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# Market Structure and Transaction Costs of Index CDSs

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## ABSTRACT

Despite regulatory efforts to promote all-to-all trading, the post–Dodd-Frank index credit default swap market remains two-tiered. Transaction costs are higher for dealer-to-client than interdealer trades, but the difference is explained by the higher, largely permanent, price impact of client trades. Most interdealer trades are liquidity motivated and executed via low-cost, low-immediacy trading protocols. Dealer-to-client trades are nonanonymous; they almost always improve upon contemporaneous executable interdealer quotes, and dealers appear to price discriminate based on the perceived price impact of trades. Our results suggest that the market structure is a consequence of the characteristics of client trades: relatively infrequent, large, and differentially informed.

THE INDEX CREDIT DEFAULT SWAP (CDS) market constitutes an important component of the corporate credit market. Index CDSs allow banks, asset managers, and other institutional investors to efficiently hedge and trade

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aggregate credit risk in the economy. Unlike single-name CDSs, index CDSs have remained popular since the financial crisis, with tens of billion dollars of notional amount traded on a daily basis. Nevertheless, little is known about the cost of trading in this important market.

The index CDS market is also interesting as a test case of how recent regulation introduced in the wake of the financial crisis affects the structure of swap markets. Since its inception in 2003, the index CDS market has operated as a classic two-tiered over-the-counter (OTC) market in which global derivatives dealers provide liquidity to clients in the dealer-to-client (D2C) segment of the market, and dealers trade among themselves in the interdealer (D2D) segment of the market. New swap market regulation following the Dodd-Frank Act had the potential to change this market structure by mandating that trades in the most liquid index CDSs be executed on so-called swap execution facilities (SEFs).[1] These regulated trading platforms are required to offer trading in order books, which opens the market to all-to-all trading where clients can compete with dealers for liquidity provision. However, the regulation also allows for trading via request for quote (RFQ) provided that at least three dealers are put in competition for trades.[2] Interestingly, several years after the new regulation was fully implemented, all-to-all trading has yet to materialize. Instead, the two-tiered market structure persists, with D2C trades taking place on one group of SEFs (almost exclusively via name-disclosed RFQs) and D2D trades taking place on another group of SEFs (via a diverse set of anonymous trading protocols).[3]

From both a regulatory and a market design perspective, it is important to understand the persistence of this bifurcated market structure. Indeed, given that index CDSs are highly standardized and centrally cleared, and the most liquid of them trade in large volumes, the lack of all-to-all trading may seem puzzling (see, for example, Duffie (2012)).

One view is that dealers have market power and therefore a vested interest in maintaining a two-tiered market structure to limit competition from nondealer liquidity providers (see, for example, Managed Funds Association (2015)). An alternative view is that the two-tiered market structure is a consequence of the nature of client order flow. If clients trade infrequently but in

[1] Other key elements of the new swap market regulation are posttrade transparency via the immediate public dissemination of trades as well as mandatory central clearing of index CDSs with standardized contract terms.

[2] RFQ is an electronic trading protocol in which executable prices for a given notional amount are requested simultaneously from multiple dealers. In a name-disclosed RFQ, the quote requester reveals his identity. Compared to traditional trading in OTC markets, where dealers are contacted sequentially, the RFQ protocol increases quote competition between dealers.

[3] Referring to both the index CDS and the interest rate swap markets, a recent article summarizes the current situation as follows: "...dealer banks still trade together privately in one segment of the market and the buy side still executes via RFQ to the dealers in another. Proponents of this view say that nothing really changed in terms of how firms execute swaps except that the buy side has gone from RFQ-ing one dealer to RFQ-ing three. This appears to be in stark contrast to the all-to-all trading model envisioned for the swaps markets by regulators under Dodd-Frank." See "SEFs: A Market Divided," *Profit & Loss*, October 22, 2015.

large sizes, then dealers' willingness to absorb sizeable supply and demand imbalances may depend on the existence of an interdealer market to manage inventory risk.[4] Moreover, if clients are differentially informed, dealers may mitigate adverse selection risk by trading nonanonymously with clients and using heterogeneous trading protocols in the anonymous interdealer market. To help distinguish between these two views, we conduct a detailed empirical study of client and dealer trade characteristics and transaction costs in the post–Dodd-Frank index CDS market.

Using transaction data from October 2, 2013 (when the first SEFs started operating), to October 16, 2015, we focus on the two most popular credit indices, CDX.IG and CDX.HY, which, respectively, cover the investment-grade and high-yield components of the North American corporate credit market. The transaction data include execution timestamps, transaction prices, and trade sizes up to certain notional caps. In addition, we develop algorithms that allow us to identify the SEF on which a trade took place and the type of trade (outright trade, index roll, curve trade, or delta hedge of an index swaption or tranche swap). Outright trades in five-year CDSs on the most recently issued (on-the-run) index account for the majority of trading volume. These trades are the focus of the paper. The SEF on which the trade took place in turn reveals whether the trade is D2C or D2D.[5]

We find that trading volumes are large, but much larger in the D2C than the D2D segment. The average daily notional amounts across all types of trades in the D2C segment are USD 9.843 billion for CDX.IG and USD 3.705 billion for CDX.HY. In the D2D segment, the corresponding figures are USD 1.354 billion and USD 0.402 billion. The client order flow consists of relatively few trades of large size. For CDX.IG, for example, there are on average 114 client trades per day with a median trade size of USD 50 million.

