Pricing Implication of Centrality in an OTC Derivative Market: An Empirical Analysis Using Transaction-Level CDS Data*

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Abstract

Using the transaction-level records accounting for the universe of the single-name credit default swap (CDS) contracts in Japan, we document whether and how (if any) the relative centrality of sellers to buyers, that proxies for their search ability and thus bargaining power, affects single-name CDS prices. First, our panel estimation, which comprehensively controls for the standard pricing factors considered in practice (e.g., entity's risk, counterparty risk, notional amount, and maturity), suggests that CDS prices become higher as the relative centrality of sellers to buyers becomes higher. Second, such centrality premium becomes more apparent in the market with higher credit risk and further increases when the buyers attempt to unwind their short position. Given the non-negligible quantitative impacts of the relative centrality on CDS prices, we confirm that the bargaining power originating from search ability to large extent determines CDS prices. Third, deeper trade relations between sellers and buyers result in centrality discount (premium) in the market with higher (lower) credit risk. This result suggests the tradeoff between the cost of maintaining relationship in good periods and the benefit of securing cheap access to CDS in bad periods.

Keywords: Credit default swap, centrality, bargaining power, search and matching frictions

JEL classification: G12, G15, G18, G20, G28.

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1. Introduction

The price heterogeneity of over-the-counter (OTC) financial markets is rooted in the nature of bilateral transactions between sellers and buyers. Specifically, in the OTC financial markets, participating parties exhibit heterogeneous abilities to find out their counterparties and such heterogeneous search abilities naturally result in heterogeneous bargaining power (Duffie et al. 2005). As a consequence of the heterogeneous bargaining power, prices in the OTC financial markets tend to be heterogeneous even for the same product. Such price heterogeneity is unlikely to be observed in the transparent financial markets of stocks and sovereign bonds where the transactions are centralized and thus quickly executed through, for example, electronic platforms.

Among various OTC financial markets such as that of foreign exchanges, corporate bonds, securitized assets, and interbank lending, OTC derivative markets have been receiving a great deal of attention from practical and policy viewpoints. Given that the lack of price transparency resulted in speculative trades with insufficient risk hedge in 2000s and thus led to the catastrophic market breakdown, financial authorities in major countries have been working on the market reform of those OTC derivative markets over the last decade (OECD 2009, FSB 2010, 2022).

Despite those efforts to improve the markets, however, a number of the recent studies based on highly granular data have been still witnessing the sizable price heterogeneity in the OTC derivative markets (interest rate swap, Cenedese et al. 2020; FX derivatives, Hau et al. 2021). Thus, understanding how price heterogeneity arises is still an informative research theme for policy makers to design effective measures achieving transparent market (Miyakawa et al. 2023). In the present paper, we are following this strand of the recent empirical studies and document that the relative bargaining power of each market participant originated from their heterogeneous search ability is the source of the price heterogeneity of the credit default swap (CDS) market in Japan. Through these empirical analyses, we aim to contribute to the active discussions toward the further development of the OTC markets.

The price determination in an OTC derivative market has been modeled in a series of the theoretical studies pioneered by Duffie et al. (2005). The main ingredient of their models is the individual parties exhibiting bargaining power and facing search friction. As a quick overview of the theoretical exposition, the participating parties are categorized into several groups characterized by their trading motives, i.e., whether they want to buy or sell the derivatives. Driven by these motives, each individual party searches for their counterparties with incurring the costs associated with the searching duration (e.g., inventory cost of their positions). On one hand, due to the cost of their searching activities, each party wants to be matched with their counterparty for their transactions to be settled as quickly as possible. On the other hand, they also want to be matched with the counterparty that offers profitable trade conditions. Such a trade-off between the need to be settled as soon as possible and the need to be matched with profitable counterparty constitutes their dynamic optimization problem on the stopping time for their searching activities. Aggregating the results of their individual dynamic optimization under a specific bargaining structure over the prices (e.g., Nash bargaining), those theoretical models provide the equilibrium prices as a function of bargaining power that rooted in search friction. If search friction faced by a buyer becomes higher, the equilibrium price increases as it becomes more expensive for the buyer to look for another counterparty, which can be interpreted as a lower outside option, and thus the bargaining power of the buyer declines. As such, the bargaining power of participating parties, that is originated from their search ability, is theoretically predicted to determine CDS prices.

Despite these simple empirical implications obtained from the theoretical expositions, it is not necessarily straightforward to test the implications. This is mainly because highly granular data, which are necessary for the empirical examination, such as transaction-level records accompanied by the identifiers of buyers and sellers and accounting for the universe of the OTC derivative market, had not been available for researchers. Given this data limitation, majority of the extant studies have been employing aggregate data to see the status of price heterogeneity (e.g., Mallick 2004; Cereda et al. 2022). Here, in the present paper, we take advantage of the granular data on OTC derivative markets in Japan, which has recently become available thanks to the efforts of regulatory authorities, to document whether and how (if any) the price heterogeneity in a CDS market is driven by the bargaining power originated from search ability.

Japanese single-name CDS market is an ideal environment for this empirical study. First, the market consists of many transactions between a decent number of sellers and buyers of CDS with active transactions (i.e., 381.02 transactions among 16.41 unique buyers and 20.39 unique sellers per a month on average over the periods of our analysis). Such data ensure reliable empirical studies. Second, as we will carefully explain in the later section, the degree of heterogeneity in terms of bargaining power is high in Japanese single-name CDS market. This is due to the core-peripheral structure of the Japanese single-name CDS market. The large variation generated by this network structure in the bargaining power makes our empirical estimation implementable. Third, as reported in the extant study (e.g., Eisfeldt et al. 2023), the network structure in Japanese single-name CDS market is stiff. The lack of flexible network formation allows us to treat the observed network structure in the most recent periods as given and interpret the estimated results as causal.

To proxy for the bargaining power originated from search ability as a key factor determining CDS prices, we focus on the centrality measures used in the recent literature (e.g., Hau et al. 2021; Hasbrouck and Levich 2021). Specifically, we employ the "relative" centrality measure of sellers to buyers, which is calculated, for example, as the ratio of the degree centrality of a seller to that of a buyer. In addition to this local centrality measure, we also employ a global centrality measure (i.e., eigenvector centrality) to check the robustness of our empirical results.

As an important feature of our analysis, we further take into account the "conditionality" of the pricing implication of such a relative centrality measure on (i) overall market risk and (ii) trade relationship between sellers and buyers. Documenting the conditionality of the pricing implication of centrality measure on overall market risk might help us to sort out the reported mixed results on the pricing implication of centrality measures (e.g., Di Maggio et al. 2017; Gabrieli and Georg 2017; Hollifield et al. 2017; Li and Schürhoff 2019). On one hand, higher centrality of sellers per se could be beneficial thanks to the reduction of search frictions especially in a normal time and thus result in lower CDS price. On the other hand, the higher centrality of sellers in the comparison with that of buyers could result in higher price if the seller aims to take advantage of its strong bargaining power when, for example, overall credit risk becomes high and thus search friction increases. The latter case, which is named as the "centrality premium" in literature, might be further aggravated when buyers of protection are desperate to uncover (i.e., buy back) their short positions as such positions makes losses under the bad market condition.

In addition, the higher centrality of sellers in the comparison with that of buyers could result in lower or higher price when those sellers and buyers have already established intimate relations. To illustrate, while the price could be lower as the accumulated relations might allow them to trade less costly, the price could be higher if buyers are captive due to the accumulated relations under switching cost of trading partners (e.g., Kim et al. 2003; Cocco et al. 2009; Hendershott et al. 2020). As such, the implications of centrality measures are multifaceted and thus its pricing implication can be conditional on various variables. In the present paper, we empirically examine such conditionality of the centrality measure by using highly granular transaction-level CDS data for the period from April 2013 to December 2021.

Our empirical findings are obtained from the panel estimation regressing CDS price on the relative centrality measure. In this regression, we control not only for the observable characteristics such as maturity and notional amount both in linear and non-linear specifications, but also for the unobservable factors such as time-variant reference-, seller-, and buyer-level fixed effects. Here, controlling for those unobservable time-variant factors are essential to identify the pricing implication of the relative centrality measure. This is because we aim to estimate the pricing implication of the relative centrality measure on top of the pricing factors considered in practice, such as the credit risk of each party and the referenced assets as well as macro factors. Fortunately, the transaction-level granular data accompanied by the identifiers of buyers and sellers allow us to implement such an estimation.

Our empirical results are summarized as follows: First, on average, CDS price becomes higher as the relative centrality of sellers to buyers become higher. This means that higher centrality of seller (i.e., relative to that of buyer) results in centrality premium as reported in a group of the extant studies. Quantitatively, an increase in the ratio of seller's centrality to buyer's centrality by one standard deviation in our dataset is accompanied by the non-negligible increase in CDS price by 35bps, which in fact accounts for 35% of the standard deviation of CDS price in our data. As another quantitative assessment of the relative centrality as a determinant of CDS price, around 70% of the standard deviation of predicted CDS prices based on our model is accounted for by the relative centrality. These back-of-the-envelope calculations suggest the significant quantitative contribution of the relative centrality to CDS prices.

Second, this centrality premium becomes more apparent in the market where the level of iTraxx Japan, which accounts for overall credit risk in Japan, is high. This result provides an important detail of the implication of centrality on CDS price. On one hand, higher centrality of seller does not largely affect CDS price in good periods characterized by the moderate or low level of iTraxx Japan. This is somewhat different from a naive conjecture that higher centrality could lead to lower search friction and thus lead to lower CDS price (i.e., centrality discount). Our result would rather imply that such benefit is not sizable at least in our dataset. Presumably, such benefit might be offset by the impact associated with sellers' bargaining power. On the other hand, such higher relative centrality of seller materializes in higher CDS price under bad market conditions. This could suggest that when buyers find it relatively difficult to find counterparties offering a reasonable price, which could be typically the case in the bad credit condition, but are still eager to buy protection, sellers with higher centrality could largely exert their bargaining power to charge premium. Note that the results associated with the bad market conditions does not necessarily mean that the seller with a high centrality could not exert their high search ability to find out counterparties. Our results would rather suggest that the pricing impacts of bargaining power originated from relative centrality overwhelms that of high search ability of the sellers equipped with high centrality.

As an important additional finding to this second result, we also find that such centrality premium paid by the buyers with lower centrality to the sellers with higher centrality becomes more apparent when the buyers attempt to unwind their short position under bad market conditions. This result implies that sellers with higher relative centrality to buyers tend to charge higher prices under the bad market condition against "desperate" buyers. Interestingly, these mechanisms are absent in the good market environment where buyers are not so much desperate or easily find counterparties offering reasonable prices and thus the sellers do not have a chance to take advantage of their higher relative centrality.

Third, against the centrality premium in the bad market environment, maintained trade relations between sellers and buyers could effectively mitigate it. Specifically, when a seller and a buyer hold a large amount OR a large number of transactions in the past three month prior to the transaction, the centrality premium under the bad market condition declines. Furthermore, when a seller and a buyer hold a large amount AND a large number of transactions, the centrality premium under the bad market condition becomes, in fact, zero. One subtle but important additional detail associated with this result is that when a seller and a buyer hold a large amount AND a large number of transactions, the CDS price of the transaction between them under the good market condition (i.e., iTraxx is smaller than its median) shows centrality "premium." In other words, the captive buyers to the accumulated relations are paying the centrality premium under the good periods. These results suggest the tradeoff between the cost of maintaining relationships in good periods and the benefit of securing an access to relatively cheap CDS in bad periods. Given the fact that the pricing implication of relatively higher centrality of sellers to buyers is positive (i.e., centrality premium) on average, we conjecture that a certain number of less central buyers refrain from maintaining relations and thus could eventually face higher CDS price in distressed periods.

The contributions of our paper are at least threefold. First, the present study is the first paper to show the existence of the (unconditional) centrality premium in CDS market. Given that such an empirical pattern has been reported for other OTC financial markets such as corporate bond (Di Maggio et al. 2017), interbank lending (Gabrieli and Georg 2017), municipal bond (Li and Schürhoff 2019), and FX derivatives (Hasbrouck and Levich 2021), the observed centrality premium in CDS market per se is not necessarily surprising. Nonetheless, our empirical results are still informative for practitioners and policy makers to understand the market structure of one of the most important OTC derivatives. It is also informative to confirm such an empirical pattern even after the introduction of various regulatory reforms installed after the global financial crisis in the late 2000s. This result can be useful in considering how financial regulators can support the further development of the market.

Second, the present study is the first to report the conditionality of the pricing implication of centrality on the market-level credit condition. Somewhat intuitively, the relative centrality of sellers to buyers is not necessarily critical when, for example, buyers can find their counterparties easily under the good market condition, while the relative centrality leads to higher CDS prices under the bad market condition. The result we report in the present paper thus encourages financial authorities to keep their eyes on the transaction network of the CDS market, because the pricing implication of the transaction network could be exacerbated under the bad market condition.

Third, we provide a novel finding to the literature on the empirical result associated with the pricing implication of maintained relations. Here, extant studies such as Hau et al. (2021) have reported that relation could be harmful. Namely, Hau et al. (2021) empirically show that stronger relations lead to higher prices when buyers are not sophisticated. They interpret this result as an evidence suggesting that those buyers are captive in the relation. Hau et al. (2021) also report that even the most sophisticated buyers still encounter sellers' centrality premium, which can be interpreted as the cost of getting an access to business activities with powerful counterparties. In our empirical results, complementing the results in Hau et al. (2021), we report a nuanced mechanism in which buyers maintaining deep relations with sellers pay premium in the good time so that they can mitigate the centrality premium in the bad time. Our result implies that buyers consider such a dynamic tradeoff between the good and bad times, which is a new finding in the literature.

