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

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December 11, 2015

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 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 central clearing on CDS pricing. 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.

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 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 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

[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.

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 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 little evidence of pricing impacts arising from counterparty credit risk for interdealer transactions. This is consistent with clients facing asymmetric collateral terms, 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.

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 recently in the past. This finding is consistent with economies of scale or scope in client trading relationships. However, such relationships do not appear to subvert counterparty risk management. When we restrict our sample to non-dealers who trade predominantly with a single dealer, we still find these non-dealers to be sensitive to counterparty risk in choice of dealer counterparty.

As an extension, we explore whether customers vary in their sensitivity to counterparty risk in their choice of dealer. We find that non-dealers with a short investment horizon are less sensitive to the default risk of the dealer and to wrong-way risk; we identify a non-dealer as short horizon if it closes at least 50 percent of new trades within a month. This finding suggests that this class of non-dealers may be more affected than others by a financial crisis if they are not able to close out their open positions in time.

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, 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 largely not priced.

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). 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.

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, three 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 in 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.

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 deriva-

[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.

tive 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 quite common, but clearing on behalf of clients is quite rare (we observe two instances in a sample of 1474 transactions on eligible single-name reference entities involving non-dealer counterparties).[3] We proceed under the assumption that central clearing is not a viable risk-mitigating option for non-dealers engaged in trading single-name CDS.

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 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.

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, 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 contract

[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.

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*

(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

[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.

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 30% of client-facing (i.e., between a non-dealer and dealer) transactions in our sample.[6] For a subset of our counterparty choice regressions in Section 4 (but not our pricing regression in Section 3), results change materially when this non-dealer is included in the sample.[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 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 84,431 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,

[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 1200 to 600. 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.

[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.

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. 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. 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 81,810 transactions.

In robustness exercises, we make use of 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 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

[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.

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 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. 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 the WWR^s_t (RWR^s_t) as a dummy equal to one if the credit risk of selling (buying) dealer and the reference entity have a correlation over 70%.[11]

Perhaps to achieve operational efficiencies, trading relationships in OTC markets often persist through time. In the case of a non-dealer buyer of protection and dealer seller of protection, $Relations^{s,b}_t$ 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. The total notional value transacted between b and s is divided by the total notional value that market participant b traded with all sellers. The variable is defined analogously when the non-dealer is selling protection.

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 of protection are less likely to fulfill their

[11] To be precise, we estimate the correlation 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 measure the WWR and RRW based on the 70% correlation between credit spreads of the dealer and reference entity.

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.

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. In Panel B, we restrict the summary statistics to the subsample in which there are at least ten trades on the identical contracts during the same day, which is about 36 percent of our baseline sample. We see that there is a significant amount of pricing dispersion within the day on the same contract, with a median within-day standard deviation of 1.2 percent. In terms of the 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 is correlated with 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

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

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. 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 ($Relations_t^{s,b}$).

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:

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

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 -0.006 is very small. A 100 percent increase in the seller's log spread translates to only a 0.6 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 214 basis points in the estimated sample and the mean dealer spreads is about 177 basis points, and hence a 100 basis point increase in the seller's credit spreads translate into about 0.7 basis point reduction in the transaction spread ($= \frac{100}{177} \times 0.006 \times 214$). In Panel B, the coefficient on the seller's credit spread increases to 0.016 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 opposite sign as 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 relations.

In Column 3, we repeat the same regressions for interdealer transactions. We obtain small negative coefficients on the seller's CDS spreads, but they are not statistically significant. For interdealer transactions a 100 basis point increase in the seller's spreads translate into about 0.2 to 0.4 basis point reduction in the transaction spread. WWR enters slightly negatively, consistent with the counterparty risk hypothesis. 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. We find that the coefficient on the seller's CDS spread is slightly positive and statistically insignificant across both fixed effect specifications. WWR does not enter significantly. Past relationship enters slightly positively without the buyer fixed effects, but loses significance after including buyer 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. 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 systematic way.

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:

$$\log(cds^{s,b}_{i,t}) - \log(\overline{cds}_{i,t}) = \alpha^s_{i,t} + \gamma \log(\overline{cds}^b_{t-1}) + \eta RWR^b + \lambda Relations^{b,s}_t + \delta \log(size) + \epsilon^{b,s}_{i,t}, \quad (3)$$

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

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

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 is slightly positive and insignificant without the additional buyer fixed effects (Panel A), but becomes significant and similar in magnitudes as the corresponding coefficients in Table 3 for seller log-spreads after the buyer's fixed effects are added (Panel B). For interdealer transactions reported in Columns 3 and 4, the buyer's CDS either enters with a slightly negative (wrong) sign. Neither right-way risk nor past relationship has 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.[12] 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 Table 5. Our baseline sample contains 386 non-dealer buyers of protection in 13,054 transactions. We have fewer observations in our seller choice model: the sample contains 288 non-dealer sellers of protection in 8,506 transactions.

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 for US dealers. A group 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,

[12] As detailed in Section 2.2, we drop a non-dealer that accounts for more than 30% of CDS protection sales. If we include this seller, the assumption that non-dealers initiate the trade may be incorrect.

the trading share is 43 percent when the US5 dealer is selling protection on one of the US5 or Wells Fargo compared to a trading share of 56 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 dealers than from a foreign bank.

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

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

where the choice set has cardinality $N_i = 13$ when the reference entity i is a US5 dealer and $N_i = 14$ otherwise. This means that the 13,054 transactions translate into 173,914 observations in our multinomial estimation.[13] 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 $t-1$; $Relations_t^{s,b}$, to allow for "stickiness" in buyer-dealer relationships; 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 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 coefficient estimates are similar to those in Column 1, the magnitude of the coefficients on WWR and the seller's CDS are smaller, but difference across estimates are not

[13] 173,914=13,054 x 14 - 8842, where 8842 is the number of observations where the dealer is the same as the reference entity and the buyer of protection does not consider that dealer to be a viable choice.

statistically significant. The results suggest that clearing eligibility has not had an impact on how non-dealers manage counterparty risk. 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 are facing a single dealer 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, and again differences across coefficient estimates are not statistically significant.

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. 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 2.5 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 6–11 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 vary across classes of customers. We re-estimate equation (5) including interactions of the independent variables with a dummy variable equal to one if the buyer of protection is a non-dealer with a short investment horizon (i.e., non-dealers who tend to close their open positions within a month). The results reported in Table 9 indicate that short-horizon buyers of protection are less sensitive to the default risk of the dealer.

We repeat these analyses from the perspective of customer-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, though the difference is not statistically significant. 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. Furthermore, in our sample of reference entities not eligible for clearing market participants are not sensitive to right-way-risk.

Finally, in Appendix Tables A1 and A2, we replicate the fixed effect specification of Section 3 in a linearized choice model. Our results are robust to the inclusion of these fixed effects.

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.

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 most index constituents had been made eligible to clear. The single-names constituents 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, which typically consist of several firms in the same sector. Table A3 summarizes the introduction of clearing eligibility during our sample period by sector for CDX.NA.IG constituents.[14] Cohorts are typically small. As an example, five 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. 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

[14] Many of the singleton observations in these tables are technical events associated, for example, with a change in RED identifier for a reference entity. We are working to identify and exclude such events from our sample.

designated 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), which matches buyer and seller anonymously. A SEF trade is cleared at inception, so appears in the repository data as two simultaneous transactions with a CCP as buyer on one leg and as seller on the other.

Table 13 presents results on how transaction characteristics affect CDS pricing. We categorize transactions into four types: (i) trade originates on a SEF; (ii) trade is backload cleared; (iii) uncleared OTC client-facing trade; and (iv) uncleared OTC interdealer trade. The fourth type is the omitted category in the regressions.

In Column 1, we hold the contract, time and the buyer fixed, and find that SEF trades are associated with significantly lower spreads than OTC interdealer trades, with magnitudes around 0.3 percent. Non-dealer sellers sell at about 0.5 percent lower spreads than spreads on comparable OTC interdealer transactions. Backloaded clearing trades do not have statistically different spreads from the interdealer spreads. In Column 2 we hold the contract, time and the seller fixed, and again find that SEF trades are associated with lower spreads, with magnitudes around 0.3 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.

