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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 single-name credit default swap (CDS) transactions. We find that counterparty risk has a modest impact on the pricing of CDS contracts, but a large impact on 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 central clearing on CDS pricing. Contrary to the previous literature, but consistent with our main findings on pricing, we find no evidence that central clearing increases transaction spreads.

Keywords: Counterparty credit risk, credit default swaps, central clearing.
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 (Duffie, 2010). 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 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. We separately analyze client-facing (i.e., between dealer and non-dealer) transactions and interdealer transactions. A priori, it is not clear which of these sets of transactions will show larger price effects of counterparty risk. On the one hand, many client-facing transactions have unilateral collateral terms in favor of the dealer, i.e., clients may be required to post initial margin in the dealer's account, while dealers may be exempt from posting any collateral to the client. In contrast, interdealer transactions have bilateral collateral terms. Given this asymmetry in market practice, prices of client-facing transactions should be more sensitive to dealer's credit spreads than interdealer transactions. On the other hand, in a market where dealers have some monopoly power, clients may be less able to

[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.

extract compensation for bearing a dealer's counterparty risk relative to other dealers (Siriwardane, 2015). In a sample of client-facing transactions, we find statistically significant but economically modest effects of counterparty credit spreads on transaction spreads. We find even smaller pricing impacts, if any at all, arising from counterparty credit risk for interdealer transactions. These findings are consistent with asymmetric collateral terms for clients, and substantively consistent with Arora, Gandhi, and Longstaff (2012), who find that the effect of dealer counterparty risk on CDS quotes is statistically significant but very small in magnitude for a single institutional investor.

We next investigate whether non-dealers manage counterparty exposure by choosing dealer counterparties based on dealer risk profiles, which, so far as we are aware, has not previously been studied. We estimate a multinomial logit model for the non-dealer buyer's choice of dealer counterparty, and find that non-dealers 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 buy CDS protection from a dealer whose credit risk is highly correlated with the credit risk of the reference entity, i.e., buyers of protection avoid wrong-way risk. We estimate a similar model for the seller's choice of dealer counterparty. Similar but somewhat weaker effects are observed in the non-dealer seller's choice of dealer counterparty. The credit-rationing implied by our results is consistent with the findings of Afonso, Kovner, and Schoar (2011), who show that weak banks are rationed in the U.S. interbank market even in normal times.

We also find evidence of stickiness in non-dealer choice of dealer counterparty, i.e., a non-dealer is more likely to choose a dealer with whom it has transacted in the recent past. Previous literature has highlighted the persistence of customer-dealer relationships in equity dealer markets (e.g., Bernhardt, Dvoracek, Hughson, and Werner, 2005) and in other over-the-counter markets (e.g., Afonso, Kovner, and Schoar, 2014; Hendershott, Li, Livdan, and Schürhoff, 2016). This finding is consistent with economies of scale or scope in client trading relationships such as efficiencies in collateral usage.

As an extension, we explore whether counterparty choice depends on the investment horizon of the non-dealer. The longer a position is to be held, the greater the exposure to the risk of the counterparty. Consistent with this intuition, we find that non-dealers with a short investment horizon are less sensitive as buyers of protection to the default risk of the dealer, relative to longer horizon buyers. A consequence is that short horizon non-dealers may be more affected than others by a sudden deterioration in the solvency of a dealer.

Lastly, we investigate whether central clearing has had an impact on how participants price CDS contracts. Clearinghouses have strict collateral and margin requirements for clearing members and maintain additional default funds to cover capital shortfall in the event of counterparty default, and thereby greatly reduce counterparty risk. Loon and Zhong (2014) 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 the time-series, the data does not support the hypothesis that central clearing eligibility increases transaction spreads. These results are consistent with our view that counterparty risk has minimal effect on pricing.

Our paper adds to the literature on counterparty risk management in OTC derivative markets. Theoretical treatments of counterparty risk valuation include Cooper and Mello (1991), Duffie and Huang (1996), Jarrow and Yu (2001), and 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). Turnbull (2014) reviews the construction of credit valuation adjustments used by dealers in marking OTC derivative portfolios. Empirical research testing these models, however, is sparse. Besides Arora, Gandhi, and Longstaff (2012), Giglio (2014) infers counterparty risk from the corporate bond-CDS basis. 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. For a broad survey of the literature on the CDS market, see Augustin, Subrahmanyam, Tang, and Wang (2014).

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 (2015). Campbell and Heitfield (2014) describe post-crisis reforms aimed at encouraging central clearing.

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. 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, four mechanisms have evolved for risk-management. First, counterparties arrange for netting of offsetting bilateral positions and collateralize trades under the terms of a credit support annex (CSA). In the aftermath of the financial crisis, interdealer CSAs have required the daily exchange of variation margin 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.

Client CSAs are subject to negotiation and are therefore more varied in terms. Exchange of collateral takes place when the unsecured exposure exceeds an agreed threshold, which essentially serves as a limit on a line of credit. For the largest and most-favored clients, the thresholds are typically symmetric between dealer and client, and often tied to an agency credit rating of the counterparty.[2] As witnessed in the case of AIG during the financial crisis, ratings-based thresholds may prove ineffective, as the event of downgrade of a large financial institution may trigger the immediate default of that institution (see Financial Crisis Inquiry Commission, 2011, Chapter 19). Furthermore, for smaller or more-risky clients, the CSA may require the posting of initial margin by client to dealer and may exempt the dealer from posting any collateral to the client (i.e., the dealer's threshold is infinite). Such clients are therefore most exposed to the credit risk of the dealer.

[2]Dealer banks all are rated by the major rating agencies. For an unrated client, the threshold may depend on an internal credit rating assigned by the dealer.

As with other studies in this literature, we are unable to observe bilateral CSA agreements, exchange of collateral between counterparties, and bilateral counterparty exposures in other derivative classes that are likely to be in the same netting set (e.g., interest rate derivatives). 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 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. While central clearing of many North American indices became mandatory recently, central clearing of single-name swaps remains voluntary. In our sample period, we find that central clearing of interdealer single-name swaps is common, but clearing on behalf of clients is quite rare (we observe two instances in a sample of over one thousand transactions on eligible single-name reference entities involving a non-dealer counterparty).[3] We proceed under the assumption that central clearing is not yet a viable risk-mitigating option for non-dealers engaged in trading single-name CDS.

Third, market participants can hedge counterparty risk by purchasing CDS protection on their dealer counterparties as reference entities. Such hedging would be difficult to execute rigorously due to the stochastic size of the exposure, but market participants might pursue approximate strategies. Gündüz (2015) shows that financial institutions buy more protection on a dealer as reference entity when exposed to that dealer through counterparty risk. However, non-dealers hedge in this manner at lower frequency than do the dealer banks.

Fourth, 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 dealer 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 dealers. 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.

[3]The financial press has reported on recent industry initiatives to lower barriers to central clearing of single-name CDS for non-dealers. See, for example, "Credit Suisse, Goldman Said Mulling Plan to Promote CDS Clearing," *Bloomberg Business*, November 9, 2015.

Finally, 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. To the extent that this cost can be imposed on the counterparty through the terms of trade, we will observe the price of a contract varying with the credit risk of the counterparties.[4] 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*

[4] In practice, compensation for CVA may be limited by the bilateral nature of counterparty risk. If two equally risky counterparties with symmetric collateral terms 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. We refer to these major US dealer-banks as the "US5." To avoid selection bias in our analyses, we will construct samples that align with one of the two entitlement windows.

Our sample period is January 2010 through December 2013.[5] Throughout our analyses, we consider only new, price-forming trades. Specifically, we drop novations, terminations, intra-family housekeeping transactions, and records resulting from trade compression. For a very small number of observations, the seller of the transaction is also the reference entity. Such contracts pose an extreme form of wrong-way risk (known as *specific* wrong-way risk in Basel capital rules), so it is somewhat puzzling that this is ever observed. We drop these few observations.

To avoid undue influence of a single market participant on the results, we exclude trades involving the largest non-dealer participant in the CDS market during our sample period. This non-dealer appears as seller of protection in over 25% of client-facing (i.e., between a non-dealer and dealer) transactions in our baseline sample (described below).[6] Results for our pricing regressions in Section 3) are robust to including this non-dealer in the sample. However, for a subset of our counterparty choice regressions in Section 4, the magnitude (but not the sign) of the coefficient changes materially.[7] To maintain confidentiality of the data, we cannot report results both with and without this non-dealer in sample, as this would reveal trading behavior specific to this firm.

We now describe construction of our *baseline sample*. To estimate a model of counterparty choice, we must observe all transactions on a given reference entity for a given non-dealer. Therefore, we restrict our baseline sample to transactions where the underlying reference entity is regulated by the

[5]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).

[6]Excluding this market participant reduces the Herfindahl index of concentration among sellers in notional value transacted from 500 to 389. The effect on concentration among buyers is much smaller.

[7]To estimate the counterparty choice regression, we assume that non-dealers chose which dealer to trade with, and not vice-versa. This assumption is not necessary in our pricing regression. Thus, it may not be surprising that our counterparty choice regression changes materially when we include this large non-dealer player, because this identifying assumption may not hold for this large non-dealer.

FRB. To mitigate any bias associated with illiquidity, we drop reference entities that are traded less than once per month on average. These restrictions leave us transactions on 12 reference entities.[8]

Similar to Arora, Gandhi, and Longstaff (2012), we restrict our analyses to trades involving at least one of the 14 largest CDS dealers: 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.[9] These 14 dealers account for 99.8% of trades in our sample of liquid, FRB-regulated reference entities.

To facilitate interpretation of the economic magnitude of our empirical estimates, we convert upfront points to par spreads using the standard ISDA conversion formula.[10] The calculated par spreads can then be compared to Markit's end-of-day par spread quotes. We drop observations if a valid par spread cannot be constructed or the underlying cannot be matched to a Markit spread for the same terms on the same date. Further, to ensure the comparison between spreads is valid, we drop trades that do not adhere to standard market conventions established by ISDA. These conventions specify reporting protocols, coupon rates, credit event settlement procedures, and other administrative details. To ensure our results are not driven by large outliers, we drop observations for which the absolute difference between the logs of the Markit and DTCC spreads is greater than 0.3. This cutoff corresponds to the 98.5 percentile of absolute differences. After imposing the full set of restrictions, we are left with a baseline sample of 83,401 transactions. Summary statistics for the difference between DTCC and Markit par spreads are given in Panel A of Table 1. The median difference is 0.8 basis points and the 95th percentile of the difference is 14 basis points in the baseline sample.

In robustness exercises, we make use of a larger sample consisting of all transactions for which at least one counterparty is a US5 dealer. We do not require that these transactions have a reference entity regulated by the FRB, but all other restrictions described above are imposed. This sample contains some highly distressed reference entities which may be subject to significant intraday

[8]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.

[9]Relative to the list of 14 dealers appearing in the sample of Arora, Gandhi, and Longstaff (2012), Lehman is dropped (as it no longer exists), Bank of America and Merrill Lynch are merged, and Nomura Holdings and Société Générale are added.

[10]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.

volatility. Therefore, we drop transactions for which the Markit par spread on the contract on that date is above 1000 basis points. This sample, which we refer to as the *US5 counterparty sample*, is comprised of over a million transactions on roughly 1600 single name reference entities. Summary statistics are provided in Table 2.

We next define several variables used in our analyses. We measure the risk of dealer default by the dealers's five year CDS spread quoted at the end of the previous trading day. For observation date t, the lagged spread is denoted $\overline{cds}^{s}_{t-1}$ when the dealer is acting as selling of protection, and $\overline{cds}^{b}_{t-1}$ when the dealer is acting as buyer. In robustness exercises, we consider an alternative measure for the risk of dealer default based on the bankruptcy hazard rate model of Chava and Jarrow (2004).

In the baseline sample of entitled reference entities, we measure wrong-way risk, WWR^{s}_{i}, as a dummy variable equal to one if both the seller of protection is a US5 dealer and the reference entity is either a US5 dealer or Wells Fargo.[11] For the case of a dealer buying protection, we construct our measure of right-way risk RWR^{b}_{i} in exactly the same way, i.e., as a dummy variable equal to one if both the buyer of protection is a US5 dealer and the reference entity is either a US5 dealer or Wells Fargo. We modify the variable name (from WWR to RWR) only to highlight that the economic interpretation is reversed. In the US5 counterparty sample, we measure WWR^{s}_{t} (RWR^{b}_{t}) as a dummy equal to one if the log CDS spreads on the reference entity and on the selling (buying) dealer have a correlation over 70%.[12]

Perhaps to achieve operational efficiencies, trading relationships in OTC markets often persist through time. In the case of buyer of protection b and seller of protection s, $Relations^{s,b}_{t-1}$ is defined as the share of notional value that market participant b traded with dealer s in the recent past. We measure this share using the past 28 business days prior to the transaction if there were more than 28 transactions in the last month, otherwise we estimate the share using the past 28 transactions, requiring a minimum of 10 transactions. To express $Relations^{s,b}_{t-1}$ in share terms, we divide the total notional value transacted between b and s by the total notional value that

[11] Wells Fargo is grouped with the US5 dealers for this purpose due to similarity in size and national scale of banking operations. It is a dealer as well, but not a significant one in the CDS market.

[12] To be precise, we estimate the correlation daily using a rolling five-year window, which implies that the measure is dynamic. However, it is so strongly persistent that it is substantively correct to describe the variable as static. Our results for the entitled reference entities are quantitatively similar if we instead construct static WWR and RWR dummies for correlation above 70% over the entire sample period.

market participant b traded. When the analysis is done from the protection seller's perspective, $Relations^{b,s}_{t-1}$ is expressed as a fraction of the total notional value that market participant s traded.

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 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 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.

Panel B of Table 1 summarizes characteristics of transactions on the same reference entity with the same tenor, tier, currency, restructuring or non-restructuring clause and fixed coupon rate, traded on the same date. We restrict these summary statistics to the subsample in which there are at least ten trades on the identical contracts during the same day, which is about 28 percent of our baseline sample. We find significant pricing dispersion within the day on the same contract, with a median within-day standard deviation of 1.4 percent. In terms of counterparty choice, we see that on average a buyer (seller) trades with more than one seller (buyer) on the same contract and the same day. Observing multiple counterparties for the same party and the same contract serves to identify whether cross-sectional pricing dispersion in transaction spreads varies with cross-sectional dispersion in counterparty credit spreads.

3.1 Effect of seller credit spreads on CDS pricing

We investigate whether counterparty risk is priced in the CDS market from the protection buyer's perspective. Our benchmark specification is similar in spirit to that of Arora, Gandhi, and Longstaff (2012). 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. Identification comes from pricing dispersion within the same day. Our benchmark specification is

$$\log(cds_{i,t}^{s,b}) - \log(\overline{cds}_{i,t}) = \alpha_{i,t}^{b} + \beta \log(\overline{cds}_{t-1}^{s}) + \eta WWR_t^s + \lambda Relations_{t-1}^{s,b} + \delta \log(size) + \epsilon_{i,t}^{s,b}, \quad (1)$$

where $\log(cds_{i,t}^{s,b})$ is the log par spread on CDS transaction i on time t. Superscripts s and b denote the seller and buyer of credit protection, respectively. We denote by $\overline{cds}_{i,t}$ the par spread quoted by Markit on reference entity i on date t. The dependent variable measures the difference between a specific transaction spread and the Markit quote on the same reference entity at time t.

Independent variables of primary interest are the log of the seller's quoted CDS spread ($\overline{cds}_{t-1}^{s}$), the wrong-way risk indicator (WWR^s), and the measure of past buyer-seller relationship ($Relations_{t-1}^{s,b}$). The fixed effect $\alpha_{i,t}^{b}$ refers to the buyer-contract-time interactive fixed effect. The log of the notional value of the traded contract, $\log(size_{i,t})$, is included in the regression to allow for the contract size to have some potential impact on transaction spreads. If seller counterparty risk is priced, we expect $\beta < 0$ and $\eta < 0$.

One potential concern with the benchmark specification is that the seller's credit spread could be correlated with other unobserved characteristics of the sellers which also affect pricing of the contract. To mitigate this concern, we also add seller fixed effects α^s to control for the impact of seller's time-invariant characteristics on pricing in the following regression:

$$\log(cds_{i,t}^{s,b}) - \log(\overline{cds}_{i,t}) = \alpha_{i,t}^{b} + \alpha^s + \beta \log(\overline{cds}_{t-1}^{s}) + \eta WWR_t^s + \lambda Relations_{t-1}^{s,b} + \delta \log(size) + \epsilon_{i,t}^{s,b}. \quad (2)$$

Estimates are reported in Table 3. We present results for equations (1) and (2) in Panels A and B, respectively, depending on the fixed effect specification. In all specifications, we restrict the sellers of protection to be the 14 largest dealers. We report the number of effective observations for which one buyer faces at least two different sellers in each fixed effect group.