The abovementioned empirical results provide several practical implications. First, as we have already mentioned, financial authorities find it beneficial to understand the pricing implications of the network structure. As the asymmetric status of centrality between buyers and sellers could materialize under bad market conditions where the demand for the protection against default is supposed to be large, the financial authorities should monitor the status so as to facilitate smooth transaction toward appropriate credit risk management. Second, market participants find it beneficial to understand the abovementioned dynamic tradeoff between the cost of maintaining relation in a good time and the access to relatively cheap insurance in a bad time so that they can optimize their hedging strategy.

The rest of the paper is organized as follows: We summarize the status of related studies in Section 2. After organizing the theoretical underpinnings we refer in Section 3 for our empirical study, we explain the institutional background of the Japanese CDS market in Section 4. Then, we show our empirical strategy and the data used for the estimation in Sections 5 and 6. We present the empirical results and their implications in Section 7. Section 8 presents the robustness check to the empirical results. Section 9 is a summary of the study and has recommendations for future works.

2. Related Literature

In this section, we briefly overview the related literature to our study. We start from a quick overview of theoretical studies. The key building block of those theoretical studies is search friction that is materialized as bargaining power. After confirming that these items are closely related to each party's centrality in transaction networks, we move to the empirical studies targeting a broad range of OTC financial markets and dealing with the importance of those frictions as well as bargaining power. Finally, we go over some recent studies using highly granular data and paying a specific attention to centrality measure of each player to empirically examine the pricing implications of the search friction and the bargaining power.

The most widely used theoretical framework to model OTC financial markets is the one developed by a seminal works starting from Duffie et al. (2005) that feature the market microstructure of OTC markets (e.g., Duffie 2012). The key items of those models are the frictions hindering an immediate matching with counterparties. In those models, it is also modeled that seller of the traded assets (e.g., protection against default in our case) encounter inventory costs and attempt to pass-through it to buyers under the relative bargaining power of sellers to buyers. These factors hindering a smooth transaction are then modeled as lack of outside option (Duffie et al. 2005, 2007), lower network centrality (Li and Schürhoff 2019), lack of expertise associated with the transaction (Glode et al. 2012), and asymmetric information (Bolton et al. 2016).

Given the empirical implications obtained from these theoretical discussions, the extant studies have used proxies of the factors behind the frictions hindering a smooth transaction and examined its pricing implication. As a convenient and plausible object accounting for the search friction and thus the bargaining power, recent studies employ the centrality measures of each party in transaction network (e.g., Hau et al. 2021; Hasbrouck and Levich 2021) and examine the association between centrality and price.

Despite such a straightforward motivation and a reasonable empirical strategy, the reported association between the transaction price and the centrality of parties in general OTC financial markets are mixed. While many papers (e.g., Di Maggio et al. 2017; Gabrieli and Georg 2017; Li and Schürhoff 2019) find the positive association between prices and centrality (i.e., centrality premium), the opposite empirical finding (i.e., centrality discount) is also reported by, for example, Hollifield et al. (2017). In this sense, the empirical association between the centrality of transacting parties and the price of traded assets is still an important target of empirical studies.

Regarding the OTC derivative markets, Cenedese et al. (2020) report that dealers selling interest rate swap tend to charge their clients higher price (i.e., fixed rate) while customers selling to dealers are charging lower price. As the dealers are presumably equipped with higher search ability and thus larger bargaining power, their results suggest the centrality premium. As for the currency swap market, Hasbrouck and Levich (2020) report that the players associated with higher centrality in the transaction network enjoy better price conditions. In a similar vein, Hau et al. (2021) report that dealers of FX swap tend to propose discriminately high price to unsophisticated buyers.

The present study follows these strands of literature that empirically examine the price formulation in OTC financial markets with paying a special attention to the centrality of each player as a proxy for the search friction and thus the bargaining power. As we detail in the following section, our study takes a similar approach to that in Hasbrouck and Levich (2020) and use the relative sizes of degree centrality of sellers and buyers. One important difference from the abovementioned extant studies is that we are interested not only in the unconditional association between the centrality and the price but also in its conditionality on market environment and transaction relations. Such a detailed documentation of the centrality's pricing implications teaches us the precise pricing mechanisms employed in the OTC financial markets.

3. Theoretical Underpinnings

In this section, we summarize the theoretical background of our empirical study by briefly sketching the model in the extant studies such as Duffie (2012).

As background practical information necessary to connect the model with our data, the CDSs featured in the present paper is a type of derivatives providing a quasi-insurance against the default events of individual business enterprise (i.e., a single-name CDS) or a country (i.e., a sovereign

CDS), which are called as a reference. Each transaction consists of a seller and a buyer of a specific protection. The buyer is obliged to pay premium that is computed by multiplying the pre-determined coupon rate to the notional amounts. In the case that the reference defaults before the contract expires at maturity, the buyer stops the payment of the premium while the seller pays the amount computed by multiplying the predetermined rate to the contracted notional amounts.

Here, suppose I am planning to hedge my exposure to a company's default risk. Different from standard well-functioning financial markets such as stock or sovereign bond markets, it takes time for me to find a seller of the protection who propose a reasonable price. To be more precise, I am virtually facing the following two difficulties. First, I might need to take a certain length of time to find the counterparty simply because there is no centralized market equipped, for example, with a standard auction mechanism. Thus, I am facing search and matching frictions. Second, even if I somehow find a chance to communicate with a potential seller of the protection, the price proposed by them might be higher than I expected. Thus, bargaining power matters.

Simply because there is no smoothly functioning market for CDS, it is not necessarily straightforward to evaluate the appropriateness of the proposed price. Regarding this point, the recent studies have reported heterogeneous prices for various markets (e.g., Cenedese et al. 2020 for interest rate swap; Hasbrouck and Levich 2020, Hau et al. 2021 for currency swap). The main message of these studies is that the proposed prices are different even after controlling for the standard factors potentially determining the prices such as maturity, notional amount, the riskiness of referenced assets, and counterparty risk. Those papers report that the characteristics of sellers and buyers are associated with price levels, and hence the mechanism featured in, for example, Duffie (2012) matters in reality.

As we explain in the following section, we proxy for the search and matching frictions and the bargaining power by using the centrality measure of each party without distinguishing the frictions and the bargaining power. This reflects our notion that those are interplaying with each other. Suppose I have some technology (e.g., electronic communication system) speeding up the search for potential counterparties. Simply because I can quickly search another transaction opportunity, I do not need to make a large concession to inferior transaction conditions. This illustration justifies our approach that does not distinguish the search/matching frictions and the bargaining power.

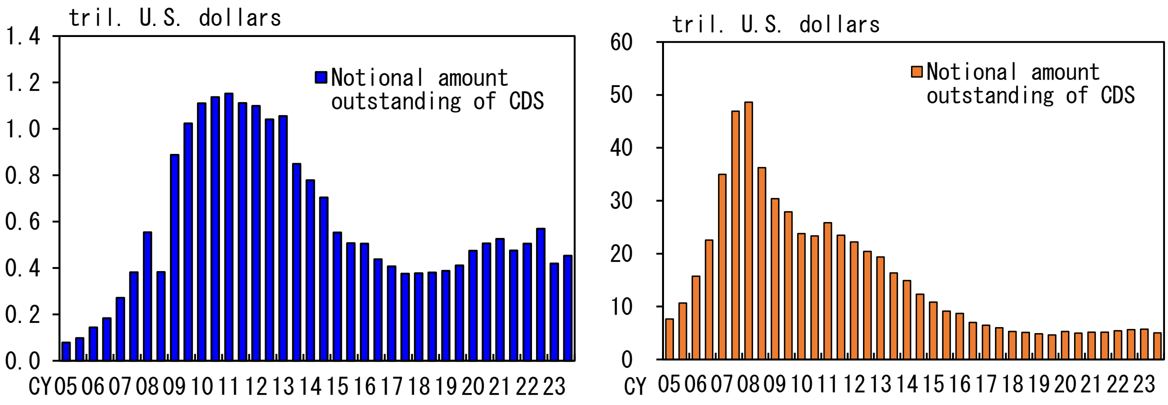
4. Institutional Background

Before presenting our empirical strategy and the data we use for our empirical study, we briefly go over some institutional features associated with the Japanese CDS market.

First, Figure 1 depicts the developments of the amount outstanding of CDS transaction (in trillion USD) since 2005. The records of the amount outstanding, that cover the 16 financial institutions located in Japan as of December 2023, are collected by Bank of Japan (BoJ) and reported to the Bank for International Settlements (BIS).

Figure 1: Notional amount outstanding of CDS contracts

(Japanese financial institutions) (Global total)

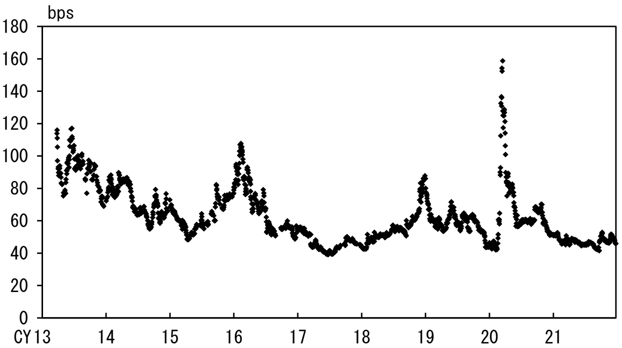


Notes: The figures are the end-of-June or end-of-December values in each year.

From this figure, we can see that the outstanding amounts of CDS transaction continued to increase toward 2008 for both Japanese financial institutions and the global total. Japanese financial institutions further continued to increase its amount outstanding until 2011, while the global total showed a downward trend until the end of 2010s. Such asymmetric trend reflects the fact that Japanese financial institutions had been paying efforts to expand their business through mergers and acquisitions so as to substitute for the U.S. and European financial institutions (Yoshizaki et al. 2017). As an anecdotal evidence, market participants explain the reason for the decline in single-name CDS transactions since 2011 is the changes in the global financial regulatory framework that have been implemented after the global financial crisis. The amount outstanding of CDS transaction also declined significantly from 2014 onward as the larger use of a framework known as "compression" to reduce the balance of OTC derivatives.

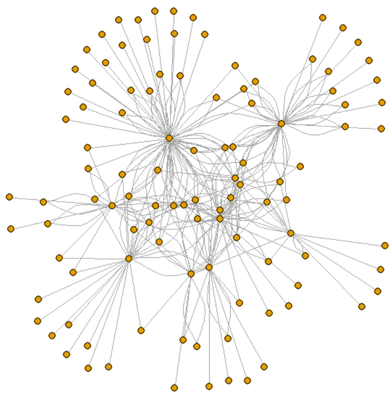
Second, Figure 2 shows the developments of iTraxx Japan, which is an index of CDS prices for highly liquid Japanese companies and is used as a representative credit index in the Japanese domestic credit risk trading market. The value of the index rises (falls) when the credit risk of the reference, i.e., Japanese enterprises, worsens (improves). In this analysis, we use 5-year data. The data shows that the credit risk of Japanese companies rose sharply from the beginning of 2020 to the period of the spread of the COVID-19 in mid-2020, and then calmed down.

Figure 2: Development of iTraxx



Third, as we will detail in the following section, the transaction network of Japanese CDS market is characterized as a core and peripheral structure. Figure 3 depicts the network structure of the single-name CDS transaction by using the data we explain in the following section. The circles denote either the buyers or the sellers of CDS, and the lines represent the existence of the transaction between a specific pair of buyer and seller. Although each transaction has the directional property between the buyer and the seller, the lines show non-directional link simply for the purpose of illustration.

Figure 3: Transaction network of CDS market in Japan



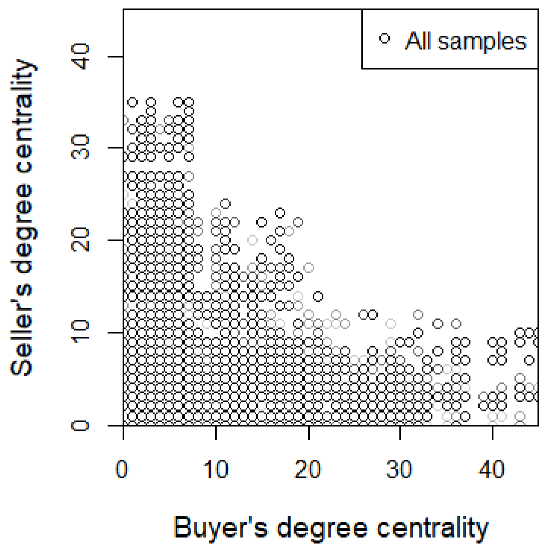
Notes: The figure shows the transaction network of CDS market in Japan (full sample). Each yellow circle represents a buyer/seller and each link represents a transaction. The more counterparties the player has, the more centered in the network they are depicted. We can confirm the core-peripheral network structure.

In the Figure 3, which covers all sample period, the numbers of unique sellers and buyers are 104 and 54, respectively. Among those, 49 parties participate transactions as both seller and buyer.

Furthermore, in this figure, 20-30 parties at the center of the network are major banks, Japanese securities companies, foreign securities companies, and trust companies. 5-6 players located in the center of the network are connected to the peripheral players as hubs. Those central players are mostly Japanese securities firms (based in Japan). The edges from these 5-6 central players are linked to the parties in various industries such as banks, life insurance companies, and then to business corporations. There are also links connecting those central players to overseas securities firms and overseas business corporations.