In Columns 3, we fix contract and time only and allow both buyer and seller's characteristics to enter simultaneously. We confirm the effects documented in Columns 1 and 2, i.e., that SEF trades are associated with significantly lower transaction spreads, with magnitudes again 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 trades by about 0.1 percent.

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 SEF trades have significantly lower spreads than OTC trades for which the non-dealer is the buyer, and significantly higher spreads than OTC trades for which the non-dealer is the seller.

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 Markit quotes and DTCC transaction spreads using a difference-in-differences (DID) approach. 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:

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

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 $Clearable_{i,t}$ 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.

We use transactions on reference entities cleared in the first cohort for each sector as the treatment group, and pre-eligibility Markit quotes or DTCC transactions on reference entities cleared in later cohorts as the control group. Entities in both treatment and control groups 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. We use treatment and control groups in the same sector to mitigate the impact of common macroeconomic and sectoral shocks on our estimates.

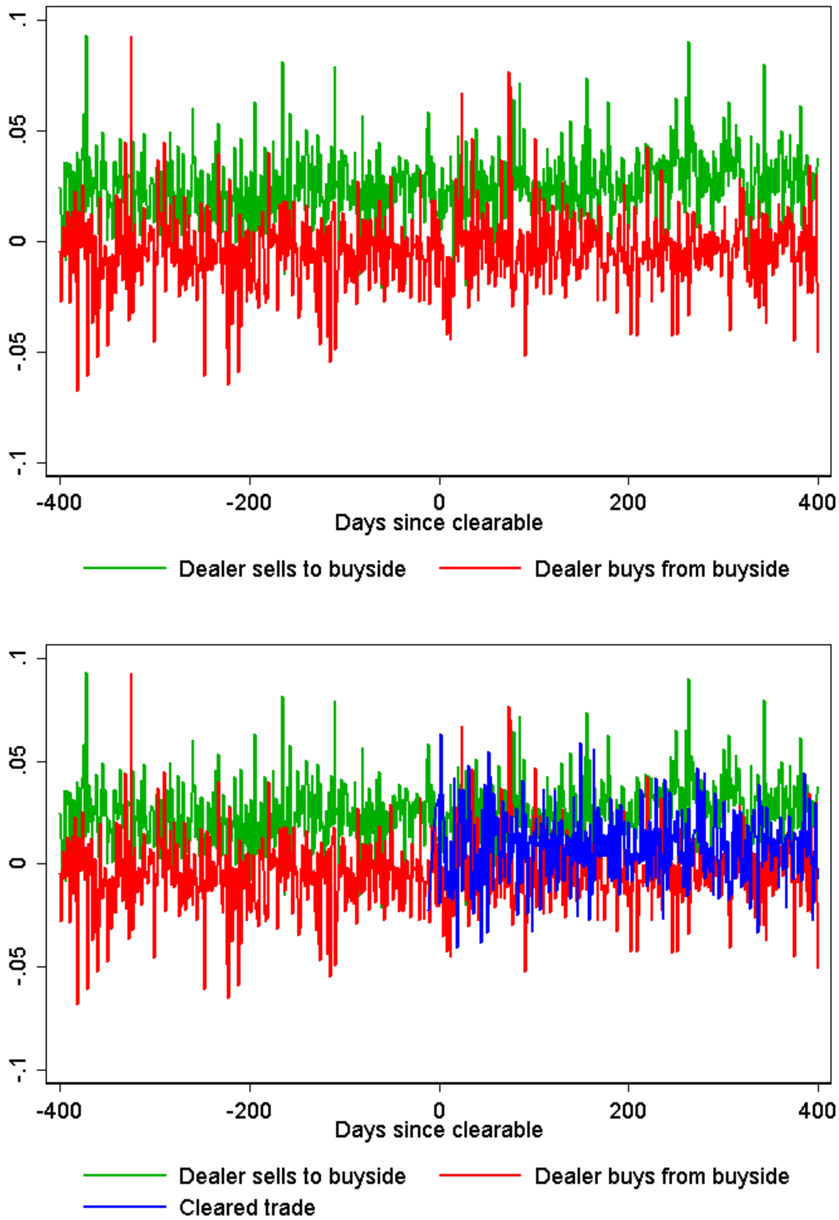
We visualize the DID results for Markit quotes in Figure 2. In all three specifications, mean Markit spreads in the treatment group co-move with those in the control group very closely before and after commencement of eligibility. There is no discrete jump in treatment group around the commencement of clearing. Regression estimates confirm this visual observation. Table 14 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 negligibly small and statistically insignificant for DTCC transaction spreads and Markit quotes on these transactions. Therefore, we do not find evidence that central clearing eligibility increases Markit quotes or transaction spreads.