We next document differences between transaction costs of D2C and D2D trades and investigate whether these can be attributed to differences in price impacts or differences in dealer profits. We measure transaction costs using the effective half-spread, which is the difference between the transaction price and the mid-point of contemporaneous quotes to buy or sell protection (henceforth, the mid-quote). We measure price impact as the change in the mid-quote over a period of approximately 15 minutes following a trade. Throughout the paper, we express transaction prices and quotes in terms of par spreads.[6] For D2C

[4] This view is expressed, for instance, by the new chairman of the Commodity Futures Trading Commission (CFTC), who writes that "[dealers] compete with each other, often deriving small profits per trade from a large volume of transactions," "[they] offer competitive prices to their customer base," and "[w]ithout access to D2D markets, the risk inherent in holding swaps inventory arguably would require dealers to charge their buy-side customers much higher prices for taking on their liquidity risk, assuming they remained willing to do so." See Giancarlo (2015).

[5] Because we identify D2C and D2D trades based on the SEF on which the trade took place, our sample is limited to the period during which SEFs were in operation and to trades that are executed on SEFs.

[6] The par spread is the annual insurance premium, as a percentage of the notional amount, such that the present value of the index CDS is zero for both the buyer and the seller at the outset of the trade.

trades, we compute effective half-spreads and price impacts using intraday quotes from Markit, which are composites of indicative quotes sent by dealers to clients. For D2D trades, we use a unique data set of executable inside quotes on the limit order book of the main D2D SEF, namely, the GFI Swaps Exchange (GFI SEF). We find that the transaction costs of D2C trades are higher than those of D2D trades, on average. For CDX.IG, average transaction costs of D2C and D2D trades are 0.138 basis points (bps) and 0.098 bps, respectively, with the difference of 0.040 bps statistically significant. The corresponding figures for CDX.HY are 0.676 bps and 0.494 bps, with the difference of 0.181 bps again statistically significant.[7]

These differences in transaction costs are fully explained by the fact that D2C trades have, on average, a higher price impact than D2D trades—the difference in average price impact is 0.042 bps for CDX.IG and 0.246 bps for CDX.HY. These results hold within each quartile of the trade-size distribution as well as in trade-by-trade regressions that control for trade characteristics and the market conditions that prevail at trade execution.

To shed light on whether price impacts are permanent (information-driven) or transitory (inventory-driven), as well as on which market segment accounts for the majority of the price discovery, we estimate the dynamic interaction between trades and mid-quotes across the two market segments using a cointegrated vector autoregressive (VAR) model in the spirit of Hasbrouck (1995). In line with our findings based on the 15-minute price impact measure described above, the model-implied price impact is higher for D2C trades. In addition, price impact is largely permanent, which is suggestive of clients trading on information. This information-based trading likely reflects the institutional nature of the index CDS market, where clients are professional investors who may have private information about the credit risk of certain index constituents (see, for example, Acharya and Johnson (2007) and Ivashina and Sun (2011)) or may have an advantage over dealers in interpreting public information in relation to the aggregate credit risk in the economy.[8] The relatively low permanent price impact of the average D2D trade is suggestive of dealers mainly using the interdealer market to manage their inventory risk. Consistent with this view, we find one-way Granger causality from D2C trades to D2D trades. In terms of price discovery, D2C trades play a more important role than D2D trades.

[7] To put these transaction costs into perspective, we translate the par-spread cost of each trade into a dollar cost paid upfront per USD 100 of notional amount. For CDX.IG, average dollar costs of D2C and D2D trades are 0.66 cents and 0.48 cents, respectively. The corresponding figures for CDX.HY are 3.04 cents and 2.24 cents. By comparison, Adrian et al. (2017) report an average bid-offer half-spread on the main interdealer limit order book for the five-year on-the-run Treasury note of 0.40 cents, Biswas, Nikolova, and Stahel (2015) report an average effective half-spread for five-year single-name CDSs of 14 cents (for D2C trades in typical sizes of approximately USD 5 million), and Harris (2015) reports an average effective half-spread for corporate par bonds of 39 cents (for institutional-sized D2C trades), all expressed per USD 100 of notional amount.

[8] Consistent with superior information processing by institutional investors, Hendershott, Livdan, and Schürhoff (2015) show that institutional order flow predicts the occurrence and sentiment of news as well as news-announcement-day equity market returns.

Dealers use a number of different trading protocols in the D2D segment of the market. These trading protocols differ in their degree of immediacy. Thus, dealers face a cost-versus-immediacy trade-off when executing trades (see, for example, Zhu (2014) and Menkveld, Yueshen, and Zhu (2017)). The lower overall cost of interdealer trades may therefore be due to the frequent use of low-cost, low-immediacy trading protocols. This may also help explain the differences between D2C and D2D transaction costs.

To explore the segmentation of the interdealer order flow and the variation in transaction costs across trading protocols, we focus on the GFI SEF. In addition to a standard limit order book, the GFI SEF offers two size-discovery trading protocols—mid-market matching and workup—where orders are matched at a known fixed price but execution is uncertain because the size that can be matched is not visible to traders (see, for example, Duffie and Zhu (2017)).[9] Mid-market matching is the dominant trading protocol. For CDX.IG and CDX.HY, it accounts for 52.2% and 58.7% of trading volume, respectively. Workup is also frequently used, accounting for 19.9% and 15.5% of trading volume, while trades in the limit order book account for 19.2% and 15.8% of trading volume. For both indices and all trade sizes, trades in the limit order book have high average transaction costs and large price impacts (both when measured over 15-minute intervals and when inferred from an extended VAR model), even exceeding those of D2C trades. Mid-market matches have significantly lower average transaction costs and price impacts, which is consistent with Zhu's (2014) venue selection model. In his model, liquidity traders prefer a mid-point dark pool (roughly equivalent to mid-market matching) that offers price improvement but does not guarantee execution, while informed traders prefer the certainty of executing against limit orders. For small- and medium-sized trades, workups have average transaction costs similar to trades in the limit order book, while for large trades, workups have lower average transaction costs. The average price impacts of workups are close to zero.

These results suggest that the price of immediacy may be lower in the D2C than the D2D segment. To explore this in more detail, we examine the extent to which dealers improve upon contemporaneous executable interdealer quotes when trading with clients. Specifically, we compare D2C transaction prices to the contemporaneous inside quotes on the GFI limit order book. The average price improvements of D2C trades are 0.229 bps for CDX.IG and 1.291 bps for CDX.HY, with the price improvements strictly positive for 95.8% and 96.4% of the trades in CDX.IG and CDX.HY, respectively. These price

[9] The two trading protocols differ with respect to how the price is fixed, how long orders can be matched, and what information about unfilled interest is available to market participants. In the case of mid-market matching, the price is fixed by a broker, orders can be matched until the next time the broker resets the price, and market participants are informed when there is interest for matching. The direction and size of interest are not revealed. In the case of workup, the price is fixed by an initiating trade in the limit order book, orders can be matched for a short period of time following the initiating trade, and market participants are informed about the direction and size of interest.

improvements are sizeable in relation to the average transaction costs of D2C trades reported above.

Finally, we investigate the role of lack of anonymity in the D2C segment. In principle, this enables dealers to price discriminate according to features other than observable trade characteristics. For each trade-size interval, we sort D2C trades into transaction cost quartiles and find significant dispersion in transaction costs. This dispersion could reflect price discrimination based on the likely information content of trades (see, for example, Seppi (1990), Benveniste, Marcus, and Wilhelm (1992), and Desgranges and Foucault (2005)), the bargaining power of clients (see, for example, Duffie, Gârleanu, and Pedersen (2005)), and/or the value of repeat business (see, for example, Hendershott et al. (2017)). We find that both price impact and dealer profits increase across transaction cost quartiles. The variation in price impact dominates, however, which suggests that dispersion in transaction costs is driven largely by dispersion in the perceived information content of trades.

To summarize, we find that overall transaction costs of index CDSs are low—about an order of magnitude lower than those of single-name CDSs and corporate bonds, and similar to Treasury bonds in the case of CDX.IG.[10] Consistent with previous studies of core-periphery trading structures in OTC markets that document higher trading costs at the periphery, we find that transaction costs are higher for D2C than D2D trades.[11] However, unlike existing literature that typically associates the difference with dealer market power, we find that it is explained by the higher and largely permanent price impact of D2C trades. Consistent with informed trading by clients, we show that D2C trades contribute most to price discovery. Further, we find that the lower average transaction cost and price impact of D2D trades reflect the frequent use of size-discovery trading protocols that forgo immediacy.[12] We also establish that D2C prices almost always improve upon contemporaneous executable interdealer quotes, in contrast to the significant number of trade-throughs documented by Harris (2015) in the corporate bond market. Finally, we show that D2C trades with higher transaction costs also exhibit higher price impact, indicating that the nonanonymity of the RFQ protocol allows dealers to price discriminate across differentially informed trades.

Taken together, our results suggest that the current fragmented market structure is a consequence of the characteristics of client trades—relatively infrequent, large in size, and differentially informed. In particular, our results are consistent with models in which nonanonymous OTC trading arises when

[10] See footnote 7. For earlier studies that also report large transaction costs of corporate bonds, see, for example, Edwards, