Counterparty Risk and Counterparty Choice in the Credit Default Swap Market*

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Abstract

We investigate how market participants price and manage counterparty risk in the post-crisis period using confidential trade repository data on credit default swap (CDS) transactions. We find no evidence that counterparty risk affects the pricing of CDS contracts, but strong evidence that counterparty risk is managed via the choice of counterparties. We show that market participants are significantly less likely to trade with counterparties whose credit risk is highly correlated with the credit risk of the reference entities and with counterparties whose credit quality is relatively low. Furthermore, we examine the impact of mandated central clearing on CDS pricing and counterparty choices. In contrast to the previous literature, we find that transaction spreads on centrally cleared trades are significantly lower relative to spreads on contemporaneous uncleared transactions. We also find that the counterparty choice of uncleared trades is more sensitive to the credit quality of the dealer than the counterparty choice of bilateral trades that are soon thereafter centrally cleared.

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JEL Classifications: G12, G13, G24

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1 Introduction

Counterparty risk in over-the-counter (OTC) derivative markets played an important role in the propagation of the global financial crisis in 2008. The inability of Bear Stearns and Lehman Brothers to find counterparties willing to trade, as their troubles became apparent, hastened their descent into insolvency. Senior policymakers justified government assistance in the sale of Bear Stearns to JP Morgan Chase, in large part by the need to avoid the further dislocations in OTC derivative markets that would have ensued in a rush to liquidate Bear Sterns' collateral and to replicate positions with new counterparties. The bailout of AIG was motivated by the fear of a cascade of counterparty defaults in credit default swap (CDS) markets.[1] Structural reforms introduced by Title VII of the Dodd-Frank Act in the United States and similar measures in the European Union were intended to reduce dramatically the scope for counterparty risk in derivative markets to generate systemic crises.

In this paper, we investigate how market participants manage and price counterparty risk in the changing regulatory environment of the post-crisis period. We use four years (2010–13) of confidential transaction level data from the CDS trade repository maintained by the Depository Trust & Clearing Corporation (DTCC) to estimate the effects of counterparty risk on the choice of counterparties and CDS prices. The data provide detailed information on counterparty identities, notional size and price, and whether the trade is centrally cleared. Therefore, we can address the effects of counterparty risk and central clearing on CDS pricing and choice of counterparty.

The literature has thus far been focused on the price effects of counterparty risk. Following Arora, Gandhi, and Longstaff (2012), we begin by investigating whether transaction spreads decrease with the credit risk of the seller and increase with the credit risk of the buyer. Since counterparty risk in the CDS market has a natural asymmetry between buyer and seller of protection, the former effect should be larger in magnitude than the latter. We

[1] The Financial Crisis Inquiry Commission (2011) report provides a detailed narrative based on primary documents and testimony of senior policymakers and industry leaders. See especially pp. 287, 291, 329, and 347.

find that the effects of buyer and seller credit spreads on CDS transaction spreads are always very close to zero and statistically insignificant in most specifications. This is substantively consistent with Arora, Gandhi, and Longstaff (2012), who find that the effect of counterparty risk on CDS quotes is statistically significant but trivial in magnitude.

We next investigate whether market participants manage counterparty exposure by choosing counterparties based on their risk profile, which, so far as we are aware, has not previously been studied. We estimate a multinomial logit model for the buyer's choice of dealer counterparty, and find that market participants are less likely to buy protection from dealers whose credit quality is relatively low. This is consistent with the view that investors manage counterparty risk via counterparty choice. We also find that market participants are less likely to trade CDS protection with a dealer whose credit risk is highly correlated with the credit risk of the reference entity, i.e. market participants avoid wrong-way risk.

In addition, we explore whether market participants vary in their sensitivity to counterparty risk in their choice of dealer. We find that hedge funds are the most sensitive to counterparty risk in their choice of dealer. Dealer-banks are less sensitive, and asset managers appear not to be sensitive at all, but both classes of firms do avoid wrong-way risk.

Lastly, we investigate whether central clearing has had an impact on how participants manage counterparty risk and price CDS contracts. Due to the asymmetry between buyer and seller in counterparty exposure, central clearing raises the value of the protection leg of a CDS contract by more than the premium leg. Loon and Zhong (2014) therefore hypothesize that centrally cleared trades should have higher spreads than uncleared trades, and report evidence in support. Contrary to their findings, we find that transaction spreads on centrally cleared trades are significantly *lower* relative to spreads on contemporaneous uncleared transactions. In addition, we find no significant increase in transaction spreads around the commencement of central clearing. These results are consistent with our view that counterparty risk is not priced.

We hypothesize that central clearing should reduce the sensitivity of counterparty choice to dealer credit risk, as counterparty exposure is limited to the window of time between the OTC transaction and novation to the clearinghouse. We find evidence to support this hypothesis, which we interpret as supporting our view that counterparty risk is managed via counterparty choice, and that central clearing is an alternative means of reducing counterparty exposure.

Our paper adds to the literature on counterparty risk management in OTC derivative markets. Campbell and Heitfield (2014) provide a comprehensive treatment of regulations of counterparty risk in OTC derivatives. Theoretical treatments of counterparty risk valuation include Cooper and Mello (1991), Duffie and Huang (1996), Jarrow and Yu (2001), Hull and White (2001). Pykhtin (2011) provides a succinct introduction to the effects of netting, collateral, thresholds, margin call frequency and grace periods on the dynamics of counterparty exposure. For a comprehensive treatment, see Gregory (2010). Empirical research testing these models, however, is sparse. Besides Arora, Gandhi, and Longstaff (2012), Giglio (2013) infers counterparty risk from the corporate bond-CDS basis.

We also contribute to the literature on the impact of central clearing, which includes recent studies by Duffie and Zhu (2011), Bernstein, Hughson, and Weidenmier (2014), Loon and Zhong (2014) and Duffie, Scheicher, and Vuillemey (forthcoming). Shachar (2012) uses the DTCC data during the global financial crisis period and shows that liquidity deteriorates as counterparty exposures between dealers accumulate. Other papers using the DTCC CDS data include Oehmke and Zawadowski (2013) and Siriwardane (2015), although the focus of these papers is not on counterparty risk.

We proceed as follows. In Section 2, we provide background on counterparty risk in the CDS market and describe the DTCC data. We re-visit the evidence in Arora, Gandhi, and Longstaff (2012) and test the effect of counterparty credit risk on CDS pricing in Section 3. In Section 4, we estimate the multinomial choice model for buyers and sellers of protection.

In Section 5, we examine the effects of central clearing on cross-sectional and time series variations in CDS pricing and the counterparty choice. Section 6 concludes.

2 Background and Data Description

2.1 Background on pricing and managing counterparty risk

Market participants respond to counterparty risk either by managing the risk or by demanding compensation for bearing the risk. Broadly, three mechanisms have evolved for risk-management. First, counterparties arrange for netting of offsetting bilateral positions and collateralize trades under the terms of a bilaterally negotiated credit support annex (CSA). In the aftermath of the financial crisis, interdealer CSAs have required the daily exchange of variation margin to be equal to the change in the market value of the bilateral portfolio. In practice, variation margin mitigates but does not eliminate counterparty risk. A counterparty in distress can exploit valuation disputes and grace periods to delay delivery of collateral, and the failure of a dealer is likely to coincide with unusual market volatility and reduced liquidity. Furthermore, dealers' most-favored clients may negotiate more flexible terms. The most notable example from before the crisis is the exemption from posting margin granted by dealers to AIG subject to a threshold agency credit rating.[2] As with other studies in this literature, we are unable to observe bilateral CSA agreements, exchange of margin collateral between counterparties, and bilateral counterparty exposures in other derivative classes. Thus, we cannot address the effects of collateralization and netting in mitigating counterparty risk, and simply maintain the assumption that these mitigants do not fully eliminate counterparty risk.