6 Conclusion

Our results show that customers 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. 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.

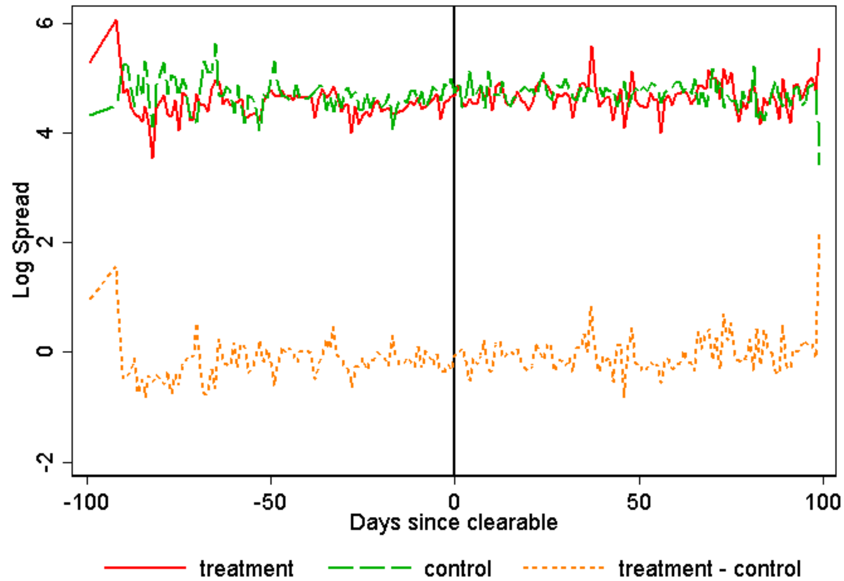
We find little evidence of material pricing impacts arising from counterparty credit risk for inter-dealer transactions. For client-facing transactions, we find statistically significant but economically small effects of dealer credit spreads on transaction spreads for hedge funds and asset managers, though somewhat larger effects for non-dealer banks. 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 compensation for counterparty risk in prices plays a less important role in CDS markets than the management of counterparty risk by counterparty choice.

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 SEF cleared transactions.

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



Notes: The figure plots mean log transaction spreads in treatment and control groups before and after the reference entities became clearable in the treatment group. The treatment group consists of reference entities that were cleared in the first cohort of each sector. The controls group consists of non-clearable reference entities that were in the CDX index before the first clearing date for each sector, but were cleared in later cohorts.

Table 1: Summary Statistics for Pricing Analysis - Baseline Sample

(A) Summary Statistics for all transaction spreads and Markit quotes ($N = 81,810$)

Percentile	p1	p5	p10	p25	p50	p75	p90	p95	p99
$cds^{DTCC} - \overline{cds}$	-28.61	-11.58	-6.80	-2.13	0.77	4.22	9.11	13.65	29.14
$\lvert cds^{DTCC} - \overline{cds} \rvert$	0.05	0.24	0.48	1.30	3.26	6.82	12.79	19.01	37.92
$\log(cds^{DTCC}) - \log(\overline{cds})$	-0.18	-0.09	-0.05	-0.02	0.01	0.03	0.07	0.11	0.22
$\lvert \log(cds^{DTCC}) - \log(\overline{cds}) \rvert$	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 ($N = 21,882$)

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	0.0226	0.0367	0.0505	0.0899
No. of transactions per day	10.0	10.0	10.0	11.0	13.0	18.0	25.0	31.0	53.0
Average No. of sellers per buyer	1.0	1.0	1.2	1.5	1.9	2.4	2.9	3.4	4.5
Average No. of buyers per buyer	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 ($N = 1,435,104$)