Our benchmark results are presented in Column 1. In this column, we examine the effect of seller's credit spreads on transaction spreads for non-dealers as buyers of protection. In Panel A, the coefficient on the seller's credit spread is negative and statistically significant, but the economic magnitude of the coefficient value -0.007 is very small. A 100 percent increase in the seller's log spread translates to only a 0.7 percent decrease in the transaction spread. To translate the change from percentages to levels, we note that the mean level of transaction spreads is about 195 basis points in the estimated sample and the mean dealer spreads is about 173 basis points, and hence a 100 basis point increase in the seller's credit spreads translate into about 0.6 basis point reduction in the transaction spread $\left(= 195 \times \left[\left(\frac{173+100}{173}\right)^{-0.007} - 1\right]\right)$. The average notional value of trades in Column 1 is about \$7.4 million, so the 0.6 basis point pricing impact on transaction spreads translates into about \$450 difference in the total cost of an average-sized trade. In Panel B, the magnitude of the coefficient on the seller's credit spread increases to 0.018 with additional seller fixed effects, but remains modest. Our finding that the impact of seller credit spread is significant, but small in economic magnitude, is broadly consistent with the finding in Arora, Gandhi, and Longstaff (2012) that a 100 basis point increase in dealer spreads translates to 0.15 basis point reduction in the quoted CDS spread. Furthermore, we note that the WWR variable enters slightly positive, the sign opposite to that predicted by the counterparty risk hypothesis, and past relationship between the buyer and the seller does not enter significantly. In Column 2, we restrict the sample to the set of reference entities which are not eligible for central clearing, and obtain coefficient estimates very similar to those in Column 1. This suggests that clearing eligibility does not significantly affect client-dealer pricing.

In Column 3, we repeat the same regressions for interdealer transactions. We obtain smaller negative coefficients on the seller's CDS spreads, marginally significant. For interdealer transactions, an increase of 100 basis point in the seller's spread translates into about 0.2 to 0.3 basis point reduction in the transaction spread. The coefficient on WWR is slightly negative, consistent with the counterparty risk hypothesis. The coefficient on past relationship is marginally negative, i.e., buyers obtain slightly more favorable prices from dealers with whom they traded more in the past.

In Column 4, we examine interdealer pricing in the US5 counterparty sample. A trade appears in this sample if one or both of the counterparties is a major US dealer-bank. We find that the coefficient on the seller's CDS spread is slightly positive and statistically insignificant across both fixed effect specifications. The coefficient on WWR is slightly negative. The coefficient on past relationship is slightly positive without the seller fixed effects, but loses significance after including seller fixed effects.

In summary, we find significant but economically small effects for non-dealers as protection buyers, and either even smaller or insignificant effects of seller's credit spreads on transaction spreads for dealers as protection buyers from other dealers. These results are consistent with the anecdotal evidence that CSA provisions are symmetric between large dealers, but are more likely to be unilateral in favor of dealers for client-facing transactions. Neither WWR nor past relationship affects transaction spreads in a robust manner.

3.2 Effect of buyer credit spreads on CDS pricing

Parallel to the previous subsection, we consider the effect of the buyer's CDS spread on transaction spreads. First, we hold the seller, contract and trade date fixed, and examine the impact of buyer's credit spreads on transaction spreads using the following regression:

$$\log(cds_{i,t}^{s,b}) - \log(\overline{cds}_{i,t}) = \alpha_{i,t}^{s} + \gamma \log(\overline{cds}_{t-1}^{b}) + \eta RWR^{b} + \lambda Relations_{t-1}^{b,s} + \delta \log(size) + \epsilon_{i,t}^{s,b}, \quad (3)$$

where $\overline{cds}_{t-1}^{b}$ denotes the buyer's CDS spread and $\alpha_{i,t}^{s}$ is the seller-contract-time fixed effect. We also include variables for the right-way risk (RWR^{b}) and buyer-seller past relationship ($Relations_{t-1}^{b,s}$). As in the previous section, we also estimate a regression with additional buyer fixed effects to control for time-invariant buyer characteristics:

$$\log(cds_{i,t}^{s,b}) - \log(\overline{cds}_{i,t}) = \alpha_{i,t}^{s} + \alpha^{b} + \gamma \log(\overline{cds}_{t-1}^{b}) + \eta RWR^{b} + \lambda Relations_{t-1}^{b,s} + \delta \log(size) + \epsilon_{i,t}^{s,b}. \quad (4)$$

If the buyer's counterparty risk is priced, we should expect $\gamma > 0$ and $\eta > 0$.

Table 4 reports our estimation results. For non-dealers as protection sellers (Columns 1 and 2), the coefficient on the buyer's CDS log-spread are positive and significant in the fixed effect specification (Panel B), but somewhat smaller in magnitude than the corresponding coefficients in Table 3. For interdealer transactions reported in Columns 3 and 4, the buyer's log-spread is insignificant. The right-way risk variable enters as slightly positive, consistent with the counterparty risk hypothesis, though not always statistically significant. Past relationship does not have a robust significant effect on transaction spreads.

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 wrong-way risk. As in Shachar (2012), we assume that trades in the OTC market are initiated by the non-dealer, and that the dealer supplies liquidity upon demand.[13] An immediate implication is that the matching of counterparties in a transaction is determined exclusively by the choice of the non-dealer as client.

Summary statistics are reported in Table 5. Our baseline sample contains 196 non-dealer buyers of protection in 11,948 transactions, of which 7,927 reference US5 dealers and the remainder reference other FRB-regulated institutions. We have fewer observations in our seller choice model: the sample contains 169 non-dealer sellers of protection in 7,767 transactions, of which 5,693 reference US5 dealers.

Table 6 provides preliminary evidence of aversion to wrong-way risk in our baseline sample. We divide the 14 dealers by domicile (US vs. foreign), and also sort the FRB-regulated reference entities into two groups by severity of WWR when the seller is a US dealer. A group of reference entities composed of the US5 dealers and Wells Fargo is deemed "high WWR," and the remaining FRB-regulated reference entities are deemed "low WWR." We then calculate for each group of dealers the aggregate share of protection sold (by notional value) on the high and low WWR groups of reference entities. For US5 dealers, the trading share is 44 percent when the US5 dealer is selling protection on one of the US5 or Wells Fargo compared to a trading share of 54 percent for other reference entities. This suggests that non-dealers are less likely to buy CDS protection on the US5 dealers or Wells Fargo from one of these five US dealers than from a foreign dealer.

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

$$\Pr(y_{i,t}^b = s | x_{i,t}^s) = \frac{\exp(x_{i,t}^s \beta)}{\sum_{\hat{s}=1}^{N_i} \exp(x_{i,t}^{\hat{s}} \beta)}, \qquad s = 1, \ldots, N_i. \tag{5}$$

[13] As detailed in Section 2.2, we drop a non-dealer that accounts for more than one-quarter of CDS protection sales. For this institution, the assumption that non-dealers initiate the trade may not hold.

where the choice set has cardinality $N_i = 13$ when the reference entity i is a US5 dealer and $N_i = 14$ otherwise. In total, our multinomial model has 159,345 ($= 7,927 \times 13 + (11,948 - 7,927) \times 14$) observations. The independent regressors are: credit risk of the seller, proxied as before by the CDS spread on the seller of protection quoted on Markit on date $t-1$; an indicator variable for general wrong-way risk (WWR_i^s); $Relations_{t-1}^{s,b}$, to allow for "stickiness" in buyer-dealer relationships; a set of dummy variables for the N dealers, 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 7. The coefficients on seller dummy variables are omitted to respect the confidentiality of the data.

In Column 1 we report coefficients estimated on the baseline sample. As predicted, the coefficient on seller's CDS is negative and statistically significant, i.e., customers are less likely to buy protection from a dealer whose own CDS spread is high relative to other dealers. The coefficient on WWR is large, negative and statistically significant, which shows that buyers avoid wrong-way risk in their choice of dealer. Finally, the coefficient on past relationship is large, positive and statistically significant, which is indicative of persistence in trading relationships.

In Column 2 we report coefficients estimated on the subsample of FRB-regulated reference entities that are not eligible for clearing. The coefficients on the seller's CDS and past relationships are similar to those in Column 1, which suggest that clearing eligibility has not had an impact on how non-dealers respond to our measure of dealer credit risk. The coefficient on WWR is not statistically significant, but this is not surprising because the reference entities that are eligible for clearing are also those that suffer least from wrong-way risk, so that dropping these observations makes it difficult to identify the impact of WWR. In Column 3 we report coefficients estimated on a subsample that excludes "captive" buyers; we designate a buyer as captive if at least 60 percent of their transactions as buyer face a single dealer as counterparty. To the extent that such buyers are truly captive to a single dealer, they may be unresponsive to our measures of dealer credit risk. Nonetheless, our coefficient estimates are similar to those in Column 1.

Marginal effects for this regression are reported in Table 8. We separately report marginal effects at sample means for the large dealers (those with unconditional transaction shares of 7–13%) and small dealers (those with unconditional transaction shares of 1–6%). 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 2.6 percentage points. Wrong-way risk reduces the probability by 2 percentage points. A one standard deviation increase in past-month transaction count increases the probability of selection by 4 percentage points. Relative to unconditional transaction shares of 7–13 percentage points, these effects are all of large economic magnitude.