Second, regulatory reform has mandated central clearing of trades on most standardized and liquid OTC contracts. Central counterparties impose standardized margining rules

[2]The CSA may also provide for initial margin. The terms of initial margins can vary significantly across market participant, and are likely to be less stringent for counterparties currently perceived as highly creditworthy.

and effectively mutualize counterparty risk. In the CDS market, recent series of the most heavily-traded indices are eligible for clearing, as are the constituent single-name swaps. Among the corporate reference entities not eligible for clearing, most notable are the dealer banks themselves. Of the 11 sovereign entities now eligible, only Italy is a G7 country. From the perspective of the clearinghouse, CDS on the dealer banks (and on the sovereigns that implicitly guarantee these banks) would be subject to an especially severe *wrong-way risk*, i.e., there is a high correlation between the distress of the reference entity and distress of the seller of CDS protection. The dealer banks are linked in ordinary times by their common exposure to systematic market factors, and in crises by their common exposure to fire sales, deleveraging and other channels of systemic risk. Furthermore, as the dealer banks are the primary members of the clearinghouse and provide its capital backstop, the failure of a dealer weakens the clearinghouse itself. In our empirical analysis, we exploit the special characteristics of CDS on the dealer banks.

Third, market participants can mitigate counterparty risk simply by trading preferentially with counterparties that are less risky or less correlated with the underlying reference entity. For example, if a counterparty ABC were to become too risky, participants might preferentially trade with ABC when a contract offsets existing bilateral exposure, but otherwise preferentially trade with other counterparties. In addition, market participants may simply avoid buying protection from counterparties whose credit risk is highly correlated with credit risk of the reference entities. For example, a buyer of CDS protection on French banks might avoid transacting with a French dealer.

Counterparty risk may be reflected in transaction prices of derivative contracts. The credit valuation adjustment (CVA) measures the difference in values between a derivative portfolio and a hypothetical equivalent portfolio that is free of counterparty risk. Intuitively, it represents the cost of hedging counterparty risk in the bilateral portfolio, though in practice such hedging may be difficult to execute due to the stochastic size of the exposure. To the extent that this cost can be imposed on the counterparty through the terms of trade, we will observe the price of a given contract varying with the credit risk of the counterparties.[3] It is important to recognize that adjustments to pricing do not mitigate counterparty risk, but rather serve as compensation for bearing the risk. The CVA is the net present value of future losses, so in normal circumstances it will be orders of magnitude smaller than the potential losses that could result from counterparty default.

Whether managed or priced, counterparty risk in the CDS market has a natural asymmetry between buyer and seller of protection. If the seller of protection defaults prior to the reference entity, loss to the buyer can be as large as the notional value of the contract. If the buyer defaults, the seller's loss is bounded above by the discounted present value of the remaining stream of premium payments, which is typically one or two orders of magnitude smaller than the notional amount. Furthermore, because financial firms (especially dealer banks) are more likely to default when prevailing credit losses are high, wrong-way risk is invariably borne by the buyer of protection. Thus, we expect the buyer of credit protection to be more sensitive to the credit risk of the seller than the seller is to the credit risk of the buyer.

2.2 DTCC CDS transaction data

DTCC maintains a trade repository of nearly all bilateral CDS transactions worldwide. Each transaction record specifies transaction type, transaction time, contract terms, counterparty names and transaction price. We access the data via the regulatory portal of the Federal Reserve Board (FRB) into DTCC servers. The portal truncates the DTCC data in accordance with so-called entitlement rules (Committee on Payment and Settlement Systems, 2013, S3.2.4). As a prudential supervisor, the FRB is entitled to view transactions for which

(i) at least one counterparty is an institution regulated by the FRB, or

[3] In practice, compensation for CVA may be limited by the bilateral nature of counterparty risk. If two equally risky counterparties enter a trade in which return distributions are roughly symmetric, then each demands similar compensation from the other. If the trade is to be executed, it will be executed near the hypothetical CVA-free price, so neither party will be compensated.

(ii) the reference entity is an institution regulated by the FRB.

In particular, the largest dealer banks in the U.S. (Bank of America, Citibank, Goldman Sachs, JP Morgan Chase and Morgan Stanley) are FRB-regulated institutions, so we observe all trades by those major dealers and all trades on those dealer banks as reference entities.

Our sample period is January 2010 through December 2013.[4] We consider only new, price-forming trades. Specifically, we drop novations, terminations, intra-family housekeeping transactions, and records resulting from trade compression. We also drop prime broker trades, for which the dealer is serving only as agent. We drop trades involving index swaptions. This leaves us with just over two million observations.

We construct two dummy variables as indicators of wrong-way risk. $SAME_i^s$ is equal to 1 if the seller of protection and the reference entity are the same, and 0 otherwise. This captures an obvious and extreme form of wrong-way risk, which is referred to as *specific* wrong-way risk in regulatory guidance. WWR_i^s is equal to 1 if the seller of protection and the reference entity are from the same country and their credit risk is highly correlated.[5] $SAME_i^b$ and WWR_i^b for the buyer of protection can be defined analogously.

3 Effects of Counterparty Credit Spreads on CDS Pricing

In this section, we study the effects of buyer and seller credit risk on CDS pricing. Under the maintained assumption that OTC CDS trades are imperfectly collateralized, protection sold by high-risk counterparties should be less valued than protection sold by low-risk counterparties. Whether this difference in CVA affects market prices, however, is an empirical question. If it does, then, holding fixed the buyer and contract, we expect sellers' CDS spreads to be negatively correlated with transaction spreads. Similarly, as high-risk buyers

[4] Our window has no overlap with the period of March 2008 to January 2009 studied by Arora, Gandhi, and Longstaff (2012), and overlaps only partially with the period of 2009–11 studied by Loon and Zhong (2014).

[5] We consider the credit risk of the reference entity and the seller of protection to be highly correlated if one-day changes in their 5-year CDS spreads have a correlation higher than 70 percent. All reported results are robust to considering a higher correlation, 80 percent, and a lower correlation, 60 percent.

of protection are less likely to fulfill their premium leg obligations than low-risk buyers, we expect buyers' CDS spreads to be positively correlated with transaction spreads, holding fixed the seller and contract.

We perform fixed effect panel regressions to test the hypotheses. In the full sample and all different subsamples and specifications we consider, we find economically trivial negative effects of seller's credit spreads and generally do not find positive effects of buyer's credit spreads on CDS pricing.

3.1 Sample construction and summary statistics

For our analysis of the effect of counterparty risk on pricing, we impose additional restrictions on the sample to ensure a clean match against the Markit database of end-of-day par spread quotes. Specifically,

- Trades must adhere to standard market conventions established by ISDA. These conventions specify reporting protocols, coupon rates, credit event settlement procedures, and other administrative details. We lose 138,000 observations that do not meet these criteria.
- We drop 170,000 observations for which the underlying cannot be matched to a Markit spread for the same terms on the same date.
- We drop 5,500 observations for which a par spread cannot be constructed.

Further, in the tables below, we have excluded index trades, which account for 457,000 observations.

We convert upfront points associated with the standard fixed coupon rates to par spreads to facilitate interpretation of the economic magnitude of our empirical estimates.[6] The calculated par spreads are compared to Markit's end-of-day par spread quotes. Summary

[6] We use initial payment, total notional amount and the ISDA convention interest accrual convention to compute the implied upfront points associated with each transaction. We then apply the program provided by the ISDA for conversion of upfront points into par spreads.

statistics for the difference between DTCC and Markit par spreads are given in Panel A of Table 1. The median difference between DTCC and Markit spreads is quite small (0.48 basis points), but the 95 percentile of this difference is 67 basis points. To ensure our results are not driven by large outliers, we drop the upper 5 percentile tail with respect to the absolute difference between DTCC and Markit par spreads.

Panel B of Table 1 summarizes characteristics of transactions on the same reference entity with the same tenor, currency, restructuring or non-restructuring clause and fixed coupon rate, traded during the same week. We restrict the summary statistics to the subsample in which there are at least 5 trades on the identical contracts during the same day, which is about 50 percent of the full sample. We see that there is a significant amount of pricing dispersion within the week on the same contract, with a median within-day standard deviation of 0.28 percent. In terms of the counterparty choice, we see that on average a buyer (seller) trades with two to three different sellers (buyers) on the same day. The existence of multiple counterparties for the same party allows us to test whether cross-sectional pricing dispersion in transaction spreads is correlated with counterparty credit spreads.

3.2 Effect of seller credit spreads on CDS pricing

To investigate whether counterparty risk is priced in the CDS market from the protection buyer's perspective, we run the following regression:

$$\log(cds_{i,t}^{s,b}) - \log(cds_{i,t}^{Markit}) = \alpha_{i,t}^{b} + \beta s_t^s + \delta \log(size) + \epsilon_{i,t}^{b,s}, \tag{1}$$

where $\log(cds_{i,t}^{s,b})$ is the log par spread of the i-th CDS contract specification traded at time t. Superscripts s and b denote the seller and buyer of credit protection, respectively. The log par spread quoted by Markit on reference entity i at time t is denoted $\log(cds_{i,t}^{Markit})$. The dependent variable measures the difference between a specific transaction spread and the Markit quote on the same reference entity at time t. We use the seller's quoted CDS spreads with a one day lag s_t^s to measure its own credit risk at the time of the CDS transaction. The fixed effect $\alpha_{i,t}^b$ refers to the buyer-contract-time interactive fixed effect. We choose a daily time fixed effect as the benchmark, so that identification comes from pricing dispersion within the same day. In addition, we control for the log of the notional value of the traded contract, $\log(size)$, to allow for the contract size to have some potential impact on transaction spreads. Our specification is similar to that of Arora, Gandhi, and Longstaff (2012). Namely, we compare the transaction spreads on the same contract, traded on the same date, bought by the same buyer, but sold by different sellers that vary in their credit risk. If seller counterparty risk is priced, we expect $\beta < 0$.

We estimate on our sample of transactions on non-clearable reference entities. Table 2 presents estimated coefficients for different subsamples and specifications. In Column 1, we show our baseline specification, as given by equation (1). The coefficient on seller's CDS spread is statistically insignificant and equal to -0.000416, which implies that a 100 percent increase in the buyer's CDS spread translates to only a 0.0416 percent decrease in the transaction spread. To translate the log CDS spread change to the level change, the mean level of CDS spreads is about 350 basis points, and hence a 0.0416 percent decrease of the mean only corresponds to a 0.15 basis point decrease in the level of CDS spreads. As shown in Table 1, the median intra-day price dispersion is between 2 to 3 percent, so the estimated effect is negligibly small by this standard as well. In Column 2 we report results on a sample restricted to interdealer transactions. The coefficient estimates are similar to those in Column 1.

In Column 3 we restrict our sample to FRB-regulated reference entities, for which we observe all transactions. The coefficient on the seller's CDS spread becomes marginally significant, but remains very small. A 100 percent increase in the seller's CDS spread translates to a 0.2 percent (or 0.7 basis points relative to the mean) decrease in the transaction spread. To control for the fact that some sellers have persistently higher or lower credit spreads, in

Column 4 we introduce seller fixed effects. The coefficient becomes significantly negative, and is similar in magnitude to the estimate in Column 3.

In Column 5, we include an indicator variable for wrong-way-risk (WWR_i^s, as defined in section 2.2) and the interaction between WWR and the log seller CDS spread. If buyers actively price counterparty risk, we expect WWR to enter negatively into transaction spreads. However, we find a small, insignificantly positive coefficient on WWR. The interaction between WWR and the seller's CDS spread is slightly negative and insignificant.

3.3 Effect of buyer credit spreads on CDS pricing

Parallel to the previous section, we consider the effect of the buyer's CDS spread on the transaction spreads by holding the seller and the contract fixed:

$$\log(cds_{i,t}^{s,b}) - \log(cds_{i,t}^{Markit}) = \alpha_{i,t}^s + \gamma s_t^b + \delta \log(size) + \epsilon_{i,t}^{b,s}, \tag{2}$$

where s_t^b denotes the buyer's CDS spread and $\alpha_{i,t}^s$ is the seller-contract-time fixed effect. If the buyer's counterparty risk is priced, we should expect $\gamma > 0$.

We estimate on our sample of transactions on non-clearable reference entities, and report results in Table 3. In Column 1, we show our baseline specification, as given by equation (2). The coefficient estimate for the buyer's CDS spread is slightly negative and not significantly different from zero. When we restrict the sample to interdealer transactions (Column 2), we find a marginally significant coefficient, but similar in magnitude to the baseline specification.

In Column 3 we repeat the estimation using FRB-regulated non-clearable reference entities. The coefficient on the buyer's CDS spread becomes positive under this subsample, but is negligible in magnitude. In Column 4 we introduce buyer fixed effects and find a significantly positive coefficient equal to 0.0045, which implies that a 100 percent increase in the buyer's CDS spread corresponds to only 0.45 percent (or about 1.5 basis points relative to the mean) increase in the transaction spread. In Column 5 we include an indicator for wrong-way risk (WWR_i^b) and retain buyer fixed effects. If sellers price wrong-way risk, we expect a positive sign on the WWR indicator variable. Instead, we obtain an insignificant negative coefficient on WWR and a very close to zero coefficient on the interaction between WWR and the buyer's CDS spread.

4 Analysis of Counterparty Choice

In this section, we show that market participants actively manage counterparty risk by choosing counterparties of better credit quality and less subject to the wrong-way risk.

4.1 Sample construction and summary statistics

To estimate a model of counterparty choice, we must observe all transactions on a given reference entity for a given market participant. Despite the entitlement restrictions imposed on the data, we are able to construct two subsamples for which this criterion is met.

First, we construct a sample that includes only transactions where the underlying reference entity is regulated by the FRB. To avoid any bias due to illiquidity, we drop reference entities that are traded less than once per month on average. This subsample consists of 74,517 trades on 12 reference entities.[7]

As shown in Panel A of Table 4, 84 percent of the transactions within this subsample have as a seller of protection one of the 14 largest dealers, 6 percent of the transactions have as a seller an asset manager, and less than one percent were centrally cleared.[8] In our

[7]The included entities are Ally Financial, American Express, Bank of America, Capital One Bank, Capital One Financial Corporation, CIT Group, CitiGroup, JPMorgan Chase, Metlife, Morgan Stanley, Goldman Sachs Group, and Wells Fargo.

[8]The 14 largest dealers in our sample are: Bank of America Merrill Lynch, Barclays, BNP Paribas, Citibank, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, JP Morgan Chase, Morgan Stanley, RBS Group, Société Générale, UBS, and Nomura. Arora, Gandhi, and Longstaff (2012) also restrict their sample to the 14 largest dealers. Our lists are very similar. The difference is that Lehman and Merrill Lynch no longer exist in our sample period. In their place we have, Bank of America Merrill Lynch, Nomura Holdings, and Société Générale.

analysis of counterparty choice, we restrict the set of choices to these 14 dealers, similar to Arora, Gandhi, and Longstaff (2012). Our results are robust to relaxing this restriction.

