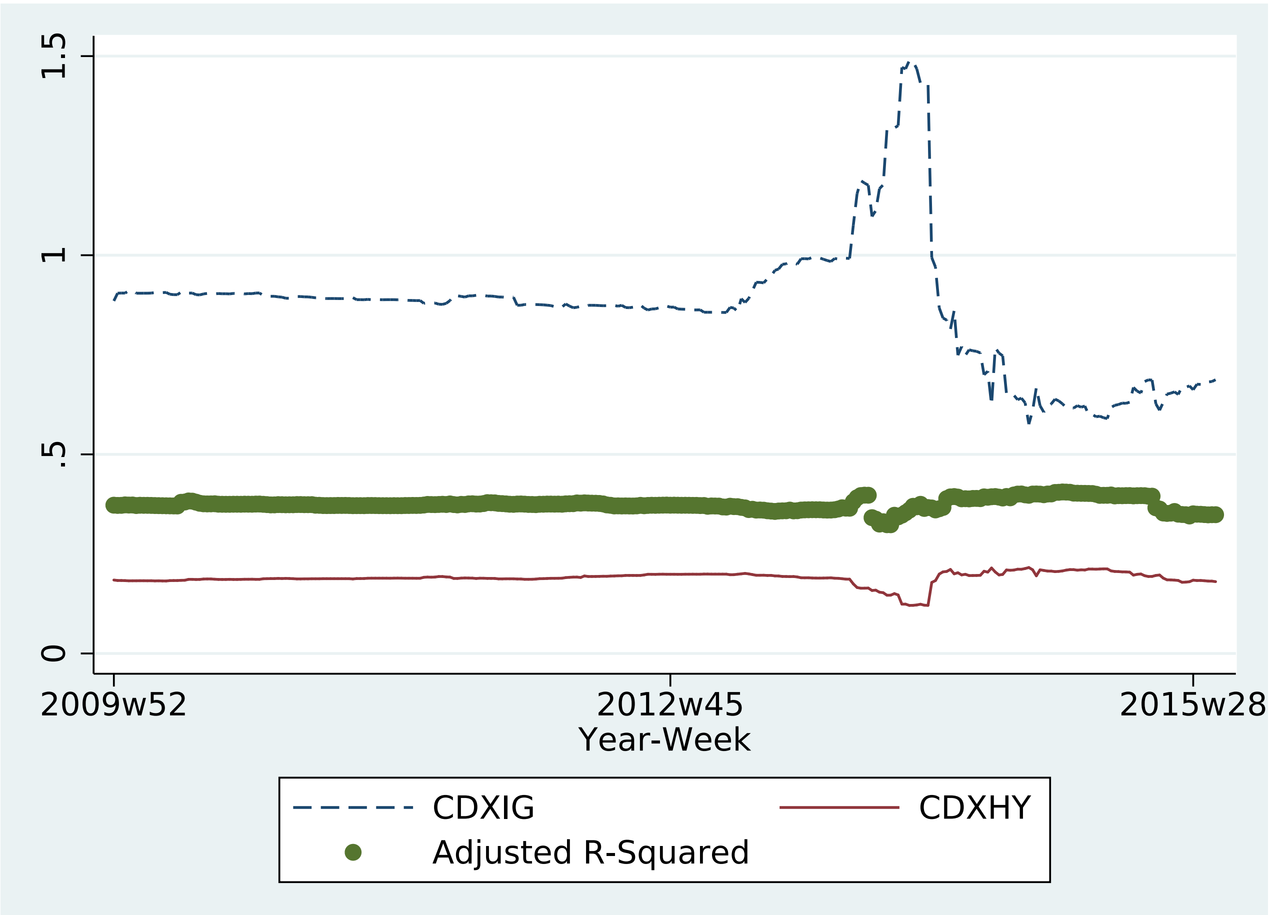


Figure 2: Time Series of Model Estimates. This figure plots an average of the weekly time series of the coefficient estimates $\beta_{IGi\tau}$ and $\beta_{HYi\tau}$ from the following model $\Delta CDS_{it} = constant + \beta_{IGi\tau}\Delta CDXNAIG_{it} + \beta_{HYi\tau}\Delta CDXNAHY_{it} + \epsilon_{it}$. ΔCDS_{it} is the weekly change in CDS spreads for CDS redcode i at time t while $\Delta CDXNAHY_{it}$ and $\Delta CDXNAHY_{it}$ are the weekly changes in the Markit's North America Investment Grade and High Yield Indexes. The model is estimated for each week τ from January 2010 through August 2015 with data for the previous 5 years.