We next consider the possibility that the determinants of the buyer's choice of seller might depend on the investment horizon of the buyer. A buyer intending to hold a CDS position for a short period of time should be less sensitive to counterparty credit risk than a buyer intending to hold a position to maturity. We define a dummy variable $SHORT^b$ equal to one if buyer b closes at least fifty percent of its new trades within 28 days of the original trade date. We re-estimate equation (5) including interactions of the independent variables with $SHORT^b$, and report results in Table 9. Consistent with our prediction, we find that short-horizon buyers of protection are less than half as sensitive to the default risk of the dealer, relative to long-horizon buyers.

We repeat these analyses from the perspective of non-dealer sellers of protection and report the results in Table 10. Consistent with the asymmetry between buyer and seller counterparty exposure, we find that the seller's choice of dealer counterparty is slightly less sensitive to the dealer's credit risk. The marginal effects for this regression, reported in Table 11, indicate that a 100 basis point increase in a large dealer's CDS spread is associated with an average decline in the likelihood of a non-dealer selling protection to that dealer of 2.2 percentage points compared to 2.6 percentage points in the buyer-choice model. In Table 12 we report results of interactions of the independent variables with $SHORT^s$. We find no difference between short-horizon and long-horizon sellers of protection in sensitivity to the default risk of the dealer.

As a robustness check, we replicate the fixed effect specification of Section 3 in a linearized choice model. As shown in Table 13, our results are robust to the inclusion of these fixed effects. As further robustness checks (not tabulated), we repeat our main analyses excluding from our sample the height of the European debt crisis.[14] We obtain slightly higher coefficients on WWR, RWR, and dealer's CDS when we exclude this period. Thus, our results are not driven by the European debt crisis period.

[14]Specifically, we exclude observations from October 4, 2011, when the Belgian government announced Dexia's bailout, to July 26, 2012, when Mario Draghi announced that "the ECB is ready to do whatever it takes to preserve the euro. And believe me, it will be enough."

In addition, we consider an alternative measure for the risk of dealer default, the dealer's five year probability of default (PD) as estimated by Kamakura Corporation using the hazard rate model of Chava and Jarrow (2004). Whereas the CDS represents an assessment of credit risk under the pricing measure $\mathbb{Q}$, the PD is an assessment under the empirical measure $\mathbb{P}$. First, we repeat these analyses replacing the dealer's five year CDS spread by the dealer's five year PD. Second, we include both measures of the risk of dealer default in our multinomial logit model. We find that both measures of risk of dealer default affect the buyer's choice of seller and the seller's choice of buyer, but the dealer's five year CDS spread has the bigger impact on the non-dealer's choice of seller and buyer.

Finally, we include as a control variable a proxy for the dealer's pricing aggressiveness. This is intended to address a concern that the risk of dealer default is somehow related to how aggressively the dealer pursues CDS trade flow from clients. We measure a dealer's pricing aggressiveness at date t as the average over the last 28 business days prior to date t of the difference between the log par spread the dealer charges its non-dealer counterparties and the log Markit par spread on the same reference entity.[15] As expected, we find that in the buyer's choice model the coefficient on dealer's price aggressiveness is negative and statistically significant, while in the seller's choice model the coefficient is positive and statistically significant. Yet, our results are robust to including this control variable because the coefficients on the dealer's five-year CDS spread, WWR, and RWR, are virtually unchanged.

5 Central Clearing

Loon and Zhong (2014) find that central clearing increases CDS spreads, and attribute this to the mitigation of counterparty risk. Their finding could be seen as inconsistent with our result in Section 3 that counterparty risk has a modest effect on pricing. Our data does not support the Loon and Zhong (2014) result. 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

[15] If there were fewer than 28 transactions in the last month, then we estimate the average using the past 28 transactions, requiring a minimum of 10 transactions. This measure is constructed on our baseline sample of FRB-regulated reference entities.

no robust evidence that a reference entity's transaction spreads increase around the commencement of eligibility for central clearing.

Clearing was introduced first 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) in waves beginning in December 2009. By the end of our sample period, most index constituents had been made eligible to clear. The single-names index constituents that remain ineligible are primarily the European dealer banks listed in iTraxx Europe. US dealer banks are excluded from the CDX.NA.IG index, and also remain ineligible for clearing.

Within an investment grade index, reference entities have been made eligible for central clearing in cohorts, which typically consist of several firms in the same sector. Table 14 summarizes the introduction of clearing eligibility during our sample period by sector for CDX.NA.IG constituents.[16] Cohorts are typically small, and selection driven by tenure within the index. As an example, five firms in the Technology sector were made eligible for clearing on 19 April 2010, two more on 28 March 2011, and a final two on 13 June 2011. The first cohort was composed of reference entities that had been continuously listed in the CDX.NA.IG since at least September 2008. The second cohort consisted of reference entities added to the index by March 2009, while the last cohort was composed of reference entities added by March 2011. 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 OTC 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 designated for clearing by the counterparties at the time of the bilateral transaction. Under the

[16] To avoid the influence of technical events, such as the issuance of new RED identifiers after corporate renamings, we exclude reference entities with clear-eligible predecessors from our analysis. Sector information comes from Markit. On February 15, 2012, Markit modified its classification scheme. To avoid inconsistencies, we categorize reference entities by their sector under the old scheme. For the small number of reference entities that did not exist before February 15, 2012, we use the sector of their most recent predecessor classified under the old scheme.

second method, the trade is cleared on the same day as the initial trading date. These same-day clearing trades are often cleared at inception and executed on a swap execution facility (SEF), which matches buyer and seller anonymously. A same-day clearing trade appears in the repository data as two simultaneous transactions with a CCP as buyer on one leg and as seller on the other. As discussed in Section 2, non-dealers rarely clear trades during our sample period, so we assume that all cleared transactions in our sample are interdealer trades.[17]

Table 15 presents results on how transaction characteristics affect CDS pricing. We categorize transactions into four types: (i) same-day clearing trade; (ii) backload clearing trade; (iii) uncleared OTC client-facing trade; and (iv) uncleared OTC interdealer trade. The fourth type is the omitted category in the regressions.

We use the subsample of transactions on clearable reference entities in the union of the baseline and US5 counterparty samples. Of the 509,248 transactions on clearable reference entities in which either the buyer of the seller is one of the 14 largest dealers, we have 368,402 transactions in which the buyer is one of the 14 largest dealers and 409,053 transactions in which the seller is one of the 14 largest dealers. In Column 1, we estimate the effect of seller characteristics when the buyer is one of the 14 largest dealers. Holding contract, time and the buyer fixed, we find that same-day clearing trades are associated with significantly lower spreads than OTC interdealer trades, with a magnitude around 0.4 percent. Non-dealer sellers sell to dealers at spreads about 0.6 percent lower than on comparable OTC interdealer transactions. Backloaded clearing trades have marginally significantly lower spreads than the interdealer spreads at about 0.1 percent. In Column 2, we estimate the effect of buyer characteristics when the seller is one of the 14 largest dealers. Holding contract, time and seller fixed, we again find that same-day clearing trades are associated with lower spreads, with a magnitude around 0.2 percent. Furthermore, non-dealers buyers of protection in OTC transactions pay dealers about 0.4 percent more than dealers pay in comparable OTC interdealer transactions. Backloaded clearing trades do not enter significantly. The dealer's pricing advantage we document is consistent with Siriwardane (2015), who shows that the market is dominated by a handful of buyers and sellers of protection, the majority of which are dealers. Siriwardane (2015) finds that a reduction in the capital of these dealers has an impact on CDS prices.

[17] Of the 210,680 instances of backload clearing trades in our data, only eight involve non-dealers. There are no instances of non-dealers engaging in same-day clearing on our entitled reference entities. Our entitlement rules preclude us from observing same-day clearing by non-US5 firms on non-entitled reference entities.

In Column 3, we fix contract and time only and allow both buyer and seller's characteristics to enter simultaneously (while either the buyer or the seller is one of the largest 14 dealers). We confirm the effects documented in Columns 1 and 2, i.e., that same-day clearing trades are associated with significantly lower transaction spreads, with a magnitude around 0.3 percent. Furthermore, dealers extract rents from non-dealer clients while buying and selling CDS protection. Estimated dealer rents in this specification are larger than in Columns 1 and 2, with magnitudes around 0.9 percent. Finally, mean spreads on backloaded clearing trades are slightly lower than on comparable interdealer OTC trades by about 0.2 percent.

As an aside, we note that dealers' pricing advantage over non-dealers is present before and after the introduction of central clearing. In Figure 1, we plot the average log-difference between transaction spreads in DTCC data and Markit spreads against the number of days since the reference entity became eligible for clearing. The top panel shows that transaction spreads are larger when dealers sell protection to non-dealers than when the dealers buy protection, and the gap does not appear to diminish following the introduction of clearing. In the bottom panel, we see that same-day clearing trades have lower spreads than OTC trades for which the non-dealer is the buyer, and higher spreads than OTC trades for which the non-dealer is the seller. Dealers' pricing advantage over non-dealers prompts us to focus on interdealer transactions in the following subsection when we examine the time series effect of clearing eligibility.