The advantage of this sample partition is that we observe counterparty choice for a wide variety of market participants, so we can discern whether different types of market participants manage counterparty risk differently. The disadvantage is that the 12 reference entities are relatively homogeneous, so we cannot investigate whether investors manage counterparty risk differently depending on the underlying reference entity. Therefore, we construct a second subsample restricted to transactions for which one (or both) counterparty is FRB-regulated. We start with a list of 24 market participants, not all of which trade frequently. We retain in the sample participants that trade at least once a month and reference entities that are traded at least once a month. This leaves us with 13 market participants and a total of over 1 million transactions. As shown in Panel B of Table 4 this second sample partition includes over 2000 different reference entities from a variety of sectors.

Using a subsample of this sample partition, Table 5 provides preliminary evidence of aversion to wrong-way risk among market participants. In this sample, the buyer of protection is an FRB-regulated institution. The seller is one of our 14 dealers (not necessarily FRB-regulated) or a frequent seller (a seller of protection who participates in at least 1 percent of all transactions). For each seller, we compute the seller's trading share (by trade count) for the CDS on the seller's sovereign ($share^{own}$) and the seller's trading share for other sovereigns ($share^{other}$). For a large majority of sellers, $share^{own} = 0$, and for most of the remaining sellers $share^{own}$ is less than 20% of $share^{other}$. This suggests that FRB-regulated buyers are much less likely to buy sovereign CDS from a bank domiciled in that sovereign than to buy protection on other reference entities from the same bank.

4.2 Multinomial choice model for non-clearable reference entities

We estimate McFadden's (1974) multinomial conditional logit model for the choice made by the buyer of protection among the $N = 14$ dealers. The probability of choosing dealer s conditional on characteristics x_t^s is specified as

$$\Pr(y_{b,t} = s|x_t^s) = \frac{\exp(x_t^s\beta)}{\sum_{s=1}^{N}\exp(x_t^s\beta)}, \qquad s = 1, \ldots, N. \tag{3}$$

The independent regressors are: credit risk of the seller, proxied as before by the CDS spread of the seller of protection s, on date t; the number of transactions in the previous month for the buyer-seller pair, standardized by its own standard deviation, to allow for "stickiness" in buyer-dealer relationships; an indicator variable for specific wrong-way risk ($SAME_i^s$), as described in section 2.2;[9] an indicator variable for general wrong-way risk (WWR_i^s), as described in section 2.2; a set of dummy variables for the N sellers, to allow for baseline differences in market share; interactions between seller dummy variables and the spread on the five-year CDX.NA.IG index, to allow for the possibility that buyers may gravitate towards particular sellers when market-wide spreads are high. Results are reported in Table 6. The coefficients on seller dummy variables are omitted to respect the confidentiality of the data.

In Column 1 we report coefficients estimated on the subsample of FRB-regulated reference entities. As predicted, the coefficient on seller's CDS is negative and statistically significant, i.e., market participants are less likely to buy protection from a dealer whose own CDS spread is high relative to other dealers. The coefficient on last month's buyer-seller pair transaction count is large, positive and statistically significant, which is indicative of persistence in trading relationships. The coefficient on WWR is large, negative and statistically significant, which shows that buyers avoid wrong-way risk in their choice of dealer. Finally, as we almost

[9] As an alternative to controlling for $SAME$, we can simply eliminate the very few observations in which the seller is also the reference entity. The results are virtually unchanged.

never observe a dealer selling protection on itself, the coefficient on $SAME_t^s$ is large and negative.

Marginal effects for this regression are reported in Table 7. We separately report marginal effects at sample means for the large dealers (those with unconditional transaction shares of 6–11%) and small dealers. We find that a 100 basis point increase in a large dealer's CDS spread is associated with an average decline in the likelihood of buying protection from that dealer of 0.5 percentage points. A one standard deviation increase in past-month transaction count increases the probability of selection by 2 percentage points. Wrong-way risk reduces the probability by 3 percentage points. Relative to unconditional transaction shares of 6–11 percentage points, these effects are all of large economic magnitude.

The remaining columns of Table 6, report coefficients estimated on subsamples of the sample of transactions in which the buyer of protection is an FRB-regulated firm. This sample spans a wide variety of reference entities, so we estimate the model separately for three sectors: financial (Column 2), sovereign (Column 3) and other (Column 4). For trades on financial reference entities, we find that dealers manage counterparty risk predominantly by avoiding wrong-way risk. The coefficient on the seller's CDS spread is negative but insignificant. For trades on sovereign CDS, we find very large and statistically significant negative coefficients on both WWR and the seller's CDS spread. For the residual "other" sector, we find that the coefficient on seller's CDS spread is insignificant. More interestingly, we find a positive and statistically significant coefficient on WWR, i.e., the dealer is more likely to buy protection from a dealer of the same country as the reference entity. We speculate that sellers of protection from the same country as the reference entity have an informational advantage over other sellers, so may be able to price more accurately the default risk of that entity. This advantage might outweigh wrong-way risk for typical reference entities.

We have repeated these analyses from the perspective of sellers of protection. We find that dealers are less sensitive to buyer counterparty risk when selling CDS protection.

We next consider the possibility that the determinants of the buyer's choice of seller might vary across classes of market participant. This analysis is conducted on our sample of transactions on FRB-regulated reference entities, in which we observe a wide variety of buyers. We classify buyers into the following categories: hedge fund, asset manager, bank-dealer, bank-nondealer, and other (i.e., a residual category which includes insurance companies, financial services, and pension plans). We interact buyer type indicators with the regressors featured in Table 6, and further include seller fixed effects and seller $\times$ buyer type fixed effects to allow preferences over dealers to vary across classes of market participant. As shown in Table 8, we find that management of counterparty risk varies across buyer type. Hedge funds are the most sensitive to counterparty risk in their choice of dealer. Dealer-banks are less sensitive, and asset managers appear not to be sensitive at all, but participants of both these types seek to avoid wrong-way risk.

5 Central Clearing

Loon and Zhong (2014) find that central clearing increases CDS spreads, and attribute this to the mitigation of counterparty risk. We find the opposite association in our data. In the cross-section, we find that transaction spreads from centrally cleared trades are associated with lower spreads than uncleared trades. In the time series, we find no evidence that a reference entity's transaction spreads increase around the commencement of eligibility for central clearing. However, we do find evidence that counterparty choice depends less on counterparty credit quality for cleared transactions than for over-the-counter uncleared transactions.

Clearing was first introduced for CDX.NA.IG, an index composed of investment grade North American corporates, and iTraxx Europe, its European counterpart. Select single-name reference entities became eligible for clearing by Intercontinental Exchange (ICE) on December 14, 2009. By the end of our sample most index constituents had been made eligible to clear. The single-names that remain ineligible are primarily the dealer banks listed on iTraxx Europe.

Within an investment grade index, reference entities are made eligible for central clearing in cohorts. A cohort typically consists of several firms in the same sector. Tables A1 and A2 summarize the number of reference entities cleared over time during our sample by sector for CDX.NA.IG and iTraxx Europe, respectively. For CDX.NA.IG, cohorts are typically small. As an example, six firms in the Healthcare sector were made eligible for clearing on 10 May 2010, three more on 2 May 2011, and a single firm was added on 14 November 2011. For many sectors in iTraxx Europe, however, most reference entities were made eligible on the same day. Our analysis exploits the staged introduction of clearing for CDX.NA.IG constituents to study time series effects of central clearing on transaction spreads.

5.1 Cross-sectional comparison for pricing

In our sample period, there were two methods by which market participants could engage in cleared trades. Under the first method, known as backload clearing, the parties initially transact bilaterally in the over-the-counter market, and later submit the trade to a central counterparty (CCP) for clearing, typically on the Friday following the trade. Our assumption is that the backloaded trades were marked for clearing by the counterparties at the time of the bilateral transaction. Under the second method, the trade is executed on a swap execution facility (SEF). With some exceptions, buyer and seller are matched anonymously on a SEF. The trade is cleared at its inception, so appears in the repository data as two simultaneous transactions with a central counterparty as buyer on one leg and as seller on the other.

Table 9 presents results on how SEF clearing, backload clearing and other counterparty characteristics affect CDS pricing. In Column 1 we hold contract, date and buyer fixed in order to study how seller characteristics affect CDS transaction spreads. We categorize trades into four groups:[10]

[10]We omit buyside to buyside OTC trades, which are very rare in the data.

(i) seller is a CCP, which implies that the trade originated on a SEF;

(ii) trade is backload cleared;

(iii) uncleared OTC trade in which seller is buyside (i.e., a non-dealer); and

(iv) uncleared OTC interdealer trade.

The fourth group is the omitted category in the regressions. Compared to OTC interdealer trades, both SEF and backload cleared trades are associated with about 0.18 percent lower spreads. Buyside sellers are associated with 0.1 percent lower spreads, but the coefficient is insignificant.

In Column 2 we hold contract, time and seller fixed in order to study how buyer characteristics affect CDS transaction spreads. Again, we find that SEF and backload cleared trades are associated with significantly lower spreads than OTC interdealer trades, with magnitudes around 0.4 and 0.2 percent, respectively. Furthermore, our results suggest that buyside firms pay dealers about 1 percent more than dealers pay in comparable OTC interdealer transactions, consistent with the view that dealers have greater market power relative to buy-side firms as protection buyers.

In Columns 3 and 4, we fix the contract and time and allow buyer and seller characteristics to vary. We confirm the effects documented in Columns 1 and 2, i.e., that SEF and backloaded cleared trades are associated with significantly lower transaction spreads, with magnitudes around 0.4 and 0.3 percent, respectively. Buyside participants in OTC transactions sell CDS protection to dealers at spreads on average 0.6 percent lower than interdealer spreads. Buyside participants buy CDS protection at spreads on average 1.6 percent higher than OTC interdealer spreads. Thus, the dealer's pricing advantage is larger when selling protection to a buyside firm than when buying protection.

Dealers' pricing advantage over buyside participantsis present before and after the introduction of central clearing. In Figure 1, we plot the average difference between transaction log-spreads in DTCC data and Markit log-spreads against the number of days since the reference entity became eligible for clearing. The left panel shows that transaction spreads are larger when dealers sell protection to buyside participants than when the dealers buy protection, and the gap does not appear to diminish following the introduction of clearing. In the right panel, we see that SEF trades have significantly lower spreads than OTC trades for which the buyside participant is the buyer.

5.2 Time series comparison for pricing

We estimate the time series effect of clearing eligibility using a difference-in-differences (DID) approach. To distinguish clearly from possible time-variation in the magnitude of pricing advantage over buyside participants, we focus on interdealer and cleared transactions only. Figure 2 plots average transaction spreads on cleared reference entities 400 days before and after the commencement of eligibility. Visually, there is no obvious change in spreads around the event. The appearance of a low-frequency time trend reflects the choice of sample period, as spreads have generally declined from crisis peaks in 2008–09.

We exploit the fact that clearing eligibility was introduced by sector in small cohorts for CDX.NA.IG, and use the DID specification to estimate the time series effect of clearing:

$$\log(cds_{i,t}^{s,b}) = \alpha_{sector,t} + \beta Treatment_i + \gamma Treatment_i * Clearable_{i,t} + \epsilon_{i,t}, \tag{4}$$

where $\alpha_{sector,t}$ denotes sector and date interactive fixed effects. The variable $Treatment_i$ is a dummy indicating whether the reference entity i is in the treatment group, and $Clearable_{i,t}$ is a dummy indicating whether the reference entity i is eligible at time t. The coefficient γ represents the time-series effect of clearing eligibility.

In the first specification, we use transactions on reference entities cleared in the first cohort for each sector as the treatment group, and pre-eligibility transactions on reference entities cleared in later cohorts as the control group. In the second specification, we use post-eligibility cleared transactions on the earlier cohorts of reference entities as the control group, and all transactions on reference entities in later cohorts in the same sector as the treatment group. In the third specification, we use all transactions on all reference entities that become eligible during the sample period as the treatment group, and transactions on other investment grade reference entities as the control group. We use treatment and control groups in the same sector to mitigate the impact of common macroeconomic and sectoral shocks on our estimates.

We visualize the DID results in Figure 3. In all three specifications, mean transaction spreads in the treatment group co-move with those in the control group very closely before and after commencement of eligibility. There is no discrete jump in treatment group around the commencement of clearing. Regression estimates confirm this visual observation. Table 10 reports DID estimates for the three specifications using a 100-day event window before and after clearing eligibility. The coefficient γ on the $Treatment \times Clearable$ interaction is negative and statistically insignificant in all three specifications. Therefore, we do not find evidence that central clearing eligibility increases transaction spreads.

5.3 Counterparty choice (work in progress)

We estimate equation (3) on a sample of transactions on constituent reference entities of the CDX.NA.IG index. We examine how clearing affects the determinants of counterparty choice. Table 11 shows that the buyer's choice of seller depends on seller CDS in both uncleared and backload cleared trades, but less so for the latter group. This result is consistent with the view that central clearing mitigates counterparty risk, and therefore makes the choice of counterparty less salient.

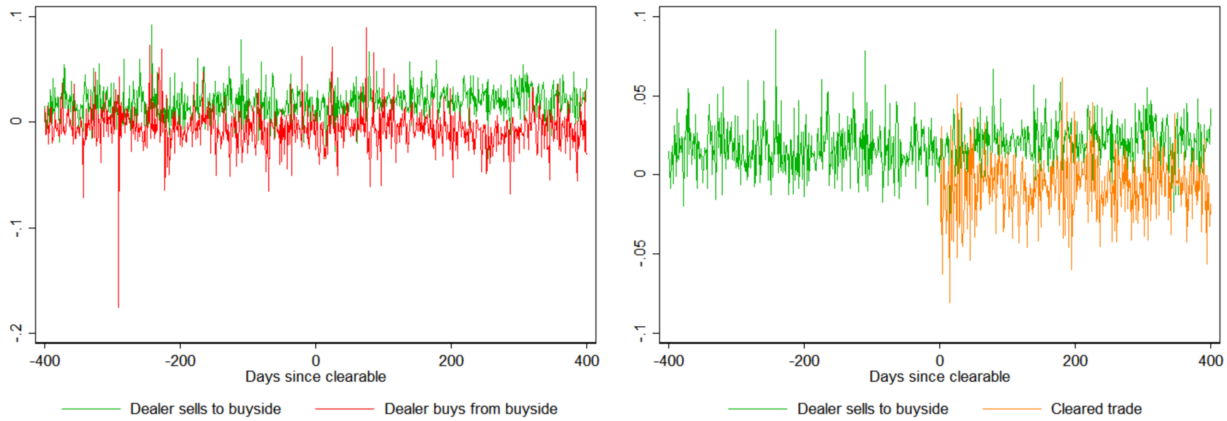
As work in progress, we also examine whether central clearing has time series effects on how market participants manage counterparty risk.

6 Conclusion

Our results show that participants in the credit default swap market manage counterparty risk by trading preferentially with counterparties of lower credit risk and lesser "wrong-way" correlation with the reference entity. Using a multinomial choice model, we show that market participants reduce the likelihood of trading with counterparties whose credit risk is highly correlated with credit risk of the reference entities. In addition, we document evidence that markets participants reduce the likelihood of trading with counterparties with deteriorating credit quality.

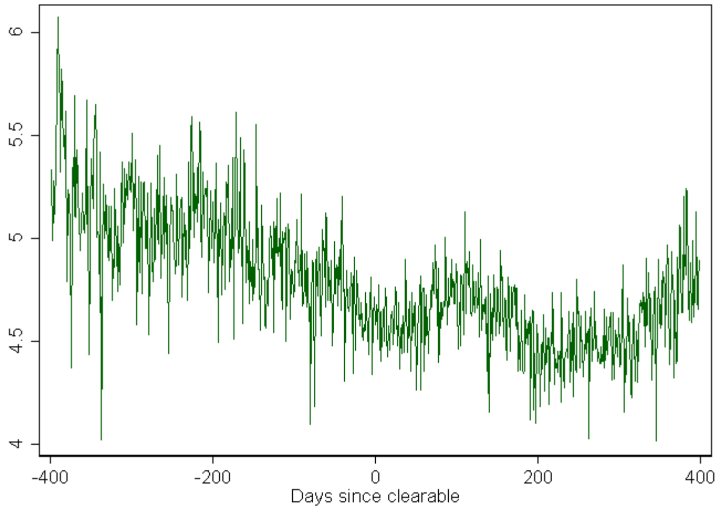
We do not find any evidence of pricing impacts arising from counterparty credit risk. In particular, holding the buyer (seller) and contract fixed, higher risk counterparties do not sell (buy) contracts at lower (higher) spreads around the same time. Furthermore, we find that centrally cleared trades are associated with lower spreads relative to comparable over-the-counter uncleared trades, which is counter to the intuition that central clearing should increase the value of credit protection by reducing counterparty risk. In the time series, using a difference-in-difference specification, we do not find evidence that transaction spreads increased after central clearing was introduced. Therefore, we conclude that counterparty risk is managed by market participants, not priced.

Figure 1: Effects of Counterparty Characteristics and Clearing on $\log(cds_t^{s,b}) - \log(cds_t^{Markit})$



Notes: The left figure plots mean transaction spreads on transactions between dealers and buyside firms before and after clearing. The right figure plots mean transaction spreads on dealer-buyside transactions when the dealer is the seller, and mean transaction spreads on SEF cleared transactions.

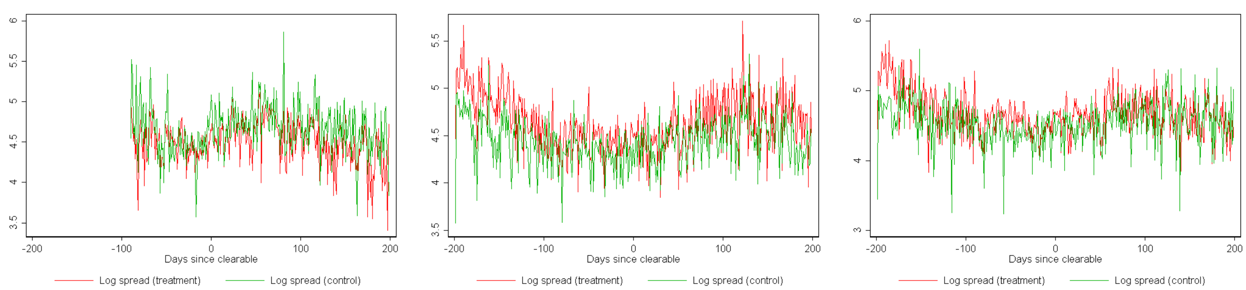
Figure 2: Average Log Transaction Spreads Before and After Clearing



Notes: This figure plots mean transaction spreads on interdealer and cleared trades on all clearable reference entities in our sample before and after the reference entities become eligible for central clearing..

Figure 3: Time Series Effects of Central Clearing on Log Transaction Spreads

(a) DID Specification 1 (b) DID Specification 2 (c) DID Specification 3



Notes: In Figure (a), the treatment group consists of transactions on reference entities cleared in the first cohort for each sector of the CDX.NA.IG index before and after clearing. The control group consists of pre-clearing transactions of reference entities in CDX.NA.IG that are cleared in later cohorts. In Figure (b), the control group consists of post-clearing reference entitiescleared in the first cohort for each sector of the CDX.NA.IG index. The treatment group consists of transactions of reference entities in the same sector of CDX.NA.IG that are cleared in later cohorts. In Figure (c), the treatment group consists of transactions on all clearable reference entities in CDX.NA.IG before and after clearing. The control group consists of transactions on all other non-clearable investment grade reference entities in North America. Only inter-dealer and cleared transactions are used in computing the means.

Table 1: Summary Statistics for Pricing Analysis

(A) Summary Statistics for all transaction spreads and Markit quotes ($N = 1,174,999$)

Percentile	p1	p5	p10	p25	p50	p75	p90	p95	p99
$cds^{DTCC} - cds^{Markit}$	-81.50	-21.47	-11.35	-3.40	0.48	5.56	23.26	67.26	488.74
$\|cds^{DTCC} - cds^{Markit}\|$	0.05	0.27	0.55	1.58	4.41	11.92	37.27	90.78	591.45
$\log(cds^{DTCC}) - \log(cds^{Markit})$	-0.31	-0.14	-0.08	-0.03	0.00	0.03	0.09	0.18	0.59
$\|\log(cds^{DTCC}) - \log(cds^{Markit})\|$	0.00	0.00	0.00	0.01	0.03	0.07	0.15	0.26	0.64

(B) Summary Statistics for contracts with at least 5 trades per day ($N = 533,482$)

Percentile	p1	p5	p10	p25	p50	p75	p90	p95	p99
$\sigma_t[\log(cds^{DTCC}) - \log(cds^{Markit})]$	0.0000	0.0000	0.0042	0.0105	0.0238	0.0529	0.1051	0.1633	0.3250
No. of transactions per week	5	5	5	5	7	10	15	19	34
Average No. of sellers per buyer	1.00	1.33	1.40	1.80	2.43	3.50	5.67	7.22	14.70
Average No. of buyers per buyer	1.00	1.33	1.40	1.80	2.45	3.59	5.83	7.22	15.13

Notes: Our sample period is from 2010 to 2013. In Panel A, we report differences between DTCC transaction spreads, cds_t^{DTCC}, and Markit quotes, cds_t^{Markit}. The spreads are expressed in basis points. The log differences in the two spreads are also reported. In Panel B, we report distribution of standard deviation for transaction spreads on the same contract within the same day, given that there are at least 5 trades per day on the same contract. In addition, we report the distribution of the number of sellers (buyers) for the same buyer (seller) on the same day.

Table 2: Effects of Seller CDS Spreads on Log Transaction Spreads

Variables	(1) Benchmark Non-Clearable	(2) Interdealer Non-Clearable	(3) Reference Entitled Non-Clearable	(4) Seller FE Non-Clearable	(5) WWR Non-Clearable
Log(Seller CDS)	-0.000416	-0.000330	-0.00205*	-0.00218**	-0.000212
	(0.000405)	(0.000418)	(0.00114)	(0.000891)	(0.000428)
WWR					0.000756
					(0.00866)
WWR x Log(Seller CDS)					-0.000470
					(0.00163)
Log(Size)	-4.61e-05	-5.02e-05	-0.00121***	-7.90e-05	-4.34e-05
	(8.53e-05)	(0.000135)	(0.000388)	(8.53e-05)	(0.000135)
Constant	0.00487**	0.00136	0.0312***	0.0860***	0.000700
	(0.00240)	(0.00292)	(0.00811)	(0.00431)	(0.00297)
Observations	706,150	604,216	47,075	706,150	604,216
C-T-B triplet	504,476	447,604	30,426	504,476	447,604
FE	C-T-B	C-T-B	C-T-B	C-T-B, S	C-T-B

Notes: The table estimates the effect of seller's credit spreads on transaction spreads holding the buyer, trade date and contract fixed. In Column 1 we use the full sample of non-clearable reference entities. In Column 2 we use transactions between dealers only. In Column 3 we restrict to the subsample of FRB entitled reference entities. In Column 4 we control for additional seller fixed effects. In Column 5 we add a dummy for the wrong-way risk (WWR) and the interaction between WWR and seller's credit spreads. In Columns 6 and 7 we estimate on clearable reference entities. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. C-T-B refers to the contract-time-buyer fixed effect, and S refers to seller fixed effect.