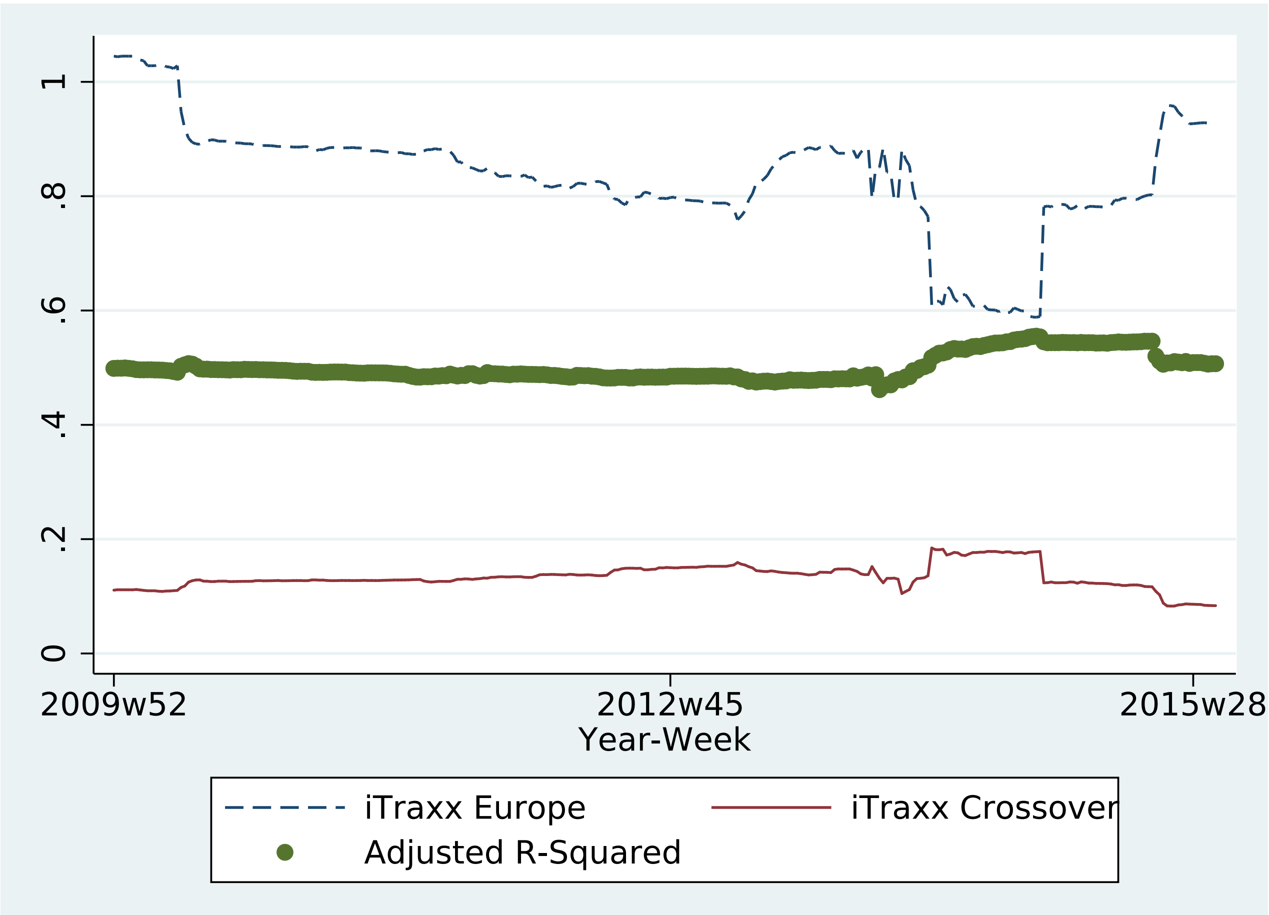
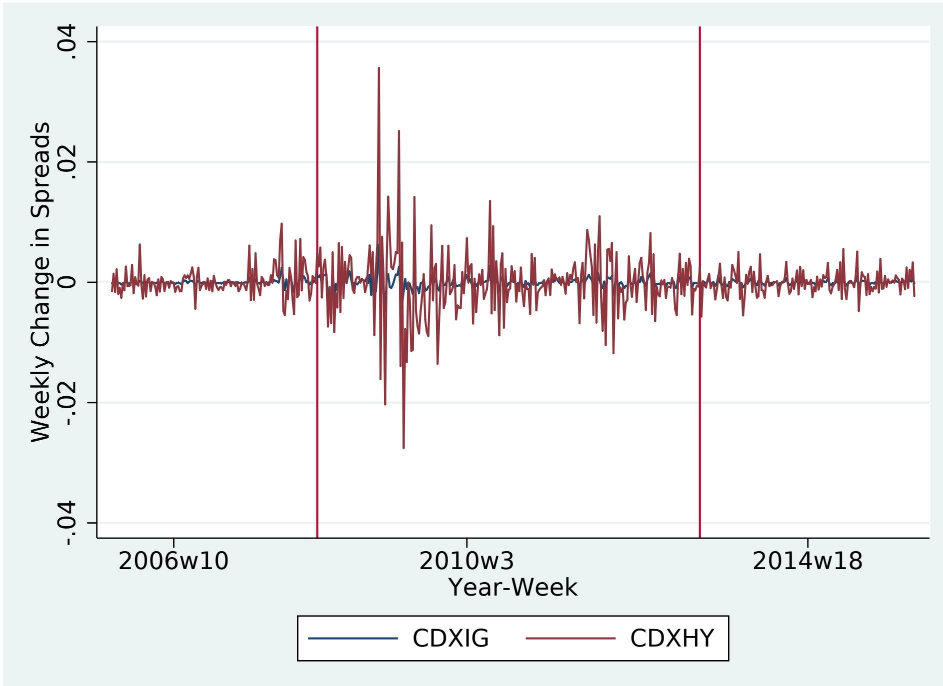