In summary, we find centrally cleared trades are associated with lower spreads compared with bilateral interdealer trades and client-facing trades when the client is a buyer, as opposed to higher spreads as a result of counterparty risk mitigation.

5.2 Time series comparison for pricing

We estimate the time series effect of clearing eligibility on DTCC transaction and Markit quotes spreads using a difference-in-differences (DID) approach. Our DTCC sample consists of transactions in the union of the baseline and US5 counterparty samples. To distinguish clearly from possible time-variation in the magnitude of pricing advantage over non-dealers, we focus on interdealer and cleared transactions only. We exploit the fact that clearing eligibility was introduced by sector in small cohorts for CDX.NA.IG constituents, and use the DID specification to estimate the time series effect of clearing:

$$\log(cds_{i,t}^{s,b}) = \alpha_{sector,t} + \beta Treatment_i + \gamma Treatment_i \times After_{i,t} + \epsilon_{i,t}, \tag{6}$$

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 $After_{i,t}$ 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. We use treatment and control groups in the same sector to mitigate the impact of common macroeconomic and sectoral shocks on our estimates.

We estimate three DID specifications. In the first specification, we use DTCC transactions or Markit quotes on reference entities cleared in the first cohort for each sector as the treatment group, and pre-eligibility DTCC transactions or Markit quotes on reference entities cleared in later cohorts as the control group. In the second specification, we use post-eligibility cleared transactions or quotes on the first cohort of clearable reference entities as the control group, and all transactions or quotes on reference entities in later cohorts in the same sector as the treatment group. We ensure that entities in both treatment and control groups of the first two DID specifications were already CDX index members before clearing was introduced, so that the effects of clearing eligibility can be separately identified from the effects of index inclusion. In the third specification, we use all transactions or quotes on all reference entities that become eligible during the sample period as the treatment group, and transactions on other North American investment grade reference entities as the control group.

We construct our event windows in two different ways. First, we use the window 50 days before and after the introduction of clearing eligibility. Second, we follow Loon and Zhong (2014) and use the window between 250 days before the introduction of clearing to 20 days after the introduction of clearing. The effects on four intervals of [-20, -10), [-10, 0), [0, 10) and [10, 20) days around the introduction of clearing eligibility are separately examined.

As a robustness check, we also perform our DID analysis using daily CDS quotes from Markit as dependent variable. We note that the numbers of observations in the DTCC and Markit samples can differ significantly in each specification. This is because daily Markit quotes are observed on almost all business days for each reference entity in our sample. However, multiple transactions or no transactions might occur on these referee entities in our DTCC sample.

DID results for transaction spreads and Markit quotes are depicted in in Figure 2. In all three specifications, mean transaction spreads and Markit quotes 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. In Panel A of Table 16, we report DID estimates for the three specifications using a 50-day event window before and after clearing eligibility. The coefficient γ on the $Treatment \times After$ interaction is negligibly small and statistically insignificant for the first five columns and is only marginally significant for the last column. In Panel B, we use a window for the DID sample from 250 days before the introduction of clearing eligibility to 20 days afterwards. Across all three DID specifications for both DTCC transaction spreads and Markit quotes, none of the coefficients on the interactions between treatment and event intervals are significantly positive. Therefore, our evidence does not support the hypothesis that central clearing eligibility increases Markit quotes or transaction spreads.

6 Conclusion

In this paper, we study how market participants price and manage counterparty credit risk in the CDS market. Our results demonstrate that participants in the credit default swap market manage counterparty risk by buying protection preferentially from counterparties of lower credit risk and lesser "wrong-way" correlation with the reference entity. These results are qualitatively consistent with the experience of Lehman and Bear Stearns in 2008 in which they could not find counterparties to trade with, and suggest that OTC dealers remain vulnerable to a run of counterparties in the post-crisis environment.

We find little evidence of material pricing impacts arising from counterparty credit risk for inter-dealer transactions. For client-facing transactions, we find statistically significant but economically small effects of dealer credit spreads on transaction spreads. Furthermore, we find that centrally cleared trades are not associated with higher spreads, which is counter to the intuition that central clearing should increase the value of credit protection by reducing counterparty risk.

Therefore, we conclude that compensation for counterparty risk in prices plays a less important role in CDS markets than the management of counterparty risk by counterparty choice.

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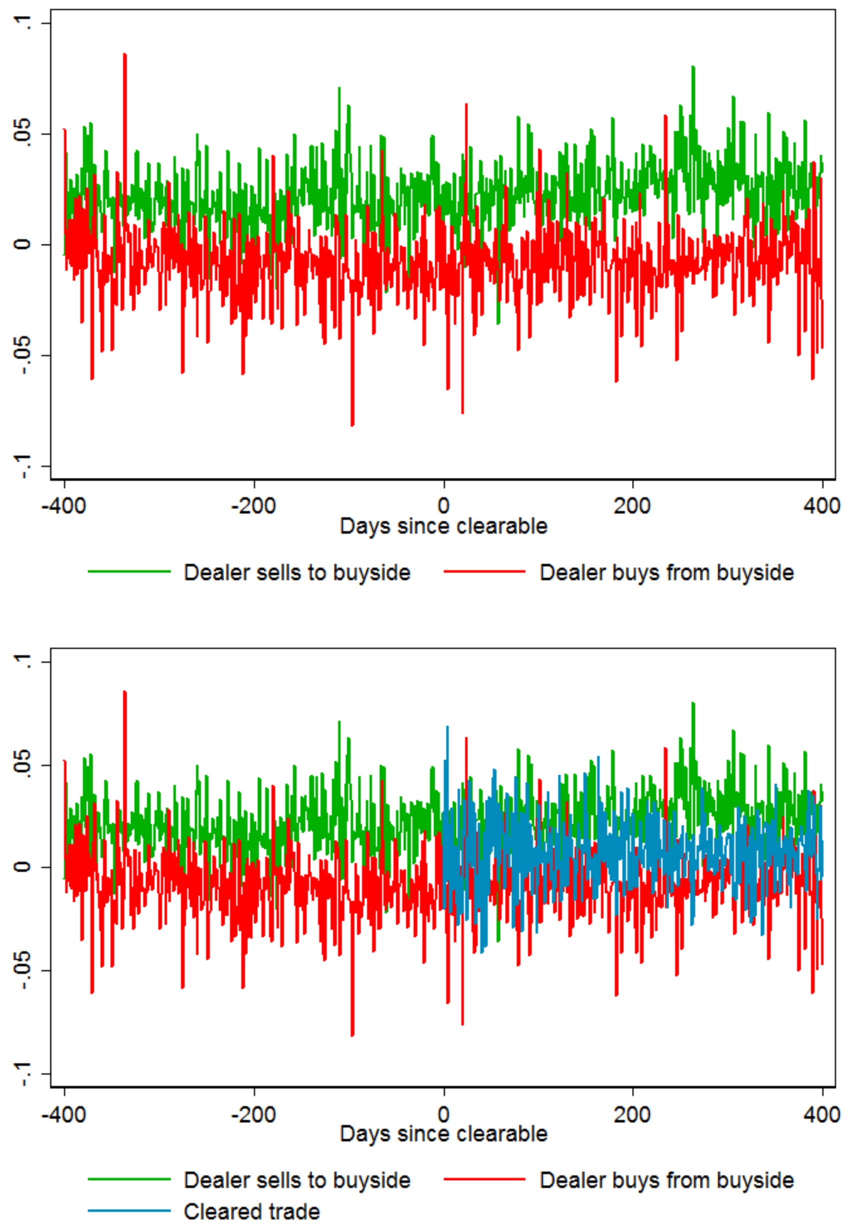
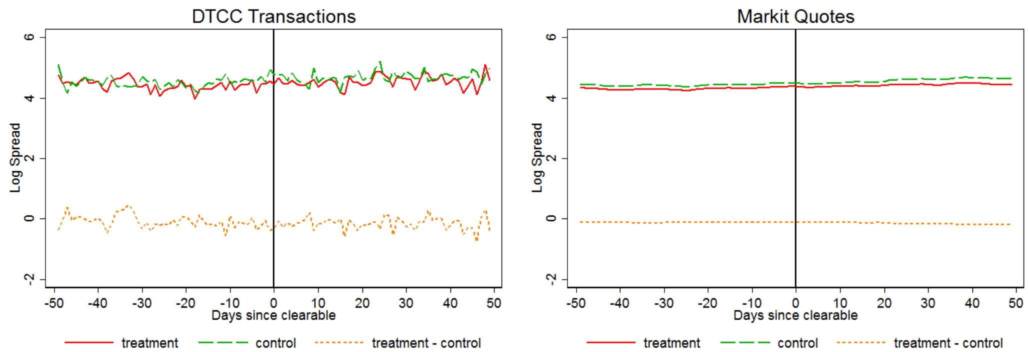
Figure 1: Effects of Transaction Type on $\log(cds_t^{s,b}) - \log(\overline{cds_t})$