Percentile	p1	p5	p10	p25	p50	p75	p90	p95	p99
$cds^{DTCC} - \overline{cds}$	-75.15	-18.03	-9.52	-2.54	1.06	6.82	20.86	45.46	386.15
$\lvert cds^{DTCC} - \overline{cds}\rvert$	0.06	0.29	0.58	1.66	4.54	11.52	29.87	63.22	484.05
$\log(cds^{DTCC}) - \log(\overline{cds})$	-0.31	-0.12	-0.07	-0.02	0.01	0.04	0.11	0.18	0.42
$\lvert \log(cds^{DTCC}) - \log(\overline{cds})\rvert$	0.00	0.00	0.00	0.01	0.03	0.07	0.15	0.23	0.51

(B) Summary Statistics for contracts with at least ten trades per day ($N = 168,872$)

Percentile	p1	p5	p10	p25	p50	p75	p90	p95	p99
$\sigma_t[\log(cds^{DTCC}) - \log(\overline{cds})]$	0.0000	0.0000	0.0011	0.0069	0.0123	0.0206	0.0341	0.0468	0.1068
No. of transactions per day	10.0	10.0	10.0	11.0	13.0	17.0	25.0	32.0	53.0
Average No. of sellers per buyer	1.0	1.0	1.0	1.3	1.8	2.2	2.8	3.3	4.5
Average No. of buyers per buyer	1.0	1.0	1.0	1.3	1.8	2.4	3.1	3.7	5.1

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	-0.00630*	-0.00709**	-0.00132	0.000424
		(0.00339)	(0.00347)	(0.000879)	(0.000389)
	Wrong-Way Risk	0.00531***	0.00545***	-0.000426	0.000172
		(0.00189)	(0.00191)	(0.000599)	(0.000693)
	Past Relationship	-0.00204	-0.000521	-0.00724**	0.00431**
		(0.00413)	(0.00444)	(0.00359)	(0.00216)
	No. of effective obs.	3,428	2,913	17,846	146,947
	No. of Transactions	13,059	11,325	49,031	695,559
	FE	Contract X Buyer X Date FE			
(B)	Log Seller CDS	-0.0158***	-0.0167***	-0.00291	0.00103
		(0.00497)	(0.00573)	(0.00194)	(0.000872)
	Wrong-Way Risk	0.0109***	0.00213	-0.00316*	0.000861
		-0.00404	(0.00340)	(0.00176)	(0.000723)
	Past Relationship	-0.00167	0.000205	-0.00853**	-0.00324
		(0.00433)	(0.00461)	(0.00368)	(0.00322)
	No. of effective obs.	3,428	2,913	17,846	146,947
	No. of Transactions	13,059	11,325	49,031	695,559
	FE	Contract X Buyer X Date FE, Seller FE			
	Seller	14 Dealers			
	Reference Entities	Entitled	Entitled	Entitled	Non-Entitled
	Clearability	Unrestricted	Non-Clearable	Non-Clearable	Non-Clearable
	Control	Log Notional			

Notes: 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	0.00142	0.00337	-0.00206**	-0.000535
		(0.00281)	(0.00299)	(0.000897)	(0.000387)
	Right-Way Risk	0.00106	-0.00123	0.00175***	0.000403
		(0.00243)	(0.00262)	(0.000637)	(0.000703)
	Past Relationship	-0.00713	0.00256	-0.00638*	-0.00629***
		(0.00769)	(0.00860)	(0.00341)	(0.00240)
	No. of effective obs.	2,145	1,935	17,394	141,533
	No. of Transactions	8,506	7,054	49,031	695,559
	FE	Contract X Seller X Date FE			
(B)	Log Buyer CDS	0.0169***	0.0166**	-0.00195	-0.000728
		(0.00651)	(0.00674)	(0.00220)	(0.000922)
	Right-Way Risk	0.00626*	0.000941	0.00257**	0.000769
		(0.00353)	(0.00406)	(0.00126)	(0.000747)
	Past Relationship	-0.00381	-0.000704	-0.00465	0.00162
		(0.00976)	(0.0103)	(0.00353)	(0.00352)
	No. of effective obs.	2,145	1,935	17,394	141,533
	No. of Transactions	8,506	7,054	49,031	695,559
	FE	Contract X Seller X Date FE, Buyer FE			
	Buyer	14 Dealers			
	Reference Entities	Entitled	Entitled	Entitled	Non-Entitled
	Clearability	Unrestricted	Non-Clearable	Non-Clearable	Non-Clearable
	Control	Log Notional			

Notes: 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 Analysis of Quantities Traded

	(1) Buyer Choice Model	(2) Seller Choice Model
Number of reference entities	12	12
Number of reference entities eligible for clearing	4	4
Percent of trades where counterparty is one of the 14 largest dealers	99%	99%
Number of non-dealers	386	288
Number of transactions between customer and one of the 14 largest dealers	13,059	8,506
Number of transactions of reference entities non-eligible for clearing	11,325	7,654

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

Table 6: Wrong-Way Risk

Trading shares	US Sellers	Foreign Sellers
Reference Entity Highly Correlated with US Seller Credit Risk (corr >=0.7)	0.43	0.57
Reference Entity Less Correlated with US Seller Credit Risk (corr <0.7)	0.56	0.44

Notes: This table tabulates trading shares for reference entities that are highly correlated with U.S. seller's credit risk (correlation is greater than or equal to 0.7) and for reference entities that are less correlated with U.S. seller's credit risk (correlation is less than 0.7). We restrict the reference entities to FRB regulated reference entities.

Table 7: Determinants of the propensity of non-dealers to buy protection from 14 dealers: Reference entities are FRB regulated entities

	Baseline sample	Not eligible for clearing	No captive buyers
	(1)	(2)	(3)
Seller's CDS	-0.274***	-0.256***	-0.270***
	(0.0375)	(0.0401)	(0.0393)
Wrong-Way-Risk	-0.257***	-0.168**	-0.369***
	(0.0452)	(0.0668)	(0.0470)
Past Relationship	3.205***	3.336***	2.822***
	(0.0479)	(0.0525)	(0.0579)
Number of Observations	173,914	149,638	153,819
Number of Transactions	13,059	11,325	11,550
Number of Buyers	386	373	221
Pseudo R-squared	0.386	0.391	0.361
Controls	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 interacted with an indicator variable for each seller.

Table 8: Marginal effects of the buyer choice model: Reference entities are FRB regulated entities

Range of probability of choice	(1) Average change in probability given a 100 bp change in seller's CDS	(2) Average change in probability from no WWR to WWR	(3) Average change in probability given a 1 Std change in proportion of buyer-seller notional
		Baseline Sample	
0.13-0.07	-0.026	-0.025	0.040
0.06-0.01	-0.009	-0.008	0.014
		Not eligible for clearing	
0.13-0.07	-0.024	-0.016	0.041
0.06-0.01	-0.009	-0.005	0.015
		No captive buyers	
0.13-0.07	-0.025	-0.034	0.035
0.06-0.01	-0.010	-0.012	0.013

Table 9: Determinants of the propensity of non-dealers to buy protection from 14 dealers: Short Horizon Buyers

	Baseline sample	Not eligible for clearing	No captive buyers
	(1)	(2)	(3)
Seller's CDS	-0.343***	-0.336***	-0.358***
	(0.0396)	(0.0426)	(0.0422)
Seller's CDS x Short Horizon Buyers	0.221***	0.243***	0.231***
	(0.0375)	(0.0402)	(0.0392)
Wrong-Way-Risk	-0.235***	-0.139**	-0.420***
	(0.0476)	(0.0686)	(0.0502)
Wrong-Way-Risk x Short Horizon Buyers	-0.0703	-0.0763	0.0943*
	(0.0465)	(0.0467)	(0.0482)
Past Relationship	3.047***	3.185***	2.494***
	(0.0489)	(0.0539)	(0.0603)
Past Relationship x Short Horizon Buyers	1.236***	1.087***	1.756***
	(0.144)	(0.150)	(0.149)
Number of Observations	173,914	149,638	153,819
Number of Transactions	13,059	11,325	11,550
Number of Buyers	386	373	221
Pseudo R-squared	0.387	0.392	0.364
Controls	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 interacted with an indicator variable for each seller.

Table 10: Determinants of the propensity of non-dealers to sell protection to 14 dealers

	Baseline sample	Not eligible for clearing	No captive sellers
	(1)	(2)	(3)
Buyer's CDS	-0.250***	-0.232***	-0.223***
	(0.0495)	(0.0521)	(0.0503)
Right-Way-Risk	-0.102*	0.0382	-0.125**
	(0.0541)	(0.0670)	(0.0558)
Past Relationship	3.608***	3.739***	3.380***
	(0.0757)	(0.0879)	(0.0897)
Number of Observations	112,863	100,935	105,232
Number of Transactions	8,506	7,654	7,935
Number of Sellers	288	280	189
Pseudo R-squared	0.371	0.370	0.356
Controls	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: B-FE: buyer fixed effect, CDXNAIG is the spread on the CDX.NA.IG index interacted with an indicator variable for each buyer. Reference entities are FRB regulated entities.

Table 11: Marginal effects of the seller choice model: Reference entities are FRB regulated entities

Range of probability of choice	(1) Average change in probability given a 100 bp change in buyer's CDS	(2) Average change in probability from no RWR to RWR	(3) Average change in probability given a 1 Std change in proportion of buyer-seller notional
		Baseline Sample	
0.16-0.07, 7 dealers	-0.022	-0.009	0.042
0.06-0.01, 7 dealers	-0.006	-0.002	0.012
		Not eligible for clearing	
0.16-0.07	-0.021	0.003	0.043
0.06-0.01	-0.007	0.001	0.015
		No captive buyers	
0.16-0.07	-0.019	-0.010	0.037
0.06-0.01	-0.009	-0.005	0.018

Table 12: Determinants of the propensity of non-dealers to sell protection to 14 dealers: Short Horizon Sellers

	Baseline sample	Not eligible for clearing	No captive sellers
	(1)	(2)	(3)
Buyer's CDS	-0.268***	-0.223***	-0.243***
	(0.0531)	(0.0565)	(0.0544)
Buyer's CDS x Short Horizon Sellers	0.0358	-0.0256	0.0325
	(0.0483)	(0.0520)	(0.0485)
Right-Way-Risk	-0.0695	0.0678	-0.0655
	(0.0612)	(0.0735)	(0.0634)
Right-Way-Risk x Short Horizon Sellers	-0.114*	-0.0958	-0.196***
	(0.0689)	(0.0732)	(0.0705)
Past Relationship	3.500***	3.619***	3.145***
	(0.0800)	(0.0940)	(0.0985)
Past Relationship x Fast Turnover	0.555***	0.575***	0.896***
	(0.174)	(0.194)	(0.182)
Number of Observations	112,863	100,935	105,232
Number of Transactions	8,506	7,654	7,935
Number of Sellers	288	280	189
Pseudo R-squared	0.371	0.370	0.356
Controls	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: B-FE: buyer fixed effect, CDXNAIG is the spread on the CDX.NA.IG index interacted with an indicator variable for each buyer.

Table 13: Effects of Clearing and Counterparty Characteristics on Log Spread Differentials

Variables	(1) Seller	(2) Buyer	(3) Pair
Seller ccp	-0.00297***		-0.00306***
	(0.000962)		(0.000467)
Buyer ccp		-0.00198**	-0.00248***
		(0.000875)	(0.000470)
Backload clear	-0.00124	-0.000139	-0.00117***
	(0.000795)	(0.000733)	(0.000403)
Seller non-dealer	-0.00491***		-0.00906***
	(0.000991)		(0.000579)
Buyer non-dealer		0.00406***	0.00939***
		(0.000818)	(0.000458)
Observations	294,778	328,475	418,517
FE	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. In Column 2 we hold time and the seller fixed and estimate effects of buyer's characteristics. In Columns 3 we hold time fixed and jointly estimate effects of buyer's and seller's characteristics. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 14: Time Series Effects of Clearing Eligibility

Variables	(1) Log Transaction	(2) Log Markit	(3) Log Difference
Treatment X Clear	-0.00603	-0.00219	-0.00384
	(0.0506)	(0.0509)	(0.00276)
Treatment	-0.365***	-0.365***	0.000346
	(0.0412)	(0.0412)	(0.00206)
Constant	4.976***	4.966***	0.0104***
	(0.00518)	(0.00523)	(0.000298)
Observations	84,165	84,165	84,165
FE	Sector-Date	Sector-Date	Sector-Date

Notes: In Column 1, the dependent variable is the DTCC transaction spread in logs. In Column 2, the dependent variable is the Markit quoted spreads in logs on the same set of transactions as in Column 1. In Column 3, the dependent is the difference between the log transaction spread and the log Markit quoted spread. The treatment group consists of reference entities that were cleared in the first cohort of each sector. The controls group consists of non-clearable reference entities were in the CDX index before the first clearing date for each sector, but were cleared in later cohorts. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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Table A1: Linear Probability Model with Fixed Effects: Determinants of the propensity of non-dealers to buy protection from 14 dealers

	Baseline sample	Not eligible for clearing	No captive buyers
	(1)	(2)	(3)
Seller's CDS	-0.0114***	-0.0115***	-0.0127***
	(0.00295)	(0.00306)	(0.00315)
Wrong-Way-Risk	-0.0141**	-0.00850	-0.0247***
	(0.00689)	(0.0105)	(0.00727)
Past Relationship	0.515***	0.545***	0.407***
	(0.0165)	(0.0147)	(0.0191)
Number of Observations	173,914	149,638	153,819
Number of Transactions	13,059	11,325	11,550
Number of Buyers	386	373	221
R-squared	0.090	0.097	0.087
Controls	S-FE, CDXNAIG, Contract-Date-Buyer	S-FE, CDXNAIG, Contract-Date-Buyer	S-FE, CDXNAIG, Contract-Date-Buyer

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 interacted with an indicator variable for each seller. Reference entities are FRB regulated entities.

Table A2: Determinants of the propensity of non-dealers to sell protection to 14 dealers

	Baseline sample	Not eligible for clearing	No captive sellers
	(1)	(2)	(3)
Buyer's CDS	-0.00922***	-0.0103***	-0.00864**
	(0.00355)	(0.00351)	(0.00358)
Right-Way-Risk	-0.00742	0.00242	-0.00958
	(0.0103)	(0.00944)	(0.0110)
Past Relationship	0.508***	0.507***	0.426***
	(0.0223)	(0.0175)	(0.0247)
Number of Observations	112,863	100,935	105,232
Number of Transactions	8,506	7,654	7,935
Number of Buyers	288	280	189
R-squared	0.070	0.067	0.052
Controls	B-FE, CDXNAIG, Seller-Contract-Date	B-FE, CDXNAIG, Seller-Contract-Date	B-FE, CDXNAIG, Seller-Contract-Date

Notes: Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The controls are as follows: B-FE: buyer fixed effect, CDXNAIG is the spread on the CDX.NA.IG index interacted with an indicator variable for each buyer. Reference entities are FRB regulated entities.

Table A3: Clearing Dates for CDX.NA.IG

	Materials	Con. Goods	Con. Srvs	Energy	Financials	Healthcare	Industrials	Oil/Gas	Technology	Telecom	Utilities
21-Dec-09											3
11-Jan-10											3
1-Feb-10										2	
15-Feb-10							14				
8-Mar-10		4		2				3			
29-Mar-10			15								
19-Apr-10	5								5		
10-May-10			1		7	5					
7-Jun-10							1				
6-Jul-10										1	
9-Aug-10		8		2							
30-Aug-10			8								
28-Feb-11									1		
28-Mar-11	2	2	4						2		
11-Apr-11					10						
2-May-11				2		3	3				
13-Jun-11		1	3		5				2		
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				1				
26-Mar-13		1									
30-Sep-13		2	2		1		2				
19-Feb-14			1								
23-Jun-14		2	2		2					1	
7-Jul-14		2	1			1	1				
21-Jul-14	1		1								
Total	8	26	40	7	27	10	23	4	10	4	7

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).