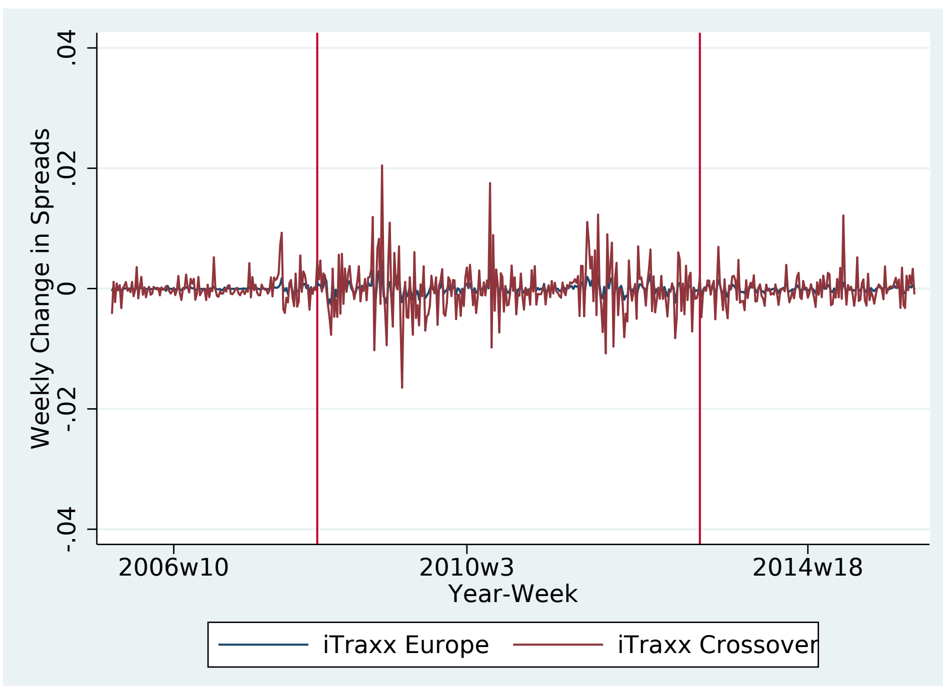