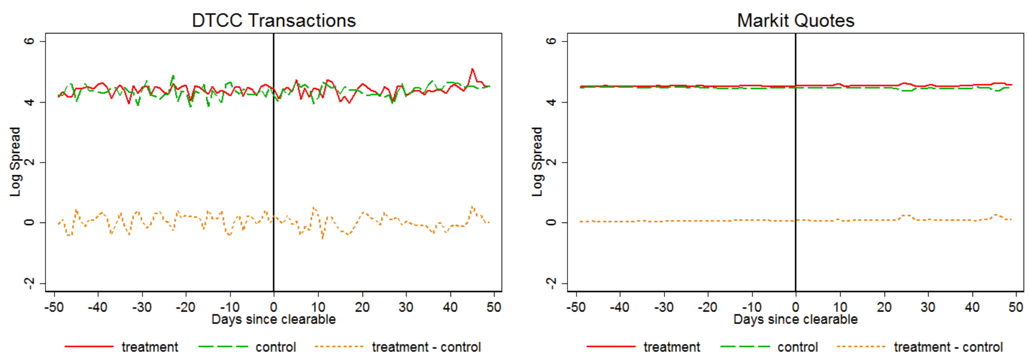
Notes: The top figure plots mean transaction spreads on transactions between dealers and non-dealers before and after clearing. The bottom figure adds mean transaction spreads on same-day cleared transactions.

Figure 2: Time Series Effects of Clearing Eligibility on Transaction Spreads

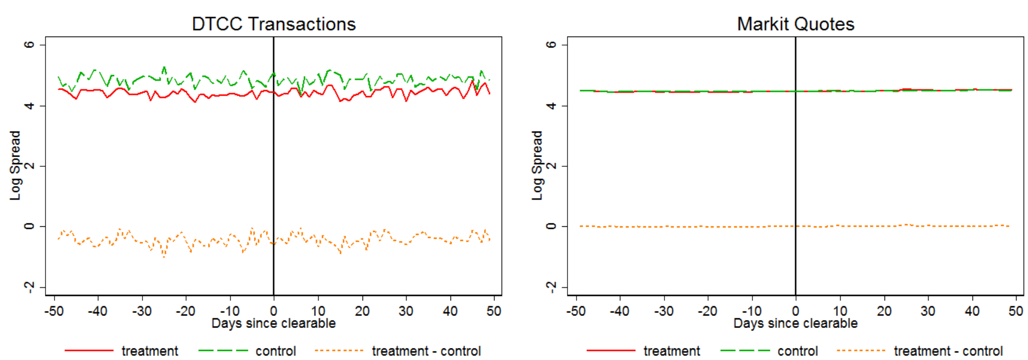
(a) DID Specification I



(b) DID Specification II



(c) DID Specification III



Notes: The left panels plot results based on DTCC transaction spreads and the right panels plot results based on Markit quotes. In Figure (a), the treatment group consists of transactions or quotes 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 or quotes of reference entities in CDX.NA.IG that are cleared in later cohorts. In Figure (b), the control group consists of post-clearing reference entities cleared in the first cohort for each sector of the CDX.NA.IG index. The treatment group consists of transactions or quotes 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 or quotes on all clearable reference entities in CDX.NA.IG before and after clearing. The control group consists of transactions or quotes on all other non-clearable investment grade reference entities in North America. Only interdealer and same-day cleared transactions are used in computing the means.

Table 1: Summary Statistics for Pricing Analysis - Baseline Sample

(A) Summary Statistics for all transaction spreads and Markit quotes ($N = 83,401$)

Percentile	p1	p5	p10	p25	p50	p75	p90	p95	p99
$cds^{DTCC} - \overline{cds}$	-28.57	-11.56	-6.74	-2.09	0.79	4.23	9.14	13.67	29.00
$\lvert cds^{DTCC} - \overline{cds}\rvert$	0.05	0.24	0.48	1.30	3.25	6.83	12.77	18.91	37.94
$\log(cds^{DTCC}) - \log(\overline{cds})$	-0.18	-0.09	-0.05	-0.01	0.01	0.03	0.07	0.07	0.07
$\lvert\log(cds^{DTCC}) - \log(\overline{cds})\rvert$	0.00	0.00	0.00	0.01	0.02	0.05	0.10	0.14	0.24

(B) Summary Statistics for contracts with at least ten trades per day ($N = 23,209$)

Percentile	p1	p5	p10	p25	p50	p75	p90	p95	p99
$\sigma_t[\log(cds^{DTCC}) - \log(\overline{cds})]$	0.0000	0.0000	0.0043	0.0088	0.0143	0.0223	0.0361	0.0478	0.0880
No. of transactions per day	10.0	10.0	10.0	11.0	13.0	18.0	25.0	31.0	56.0
Average No. of sellers per buyer	1.0	1.0	1.2	1.5	1.9	2.4	2.9	3.3	4.4
Average No. of buyers per seller	1.0	1.0	1.2	1.5	1.9	2.4	3.0	3.4	4.6

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, $\overline{cds}_t$. 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 ten 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: Summary Statistics for Pricing Analysis – US5 Counterparty Sample

(A) Summary Statistics for all transaction spreads and Markit quotes ($N = 1,519,410$)

Percentile	p1	p5	p10	p25	p50	p75	p90	p95	p99
$cds^{DTCC} - \overline{cds}$	-39.34	-15.52	-8.98	-2.65	0.85	5.77	15.13	25.60	63.00
$\lvert cds^{DTCC} - \overline{cds}\rvert$	0.06	0.27	0.56	1.57	4.18	9.84	20.69	32.30	71.29
$\log(cds^{DTCC}) - \log(\overline{cds})$	-0.21	-0.11	-0.07	-0.02	0.01	0.04	0.09	0.14	0.24
$\lvert\log(cds^{DTCC}) - \log(\overline{cds})\rvert$	0.00	0.00	0.00	0.01	0.03	0.06	0.12	0.17	0.26

(B) Summary Statistics for contracts with at least ten trades per day ($N = 182,502$)

Percentile	p1	p5	p10	p25	p50	p75	p90	p95	p99
$\sigma_t[\log(cds^{DTCC}) - \log(\overline{cds})]$	0.0000	0.0000	0.0000	0.0067	0.0121	0.0204	0.0336	0.0458	0.0913
No. of transactions per day	10.0	10.0	10.0	11.0	13.0	18.0	26.0	34.0	60.0
Average No. of sellers per buyer	1.0	1.0	1.0	1.2	1.7	2.2	2.8	3.3	4.4
Average No. of buyers per seller	1.0	1.0	1.0	1.3	1.8	2.4	3.1	3.7	5.2

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, $\overline{cds}_t$. 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 ten 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 3: Effects of Seller CDS Spreads on Log Spread Differentials

		(1)	(2)	(3)	(4)
	Buyer Type	Non-dealer	Non-dealer	14 Dealers	14 Dealers
(A)	Log Seller CDS	-0.00686**	-0.00785**	-0.00164*	0.000170
		(0.00349)	(0.00357)	(0.000865)	(0.000342)
	Wrong-Way Risk	0.00569***	0.00589***	-0.00122**	-0.00230***
		(0.00211)	(0.00213)	(0.000561)	(0.000565)
	Past Relationship	-0.000627	0.00136	-0.00551*	0.00577***
		(0.00409)	(0.00431)	(0.00322)	(0.00202)
	No. of effective obs.	3,403	2,909	17,477	172,097
	No. of transactions	11,948	10,311	52,750	1,012,029
	Fixed effects	Contract × Buyer × Date			
(B)	Log Seller CDS	-0.0176***	-0.0186***	-0.00338*	-0.000758
		(0.00549)	(0.00642)	(0.00188)	(0.000757)
	Wrong-Way Risk	0.0124***	0.00434	-0.00491***	-0.00271***
		(0.00406)	(0.00350)	(0.00155)	(0.000606)
	Past Relationship	0.000111	0.00211	-0.00646*	0.000924
		(0.00425)	(0.00451)	(0.00341)	(0.00276)
	No. of effective obs.	3,403	2,909	17,477	172,097
	No. of transactions	11,948	10,311	52,750	1,012,029
	Fixed effects	Contract × Buyer × Date, Seller			
	Reference entities	Entitled	Entitled	Entitled	Non-Entitled
	Clearability	Unrestricted	Non-Clearable	Non-Clearable	Non-Clearable

Notes: In all columns, we consider only transactions where the seller is one of the 14 largest dealers. We use the log of the notional value of the contract as a control. In Column 1, we use the sample of transactions on all entitled reference entities in which the buyer is a non-dealer and the seller is one of the 14 largest dealers. In Column 2, we use the sample of transactions on all non-clearable entitled reference entities in which the buyer is a non-dealer and the seller is one of the 14 largest dealers. In Column 3, we use the sample of transactions on non-clearable entitled reference entities in which both the buyer and the seller are one of the 14 largest dealers. In Column 4, we use the sample of interdealer transactions on non-clearable non-entitled reference entities in which at least one of the counterparties is a US5 bank. The two panels differ by the fixed effect specifications. In Panel A, we include contract-buyer-date fixed effects. In Panel B, we include contract-buyer-date fixed effects and additional seller fixed effects. The number of effective observations is reported for buyers facing at least two different sellers for the same contract on a single trading date. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4: Effects of Buyer CDS Spreads on Log Spread Differentials

		(1)	(2)	(3)	(4)
	Seller Type	Non-dealer	Non-dealer	14 Dealers	14 Dealers
(A)	Log Buyer CDS	0.000810	0.0115**	-0.000700	-0.000516
		(0.00265)	(0.00474)	(0.000838)	(0.000341)
	Right-Way Risk	0.00158	0.00770**	0.00108*	0.000974*
		(0.00165)	(0.00327)	(0.000583)	(0.000535)
	Past Relationship	0.00647	0.00488	-0.00726*	-0.00177
		(0.00504)	(0.00545)	(0.00400)	(0.00207)
	No. of effective obs.	2,158	1,946	16,691	162,792
	No. of transactions	7,767	6,955	52,750	1,012,029
	Fixed effects	Contract × Seller × Date			
(B)	Log Buyer CDS	0.0115**	0.0109**	-0.00152	0.000328
		(0.00474)	(0.00461)	(0.00210)	(0.000818)
	Right-Way Risk	0.00770**	0.00305	0.00201	0.000566
		(0.00327)	(0.00391)	(0.00126)	(0.000638)
	Past Relationship	0.00488	0.00520	-0.00716*	0.000112
		(0.00545)	(0.00568)	(0.00400)	(0.00272)
	No. of effective obs.	2,158	1,946	16,691	162,792
	No. of transactions	7,767	6,955	52,750	1,012,029
	Fixed effects	Contract × Seller × Date, Buyer			
	Reference entities	Entitled	Entitled	Entitled	Non-Entitled
	Clearability	Unrestricted	Non-Clearable	Non-Clearable	Non-Clearable

Notes: In all columns, we consider only transactions where the buyer is one of the 14 largest dealers. We use the log of the notional value of the contract as a control. In Column 1, we use the sample of transactions on all entitled reference entities in which the seller is a non-dealer and the buyer is one of the 14 largest dealers. In Column 2, we use the sample of transactions on all non-clearable entitled reference entities in which the seller is a non-dealer and the buyer is one of the 14 largest dealers. In Column 3, we use the sample of transactions on non-clearable entitled reference entities in which both the buyer and the seller are one of the 14 largest dealers. In Column 4, we use the sample of interdealer transactions on non-clearable non-entitled reference entities in which at least one of the counterparties is a US5 bank. The two panels differ by the fixed effect specifications. In Panel A, we include contract-seller-date fixed effects. In Panel B, we include contract-seller-date fixed effects and additional buyer fixed effects. The number of effective observations is reported for sellers facing at least two different buyers for the same contract on a single trading date. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5: Sample Description for Counterparty Choice Analysis

	(1) Buyer Choice Model	(2) Seller Choice Model
Number of reference entities	12	12
Number of reference entities eligible for clearing	4	4
Number of non-dealers	196	169
Number of transactions between non-dealers and one of the 14 largest dealers	11,948	7,767
Of which...		
A US5 dealer appear as the reference entity	7,927	5,693
The reference entity is not eligible for clearing	10,311	6,955

Notes: Our sample period is from 2010 to 2013. In Column (1) we only consider transactions where a non-dealer is buying protection on an FRB regulated reference entity. In Column (2) we only consider transactions where a non-dealer is selling protection on an FRB regulated reference entity.

Table 6: Wrong-Way Risk

Trading Shares	US Sellers	Foreign Sellers
Reference entity is a US5 dealer or Wells Fargo	0.44	0.56
Reference entity is not a US5 dealer nor Wells Fargo	0.54	0.46

Notes: This table tabulates trading shares for reference entities that are highly correlated with U.S. seller's credit risk (the reference entity is a US5 dealer or Wells Fargo) and for reference entities that are less correlated with U.S. seller's credit risk (the reference entity is not a US5 dealer nor Wells Fargo). We restrict the reference entities to FRB regulated reference entities.

Table 7: Counterparty choice of Non-dealers Buying Protection from 14 Dealers

	(1) Baseline sample	(2) Not eligible for clearing	(3) No captive buyers
Seller CDS	-0.279***	-0.268***	-0.267***
	(0.0397)	(0.0425)	(0.0411)
Wrong-Way Risk	-0.217***	-0.069	-0.318***
	(0.0473)	(0.0692)	(0.0481)
Past Relationship	3.475***	3.659***	3.066***
	(0.0497)	(0.0542)	(0.0598)
Number of observations	159,345	136,427	146,443
Number of transactions	11,948	10,311	10,979
Number of buyers	196	195	155
Pseudo R-squared	0.383	0.389	0.359

Notes: We include seller fixed effects and the spread of the CDX.NA.IG index interacted with an indicator variable for each seller as controls. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 8: Marginal Effects of the Buyer Choice Model

Range of probability of choice	(1) Average change in probability given a 100 bp change in seller CDS	(2) Average change in probability from no WWR to WWR	(3) Average change in probability given a 1 std. dev. change in past relationship
		Baseline sample	
0.13-0.07	-0.026	-0.020	0.042
0.06-0.01	-0.010	-0.007	0.016
		Not eligible for clearing	
0.13-0.07	-0.025	-0.006	0.043
0.06-0.01	-0.010	-0.003	0.017
		No captive buyers	
0.13-0.07	-0.025	-0.029	0.034
0.06-0.01	-0.010	-0.011	0.013

Notes: Marginal effects are based on coefficients reported in Table 7.

Table 9: Counterparty Choice of Non-dealers Buying Protection from 14 Dealers: Short Horizon Buyers

	(1)	(2)	(3)
	Baseline sample	Not eligible for clearing	No captive buyers
Seller CDS	-0.362***	-0.372***	-0.370***
	(0.0423)	(0.0457)	(0.0446)
Seller CDS x Short Horizon Buyer	0.213***	0.254***	0.239***
	(0.0379)	(0.0407)	(0.0395)
Wrong-Way Risk	-0.205***	-0.047	-0.359***
	(0.0505)	(0.0717)	(0.0520)
Wrong-Way Risk x Short Horizon Buyer	-0.043	-0.052	0.064
	(0.0467)	(0.0470)	(0.0482)
Past Relationship	3.361***	3.562***	2.797***
	(0.0533)	(0.0569)	(0.0650)
Past Relationship x Short Horizon Buyer	0.608***	0.480***	1.138***
	(0.121)	(0.128)	(0.131)
Number of observations	159,345	136,427	146,443
Number of transactions	11,948	10,311	10,979
Number of buyers	196	195	155
Pseudo R-squared	0.384	0.389	0.361

Notes: We include seller fixed effects and the spread of the CDX.NA.IG index interacted with an indicator variable for each seller as controls. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 10: Counterparty Choice of Non-dealers Selling Protection to 14 Dealers

	(1) Baseline sample	(2) Not eligible for clearing	(3) No captive sellers
Buyer CDS	-0.250***	-0.186***	-0.255***
	(0.0528)	(0.0558)	(0.0532)
Right-Way Risk	-0.080	0.280***	-0.068
	(0.0583)	(0.0759)	(0.0598)
Past Relationship	3.392***	3.375***	3.179***
	(0.0657)	(0.0716)	(0.0740)
Number of observations	103,045	91,677	97,337
Number of transactions	7,767	6,955	7,340
Number of sellers	169	165	123
Pseudo R-squared	0.383	0.382	0.368

Notes: We include buyer fixed effects and the spread on the CDX.NA.IG index interacted with an indicator variable for each buyer as controls. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Marginal Effects of the Seller Choice Model

Range of probability of choice	(1) Average change in probability given a 100 bp change in buyer CDS	(2) Average change in probability from no RWR to RWR	(3) Average change in probability given a 1 std. dev. change in past relationship
		Baseline sample	
0.16-0.07	-0.022	-0.007	0.037
0.06-0.01	-0.006	-0.002	0.010
		Not eligible for clearing	
0.16-0.07	-0.016	0.024	0.034
0.06-0.01	-0.005	0.008	0.011
		No captive sellers	
0.16-0.07	-0.022	-0.006	0.034
0.06-0.01	-0.006	-0.002	0.010

Notes: Marginal effects are based on coefficients reported in Table 10.

Table 12: Counterparty Choice of Non-dealers Selling Protection to 14 Dealers: Short Horizon Sellers

	(1) Baseline sample	(2) Not eligible for clearing	(3) No captive sellers
Buyer CDS	-0.264***	-0.175***	-0.266***
	(0.0572)	(0.0613)	(0.0577)
Buyer CDS x Short Horizon Seller	0.0337	-0.0194	0.0295
	(0.0502)	(0.0541)	(0.0509)
Right-Way Risk	-0.0972	0.239***	-0.0807
	(0.0645)	(0.0805)	(0.0662)
Right-Way Risk x Short Horizon Seller	0.0584	0.0823	0.0465
	(0.0588)	(0.0596)	(0.0597)
Past Relationship	3.151***	3.097***	2.773***
	(0.0728)	(0.0798)	(0.0861)
Past Relationship x Short Horizon Seller	0.896***	0.980***	1.284***
	(0.136)	(0.144)	(0.145)
Number of observations	103,045	91,677	97,337
Number of transactions	7,767	6,955	7,340
Number of sellers	169	165	123
Pseudo R-squared	0.384	0.383	0.370

Notes: We include buyer fixed effects and the spread on the CDX.NA.IG index interacted with an indicator variable for each buyer as controls. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 13: Linear Probability Model with Fixed Effects

(A) Counterparty Choice of Non-dealers Buying Protection from 14 Dealers

	(1)	(2)	(3)
	Baseline sample	Not eligible for clearing	No captive buyers
Seller CDS	-0.0114***	-0.0113***	-0.0129***
	(0.00322)	(0.00331)	(0.00339)
Wrong-Way Risk	-0.0110	-0.000276	-0.0210***
	(0.00693)	(0.00808)	(0.00713)
Past Relationship	0.536***	0.572***	0.427***
	(0.0187)	(0.0174)	(0.0213)
Number of observations	159,345	136,427	146,443
Number of transactions	11,948	10,311	10,979
Number of buyers	196	195	155
R-squared	0.088	0.095	0.060

(B) Counterparty Choice of Non-dealers Selling Protection to 14 Dealers

	(1)	(2)	(3)
	Baseline sample	Not eligible for clearing	No captive sellers
Buyer CDS	-0.0112***	-0.0101***	-0.0126***
	(0.00367)	(0.00378)	(0.00377)
Right-Way Risk	-0.00317	0.0201*	-0.00367
	(0.0101)	(0.0113)	(0.0109)
Past Relationship	0.504***	0.500***	0.439***
	(0.0230)	(0.0214)	(0.0253)
Number of observations	103,058	91,690	97,350
Number of transactions	7,767	6,955	7,340
Number of sellers	169	165	123
R-squared	0.083	0.081	0.066

Notes: We include dealer fixed effects, the spread on the CDX.NA.IG index interacted with an indicator variable for each dealer, and contract-date-dealer fixed effects as controls. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 14: Clearing Dates for CDX.NA.IG Constituents

	Materials	Con. Goods	Con. Srvs	Financials	Healthcare	Industrials	Oil/Gas	Technology	Telecom	Utilities
12/21/2009	0	0	0	0	0	0	0	0	0	3
1/11/2010	0	0	0	0	0	0	0	0	0	3
2/1/2010	0	0	0	0	0	0	0	0	3	0
2/15/2010	0	0	0	0	0	15	0	0	0	0
3/8/2010	0	4	0	0	0	0	5	0	0	0
3/29/2010	0	0	14	0	0	0	0	0	0	0
4/19/2010	5	0	0	0	0	0	0	5	0	0
5/10/2010	0	0	1	6	4	0	0	0	0	0
6/7/2010	0	0	0	1	1	0	0	0	0	0
6/28/2010	0	0	1	0	0	0	0	0	0	0
8/9/2010	0	8	0	0	0	0	2	0	0	0
8/30/2010	0	0	8	0	0	0	0	0	0	0
3/28/2011	2	2	4	0	0	0	0	2	0	0
4/11/2011	0	0	0	10	0	0	0	0	0	0
5/2/2011	0	0	0	0	3	3	2	0	0	0
6/13/2011	0	1	3	5	0	0	0	2	0	0
11/14/2011	0	1	1	0	1	0	1	0	0	0
10/9/2012	0	0	0	5	0	0	0	0	0	0
10/22/2012	0	0	0	0	0	0	6	0	0	0
11/5/2012	1	2	1	1	0	1	0	0	0	2
11/19/2012	0	0	0	1	0	0	0	0	0	0
9/30/2013	0	2	2	2	0	2	0	0	0	0
Total	8	20	35	31	9	21	16	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). We exclude clearable reference entities that had a cleared predecessors. Source: ICE.

Table 15: Effects of Clearing and Counterparty Characteristics on Log Spread Differentials

	(1) Seller	(2) Buyer	(3) Pair
Seller CCP	-0.00363***		-0.00332***
	(0.000871)		(0.000437)
Buyer CCP		-0.00217**	-0.00290***
		(0.000891)	(0.000440)
Backload clear	-0.00128*	-0.000462	-0.00160***
	(0.000734)	(0.000732)	(0.000380)
Seller non-dealer	-0.00555***		-0.00939***
	(0.000939)		(0.000533)
Buyer non-dealer		0.00402***	0.00896***
		(0.000810)	(0.000426)
Number of observations	368,402	409,053	509,248
Fixed effects	Contract × Date × Buyer	Contract × Date × Seller	Contract × Date

Notes: This table shows effects of counterparty characteristics and clearing on transaction spreads. In Column 1 we hold time and the buyer fixed and estimate effects of seller's characteristics. The buyer is one of the 14 largest dealers. In Column 2 we hold time and the seller fixed and estimate effects of buyer's characteristics. The seller is one of the 14 largest dealers. In Columns 3 we hold time fixed and jointly estimate effects of buyer's and seller's characteristics. Either the buyer of the seller is one of the 14 largest dealers. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 16: Time Series Effects of Clearing Eligibility

		Specification I		Specification II		Specification III	
		(1)	(2)	(3)	(4)	(5)	(6)
		DTCC	Markit	DTCC	Markit	DTCC	Markit
(A)	Treatment X After	-0.0141	-0.0293	-0.0770	0.00536	0.0487	0.0191*
		(0.0585)	(0.0191)	(0.0544)	(0.0205)	(0.0391)	(0.0113)
	Treatment	-0.110**	-0.0701***	0.0941**	0.152***	-0.446***	0.000226
		(0.0484)	(0.0117)	(0.0425)	(0.0151)	(0.0306)	(0.00813)
	Observations	44,691	72,685	129,286	74,391	231,022	930,404
(B)	Treatment X [-20, -10)	-0.0190	0.0186	-0.158**	-0.166***	-0.215***	0.00821
		(0.0992)	(0.0251)	(0.0699)	(0.0344)	(0.0521)	(0.0177)
	Treatment X [-10, 0)	-0.0171	-0.000179	-0.0833	0.000858	0.115	0.00666
		(0.0952)	(0.0363)	(0.102)	(0.0475)	(0.0777)	(0.0236)
	Treatment X [0, 10)	0.0380	-0.00112	-0.116	0.00119	0.117	0.00860
		(0.111)	(0.0398)	(0.110)	(0.0479)	(0.0788)	(0.0238)
	Treatment X [10, 20)	-0.0486	0.0184	-0.446***	-0.159***	-0.229***	0.0223
		(0.0699)	(0.0342)	(0.114)	(0.0357)	(0.0495)	(0.0180)
	Treatment	-0.128***	-0.0870***	0.273***	0.267***	-0.295***	-0.0203***
		(0.0488)	(0.00603)	(0.0203)	(0.00740)	(0.0189)	(0.00466)
	Observations	40,305	82,368	145,859	86,450	249,597	574,493
	FE	Sector-Date	Sector-Date	Sector-Date	Sector-Date	Sector-Date	Sector-Date

Notes: This table shows results for three DID specifications for the time series effects of clearing eligibility on DTCC transaction spreads and Markit quotes. Fixed effects for the interaction of sector and trade dates are used in all specifications. Panel A uses the event window from 50 days before and after the introduction of clearing eligibility. Panel B uses the event from 250 days before the introduction of clearing eligibility to 20 days afterwards. In Specification I, the treatment group consists of transactions or quotes 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 or quotes of reference entities in CDX.NA.IG that are cleared in later cohorts. In Specification II, the control group consists of post-clearing reference entities cleared in the first cohort for each sector of the CDX.NA.IG index. The treatment group consists of transactions or quotes of reference entities in the same sector of CDX.NA.IG that are cleared in later cohorts. In Specification III, the treatment group consists of transactions or quotes on all clearable reference entities in CDX.NA.IG before and after clearing. The control group consists of transactions or quotes on all other non-clearable investment grade reference entities in North America. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.