Fourth, the matching pattern in the Japanese CDS market is sketched in Figure 4. In this figure, we plot each transaction over the number of sellers faced by the buyer of the transaction (i.e., buyer's degree centrality) in the horizontal axis and the number of buyers faced by the seller of the transaction (i.e., seller's degree centrality) in the vertical axis. The thick (pale) color of the dot denote the number of observations of the case accounting for the specific centralities of sellers and buyers are more (less) frequent. We can find the negative assortativity for those matching pattern. Namely, the buyers (sellers) with high degree centrality tend to be connected to the sellers (buyers) with low degree centrality. While there are cases where both buyers and sellers exhibit low degree centrality, the assortativity is negative. Such a funnel shape is characterized as one type of the disassortative matching patterns. As we detail in the next section, we use the relative size of the seller's centrality measure to that of the buyer's as a proxy for their relative difference in search ability, and thus bargaining power.

Figure 4: Assortativity of degree centrality in CDS market



Notes: This figure plots each transaction over the buyer b's degree centrality and the seller s's degree centrality. Each dot accounts for a pair of sellers' degree centrality (vertical axis) and that for buyers (horizontal axis). The thick (pale) color of the dot denote the number observations of the case accounting for the specific centralities of sellers and buyers are more (less) frequent.

To summarize, over the last decades, Japanese CDS market has experienced significant developments of transaction amounts and prices under the stiff core-periphery structure consisting for various matching patterns in terms of assortativity. Our interest lies in how such a transaction pattern is associated with CDS prices.

5. Empirical Strategy

In this section, we present our empirical strategy to examine the pricing implications of each party's centrality. As a benchmark estimation, we employ the following estimation equation to understand the unconditional association between CDS price and the relative centrality of parties.

$$CDS\ Price_{b,s,k,i,t} = \alpha + \beta \cdot \frac{Link_{s,t}}{Link_{b,t}} + \gamma_1 \cdot Maturity_{i,t} + \gamma_2 \cdot Maturity_{i,t}^2 + \delta_1 \cdot Notional_{i,t} + \delta_2 \cdot Notional_{i,t}^2 + fixed\ effect + \varepsilon_{i,t} \quad (1)$$

In this equation, $CDS\ Price_{b,s,k,i,t}$ accounts for the premium paid by the buyer b to the seller s of a specific referenced entity k in the period t in which t accounts for year-month-date. Given that such transaction identified by (b, s, k, t) could be done multiple times in a single specific date, we also denote the identifier of each transaction by i.[4] As the most important objects in equation (1), $Link_{s,t}$ and $Link_{b,t}$ account for the degree centrality of the seller s and the buyer b, respectively. The degree centrality measure is the number of edges (i.e., links) each player has. We measure the number of the edges with taking into account the direction of the edges. Specifically, the degree centrality of the buyer b (seller s) is the number of edges the buyer b (seller s) has as a buyer (as a seller) in the period t. As a key determinant of $CDS\ Price_{b,s,k,i,t}$, we compute the ratio of those two numbers $(Link_{s,t}/Link_{b,t})$ and use it to indicate the relative centrality of the seller s to the buyer b in the period t. $Maturity_{i,t}$ and $Notional_{i,t}$ account for the basic characteristics of the transaction i, and we include these series and their squared terms as $control\ variables$.

To avoid various endogeneity concerns associated with this measure accounting for their relative search ability and thus relative bargaining power, first, we measure those local centrality measures over the three months preceding to the period t. Second, we also include $fixed\ effect$ that denotes the high-dimensional unobservable individual effects to take care of potential omitted variable biases. As we attempt to identify the causal relation running from $(Link_{s,t}/Link_{b,t})$ to $CDS\ Price_{b,s,k,i,t}$, it is necessary to control for various potential confounding factors, most of which

[4] Here, as this index i is enough to identify a specific transaction, the other indexes (b, s, k, t) are in fact redundant. Nonetheless, we incorporate those indexes in the estimation equation so that readers are not confused about the definition of each variable.

are used as the pricing factors in practice, as much as possible so that we can satisfy the conditional independence assumption. Given this motivation, we include the time-variant individual effect of referenced entities denoted by $k \times t$. The inclusion of this time-variant reference-level individual effect takes care of the variation in the fundamental risk of the referenced asset k in a specific year-month-date. Then, we include the time-variant individual effect of buyers denoted by $b \times ym(t)$. Here, $ym(t)$ denotes the year-month including the year-month-date t. Given the number of observations is limited, we employ $ym(t)$ instead of t. The inclusion of this time-variant buyer-level individual effect takes care of the variation in the hedge demand held by the buyer b in a specific year-month. Finally, we include the time-variant individual effect of sellers denoted by $s \times ym(t)$. The inclusion of this time-variant seller-level individual effect takes care of the variation in the counterparty risk associated with the seller s in a specific year-month.

We estimate the equation (1) for the entire sample as well as the subsample corresponding to good and bad periods, which we will define in the following section. As a criterion of market-level credit risk condition, we use the level of iTraxx.[5] Through this subsample analyses, we explicitly examine how the pricing implication of the relative centrality measure depends on the market condition. In this paper, centrality is used as a proxy for bargaining power and search ability. The extant theoretical studies presume sellers and buyers with higher centrality could be characterized as the one equipped with better search and matching technology. If this presumption is the case, we should observe the centrality discount (premium) when the centrality of the seller s is relatively higher (lower) in the comparison with the centrality of the buyer b. Here, under the worse market condition, such superior technology might not work well and the sellers with the high centrality might instead attempt to exert their relatively strong bargaining power to charge higher price to the buyers with the low centrality. Our conjecture is that the search ability story and the bargaining power story fit more to the good and bad market condition, respectively. The abovementioned subsample analyses help us to test this conjecture.

To see more detailed pricing implications of the relative centrality of seller and buyer, we also estimate the following augmented equation (2):

$$
\begin{aligned}
CDS\ Price_{b,s,k,i,t} = {} & \alpha + \beta \cdot \frac{Link_{s,t}}{Link_{b,t}} + \gamma_1 \cdot Unwind^{M}_{i,t} \cdot \frac{Link_{s,t}}{Link_{b,t}} + \gamma_2 \cdot Unwind^{C}_{i,t} \cdot \frac{Link_{s,t}}{Link_{b,t}} \\
& + \delta_1 \cdot Unwind^{M}_{i,t} + \delta_2 \cdot Unwind^{C}_{i,t} + control\ variables \\
& + fixed\ effect + \varepsilon_{i,t} \qquad (2)
\end{aligned}
$$

In this equation, $Unwind^{M}_{i,t}$ and $Unwind^{C}_{i,t}$ denote the amount and frequency of buyer b's "selling"

[5] A possible alternative measure for the market condition is the volatility index (e.g., VIX). As the credit risk measured by iTraxx is closely related to such volatility index, we focus on the level of iTraxx.

of a specific referenced entity k over the three-month periods preceding to the period t. Including these variables in the form of the single term as well as its interaction term to $(Link_{s,t}/Link_{b,t})$, we examine whether and how the pricing implications of the relative centrality measure changes when the buyers need to "unwind" their short position. In practice, buyers might face inferior price conditions when they are desperate to cover their short position. Our interest lies in whether such a phenomenon called "short-squeeze" is in fact the case in our dataset or not. If this is the case, it helps us to understand under what circumstances the exertion of seller's relative bargaining power against buyers could be more pronouncing. As Schultz (2024) summarizes, it should be noted that the empirical studies on short-squeeze are limited although Schultz (2024) reports that more than two thirds of the excess return from short-selling is lost through short-squeeze. Thus, it could be informative to empirically examine if the short-squeeze could be the case in CDS markets or not.

As another attempt to understand the conditionality of the pricing implications of the relative centrality, we estimate the following equation (3):

$$CDS\ Price_{b,s,k,i,t} = \alpha + \beta \cdot \frac{Link_{s,t}}{Link_{b,t}} + \gamma \cdot Relation_{i,t} \cdot \frac{Link_{s,t}}{Link_{b,t}} + \delta \cdot Relation_{i,t} + control\ variables + fixed\ effect + \varepsilon_{i,t} \quad (3)$$

Here, $Relation_{i,t}$ denotes the dummy variable taking the value of one if both the amount $(Rel^M_{i,t})$ and frequency $(Rel^C_{i,t})$ of the past transactions between buyer b and seller s over the three-month periods prior to the period t are large. Alternatively, we also define $Relation_{i,t}$ as the dummy variable taking the value of one if at least one of the amount or frequency of the past transactions between buyer b and seller s over the three-month periods prior to the period t is large. Including these variables in the form of the single term as well as its interaction term to $(Link_{s,t}/Link_{b,t})$, we examine whether and how the pricing implications of the relative centrality measure changes when the buyers and the sellers hold the tight transaction relations in advance. In a group of the extant studies such as Cocco et al. (2009) and Hendershott et al. (2020), sustained relations are reported to result in cheaper transaction costs while other studies such as Hau et al. (2021) find that, except for a few sophisticated parties, most of the parties in OTC markets are paying premium to the counterparties in long relations with them. Thus, the pricing implications of relation are purely empirical question, which we aim to examine in the present paper.

6. Data

The data we use in the present paper are the trade repository data (TR data) obtained from Japan Financial Services Agency (FSA). To construct the data, Japan FSA asks all the financial instruments clearing organization, foreign financial instruments clearing organization, financial instruments business operator, and registered financial institution to report all of their derivative transaction records. As detailed in Kawai et al. (2021) and Miyakawa et al. (2023), financial instruments business operator and registered financial institution include the business operator that conducts Type I Financial Instruments Business, all the banks, The *Shoko Chukin* Bank, Ltd., Development Bank of Japan Inc., a federation of *Shinkin* banks whose district is the entire nation, The *Norinchukin* Bank, and insurance companies. This reporting practice allows us to assume that our dataset covers the entire universe of the CDS contracts involving at least one party located in Japan.

The CDS section of this TR data accounts for the individual transactions reported to Japan FSA and stores the following information on (i) the identifiers of sellers and buyers of each CDS, (ii) the name of the referenced asset, (iii) the price of the traded CDS, (iv) the notional amount of the traded CDS, (v) the date of the transaction, and (vi) the mode of the clearing (i.e., central counterparty of bilateral transactions). In addition to these basic characteristics of each transaction, the TR data also account for various detailed information related to each transaction such as the use of electronic ordering system. The TR data is shared from Japan FSA to BoJ and is used in some preceding empirical studies such as Miyakawa et al. (2023).

Given the motivation of this study is on the pricing implications of each parties' centrality, we focus on the single-name CDS that is presumed to exhibit larger heterogeneity in terms of price dynamics and associated with lower liquidity. The original data file consists of the trades observed as new transactions over the periods from April 1, 2013 to December 31, 2021. As a first step of our data cleaning, we omit the duplicated records with the same i of each transaction. This original duplication occurs simply because both the seller and buyer of a specific transaction report their transaction to Japan FSA. The number of transaction-level observations after dropping the duplicated records is 118,983. Among these records, 9,547 records are reported from Japan Securities Clearing Corporation (JSCC) and thus need to be linked to the corresponding transactions reported by its counterpart. This matching process reduces the 9,547 records to 4,842 records, and thus the total observation becomes 114,278.[6]

Regarding the price data, we follow the data cleaning process proposed in Loon and Zhong (2016): First, we omit 14,717 records without the price information, which reduces our data size to 99,561. Second, we drop the records not cleared through JSCC but reported as if it is, which leads to 95,117 records. Third, following Loon and Zhong (2016), we drop all the records reported with a round number such as 0, 0.01, and so on. After dropping these data accompanied by suspicious fixed coupon,

[6] Regarding the abovementioned reduction of the observation from 9,547 to 4,842, we keep the records reported by JSCC, in the form of either JSCC-Company A or Company B-JSCC, satisfying the following conditions: (i) transaction identification number is in next to each other, (ii) all the conditions consisting of (a) benchmark date for transaction, (b) transaction date, (c) starting date of transaction, (d) final date of transaction, (e) reporting institution, (f) reference asset, (g) contract type, (h) product classification, (i) centrally cleared or not, (j) the way to display the number, (k) the way to display the price type, (l) currency, (m) notional amount, and (n) maturity.

we have 45,505 observations. The substantial reduction of the number of observation through this treatment reflects the fact that the non-negligible part of the price information stored in the TR data might not necessarily be reliable. Instead of using those price records reported with a round number, in the present paper, we decide to focus on the more reliable part of the data. Fourth, we drop the transactions with foreign central counterparties (i.e., CCPs) and the case in which price type is reported as "upfront points", which results in the remained data of 40,007 records. We also winsorize the data over or below the thresholds, which are defined as mean plus or minus the two standard deviation.

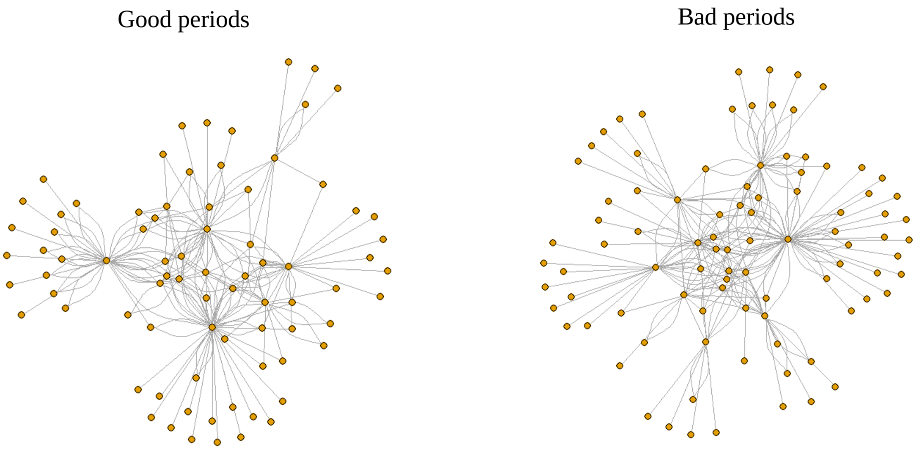
Table 1: Data cleaning of TR data

Reported CDS price (bps)		Number of observation	Total amount
Total		95,117	660,680
Excluded data	0	3,649	23,163
	0.01	11	81
	0.1	4	16
	0.25	134	1,187
	0.5	17	94
	1	20,668	125,938
	10	60	432
	100	21,617	150,915
	1,000	2	6
	10,000	26	923
	2.5	14	45
	25	363	2,632
	2,500	1	18
	5	1,121	5,307
	50	271	2,079
	500	1,650	8,598
	5,000	1	7
	50,000	3	48
Remaining data		45,505	339,191

Notes: This table illustrates how the reported CDS price in the TR data include the dubiously misreported number. According to Loon and Zhong (2016), if the reported number is round, such as "100" or "50," there is usually confusion between spreads (which should be reported) and coupon (which should not be reported). We regard these numbers (from "0" to "50,000" in the table) as the misreport and exclude these reports from our dataset.