Figure 3: Time Series of Model Estimates. This figure plots an average of the weekly time series of the coefficient estimates $\beta_{IGi\tau}$ and $\beta_{HYi\tau}$ from the following model $\Delta CDS_{it} = constant + \beta_{IGi\tau}\Delta iTraxxEU_{it} + \beta_{HYi\tau}\Delta iTraxxCrossover_{it} + \epsilon_{it}$. ΔCDS_{it} is the weekly change in CDS spreads for CDS redcode i at time t while $\Delta iTraxxEU_{it}$ and $\Delta iTraxxCrossover_{it}$ are the weekly changes in the Markit's iTraxx Europe and iTraxx Crossover Indexes. The model is estimated for each week τ from January 2010 through August 2015 with data for the previous 5 years.

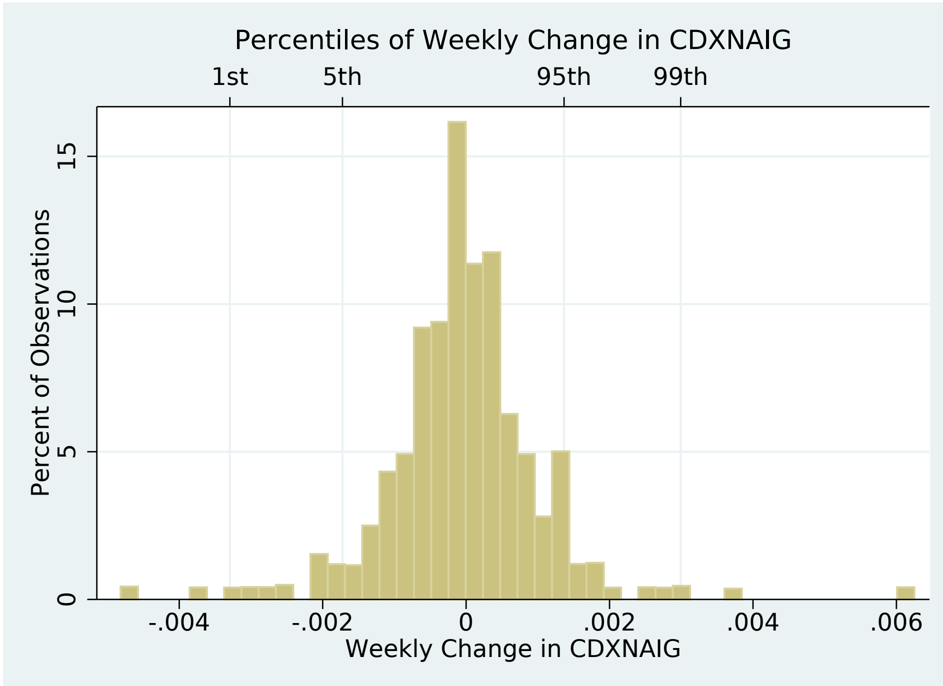


(a) *US Indexes*

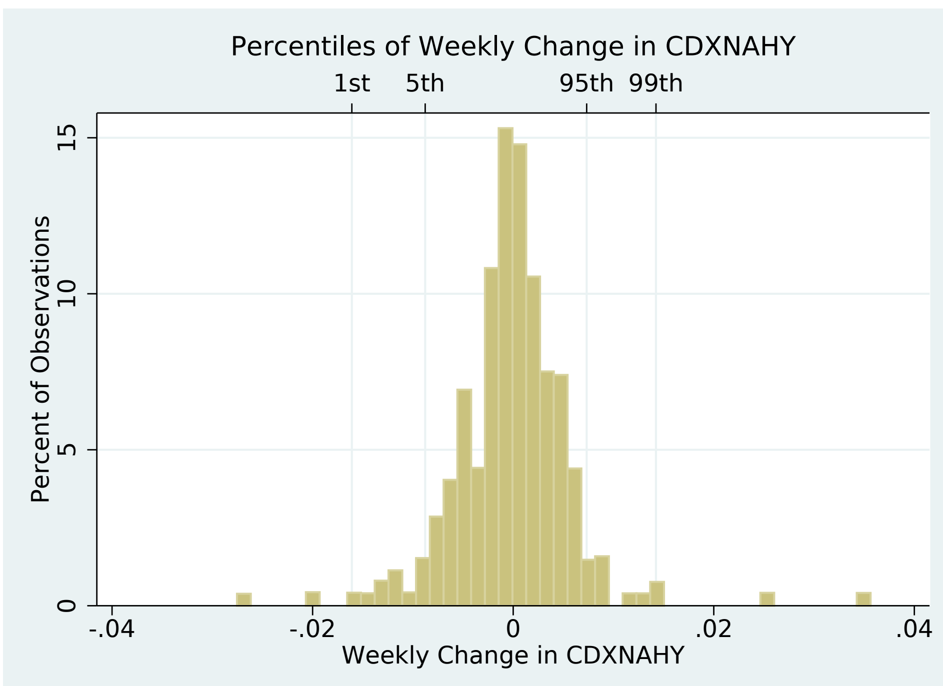


(b) *European Indexes*

Figure 4: Weekly CDS Changes over Time. Panel A this figure plots the time series distribution of changes in CDXNAIG and CDXNAHY for each week τ from January 2010 through August 2015. Panel B plots the time series distribution of changes in iTraxxEurope and iTraxxCrossover over the same time period.

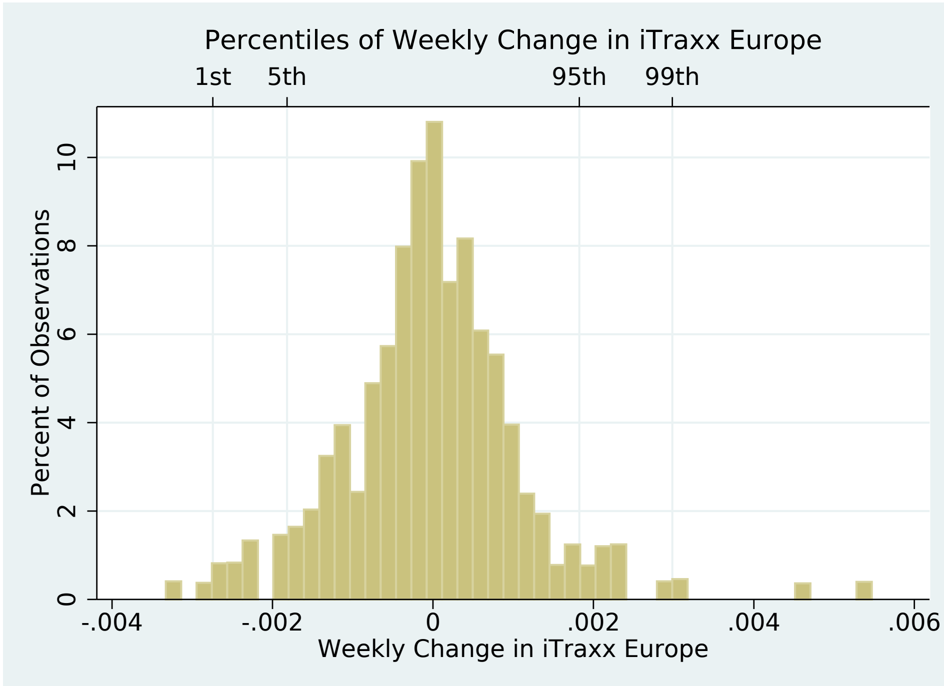


(a) $\Delta CDXNAIG$

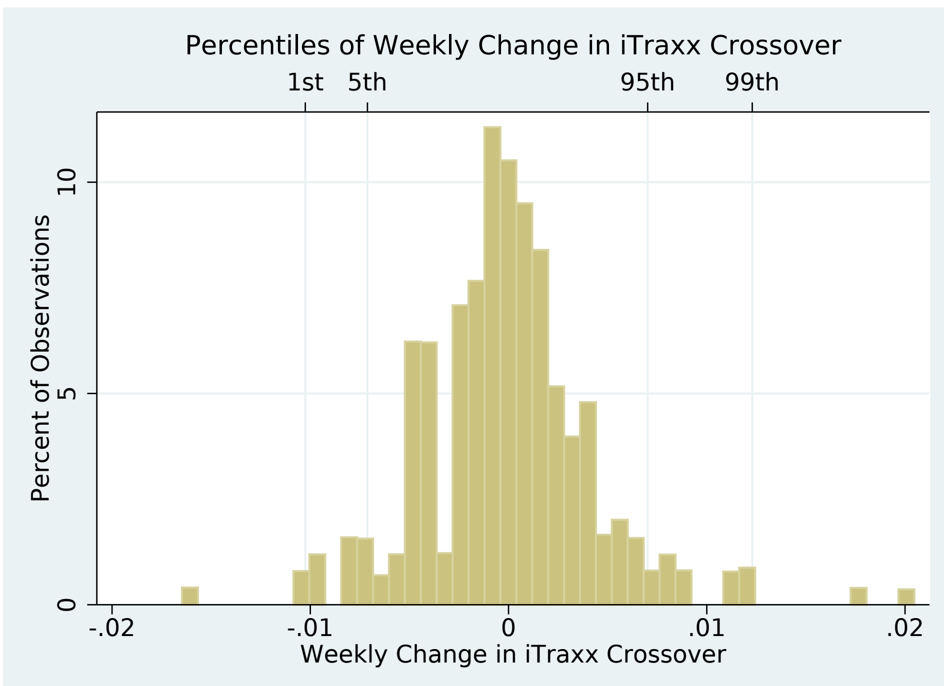


(b) $\Delta CDXNAHY$

Figure 5: Distribution of Simulated $\Delta CDXNAIG$ and $\Delta CDXNAHY$. This figure plots the distribution of simulated changes in CDXNAIG and CDXNAHY. The weekly changes in CDXNAIG and CDXNAHY are bootstrapped 50,000 times from the distribution of the weekly $\Delta CDXNAIG$ and $\Delta CDXNAHY$ in the period January 2008 through December 2012.



(a) $\Delta iTraxxEU$



(b) $\Delta iTraxxCrossover$

Figure 6: Distribution of Simulated $\Delta iTraxxEU$ and $\Delta iTraxxCrossover$. This figure plots the distribution of simulated changes in iTraxxEurope and iTraxxCrossover. The weekly changes in iTraxxEurope and iTraxxCrossover are bootstrapped 50,000 times based on the weekly $\Delta iTraxxEU$ and $\Delta iTraxxCrossover$ in the period January 2008 through December 2012.