Table 3: Effects of Buyer CDS Spreads on Log Transaction Spreads

Variables	(1) Benchmark Non-Clearable	(2) Interdealer Non-Clearable	(3) Reference Entitled Non-Clearable	(4) Buyer FE Non-Clearable	(5) WWR Non-Clearable
Log(Buyer CDS)	-0.000468	-0.000598*	0.000588	0.00446***	-0.000449
	(0.000362)	(0.000356)	(0.00122)	(0.000819)	(0.000370)
WWR					-0.00361
					(0.00817)
WWR x Log(Buyer CDS)					0.000542
					(0.00151)
Log(Size)	3.25e-05	0.000139	-0.000929***	0.000100	3.55e-05
	(9.17e-05)	(0.000133)	(0.000348)	(9.08e-05)	(9.18e-05)
Constant	0.000934	-0.000160	0.0103	-0.0252	0.000815
	(0.00224)	(0.00271)	(0.00798)	(218.6)	(0.00227)
Observations	681,382	599,473	46,275	681,382	681,382
C-T-S triplet	419,554	386,599	22,257	419,554	419,554
FE	C-T-S	C-T-S	C-T-S	C-T-S, B	C-T-S

Notes: The table estimates the effect of buyer's credit spreads on transaction spreads holding the seller, trade date and contract fixed. In Column 1 we use the full sample of non-clearable reference entities. In Column 2 we use transactions between dealers only. In Column 3 we restrict to the subsample of FRB entitled reference entities. In Column 4 we control for additional seller fixed effects. In Column 5 we add a dummy for the wrong-way risk (WWR) and the interaction between WWR and buyer's credit spreads. In Columns 6 and 7 we estimate on clearable reference entities. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. C-T-S refers to the contract-time-buyer fixed effect, and B refers to buyer fixed effect.

Table 4: Sample Description for Analysis of Quantities Traded

	Panel A	Panel B
	FRB Regulated Reference Entities	Buyers are FRB Regulated Counterparties
Number of reference entities	12	2394
Number of reference entities eligible for clearing	4	429
Percent of trades where buyer is one of the 14 active dealers	84%	72%
Percent of trades where buyer is an asset manager	5%	8%
Percent of trades where buyer is a CCP	<1%	2%
Percent of trades where seller is one of the 14 active dealers	80%	78%
Percent of trades where seller is an asset manager	7%	9%
Percent of trades where seller is a CCP	<1%	2%

Notes: Our sample period is from 2010 to 2013. In Panel A we only consider transactions where the reference entity is one of the 12 FRB regulated references entities for which we observe all transactions. In Panel B we only consider transactions where the buyer or seller of protection is an FRB regulated entity and for whom we observe all transactions.

Table 5: Wrong-Way Risk: Government as Reference Entities

Relative trading shares	14 Largest Sellers	All frequent Sellers
$share^{own}/share^{other} = 0$	10	37
$share^{own}/share^{other} \in (0, 0.2]$	3	5
$share^{own}/share^{other} > 0.2$	1	3
Total Counts	14	45

Notes: This table tabulates seller counts based on individual seller's trading share for reference entities in its own country ($share^{own}$) over its mean trading share for reference entities in other countries ($share^{other}$) for FRB entitled buyers. We restrict the reference entities to governments.

Table 6: Determinants of the propensity to buy protection from 14 sellers: Reference entities are not eligible for clearing

	Reference Entity is a US Regulated Entity	Buyer is a US Regulated Entity		
	Financials	Financials	Government	Other
	(1)	(2)	(3)	(4)
Seller's CDS	-0.0773***	-0.0185	-0.0520***	-0.00859
	(0.0198)	(0.0117)	(0.0164)	(0.00833)
Pat Buyer-Seller Transactions	0.260***	0.260***	0.0171***	0.143***
	(0.00443)	(0.00298)	(0.000255)	(0.00162)
Wrong Way Risk	-0.441***	-0.585***	-3.518***	0.213***
	(0.0399)	(0.0345)	(0.367)	(0.0119)
Wrong Way Risk x Seller's CDS	0.0112	0.0240	0.147	0.0404***
	(0.0175)	(0.0177)	(0.188)	(0.00632)
Dealer same as reference entity	-4.178***	-4.085***	NA	NA
	(0.123)	(0.193)		
Observations	756,420	1,909,432	980,518	4,369,414
Pseudo R-squared	0.32209	0.30795	0.29812	0.31024
Controls	S-FE, CDXNAIG	S-FE, CDXNAIG	S-FE, CDXNAIG	S-FE, CDXNAIG

Notes: Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The controls are as follows: S-FE: seller fixed effect, CDXNAIG is the spread on the CDX.NA.IG index.

Table 7: Marginal effects: Reference entities are FRB regulated entities and are not eligible for clearing

(1)	(2)	(3)	(4)
Range of probability of choice	Average change in probability given a 100 bp change in seller's CDS	Change in probability given a 1 Std change in buyer-seller transactions	Wrong-way-risk
0.11-0.06	-0.005	0.021	-0.03
0.05-0.01	-0.002	0.010	NA

Table 8: Determinants of the propensity to buy protection from 14 sellers, reference entities are US regulated entities: Different buyers

Buyer is a ...		Buyer is a ...	
Hedge Fund x Seller's CDS, β_H^{CDS}	-0.218***	Hedge Fund x WWR, β_H^{WWR}	0.0575
	(0.0647)		(0.144)
Bank-Dealer x Seller's CDS, β_{BD}^{CDS}	-0.0346	Bank-Dealer x WWR, β_{BD}^{WWR}	-0.416***
	(0.0211)		(0.0420)
Bank Non-Dealer x Seller's CDS, β_{BND}^{CDS}	-0.00158	Bank Non-Dealer x WWR, β_{BND}^{WWR}	-0.104
	(0.132)		(0.272)
Asset Manager x Seller's CDS, β_{AM}^{CDS}	-0.553***	Asset Manager x WWR, β_{AM}^{WWR}	-1.702***
	(0.0916)		(0.197)
Other x Seller's CDS, β_O^{CDS}	0.436	Other x WWR, β_O^{WWR}	0.107
	(0.332)		(0.989)
Hedge Fund x Past Buyer-Seller Transactions, β_H^{PR}	0.696***	Hedge Fund x WWR x Seller's CDS, $\beta_H^{WWR,CDS}$	-0.0551
	(0.0273)		(0.0506)
Bank-Dealer x Past Buyer-Seller Transactions, β_{BD}^{PR}	0.239***	Bank-Dealer x WWR x Seller's CDS, $\beta_{BD}^{WWR,CDS}$	-0.0110
	(0.00462)		(0.0184)
Bank Non-Dealer x Past Buyer-Seller Transactions, β_{BND}^{PR}	0.528***	Bank Non-Dealer x WWR x Seller's CDS, $\beta_{BND}^{WWR,CDS}$	-0.312***
	(0.113)		(0.121)
Asset Manager x Past Buyer-Seller Transactions, β_{AM}^{PR}	0.573***	Asset Manager x WWR x Seller's CDS, $\beta_{AM}^{WWR,CDS}$	0.516***
	(0.0307)		(0.0704)
Other x Past Buyer-Seller Transactions, β_O^{PR}	4.337***	Other x WWR x Seller's CDS, $\beta_O^{WWR,CDS}$	-0.227
	(0.427)		(0.245)
F-test: $\beta_H^{CDS} = \beta_{BD}^{CDS} = \beta_{BND}^{CDS} = \beta_{AM}^{CDS} = \beta_O^{CDS}$	39.3	F-test: $\beta_H^{WWR} = \beta_{BD}^{WWR} = \beta_{BND}^{WWR} = \beta_{AM}^{WWR} = \beta_O^{WWR}$	55.98
p-value	0	p-value	0
F-test: $\beta_H^{PR} = \beta_{BD}^{PR} = \beta_{BND}^{PR} = \beta_{AM}^{PR} = \beta_O^{PR}$	476.09	F-test: $\beta_H^{WWR,CDS} = \beta_{BD}^{WWR,CDS} =$	64.9
p-value	0	$= \beta_{BND}^{WWR,CDS} = \beta_{AM}^{WWR,CDS} = \beta_O^{WWR,CDS}$	
		p-value	0
Observations	756,420		
Pseudo R-squared	0.3269		
Controls	S-FE, BC-FE, CDXNAIG,Same x BC, WWR x BC		

Notes: Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The controls are as follows: S-FE: seller fixed effect, S-BC-FE: seller-buyer-class fixed effect, CDXNAIG is the spread on the CDX.NA.IG index. We report coefficients on the interaction between SAME and the buyer class and between WWR and the buyer class.

Table 9: Effects of Clearing and Counterparty Characteristics on Log Transaction Spreads

	(1)	(2)	(3)	(4)
Variables	Seller	Buyer	Pair	Pair
Seller ccp	-0.00179*			-0.00364***
	(0.00107)			(0.000646)
Buyer ccp		-0.00443***		-0.00404***
		(0.00108)		(0.000653)
Seller/buyer ccp			-0.00388***	
			(0.000603)	
Backload clear	-0.00177**	-0.00205**	-0.00332***	-0.00321***
	(0.000788)	(0.000815)	(0.000476)	(0.000474)
Seller buyside	-0.00114			-0.00675***
	(0.00115)			(0.000658)
Buyer buyside		0.00997***		0.0163***
		(0.00108)		(0.000596)
Seller/buyer buyside			0.00807***	
			(0.000539)	
Log(Size)	3.52e-05	9.58e-05	-6.71e-05	-0.000182
	(0.000163)	(0.000144)	(0.000130)	(0.000129)
Constant	-0.00608**	-0.00409*	-0.00209	-0.000394
	(0.00256)	(0.00231)	(0.00203)	(0.00202)
Observations	251,993	269,367	327,562	327,562
FE groups	184,221	193,430	132,947	132,947
FE	C-T-B	C-T-S	C-T	C-T

Notes: This table shows effects of counterparty characteristics and clearing on transaction spreads. In Column 1 we hold the contract, time and buyer fixed and estimate effects of seller's characteristics. In Column 2 we hold the contract, time and seller fixed and estimate effects of buyer's characteristics. In Columns 3-4 we hold the contract and time fixed and jointly estimate effects of buyer's and seller's characteristics. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. C-T-B refers to the contract-time-buyer FE, C-T-S refers to the contract-time-seller FE, and C-T refers to the contract-time FE.

Table 10: DID Effects of Central Clearing on Log Transaction Spreads

	(1)	(2)	(3)
VARIABLES	First Cleared as Treatment	First Cleared as Control	IG as control
Treatment	-0.0513	0.145***	0.0973***
	(0.0363)	(0.0309)	(0.0179)
Treatment x Clearable	-0.0943*	-0.0311	-0.0127
	(0.0500)	(0.0381)	(0.0232)
Constant	4.642***	4.302***	4.730***
	(0.0120)	(0.00370)	(0.00164)
Observations	36,917	98,360	317,046
FE group	3,025	7,315	9,505
FE	Sector-Date	Sector-Date	Sector-Date

Notes: In Column 1, the treatment group consists of transactions on reference entities cleared in the first cohort for each sector of the CDX.NA.IG index 100 days before and after clearing. The control group consists of pre-clearing transactions of reference entities in CDX.NA.IG that are cleared in later cohorts. In Column 2, the control group consists of post-clearing reference entitiescleared in the first cohort for each sector of the CDX.NA.IG index. The treatment group consists of transactions of reference entities in the same sector of CDX.NA.IG that are cleared in later cohorts. We use transactions that occur 100 days before and after the commencement of central clearing in the treatment group. In Column 3, the treatment group consists of transactions on all clearable reference entities in CDX.NA.IG 100 days before and after clearing. The control group consists of transactions on all other non-clearable investment grade reference entities in North America. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 11: Determinants of the propensity to buy protection from 14 sellers: Reference entity is eligible for clearing

	Buyers are US Regulated Entities
	CDX NA IG Constituents
Reference Entity is Not Eligible for Clearing x Seller's CDS, β_E^{CDS}	-0.179***
	(0.0457)
Reference Entity is Eligible for Clearing x Seller's CDS, β_{NE}^{CDS}	-0.119***
	(0.0335)
Reference Entity is Not Eligible for Clearing x Past Buyer-Seller Transactions, β_E^{PR}	0.045***
	(0.0114)
Reference Entity is Eligible for Clearing x Past Buyer-Seller Transactions, β_{NE}^{PR}	0.246***
	(0.0055)
F-test: $\beta_E^{CDS} = \beta_{NE}^{CDS}$	3.58
p-value	0.0584
F-test: $\beta_E^{PR} = \beta_{NE}^{PR}$	249.36
p-value	0
Observations	478,016
Pseudo R-squared	0.7759
Controls	S-FE, CDXNAIG

Notes: Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The controls are as follows: S-FE: seller fixed effect, CDXNAIG is the spread on the CDX NA IG index.

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Table A1: Clearing Dates for NA.IG.CDX

	Basic Materials	Consumer Goods	Consumer Services	Energy	Financials	Healthcare	Industrials	Oil/Gas	Technology	Telecom	Utilities
21-Dec-09											3
11-Jan-10											3
1-Feb-10										2	
15-Feb-10		1					11				
8-Mar-10		4		2				2			1
29-Mar-10			15								
19-Apr-10	5								4		
10-May-10					6	6	1				
7-Jun-10							1				
6-Jul-10										1	
9-Aug-10		8						1			
30-Aug-10			8								
28-Feb-11									1		
28-Mar-11	2	2	4						2		
11-Apr-11					9						
2-May-11		1		1		3	2	1			
13-Jun-11		1	3		5				2		
17-Oct-11							1				
14-Nov-11		1	1	1		1					
16-Jan-12		1									
29-Mar-12							1				
2-Apr-12					1						
7-May-12											1
17-Sep-12		1									
9-Oct-12					1						
22-Oct-12				1							
5-Nov-12		1	1								
26-Mar-13		1									
30-Sep-13		2	2		1		2				
Total	7	24	35	5	23	10	19	4	9	3	8

Notes: This table reports clearing dates by sector for reference entities in CDX.NA.IG that become eligible for central clearing at Intercontinental Exchange (ICE).

Table A2: Clearing Dates for iTraxx Investment Grade Index

	Basic Materials	Consumer Goods	Consumer Services	Energy	Financials	Govt	Healthcare	Industrials	Oil/Gas	Technology	Telecom	Utilities
14-Dec-09												4
11-Jan-10						1						11
1-Feb-10											11	
15-Feb-10								6				
8-Mar-10		12							1			
29-Mar-10			22									
19-Apr-10	10									1		
10-May-10					14		2					
14-Mar-11								1				
11-Apr-11	1	5	1	2				2				
3-May-11		2	1		1			1	2			
9-Sep-13			1									
16-Dec-13		3	1	2			1	2		1	1	
Total	11	22	26	4	15	1	3	12	3	2	12	15

Notes: This table reports clearing dates by sector for reference entities in CDX.NA.IG that become eligible for central clearing at Intercontinental Exchange (ICE).