Figure 5 depicts the network structure of the single-name CDS transaction in our dataset by market condition. As mentioned in Section 4, each dot and line account for the participating party and the transaction between those parties. In the Figure 5, regardless of whether the market condition is good (i.e., the level of iTraxx Japan is lower than its sample median) or bad (i.e., the level of iTraxx Japan is equal to or higher than its sample median), we can find some parties centered in the network and many located in the peripheral, as discussed in Section 4.

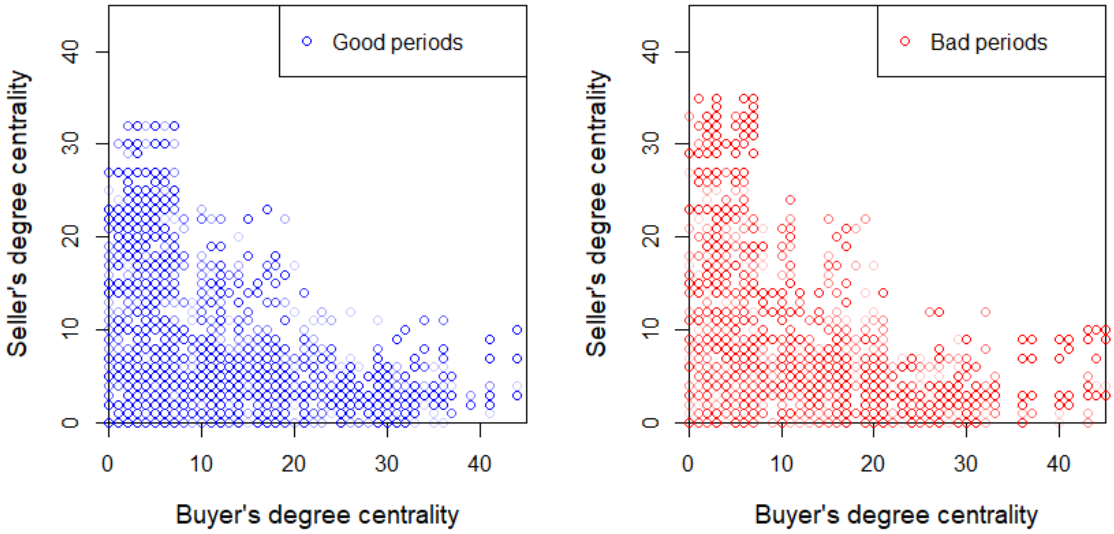
Figure 5: Transaction network of CDS market in Japan by market condition



Notes: The figure shows the transaction network of CDS market in Japan (good periods in the left panel, and bad periods in the right panel). The distinction between good and bad periods is judged by the level of iTraxx. Each yellow circle represents a buyer/seller and each link represents a transaction. The more counterparties the player has, the more centered in the network they are depicted. We can confirm the core-peripheral network structure in each sample period.

Next, Figure 6 plots each transaction over the buyer b's degree centrality and the seller s's degree centrality separately for the good and bad periods. Each dot accounts for a pair of sellers' degree centrality (vertical axis) and that for buyers (horizontal axis). The thick (pale) color of the dot denote the number observations of the case accounting for the specific centralities of sellers and buyers are more (less) frequent. First, even when viewed by market condition, we can immediately notice the disassortative matching pattern. Sellers with higher (lower) centrality tend to be matched with lower (higher) counterparties. We can find that the sellers with lower centrality are also matched with the buyers with lower centrality. Second, somewhat unexpectedly, the matching pattern in terms of the centrality of sellers and buyers is quite stable over the market conditions. Namely, regardless of the level of iTraxx Japan, the pattern of disassortativeness is confirmed. As we will study the pricing implications of the relative centrality measure in the next section, it is informative to find such a stability of matching pattern. Suppose the disassortativity becomes less apparent under the bad market. This might imply that buyers refrain from trading with the sellers with higher centrality so as to, for example, avoid the high price reflecting their high bargaining power (e.g., Du et al. 2023). Such a selection (if any) asks us to be careful about interpretation of the estimation results of equation (1) as the estimated parameter β is affected by this selection process. However, as Figure 6 clarifies, the degree of disassortativity is almost identical between the good and bad periods, and therefore, our estimation results are considered not to be largely affected by this selection process.[7]

Figure 6: Assortativity of degree centrality in CDS market by market condition



Notes: This figure plots each transaction over the buyer b's degree centrality and the seller s's degree centrality separately for the good and bad periods. Each dot accounts for a pair of sellers' degree centrality (vertical axis) and that for buyers (horizontal axis). The thick (pale) color of the dot denote the number observations of the case accounting for the specific centralities of sellers and buyers are more (less) frequent. We split all sample into good periods and bad periods by the level of iTraxx Japan. In both subsample periods, there are not significant differences.

Table 2 shows the summary statistics of each variable we use for our empirical analysis. First, bp denotes the price of CDS, which the seller of the CDS receives, measured in basis point. Second, Notional denotes the notional amount of CDS transactions, which is measured in 100 million JPY.[8] Third, Maturity denotes the difference between the starting point of each transaction (i.e., effective data) and the end point (i.e., scheduled termination date), which is measured in months. Fourth, Link ratio denotes $(Link_{s,t}/Link_{b,t})$. Fifth, Seller degree centrality and Buyer degree centrality denote the aforementioned degree centrality measures with taking into account the direction of the transaction. Sixth, iTraxx Japan denotes the composite index of creditworthiness accounting for investment grade Japanese firms as of the date t. In the case that iTraxx Japan is not available in the date t, we use that as of $t-1$. Seventh, Unwind(value) and Unwind(count) denote how much

[7] The coefficient of disassortativity is -0.581 for the good period and -0.5104 for the bad period.

[8] As a robustness check, we also employ the log value of the notional amount. The qualitative implications we report in the later section are not affected by this modification.

amount (100 million JPY) and how many times the CDS of the reference k was bought and sold by the seller and the buyer of the transaction (b, s, k, i, t) over the three months prior to t. Eighth, Relation(value) and Relation(count) denote how much amount and how many times the buyer and seller of the transaction (b, s, k, i, t) transacted over the three months prior to t, which we use to define $Relation_{i,t}$. In our estimation, we set up a specific threshold and convert these numbers to dummy variables.

Table 2: Summary statistics of the variables

Variable	N	Mean	Std. dev.	Min	Pctl. 25	Pctl. 75	Max
bp	40,007	130.967	98.567	15	60	176.125	537.136
Notional	40,007	6.996	9.054	0	2.5	8.039	221.72
Maturity	40,007	47.396	22.7	0	33	59	241
Link ratio	32,619	3.115	5.031	0	0.094	5	35
Seller degree centrality	33,533	10.067	9.506	0	3	15	35
Buyer degree centrality	33,533	14.53	12.549	0	3	26	45
iTraxx Japan	40,007	64.39	16.533	39.056	51.593	74.7	158.736
Unwind(value)	30,686	73.421	333.017	0	0	20.722	4409.288
Unwind(count)	30,686	6.488	24.094	0	0	4	330
Relation(value)	33,533	393.366	803.765	0	29.101	409.9	6423.39
Relation(count)	33,533	61.604	111.929	0	6	74	932

Notes: This table reports summary statistics (by transaction) of the main variables used in our analysis. "bp" denotes the price of CDS, which the seller of the CDS receives, measured in basis point. "Notional" is the notional amount of CDS transaction, measured in 100 million JPY. "Maturity" refers to the number of months between the effective date and maturity date of the CDS contract. "Link ratio" denotes $(Link_{s,t}/Link_{b,t})$. "Seller degree centrality" and "Buyer degree centrality" denote the aforementioned degree centrality measures with taking into account the direction of the trades. "iTraxx Japan" denotes the composite index of creditworthiness accounting for investment grade Japanese firms as of the date t. "Unwind(value)" and "Unwind(count)" denote how much amount and how many times the CDS of the reference k was bought and sold by the seller and the buyer of the transaction (b, s, k, i, t) over the three months prior to t. "Relation(value)" and "Relation(count)" denote how much amount and how many times the seller and buyer of the transaction (b, s, k, i, t) transacted over the three months prior to t, which we use to define $Relation_{i,t}$. In our estimation, we set up a specific threshold and convert "Relation(value)" and "Relation(count)" to $Relation_{i,t}$. The sample covers every CDS transaction by Japan-based counterparties for the period between April 1, 2013 and December 31, 2021.

7. Empirical Results

Before running the regressions based on the three equations introduced in the previous section, we show the results based on the specification employed in Hasbrouck and Levich (2021). Specifically, we regress the CDS price measured in basis point on the six dummy variables accounting for the configuration of buyers' degree centrality and sellers' degree centrality. Following Hasbrouck and Levich (2021), we categorize the buyers and sellers into the three groups according to the level of their degree centrality, respectively. First, we put the ascending order (i.e., ranking) to the firms in each year-month based on their degree centrality. Second, we measure the monthly trading volume of each party in each month. Third, we compute the cumulative trading volume of the parties up to each ascending order in each month. Finally, we categorize the firms in each month as High, Middle, and Low if they are associated with the cumulative trading volume smaller than 0.33 (High), equal to or larger than 0.33 and smaller than 0.66 (Middle), and equal to or larger than 0.66 (Low), respectively. As the independent variables, we also control for maturity, the squared term of the maturity, notional amount, the squared term of the notional amount, and a dummy variable taking value of one if the trade is cleared at CCP, with controlling for reference-date fixed effects. We run the separate regressions for the data of the good and bad periods.

Table 3 shows the estimated coefficients associated with those categorical dummy variables. First, we confirm that, under the bad market, the case of the buyers with low centrality measure and the sellers with high centrality measure is associated with higher CDS price by around 9 bps. This suggests the price heterogeneity favoring for the sellers with the high relative centrality against buyers. Second, although it is not statistically significantly away from zero, under the good market, the case of the buyers with low centrality measure and the sellers with high centrality measure is associated with higher CDS price around 1 bps. Third, we also find that, under the good market, the case of the buyers with high centrality measure and the sellers with low centrality measure is associated with lower CDS price around -6 bps.

Table 3: The estimation results of the specification employed in Hasbrouck and Levich (2021)

(Panel A. All samples)

		Seller Centrality Group		
		Low	Middle	High
Buyer Centrality Group	Low	—	-11.27 (8.007)	7.983*** (2.713)
	Middle	-7.735 (6.150)	—	4.076** (1.747)
	High	-0.1961 (2.852)	2.131 (1.827)	—

(Panel B. Good periods) (Panel C. Bad periods)

		Panel B: Seller Centrality Group			Panel C: Seller Centrality Group		
		Low	Middle	High	Low	Middle	High
Buyer Centrality Group	Low	—	-16.24 (10.09)	1.251 (2.235)	—	3.825 (5.343)	9.457*** (3.280)
	Middle	-12.23 (7.467)	—	2.597* (1.558)	1.758 (10.13)	—	4.420* (2.425)
	High	-5.901** (2.408)	-0.7539 (1.566)	—	1.342 (3.667)	3.331 (2.541)	—

* p < 0.1, ** p < 0.05, *** p < 0.01

Figures in parentheses are the standard errors of the estimated coefficients.

Notes: This table reports the results of transaction-level panel regression in which CDS price is regressed on a dummy variable that takes the value of one for each group (Low/Middle/High) of buyers and sellers, with control variables and time-reference fixed effects, following the specification in Hasbrouck and Levich (2021):

$$bp_{b,s,i,t} = \beta_1 1(High_b, Mid_s) + \beta_2 1(High_b, Low_s) + \beta_3 1(Mid_b, High_s) + \beta_4 1(Mid_b, Low_s) + \beta_5 1(Low_b, High_s) + \beta_6 1(Low_b, Mid_s) + \beta_7 CCP_{b,s,i,t} + X_{i,t}\gamma + \eta_{r,t} + \varepsilon_{i,t}$$

We classify buyers and sellers into three groups of Low/Middle/High respectively as follows. First, we put buyers (sellers) in the ascending order of degree centrality, and then the notional amount and its ratio to the total amount are calculated for each of these buyers (sellers). Starting from the member of the highest centrality, "High" if the cumulative amount ratio is less than 0.33; "Middle" if the cumulative amount ratio is between 0.33 and 0.66; and "Low" if the cumulative amount ratio is greater than 0.66. The sample period is from April 1, 2013 to December 31, 2021. We report clustered standard errors (by time and reference) in parentheses. ***, **, * denotes significance at 1%, 5%, and 10% confidence level, respectively. The statistically significant coefficients in the table show the association between the relative centrality and CDS prices. For example, in the Panel A, when a buyer in low-centrality group trades with a seller in high-centrality group, the average incremental CDS price is 7.983 bps, that is, a loss to the buyer and a gain to the seller, indicating the centrality premium.

This exercise suggests the positive association between the relative centrality measure of sellers against buyers and CDS price. One drawback of this analysis is that the standard factors such as the credit risk of sellers and buyers are not controlled and thus it does not necessarily provide a concrete evidence on the association between the relative centrality and the price. Against this concern, we control for a comprehensive set of fixed-effects as already mentioned in Section 5. We first show the estimation results based on the equation (1). Table 4 summarizes the estimated coefficients.

Table 4: Baseline estimation results of equation (1)

	All samples	Good periods	Bad periods
Link ratio	7.049**	2.592	11.984**
	(2.974)	(3.873)	(5.893)
Maturity	0.421*	0.381	0.399
	(0.216)	(0.420)	(0.253)
Maturity (squared)	0.002	0.001	0.003
	(0.002)	(0.003)	(0.002)
Notional principal	-0.103	0.339	-0.211
	(0.164)	(0.300)	(0.201)
Notional principal (squared)	-0.001	-0.003	-0.001
	(0.002)	(0.003)	(0.003)
CCP dummy	-2.091	-4.937	-2049.043
	(7.101)	(5.891)	(20878.592)
Observations	32,614	16,303	16,311
R^2	0.889	0.943	0.839
Fixed effects			
Reference × date	Yes	Yes	Yes
Seller× month/year	Yes	Yes	Yes
Buyer × month/year	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: This table reports the results of transaction-level panel regressions in which CDS price is regressed on Link ratio and a bunch of control variables. All specifications include time-reference ID, time-seller ID and time-buyer ID fixed effects. Link ratio denotes the ratio of link $(Link_{s,t}/Link_{b,t})$. Column "All samples" shows the results of all transactions. In columns "Good periods" and "Bad periods," we divide samples depending on the level of iTraxx Japan on the day when the transaction takes place. The sample period is from April 1, 2013 to December 31, 2021. We report clustered standard errors (by time and reference) in parentheses. ***, **, * denotes significance at 1%, 5%, and 10% confidence level, respectively. The relationship between the seller's relatively high centrality to the buyer (the ratio of seller centrality to buyer centrality) and price is positively correlated on average, suggesting that sellers with higher centrality are charging premium from buyers with lower centrality (i.e., centrality premium).

The baseline estimation results suggest the following. First, from the column labeled as "All samples," we can confirm that the ratio of sellers' centrality to buyers' centrality is positively associated with the CDS price. This result suggests that the impact of more central sellers' bargaining power against less central buyers overwhelms the technical advantage of sellers with higher centrality in searching the trading counterpart. Second, nonetheless, from the column labeled as "Good samples," we cannot find such a pattern in the case of good market. This suggests that the theoretical implication on centrality discount under a good period is not the case at least in our dataset. Third, from the column labeled as "All samples" and "Bad samples," the centrality premium we observe for the entire sample (i.e., 7.049) becomes larger in the bad period (i.e., 11.984). In general, in bad market conditions, the difficulty for buyers to find counterparties will rise compared to good conditions. The baseline result implies that sellers with higher centrality may use their bargaining power and charge a premium when buyers still want to buy protection under such a situation. Thus, the relative centrality between sellers and buyers become apparent as the higher prices in bad market conditions. This result is consistent with the story that sellers with higher centrality takes advantage of their bargaining power to set higher prices.[9]

Given the results above, we might wonder how quantitatively important the relative centrality in terms of CDS price determination is. As a back-of-the-envelope calculation, suppose the ratio of seller's centrality to buyer's centrality increases by one standard deviation. Then, CDS price increases by 35 bps, which is in fact not negligible as it accounts for 35% of the standard deviation of CDS price in our data. As an additional illustration of the quantitative importance of the relative centrality, we also take a look at the standard deviation of the predicted CDS price obtained from our estimated model. For this exercise, using the results listed in the first column of Table 4 and the data of the independent variables, we predict the CDS prices of each transaction and compute its standard deviation being 56.4. Here, using the same set of the estimated coefficients except for that associated with the link ratio, we repeat the same exercise and obtain the standard deviation of the predicted CDS price being 15.9. The difference between those two numbers suggest that the predicted prices become much more volatile once we take into account the relative centrality between sellers and buyers to predict the CDS prices. In fact, around 70% (i.e., =(56.4-15.9)/56.4) of the standard deviation of predicted CDS prices based on our model is accounted for by the relative centrality. These exercises exemplify the quantitative importance of the relative centrality in the determination of CDS prices.

To see under what circumstance such centrality premium become higher, we estimate the equation (2). Table 5 summarizes the results. Here, Unwind(value) and Unwind(count) denote how much amount and how many times the buyer sold the CDS of the referenced entity of which the buyer is about to buy the CDS. In this sense, Unwind(value) and Unwind(count) proxy for the degree of the short cover the buyer attempts to do.[10] First, the estimated coefficient of the relative centrality measure is positive where the coefficient is larger for the bad periods, which is consistent with the results of our benchmark regression. Second, the positive coefficient associated with the interaction term between the relative centrality measure and the amount of selling, Unwind(value), in the case of the bad periods, suggests that the buyer attempting to make its short position square is likely to face an additional centrality premium. As the standard deviation of Unwind(value) is 333, the marginal impact of the relative centrality measure increases by 333*0.012=3.996. This is sizable in the comparison with the coefficient of the relative centrality measure (i.e., 13.335). It is informative to see that buyers

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[9] As a robustness check, we define the good and bad periods by referring to the records of iTraxx Japan up to each data point instead of referring to the median value of the entire iTraxx Japan records. This reflects a possible concern on the information leakages originating from the employment of "future" value of iTraxx Japan in our empirical analysis. To avoid such potential information leakages from the future data, we strictly limit the employment of the data for the purpose of defining the good and bad periods to the available record as of each transaction records. For example, when we judge whether a specific date is good or bad, we only use the information prior to the date and assign good (bad) to the record if the iTraxx Japan on the specific day is equal to or lower (higher) than the median level of iTraxx Japan up to the day. Even in that case, our empirical finding is almost unchanged. For details, see the robustness check A.7 in Section 8.

[10] In addition to the case where we measure the gross short position to measure "Unwind," we also measure the short cover needs by computing the net position of short selling. The results are almost identical to the case we mention in the main body of the paper.

tend to face inferior price condition when they attempt to make their short position neutral under the bad market condition. This result fits the story that sellers with higher centrality take advantage of their bargaining power to set higher prices, particularly against "desperate" buyers who wish to square their short positions.

Table 5: Estimation results of short cover motive and short squeeze of equation (2)

	All samples	Good periods	Bad periods
Link ratio	10.176*** (2.464)	7.334*** (2.369)	13.335** (6.201)
Unwind (value)	0.016 (0.021)	-0.025 (0.023)	0.027 (0.026)
Link ratio × Unwind (value)	0.010* (0.006)	-0.003 (0.006)	0.012* (0.007)
Unwind (count)	0.156 (0.291)	0.613 (0.545)	0.055 (0.369)
Link ratio × Unwind (count)	-0.051 (0.079)	0.072 (0.109)	-0.079 (0.095)
Maturity	0.478** (0.222)	0.360 (0.428)	0.483* (0.261)
Maturity (squared)	0.002 (0.002)	0.002 (0.003)	0.002 (0.002)
Notional principal	-0.104 (0.166)	0.359 (0.309)	-0.224 (0.199)
Notional principal (squared)	-0.001 (0.002)	-0.003 (0.003)	-0.001 (0.003)
CCP dummy	1.175 (7.557)	-5.307 (5.942)	-3359.007 (20627.901)
Observations	30,084	15,041	15,043
R^2	0.883	0.937	0.832
Fixed effects			
Reference × date	Yes	Yes	Yes
Seller× month/year	Yes	Yes	Yes
Buyer × month/year	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: This table reports the results of transaction-level panel regressions in which CDS price is regressed on Link ratio and a bunch of control variables. All specifications include time-reference ID, time-seller ID and time-buyer ID fixed effects. Link ratio denotes the ratio of link $(Link_{s,t}/Link_{b,t})$. Unwind(value) and Unwind(count) denote how much amount and how many times the buyer sold the CDS of the referenced entity of which the buyer is about to buy the CDS. Column "All samples" shows the results of all transactions. In columns "Good periods" and "Bad periods," we divide samples depending on the level of iTraxx Japan on the day when the transaction takes place. The sample period is from April 1, 2013 to December 31, 2021. We report clustered standard errors (by time and reference) in parentheses. ***, **, * denotes significance at 1%, 5%, and 10% confidence level, respectively.

Is there any chance to avoid the centrality premium in the bad market? Table 6 summarizes the results based on the equation (3) where we define the relation as the case with both $Rel_{i,t}^{M}$ and $Rel_{i,t}^{C}$ are higher than a specific threshold. As a benchmark analysis, we use 68 percentile point of $Rel_{i,t}^{M}$ and $Rel_{i,t}^{C}$, which corresponds to the mean plus one standard deviation in the case of normal distribution, respectively.

Table 6: Estimation results of relation defined by "AND" condition of equation (3)

	All samples	Good periods	Bad periods
Link ratio	9.703***	6.247***	12.824**
	(2.522)	(1.829)	(6.116)
Relation dummy	20.429*	8.598	-29.997*
	(12.380)	(15.435)	(16.345)
Link ratio × Relation dummy	6.424*	7.113*	-12.673**
	(3.894)	(4.045)	(5.573)
Maturity	0.420*	0.378	0.399
	(0.216)	(0.421)	(0.253)
Maturity (squared)	0.002	0.001	0.003
	(0.002)	(0.003)	(0.002)
Notional principal	-0.103	0.340	-0.211
	(0.164)	(0.300)	(0.201)
Notional principal (squared)	-0.001	-0.003	-0.001
	(0.002)	(0.003)	(0.003)
CCP dummy	-2.093	-4.947	-2049.407
	(7.103)	(5.894)	(20916.030)
Observations	32,614	16,303	16,311
R^2	0.889	0.943	0.839
Fixed effects			
Reference × date	Yes	Yes	Yes
Seller× month/year	Yes	Yes	Yes
Buyer × month/year	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports the results of transaction-level panel regressions in which CDS price is regressed on Link ratio and a bunch of control variables. All specifications include time-reference ID, time-seller ID and time-buyer ID fixed effects. Link ratio denotes the ratio of link $(Link_{s,t}/Link_{b,t})$. Relation dummy denotes the dummy variable taking the value of one if the amount and frequency of the past transactions between buyer b and seller s over the three-month periods prior to the period t is large. Column "All samples" shows the results of all transactions. In columns "Good periods" and "Bad periods," we divide samples depending on the level of iTraxx Japan on the day when the transaction takes place. The sample period is from April 1, 2013 to December 31, 2021. We report clustered standard errors (by time and reference) in parentheses. ***, **, * denotes significance at 1%, 5%, and 10% confidence level, respectively.

The results suggest that when the relation is stronger in the sense that both the amount and frequency are large enough, it turns out that the centrality premium disappears (i.e., 12.824bps – 12.673bps) in the bad periods.

Next, we show the results based on the equation (3) where we define the relation as the case with one of $Rel_{i,t}^{M}$ or $Rel_{i,t}^{C}$ are higher than mean plus one standard deviation of the data.

Table 7: Estimation results of relation defined by "OR" condition of equation (3)

	All samples	Good periods	Bad periods
Link ratio	9.547***	7.425***	12.987**
	(2.504)	(1.944)	(6.151)
Relation dummy	19.033	24.143	-33.723**
	(12.011)	(15.971)	(14.645)
Link ratio × Relation dummy	6.274	5.503	-13.778***
	(3.872)	(4.054)	(5.107)
Maturity	0.420*	0.377	0.399
	(0.216)	(0.421)	(0.253)
Maturity (squared)	0.002	0.001	0.003
	(0.002)	(0.003)	(0.002)
Notional principal	-0.103	0.341	-0.211
	(0.164)	(0.300)	(0.201)
Notional principal (squared)	-0.001	-0.003	-0.001
	(0.002)	(0.003)	(0.003)
CCP dummy	-2.093	-4.955	-2039.985
	(7.103)	(5.892)	(20923.100)
Observations	32,614	16,303	16,311
R^2	0.889	0.943	0.839
Fixed effects			
Reference × date	Yes	Yes	Yes
Seller× month/year	Yes	Yes	Yes
Buyer × month/year	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports the results of transaction-level panel regressions in which CDS price is regressed on Link ratio and a bunch of control variables. All specifications include time-reference ID, time-seller ID and time-buyer ID fixed effects. Link ratio denotes the ratio of link $(Link_{s,t}/Link_{b,t})$. Relation dummy denotes the dummy variable taking the value of one if the amount or frequency of the past transactions between buyer b and seller s over the three-month periods prior to the period t is large. Column "All samples" shows the results of all transactions. In columns "Good periods" and "Bad periods", we divide samples depending on the level of iTraxx on the day when the transaction takes place. The sample period is from April 1, 2013 to December 31, 2021. We report clustered standard errors (by time and reference) in parentheses. ***, **, * denotes significance at 1%, 5%, and 10% confidence level, respectively.

Again, the centrality premium is completely offset by the maintained relations (i.e., 12.987bps – 13.778bps) in the bad periods.

As the last exercise, we define the relation by paying attention only one of $Rel_{i,t}^{M}$ or $Rel_{i,t}^{C}$ is higher than mean plus one standard deviation of the data. Consistent with the abovementioned results, first, regardless of whether the relation is measured by the amount ($Rel_{i,t}^{M}$) or the frequency ($Rel_{i,t}^{C}$), buyers holding closer relation with the seller enjoy the relatively lower CDS price in the bad periods. The reduction of the centrality premium is sizable to offset the centrality premium. Second, there is a sign that buyers pay a premium to maintain the relation in the good periods in the case that we measure the relation by the frequency ($Rel_{i,t}^{C}$). Although the level of CDS price in the good period is presumably lower than that in the bad period, our estimation result suggests that less central buyers aiming to maintain the relation with more central sellers need to pay premium.

Table 8: Estimation relation measured by amount or frequency of equation (3)

	Panel (a) In the case that relation dummy is captured by transaction value			Panel (b) In the case that relation dummy is captured by transaction count		
	All samples	Good periods	Bad periods	All samples	Good periods	Bad periods
Link ratio	9.702***	7.425***	12.824**	9.547***	6.247***	12.988**
	(2.522)	(1.945)	(6.116)	(2.504)	(1.829)	(6.151)
Relation dummy	20.424*	24.143	-30.007*	19.039	8.599	-33.745*
	(12.380)	(15.971)	(16.347)	(12.011)	(15.430)	(14.643)
Link ratio × Relation dummy	6.423*	5.503	-12.660**	6.276	7.116*	-13.785***
	(3.894)	(4.054)	(5.574)	(3.872)	(4.045)	(5.107)
Maturity	0.420*	0.377	0.399	0.420*	0.378	0.399
	(0.216)	(0.421)	(0.253)	(0.216)	(0.421)	(0.253)
Maturity (squared)	0.002	0.001	0.003	0.002	0.001	0.003
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Notional principal	-0.103	0.341	-0.211	-0.103	0.340	-0.211
	(0.164)	(0.300)	(0.201)	(0.164)	(0.300)	(0.201)
Notional principal (squared)	-0.001	-0.003	-0.001	-0.001	-0.003	-0.001
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
CCP dummy	-2.093	-4.955	-2050.642	-2.093	-4.947	-2072.870
	(7.103)	(5.892)	(20916.033)	(7.103)	(5.894)	(20922.996)
Observations	32,614	16,303	16,311	32,614	16,303	16,311
R^2	0.889	0.943	0.839	0.889	0.943	0.839
Fixed effects						
Reference × date	Yes	Yes	Yes	Yes	Yes	Yes
Seller× month/year	Yes	Yes	Yes	Yes	Yes	Yes
Buyer × month/year	Yes	Yes	Yes	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes. This table reports the results of transaction-level panel regressions in which CDS price is regressed on Link ratio and a bunch of control variables. All specifications include time-reference ID, time-seller ID and time-buyer ID fixed effects. Link ratio denotes the ratio of link $(Link_{s,t}/Link_{b,t})$. In the panel (a), "Relation dummy" denotes the dummy variable taking the value of one if the amount of the past transactions between buyer b and seller s over the three-month periods prior to the period t is large. In the panel (b), "Relation dummy" denotes the dummy variable taking the value of one if the frequency of the past transactions between buyer b and seller s over the three-month periods prior to the period t is large. As common to both panels A and B, column "All samples" shows the results of all transactions. In columns "Good periods" and "Bad periods", we divide samples depending on the level of iTraxx Japan on the day when the transaction takes place. The sample period is from April 1, 2013 to December 31, 2021. We report clustered standard errors (by time and reference) in parentheses. ***, **, * denotes significance at 1%, 5%, and 10% confidence level, respectively.

8. Robustness Check

In this section, we list what we have done to confirm the robustness of our empirical results. All the results are provided in the appendix and we only briefly explain how we take care of various concerns against our empirical results.

First, it could be our concern to what extent the reported results are sensitive to the choice of the centrality measure. Against this concern, we employ various alternative ways to measure the relative centrality: (i) Even if we measure the ratio of sellers' and buyers' degree centrality over the past six months prior to each transaction records instead of the three months, the qualitative features of our empirical results are unchanged (Table A1). (ii) We drop the transaction records associated with the sellers not having any transaction over the past three months from the computation of the link ratio and confirm that the results are unchanged (Table A2). Note that in the baseline estimation, we drop the transaction records associated with the buyers not having any transaction over the past three months from the computation of the link ratio because this number needs to be used as the denominator of the link ratio. This robustness check aims to confirm our results are unchanged even if we treat the buyers and sellers in the same manner in this regard. (iii) Unlike the baseline estimation where we take into account the direction of the transaction, we intentionally do not take into account the direction of the transaction (i.e., either a buyer or a seller in a transaction) to compute the degree centrality and we confirm the qualitative feature is unchanged (Table A3). (iv) To extract the variation of the link ratio, which can be generated both by the variation in the numerators (i.e., sellers' centrality) and that in the denominator (i.e., buyers' centrality) in our main specification, we focus on either (a) the sellers with a small centrality versus the buyers with a small or large centrality (Table A4 (A)) or (b) the sellers with a small or large centrality versus the buyers with a small centrality (Table A4 (B)).[11] It turns out that the obtained empirical results in both cases (a) and (b) are consistent with the main results. (v) Instead of using the local centrality measure (i.e., degree centrality), we employ the eigenvector centrality as a global centrality measure and confirm the results are unchanged (Table A5). (vi) Instead of using the transaction frequency, we use the transaction amounts to measure each player's search ability. Then, we obtain the qualitatively same results as in the baseline estimation (Table A6). (vii) When judging whether a specific date is in a good period or a bad period, we only use the information prior to the date of the transaction and assign good (bad) to the record if the iTraxx Japan on the specific day is equal to or lower (higher) than the median level of iTraxx Japan up to the day. This calculation enables us to refrain from the information leakages originating from the employment of "future" value. Even in this case, we confirm the qualitative feature is unchanged (Table A7).

Second, as additional subsample analyses, we have done the following: (i) We limit the sample to the transaction among the domestic institutions in terms of nationality or geographic location (Table B1). (ii) We limit our sample to that cleared in CCP or that in non-CCP (Table B2). (iii) We limit the records to the dealer-to-customer (i.e., the dealers play a role of seller while the non-dealer parties play a role of buyer, D2C) or C2D (Table B3). (iv) We limit the samples to either inter- or intra-group transactions (Table B4). (v) We limit the samples to the seller-buyer pairs that had not been observed in the past (i.e., newly established relations) (Table B5). (vi) We limit the data to the pairs of sellers and buyers transacting more than a certain number throughout the data periods (Table B6). The baseline results reported in the previous section are kept against these robustness checks.

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[11] Note that the cases consisting of the sellers with a large centrality and the buyers with a large centrality rarely exist in our data, as illustrated in Figure 4 and 6.

9. Conclusion

In the present paper, we use the transaction-level records of CDS contracts in Japan to document whether and how (if any) the relative centrality of sellers to buyers affects CDS price. Our panel estimation controlling for various pricing factors employed in practice suggests the positive association between CDS price and the relative centrality of sellers to buyers. Such centrality premium is observed in the market with higher credit risk and exhibits the pronounced centrality premium in the case of short squeeze. Interestingly, deeper trade relations between sellers and buyers result in centrality discount (premium) in the market with higher (lower) credit risk. These results illustrate the tradeoff between the cost of maintaining relationship in good periods and the benefit of securing cheap access to CDS in bad periods. Given the fact that we observe the centrality premium under bad market conditions, it is likely that peripheral buyers without accumulated trade relations are facing higher CDS price in distressed periods.

As discussed in the present paper, financial authorities could find it beneficial to understand the asymmetric status of centrality between buyers and sellers as those lead to the surge of derivative price under bad market conditions. Simply because such a market environment is the one in which market participants need protection against default, such an increase in CDS price due to the relative network centrality on top of the hike in reference's credit risk should be considered from policy perspective.

While we provide a novel finding to literature, there are further potential routes toward additional useful works. Specifically, it could be a sensible question to ask how parties initiate and terminate their transaction relations, which accounts for the extensive margin of relations. In the present paper, we focus on the incumbent relations between sellers and buyers (i.e., intensive margin) and do not pay a specific attention to the extensive margin given the fact that the network structure is stiff. Documenting the entry and exit of relations and examining its pricing implication would be a promising direction of future researches.

APPENDIX A

A1. Six months

	All samples	Good periods	Bad periods
Link ratio	5.500 (6.280)	-3.979 (3.873)	16.001** (5.893)
Maturity	0.426** (0.216)	0.384 (0.420)	0.402 (0.253)
Maturity (squared)	0.002 (0.002)	0.001 (0.003)	0.003 (0.002)
Notional principal	-0.091 (0.165)	0.338 (0.299)	-0.194 (0.202)
Notional principal (squared)	-0.001 (0.002)	-0.003 (0.003)	-0.001 (0.003)
CCP dummy	-2.154 (7.016)	-4.960 (5.863)	-1767.393 (20878.592)
Observations	32,507	16,441	16,066
R^2	0.889	0.944	0.838
Fixed effects			
Reference × date	Yes	Yes	Yes
Seller× month/year	Yes	Yes	Yes
Buyer × month/year	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: This table reports the results of transaction-level panel regressions in which CDS price is regressed on Link ratio and a bunch of control variables. All specifications include time-reference ID, time-seller ID and time-buyer ID fixed effects. Link ratio denotes the ratio of link $(Link_{s,t}/Link_{b,t})$. While the measurement of the link is calculated over 3-month period in the main specification, we use the measurement of the link to be 6-month period as a robustness check in A1. Column "All samples" shows the results of all transactions. In columns "Good periods" and "Bad periods", we divide samples depending on the level of iTraxx Japan on the day when the transaction takes place. The sample period is from April 1, 2013 to December 31, 2021. We report clustered standard errors (by time and reference) in parentheses. ***, **, * denotes significance at 1%, 5%, and 10% confidence level, respectively. We observe the centrality premium in the bad periods (i.e., 16.001).

A2. Dropping the transaction records associated with the sellers not having any transaction

	All samples	Good periods	Bad periods
Link ratio	10.384***	4.963**	14.729**
	(2.770)	(2.140)	(6.694)
Maturity	0.374*	0.226	0.371
	(0.227)	(0.458)	(0.264)
Maturity (squared)	0.003	0.003	0.003
	(0.002)	(0.003)	(0.002)
Notional principal	-0.074	-0.446	-0.177
	(0.166)	(0.337)	(0.197)
Notional principal (squared)	-0.001	-0.004	-0.001
	(0.002)	(0.003)	(0.003)
CCP dummy	-2.323	-5.738	-3468.071
	(7.043)	(6.105)	(20416.097)
Observations	30,815	15,157	15,658
R^2	0.899	0.943	0.841
Fixed effects			
Reference × date	Yes	Yes	Yes
Seller× month/year	Yes	Yes	Yes
Buyer × month/year	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes. This table reports the results of transaction-level panel regressions in which CDS price is regressed on Link ratio and a bunch of control variables. All specifications include time-reference ID, time-seller ID and time-buyer ID fixed effects. Link ratio denotes the ratio of link $(Link_{s,t}/Link_{b,t})$. In this table, we exclude the data from the regression not only with zero links for buyers, but also with zero links for sellers. Column "All samples" shows the results of all transactions. In columns "Good periods" and "Bad periods", we divide samples depending on the level of iTraxx Japan on the day when the transaction takes place. The sample period is from April 1, 2013 to December 31, 2021. We report clustered standard errors (by time and reference) in parentheses. ***, **, * denotes significance at 1%, 5%, and 10% confidence level, respectively. We observe the centrality premium (i.e., 10.384 for all samples, 4.963 for good periods, and 14.729 for bad periods).

A3. Direction

	All samples	Good periods	Bad periods
Link ratio	3.904 (4.648)	-4.458 (6.174)	12.321* (7.220)
Maturity	0.419* (0.215)	0.368 (0.414)	0.402 (0.253)
Maturity (squared)	0.002 (0.002)	0.002 (0.003)	0.003 (0.002)
Notional principal	-0.107 (0.164)	0.321 (0.297)	-0.211 (0.201)
Notional principal (squared)	-0.001 (0.002)	-0.003 (0.003)	-0.001 (0.003)
CCP dummy	-2.098 (7.089)	-4.911 (5.895)	-3483.707 (20700.644)
Observations	32,814	16,459	16,355
R^2	0.889	0.943	0.39
Fixed effects			
Reference × date	Yes	Yes	Yes
Seller× month/year	Yes	Yes	Yes
Buyer × month/year	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: This table reports the results of transaction-level panel regressions in which CDS price is regressed on Link ratio and a bunch of control variables. All specifications include time-reference ID, time-seller ID and time-buyer ID fixed effects. Link ratio denotes the ratio of link $(Link_{s,t}/Link_{b,t})$. In this table, we use the undirected transaction as the link. Column "All samples" shows the results of all transactions. In columns "Good periods" and "Bad periods", we divide samples depending on the level of iTraxx Japan on the day when the transaction takes place. The sample period is from April 1, 2013 to December 31, 2021. We report clustered standard errors (by time and reference) in parentheses. ***, **, * denotes significance at 1%, 5%, and 10% confidence level, respectively. We observe the centrality premium in the bad periods (i.e., 12.321).

A4. (A) The sellers with a small centrality versus the buyers with a small or large centrality

	The sellers with a small centrality versus the buyers with a small centrality	The sellers with a small centrality versus the buyers with a large centrality	The sellers with a small centrality
Link ratio	7.657*** (2.175)	—	9.002*** (2.603)
Maturity	-0.154 (0.310)	1.188*** (0.323)	0.203 (0.242)
Maturity (squared)	0.005** (0.002)	0.000 (0.003)	0.003* (0.002)
Notional principal	-0.072 (0.318)	-0.125 (0.240)	-0.053 (0.232)
Notional principal (squared)	-0.001 (0.004)	0.000 (0.003)	-0.002 (0.003)
CCP dummy	-5358.779 (60782.206)	-1.992 (2.961)	1.921 (3.983)
Observations	16,345	8,147	24,492
R^2	0.845	0.934	0.868
Fixed effects			
Reference × date	Yes	Yes	Yes
Seller× month/year	Yes	Yes	Yes
Buyer × month/year	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: This table reports the results of transaction-level panel regressions in which CDS price is regressed on Link ratio and a bunch of control variables. All specifications include time-reference ID, time-seller ID and time-buyer ID fixed effects. Link ratio denotes the ratio of link $(Link_{s,t}/Link_{b,t})$. In this table, seller's link is limited to the 75th percentile of its sample, and hence, the transaction whose seller's link is above the 75th percentile are excluded. Buyers are classified as large if its centrality is greater than the 75th percentile, and small if its centrality is less than the 75th percentile. The sample period is from April 1, 2013 to December 31, 2021. We report clustered standard errors (by time and reference) in parentheses. ***, **, * denotes significance at 1%, 5%, and 10% confidence level, respectively. We observe the centrality premium in the case of the transaction between the sellers with a small centrality and the buyers with a small centrality (i.e., 7.657), and the transaction between the sellers with a small centrality and general buyers (i.e., 9.002).

A4. (B) The sellers with a small or large centrality versus the buyers with a small centrality

	The sellers with a small centrality versus the buyers with a small centrality	The sellers with a small centrality versus the buyers with a large centrality	The buyers with a small centrality
Link ratio	7.657***	1.994	6.978**
	(2.175)	(655385.549)	(3.110)
Maturity	-0.154	2.179***	0.053
	(0.310)	(0.345)	(0.275)
Maturity (squared)	0.005**	-0.009***	0.004*
	(0.002)	(0.002)	(0.002)
Notional principal	-0.072	-0.175	-0.109
	(0.318)	(0.117)	(0.210)
Notional principal (squared)	-0.001	0.001	-0.001
	(0.004)	(0.001)	(0.002)
CCP dummy	-5358.779	7.184	-31.807
	(60782.206)	(8.329)	(24.680)
Observations	16,345	8,122	24,467
R^2	0.845	0.984	0.879
Fixed effects			
Reference × date	Yes	Yes	Yes
Seller× month/year	Yes	Yes	Yes
Buyer × month/year	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: This table reports the results of transaction-level panel regressions in which CDS price is regressed on Link ratio and a bunch of control variables. All specifications include time-reference ID, time-seller ID and time-buyer ID fixed effects. Link ratio denotes the ratio of link $(Link_{s,t}/Link_{b,t})$. In this table, buyer's link is limited to the 75th percentile of its sample, and hence, the transaction whose buyer's link is above the 75th percentile are excluded. Sellers are classified as large if its centrality is greater than the 75th percentile, and small if its centrality is less than the 75th percentile. The sample period is from April 1, 2013 to December 31, 2021. We report clustered standard errors (by time and reference) in parentheses. ***, **, * denotes significance at 1%, 5%, and 10% confidence level, respectively. We observe the centrality premium in the case of the transaction between the sellers with a small centrality and the buyers with a small centrality (i.e., 7.657), and the transaction between the buyers with a small centrality and general sellers (i.e., 6.978).

A5. The eigenvector centrality

	All samples	Good periods	Bad periods
Eigen ratio	6.202***	-19.893	8.495*
	(1.701)	(18.530)	(4.725)
Maturity	0.484**	0.941***	0.385
	(0.223)	(0.239)	(0.264)
Maturity (squared)	0.002	-0.001	0.003
	(0.002)	(0.001)	(0.002)
Notional principal	-0.205	-0.121	-0.188
	(0.150)	(0.138)	(0.198)
Notional principal (squared)	0.000	0.001	-0.001
	(0.002)	(0.001)	(0.003)
CCP dummy	-1.463	-1.764	-1425.871
	(7.148)	(4.919)	(22725.042)
Observations	31,076	14,978	16,098
R^2	0.900	0.981	0.843
Fixed effects			
Reference × date	Yes	Yes	Yes
Seller× month/year	Yes	Yes	Yes
Buyer × month/year	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: This table reports the results of transaction-level panel regressions in which CDS price is regressed on Link ratio and a bunch of control variables. All specifications include time-reference ID, time-seller ID and time-buyer ID fixed effects. Link ratio denotes the ratio of link $(Link_{s,t}/Link_{b,t})$. In this table, link is defined as the sum of the notional amounts (eigenvector centrality) that the buyer (seller) of the transaction has traded with as buyer (seller) over the past three months. Column "All samples" shows the results of all trades. In columns "Good periods" and "Bad periods", we divide samples depending on the level of iTraxx Japan on the day when the transaction takes place. The sample period is from April 1, 2013 to December 31, 2021. We report clustered standard errors (by time and reference) in parentheses. ***, **, * denotes significance at 1%, 5%, and 10% confidence level, respectively. We observe the centrality premium (i.e., 6.202 for all samples, and 8.495 for bad periods).

A6. The employment of transaction amounts instead of transaction frequencies (i.e., degree centrality)

	All samples	Good periods	Bad periods
Amount ratio	0.372*	0.167	0.510*
	(0.211)	(0.156)	(0.308)
Maturity	0.377*	0.239	0.373
	(0.225)	(0.446)	(0.265)
Maturity (squared)	0.003	0.003	0.003
	(0.002)	(0.003)	(0.002)
Notional principal	-0.082	0.397	-0.179
	(0.165)	(0.328)	(0.197)
Notional principal (squared)	-0.001	-0.003	-0.001
	(0.002)	(0.003)	(0.003)
CCP dummy	-2.308	-5.532	-2151.161
	(7.030)	(6.057)	(23541.092)
Observations	31,618	15,849	15,769
R^2	0.891	0.944	0.842
Fixed effects			
Reference × date	Yes	Yes	Yes
Seller× month/year	Yes	Yes	Yes
Buyer × month/year	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: This table reports the results of transaction-level panel regressions in which CDS price is regressed on Link ratio and a bunch of control variables. All specifications include time-reference ID, time-seller ID and time-buyer ID fixed effects. Link ratio denotes the ratio of link $(Link_{s,t}/Link_{b,t})$. In this table, we use the transaction amount to gauge the link. Column "All samples" shows the results of all transactions. In columns "Good periods" and "Bad periods", we divide samples depending on the level of iTraxx Japan on the day when the transaction takes place. The sample period is from April 1, 2013 to December 31, 2021. We report clustered standard errors (by time and reference) in parentheses. ***, **, * denotes significance at 1%, 5%, and 10% confidence level, respectively. We observe the centrality premium (i.e., 0.372 for all samples, and 0.510 for for bad periods).

A7. Moving average

	All samples	Good periods	Bad periods
Link ratio	7.049**	-3.264	9.858***
	(2.974)	(2.041)	(2.895)
Maturity	0.421*	1.936***	0.270
	(0.216)	(0.283)	(0.239)
Maturity (squared)	0.002	-0.007***	0.003*
	(0.002)	(0.002)	(0.002)
Notional principal	-0.103	-0.508***	-0.012
	(0.164)	(0.160)	(0.198)
Notional principal (squared)	-0.001	0.004***	-0.002
	(0.002)	(0.001)	(0.002)
CCP dummy	-2.091	1.853	-1912.274
	(7.101)	(3.958)	(50855.543)
Observations	32,614	12341	20273
R^2	0.889	0.988	0.847
Fixed effects			
Reference × date	Yes	Yes	Yes
Seller× month/year	Yes	Yes	Yes
Buyer × month/year	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: This table reports the results of transaction-level panel regressions in which CDS price is regressed on Link ratio and a bunch of control variables. All specifications include time-reference ID, time-seller ID and time-buyer ID fixed effects. Link ratio denotes the ratio of link ($Link_{s,t}/Link_{b,t}$). We define the good and bad periods by referring to the records of iTraxx Japan up to each data point instead of referring to the median value of the entire iTraxx Japan records. The figures is 75-day backward moving averages. Moreover, to confirm the robustness, 25-, 100- and 200-day moving averages are used, and the results were almost identical. To avoid the information leakages originating from the usage of future data, we strictly limit the employment of the data for defining the good and bad periods to the available record as of each transaction records. For example, when we judge whether a specific date is good or bad in this robustness check, we only use the information prior to the date and assign good (bad) to the record if the iTraxx Japan on the specific day is equal to or lower (higher) than the median level of iTraxx Japan up to the day. Column 1 “All samples” shows the results of all transactions. In columns “Good periods” and “Bad periods”, we divided samples depending on the level of iTraxx Japan on the day when the transaction takes place. The sample period is from April 1, 2013 to December 31, 2021. We report clustered standard errors (by time and reference) in parentheses. ***, **, * denotes significance at 1%, 5%, and 10% confidence level, respectively. We observe the centrality premium (i.e., 7.049 for all samples, and 9.858 for bad periods).

Appendix B

B1. The domestic institutions in terms of nationality or geographic location

	Both of counter participants located in Japan			Either of counter participants located in Japan		
	All samples	Good periods	Bad periods	All samples	Good periods	Bad periods
Link ratio	3.945 (2.804)	0.713 (3.139)	8.472* (4.657)	9.837*** (2.568)	8.311*** (2.186)	11.577** (5.894)
Domestic institutions dummy	16.464* (9.924)	31.852*** (10.961)	5.469 (9.903)	-14.117** (7.079)	-25.340*** (8.525)	-5.507 (6.363)
Link ratio × Domestic institutions dummy	5.973** (2.480)	7.517** (3.022)	3.159 (2.144)	-5.930** (2.483)	-7.695** (3.031)	-3.045 (2.106)
Maturity	0.412* (0.217)	0.378 (0.421)	0.390 (0.254)	0.412* (0.217)	0.378 (0.420)	0.390 (0.254)
Maturity (squared)	0.002 (0.002)	0.001 (0.003)	0.003 (0.002)	0.002 (0.002)	0.001 (0.003)	0.003 (0.002)
Notional principal	-0.093 (0.165)	0.340 (0.300)	-0.210 (0.202)	-0.093 (0.165)	0.339 (0.300)	-0.200 (0.202)
Notional principal (squared)	-0.001 (0.002)	-0.003 (0.003)	-0.001 (0.003)	-0.001 (0.002)	-0.003 (0.003)	-0.001 (0.003)
CCP dummy	-2.142 (7.125)	-4.947 (5.894)	-345.872 (21114.311)	-2.142 (7.125)	-4.946 (5.887)	-247.346 (21105.952)
Observations	32,324	16,261	16,063	32,324	16,261	16,063
R^2	0.888	0.943	0.838	0.888	0.943	0.838
Fixed effects						
Reference × date	Yes	Yes	Yes	Yes	Yes	Yes
Seller× month/year	Yes	Yes	Yes	Yes	Yes	Yes
Buyer × month/year	Yes	Yes	Yes	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: This table reports the results of transaction-level panel regressions in which CDS price is regressed on Link ratio and a bunch of control variables. All specifications include time-reference ID, time-seller ID and time-buyer ID fixed effects. Link ratio denotes the ratio of link $(Link_{s,t}/Link_{b,t})$. In this table, the sample is limited by the location of the participants: In columns 1-3, the sample is limited to the case where both seller and buyer are located in Japan. In columns 4-6, the sample is limited to the case where either seller or buyer is located in Japan. The sample period is from April 1, 2013 to December 31, 2021. We report clustered standard errors (by time and reference) in parentheses. ***, **, * denotes significance at 1%, 5%, and 10% confidence level, respectively. We observe the centrality premium in bad periods (i.e., 8.472 for the case where both seller and buyer are located in Japan, and 11.577 for the case where either buyer or seller is located in Japan).

B2. CCP or that in non-CCP

	CCP			Non-CCP		
	All samples	Good periods	Bad periods	All samples	Good periods	Bad periods
Link ratio	—	—	—	7.045** (2.978)	2.619 (3.890)	11.917** (5.891)
Maturity	2.505** (0.972)	2.950*** (0.724)	5.058*** (0.000)	0.408* (0.217)	0.314 (0.431)	0.400 (0.253)
Maturity (squared)	-0.009 (0.011)	-0.019*** (0.006)	-0.022*** (0.000)	0.002 (0.002)	0.002 (0.003)	0.003 (0.002)
Notional principal	0.048 (0.804)	-0.298 (0.785)	0.000 (0.000)	0.094 (0.168)	0.375 (0.312)	-0.211 (0.201)
Notional principal (squared)	0.001 (0.005)	0.004 (0.005)	—	-0.001 (0.002)	-0.003 (0.003)	-0.001 (0.003)
Observations	432	417	15	32,182	15,886	16,296
R^2	0.992	0.995	1.000	0.888	0.941	0.839
Fixed effects						
Reference × date	Yes	Yes	Yes	Yes	Yes	Yes
Seller× month/year	Yes	Yes	Yes	Yes	Yes	Yes
Buyer × month/year	Yes	Yes	Yes	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: This table reports the results of transaction-level panel regressions in which CDS price is regressed on Link ratio and a bunch of control variables. All specifications include time-reference ID, time-seller ID and time-buyer ID fixed effects. Link ratio denotes the ratio of link $(Link_{s,t}/Link_{b,t})$. In this table, the sample is limited by whether the transaction is cleared at CCP or not: In columns 1-3, the sample is limited to the case where the transaction is centrally cleared. In columns 4-6, the sample is limited to the case where the transaction is not centrally cleared. Column "All samples" shows the results of all transactions. In columns "Good periods" and "Bad periods", we divide samples depending on the level of iTraxx Japan on the day when the transaction takes place. The sample period is from April 1, 2013 to December 31, 2021. We report clustered standard errors (by time and reference) in parentheses. ***, **, * denotes significance at 1%, 5%, and 10% confidence level, respectively. We observe the centrality premium (i.e., 7.045 for all samples in non-CCP, and 11.917 for bad periods in non-CCP).

B3. D2C or C2D

	D2C			C2D		
	All samples	Good periods	Bad periods	All samples	Good periods	Bad periods
Link ratio	6.962** (3.363)	2.713 (3.970)	13.916* (7.520)	7.114** (2.992)	2.694 (3.912)	11.745** (5.653)
Type dummy	-0.001 (9.924)	0.014 (198320.004)	—	249.783 (7694.999)	722.770 (87538.249)	1681.168 (24961.307)
Link ratio × Type dummy	0.397 (4.697)	-7.638 (9.258)	-4.941 (7.640)	3.888 (6.541)	6.305 (6.153)	-10.175 (65.502)
Maturity	0.421* (0.216)	0.380 (0.420)	0.399 (0.253)	0.421* (0.216)	0.381 (0.420)	0.399 (0.253)
Maturity (squared)	0.002 (0.002)	0.001 (0.003)	0.003 (0.002)	0.002 (0.002)	0.001 (0.003)	0.003 (0.002)
Notional principal	-0.103 (0.164)	0.338 (0.300)	-0.211 (0.201)	-0.103 (0.164)	0.339 (0.300)	-0.211 (0.201)
Notional principal (squared)	-0.001 (0.002)	-0.003 (0.003)	-0.001 (0.003)	-0.001 (0.002)	-0.003 (0.003)	-0.001 (0.003)
CCP dummy	-2.091 (7.101)	-4.933 (5.893)	-2086.489 (20568.355)	-2.091 (7.101)	-4.938 (5.893)	-2147.066 (20906.030)
Observations	32,614	16,303	16,311	32,614	16,303	16,311
R^2	0.888	0.943	0.839	0.888	0.943	0.839
Fixed effects						
Reference × date	Yes	Yes	Yes	Yes	Yes	Yes
Seller× month/year	Yes	Yes	Yes	Yes	Yes	Yes
Buyer × month/year	Yes	Yes	Yes	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: This table reports the results of transaction-level panel regressions in which CDS price is regressed on Link ratio and a bunch of control variables. All specifications include time-reference ID, time-seller ID and time-buyer ID fixed effects. Link ratio denotes the ratio of link $(Link_{s,t}/Link_{b,t})$. In this table, the sample is limited to D2C (dealer to customer transaction) or C2D (customer to dealer transaction). Here, dealers are defined as "foreign securities", "foreign banks", and "Japanese securities". In column 1-3, the transaction is between dealers (sellers) and customers (buyers). In column 4-6, the transaction is between customers (sellers) and dealers (buyers). Column “All samples” shows the results of all transactions. In columns “Good periods” and “Bad periods”, we divide samples depending on the level of iTraxx Japan on the day when the transaction takes place. The sample period is from April 1, 2013 to December 31, 2021. We report clustered standard errors (by time and reference) in parentheses. ***, **, * denotes significance at 1%, 5%, and 10% confidence level, respectively. We observe the centrality premium in bad periods (i.e., 13.916 for D2C, and 11.745 for C2D).

B4. Either inter- or intra-group transactions

	Intra-group transactions			Not Intra-group transactions		
	All samples	Good periods	Bad periods	All samples	Good periods	Bad periods
Link ratio	—	1.828 (190601.842)	—	7.108** (2.973)	2.835 (3.875)	11.983** (5.892)
Maturity	0.691 (1.332)	0.678 (1.310)	1.761*** (0.014)	0.424* (0.218)	0.418 (0.444)	0.399 (0.253)
Maturity (squared)	-0.009 (0.014)	-0.010 (0.014)	—	0.002 (0.002)	0.002 (0.003)	0.003 (0.002)
Notional principal	1.164** (0.499)	1.208** (0.504)	-0.580*** (0.219)	-0.137 (0.168)	0.266 (0.343)	-0.211 (0.201)
Notional principal (squared)	-0.017*** (0.006)	-0.017** (0.006)	0.011** (0.004)	-0.001 (0.002)	-0.002 (0.003)	-0.001 (0.003)
CCP dummy	—	—	—	-1.954 (7.106)	-4.601 (5.746)	-4721.045 (21199.804)
Observations	809	715	94	31805	15588	16217
R^2	0.897	0.865	1.000	0.889	0.946	0.838
Fixed effects						
Reference × date	Yes	Yes	Yes	Yes	Yes	Yes
Seller× month/year	Yes	Yes	Yes	Yes	Yes	Yes
Buyer × month/year	Yes	Yes	Yes	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: This table reports the results of transaction-level panel regressions in which CDS price is regressed on Link ratio and a bunch of control variables. All specifications include time-reference ID, time-seller ID and time-buyer ID fixed effects. Link ratio denotes the ratio of link $(Link_{s,t}/Link_{b,t})$. In this table, the sample is limited to whether the transaction is either inter-/intra-group or not: In column 1-3, the transaction is either inter- or intra-group transaction. In column 4-6, the transaction is neither inter- nor intra-group transaction. Column "All samples" shows the results of all transactions. In columns "Good periods" and "Bad periods", we divide samples depending on the level of iTraxx Japan on the day when the transaction takes place. The sample period is from April 1, 2013 to December 31, 2021. We report clustered standard errors (by time and reference) in parentheses. ***, **, * denotes significance at 1%, 5%, and 10% confidence level, respectively. We observe the centrality premium for the transaction with neither inter- nor intra-group (i.e., 7.108 for all periods, and 11.983 for bad periods).

B5. Newly established relations

	Newly established relations			Not newly established relations		
	All samples	Good periods	Bad periods	All samples	Good periods	Bad periods
Link ratio	5.665 (134409.592)	—	8.216 (135360.695)	8.920*** (2.402)	10.579* (5.621)	5.301*** (1.958)
Maturity	1.228** (0.542)	1.526** (0.691)	1.447 (0.911)	0.392* (0.224)	0.378 (0.262)	0.313 (0.459)
Maturity (squared)	-0.004 (0.004)	-0.005 (0.005)	-0.012 (0.009)	0.003 (0.002)	0.003 (0.002)	0.002 (0.003)
Notional principal	0.187 (0.420)	-0.121 (0.673)	0.904* (0.477)	-0.121 (0.168)	-0.202 (0.199)	0.328 (0.353)
Notional principal (squared)	-0.004 (0.005)	-0.001 (0.007)	-0.015** (0.006)	-0.001 (0.002)	-0.001 (0.003)	-0.002 (0.003)
CCP dummy	—	—	—	-2.143 (7.045)	-2047.124 (20929.545)	-5.081 (5.935)
Observations	1,650	725	925	30,964	15,586	15,378
R^2	0.879	0.860	0.89	0.893	0.845	0.946
Fixed effects						
Reference × date	Yes	Yes	Yes	Yes	Yes	Yes
Seller× month/year	Yes	Yes	Yes	Yes	Yes	Yes
Buyer × month/year	Yes	Yes	Yes	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: This table reports the results of transaction-level panel regressions in which CDS price is regressed on Link ratio and a bunch of control variables. All specifications include time-reference ID, time-seller ID and time-buyer ID fixed effects. Link ratio denotes the ratio of link $(Link_{s,t}/Link_{b,t})$. In this table, the sample is limited to whether the transaction is newly established or not. The newly established transaction means that the pair of parties to the transaction in question is trading for the first time (considering direction): In column 1-3, the transaction is newly established. In column 4-6, the transaction is not newly established. Column "All samples" shows the results of all transactions. In columns "Good periods" and "Bad periods", we divide samples depending on the level of iTraxx Japan on the day when the transaction takes place. The sample period is from April 1, 2013 to December 31, 2021. We report clustered standard errors (by time and reference) in parentheses. ***, **, * denotes significance at 1%, 5%, and 10% confidence level, respectively. We observe the centrality premium for the not newly established transaction.

B6. Transacting more than a certain number throughout the data periods

	Coefficient of Link ratio			Observations		
	All samples	Good periods	Bad periods	All samples	Good periods	Bad periods
More than 2 months	7.123** (2.988)	2.822 (3.904)	12.030** (5.912)	32,614	16,303	16,311
More than 3 months	7.289** (2.998)	2.879 (3.916)	11.902** (5.869)	31,869	15,637	16,232
More than 5 months	7.397** (3.028)	2.906 (3.967)	12.124** (5.886)	31,781	15,576	16,205
More than 10 months	9.697*** (2.572)	5.386*** (1.885)	12.230** (5.895)	31,577	15,474	16,103
More than 20 months	9.794*** (2.719)	6.272*** (0.003)	18.459 (12.023)	31,139	15,223	15,916
More than 30 months	7.733 (4.899)	-10.313 (148.383)	8.196** (3.345)	30,036	14,693	15,343
Fixed effects						
Reference × date	Yes	Yes	Yes	Yes	Yes	Yes
Seller× month/year	Yes	Yes	Yes	Yes	Yes	Yes
Buyer × month/year	Yes	Yes	Yes	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: This table reports the results of transaction-level panel regressions in which CDS price is regressed on Link ratio and a bunch of control variables. All specifications include time-reference ID, time-seller ID and time-buyer ID fixed effects. Link ratio denotes the ratio of link $(Link_{s,t}/Link_{b,t})$. Column 1-3 shows only the regression coefficients of the link ratios, with the sample divided and regressed according to how many months each trading pair transacted during the sample period. Column 4-6 show the number of samples divided according to the month of each transaction. Column "All samples" shows the results of all transactions. In columns "Good periods" and "Bad periods", we divide samples depending on the level of iTraxx Japan on the day when the transaction takes place. The sample period is from April 1, 2013 to December 31, 2021. We report clustered standard errors (by time and reference) in parentheses. ***, **, * denotes significance at 1%, 5%, and 10% confidence level, respectively.

REFERENCES

Bolton P, Freixas X, Gambacorta L, Mistrulli P E (2016) Relationship and Transaction Lending in a Crisis. The Review of Financial Studies, 29(10):2643-2676.

Cenedese G, Ranaldo A, Vasios M (2020) OTC premia. Journal of Financial Economics, 136(1):86-105.

Cereda F, Chague F, De-Losso R, Genaro A, Giovannetti B (2022) Price transparency in OTC equity lending markets: Evidence from a loan fee benchmark. Journal of Financial Economics, 143(1): 569-592.

Cocco JF, Gomes FJ, Martins NC (2009) Lending relationships in the interbank market. Journal of Financial Intermediation 18(1):24–48.

Du W, Gadgil S, Gordy MB, Vega C (2023) Counterparty Risk and Counterparty Choice in the Credit Default Swap Market. Management Science 0(0).

Duffie D, Gârleanu N, Pedersen L (2005) Over-the-counter markets. Econometrica 73(6):1815–1847.

Duffie D, Gârleanu N, Pedersen L (2007) Valuation in Over-the-Counter Markets. The Review of Financial Studies, 20(6):1865-1900.

Duffie D (2012) Dark Markets: Asset Pricing and Information Transmission in Over-the-Counter Markets (Princeton University Press, Princeton, NJ).

Di Maggio M, Kermani A, Song Z (2017) The value of trading relations in turbulent times. Journal of Financial Economics. 124(2):266–284.

Eisfeldt AL, Herskovic B, Rajan S, Siriwardane E (2023) OTC intermediaries. The Review of Financial Studies, 36(2): 615-677.

FSB (2010) Implementing OTC Derivatives Market Reforms. October, 2010.

FSB (2022) FSB Progress Report: Implementing OTC Derivatives Market Reforms Implementation progress in 2022. November, 2022.

Gabrieli S, Georg CP (2017) A network view on Interbank Liquidity. Deutsche Bundesbank Discussion Paper 44/2014, Banque de France Working Paper No. 531.

Glode V, Green RC, Lowery R (2012) Financial Expertise as an Arms Race, Journal of Finance, 67(5): 1723-1759.

Hasbrouck J, Levich R M (2021) Network structure and pricing in the FX market, Journal of Financial Economics, 141(2): 705-729.

Hau H, Hoffmann P, Langfield S, Timmer Y (2021) Discriminatory Pricing of Over-the-Counter Derivatives. Management Science 67(11): 6660-6677.

Hendershott T, Li D, Livdan D, Schurhoff N (2020) Relationship trading in OTC markets. Journal of Finance 75(2):683–734.

Hollifield B, Neklyudov A, Spatt C (2017) Bid-ask spreads, trading networks, and the pricing of securitizations. The Review of Financial Studies, 30(9): 3048–3085.

Kawai D, Hasegawa M, Yagi R (2021) An Analysis of the Transaction Network in the Japanese OTC Derivatives Markets. FSA Staff Reports, Policy and Markets Bureau, FSA. Accessed Dec 12, 2023, https://www.fsa.go.jp/frtc/english/seika/srhonbun/20210707_SR_Derivative_ArticleEN.pdf.

Kim M, Kliger D, Vale B (2003) Estimating switching costs: the case of banking. Journal of Financial Intermediation, 12, 25-56.

Li D, Schürhoff N (2019) Dealer Networks. Journal of Finance, 74(1): 91-144.

Loon YC, Zhong, ZK (2016) Does Dodd-Frank Affect OTC Transaction Costs and Liquidity? Evidence from Real-Time CDS Trade Reports. Journal of Financial Economics, 119(3): 645–672.

Mallick I (2004) Inefficiency of bilateral bargaining in interbank markets. International Review of Economics & Finance 13(1), 43-55.

Miyakawa D, Oda T, Sone T (2023) Regulatory Reforms and Price Heterogeneity in an OTC Derivative Market, Bank of Japan Working Paper Series 23-E-12, Bank of Japan.

OECD (2009) Leaders' Statement. The Pittsburgh Summit, September 24-25, 2009.

Schultz P (2024) Short Squeezes and Their Consequences. Journal of Financial and Quantitative Analysis. 59(1): 68-96.

Yoshizaki Y, Inoue M, Shiotani K (2017) Recent Trends in OTC Derivatives Markets --Highlights Observed through OTC Derivatives Statistics—, Bank of Japan Review Series, 17-E-4.