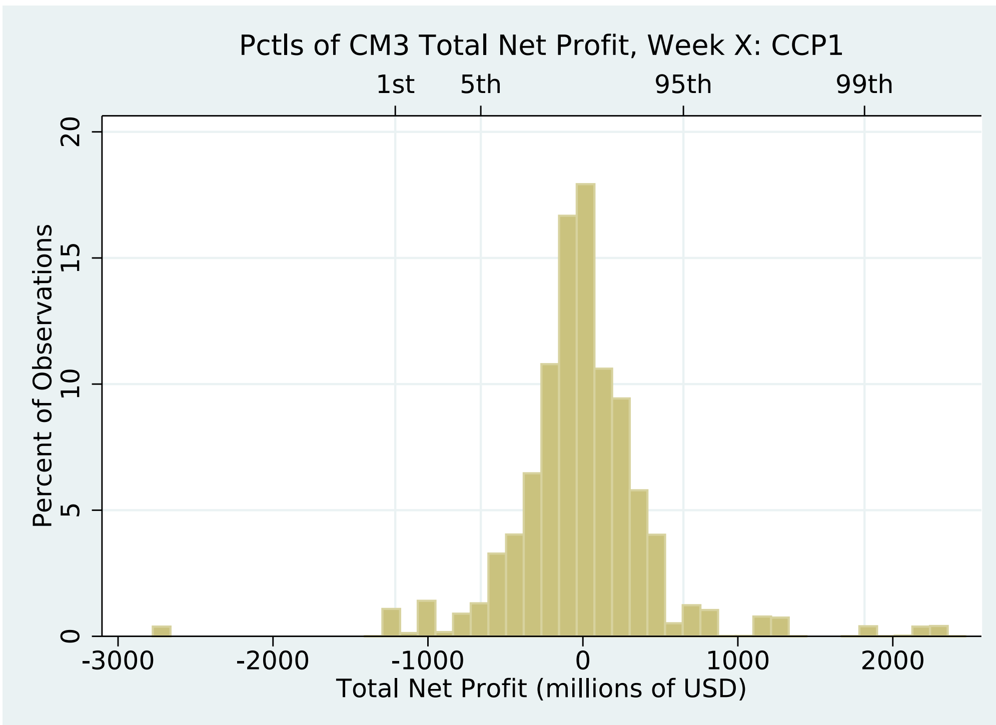
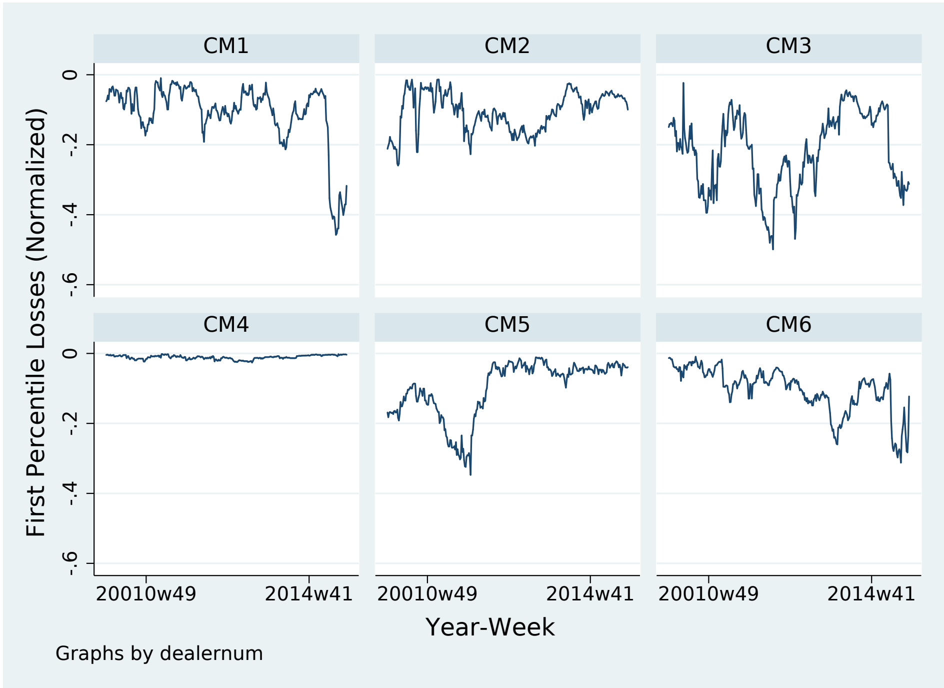
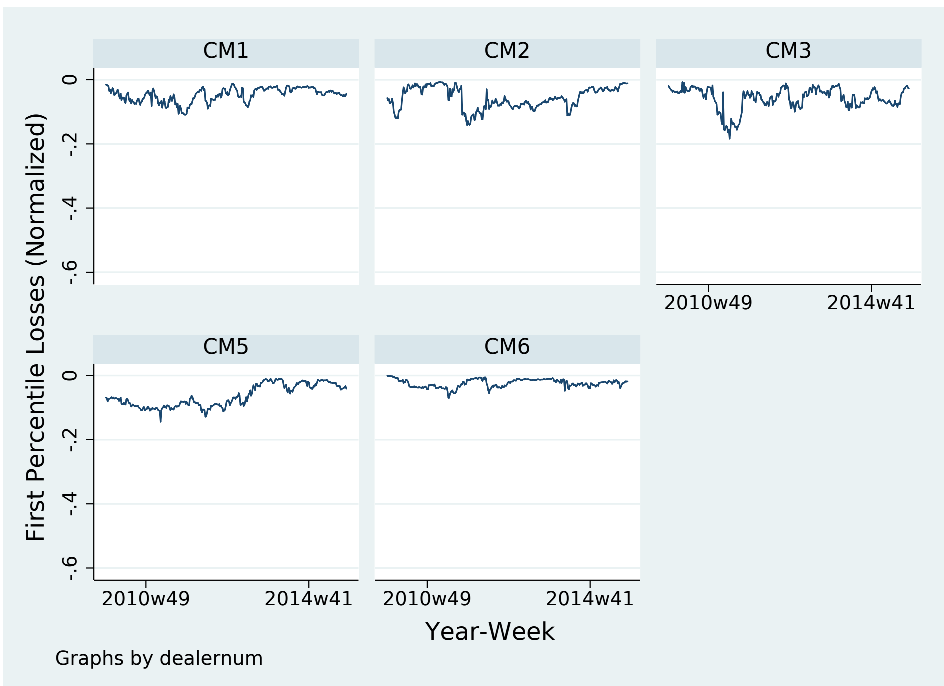


Figure 7: Simulated Total Net Profit of CM3. This figure plots the simulated distribution of total net profit of one of the clearing members, CM3, with one of the CCPs in our sample, CCP 1 in one of the weeks in our sample. Net profits are measured in millions of US dollars.

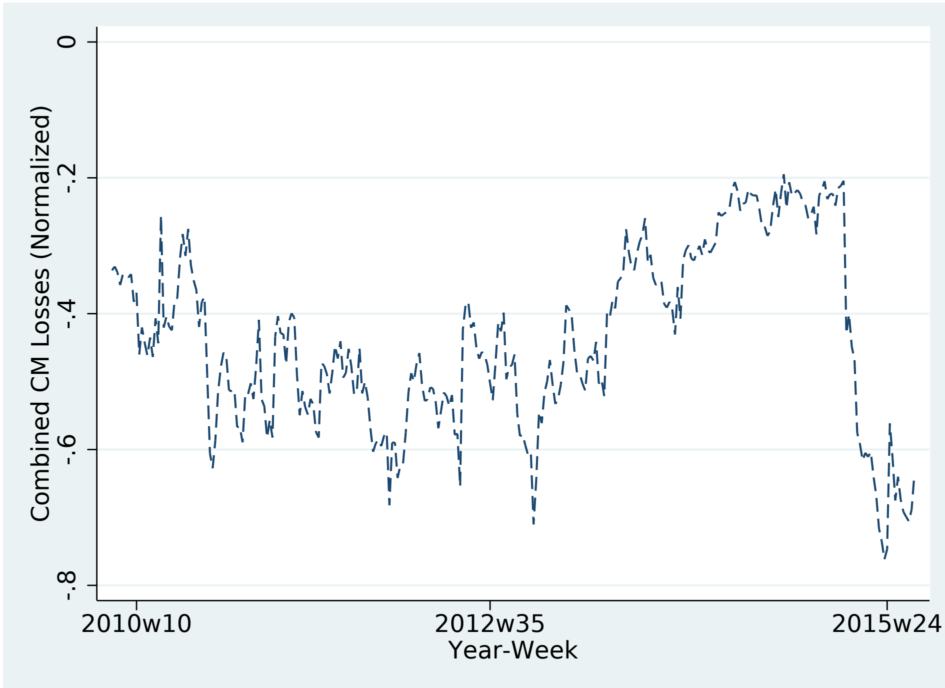


(a) *Stress Losses to CCP* 1

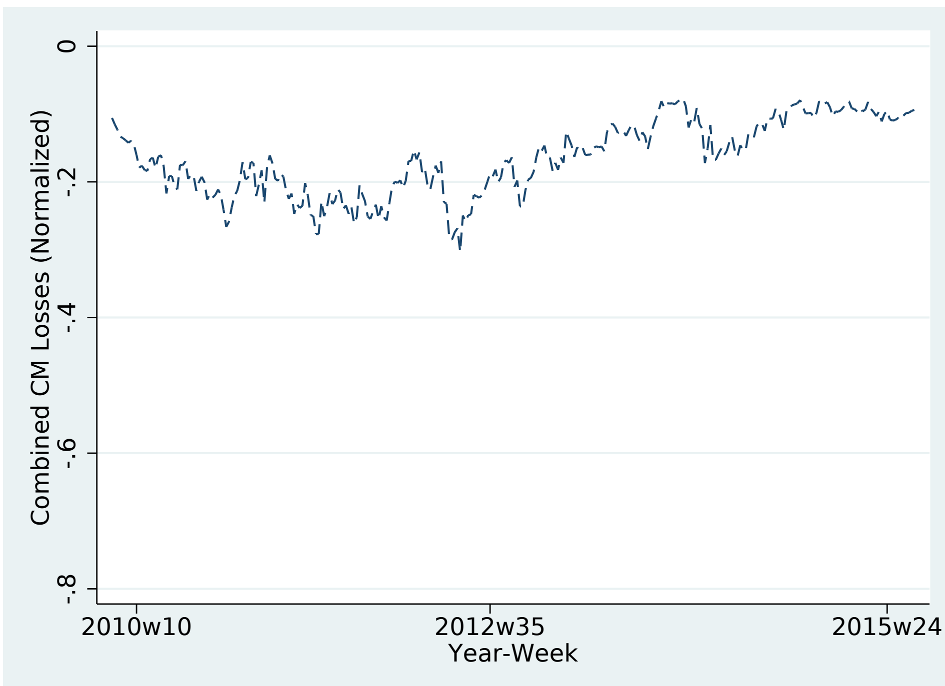


(b) *Stress Losses to CCP* 2

Figure 8: Stress Losses of each CM to *CCP* 1 and *CCP* 2. This figure plots the first percentile of simulated losses of each clearing member to both *CCP* 1 (Panel A) and *CCP* 2 (Panel B). Stress losses are normalized by the maximum of the weekly net CDS exposures across all clearing members. For the sake of presentation the y-axes are multiplied by 100.



(a) CCP 1



(b) CCP 2

Figure 9: Combined Losses of all CMs to each CCP. This figure plots the first percentile of combined losses of all CMs to each CCP. Panel (a) plots the stress losses to CCP 1 while panel (b) depicts the losses of all CMs to CCP 2. Stress losses are normalized by the maximum of the weekly net CDS exposures across all clearing members. For the sake of presentation the y-axes are multiplied by 100.

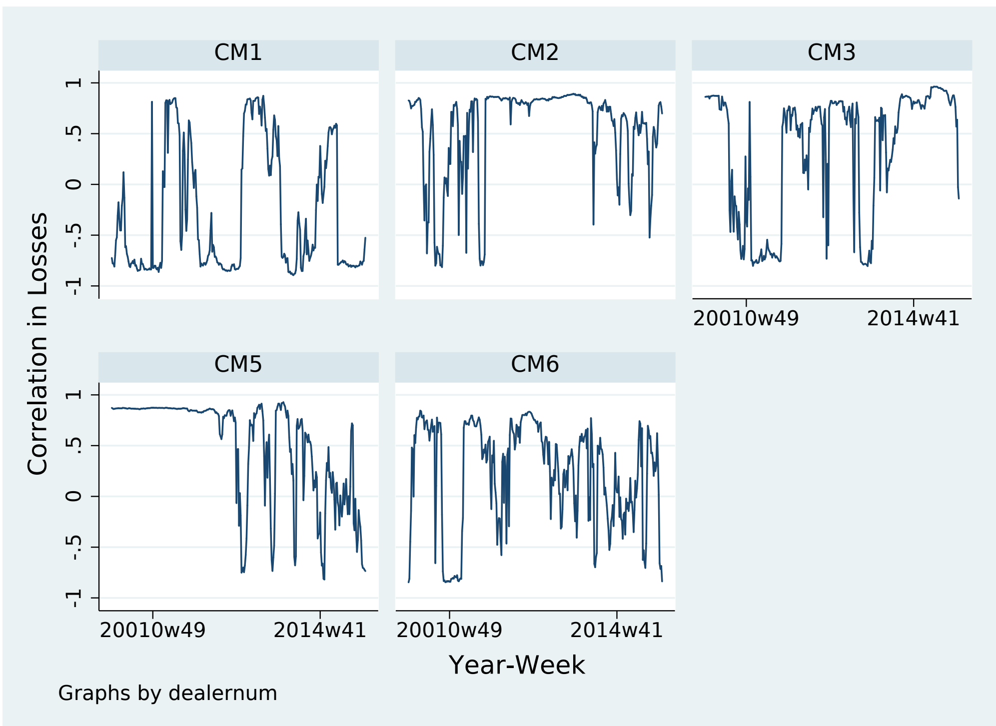


Figure 10: Rank Correlations for Total Net Profit of each CM across the two CCPs. This figure plots the time-series of rank correlations of profits-losses of each clearing member across the two CCPs.

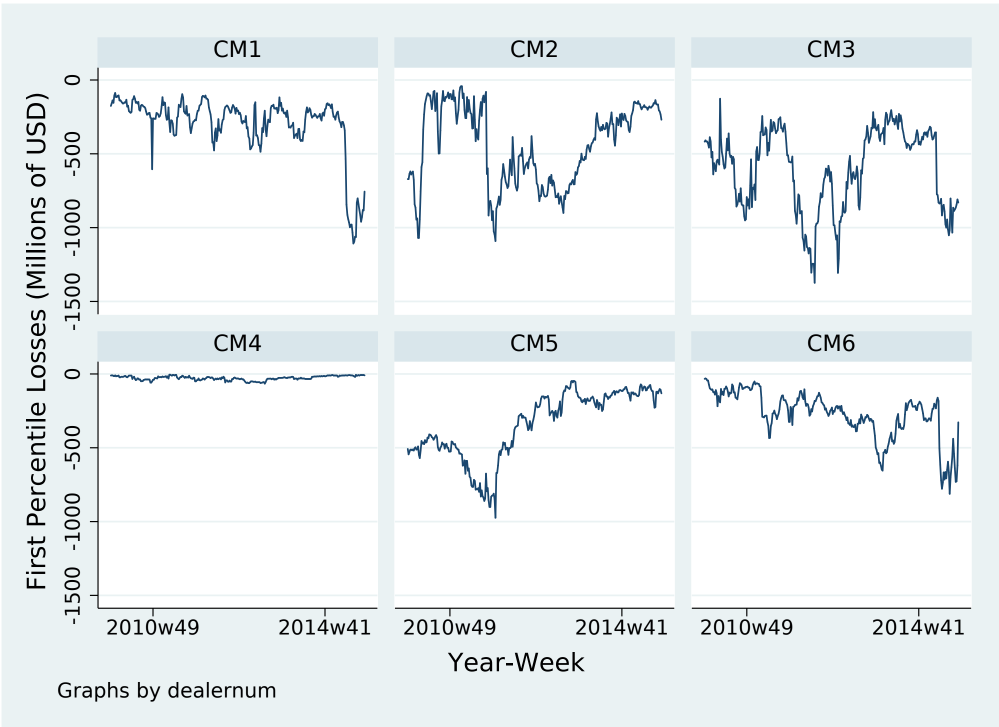


Figure 11: Stress Losses of each CM to both CCPs. This figure plots the first percentile of the simultaneous simulated losses of each CM to both CCPs.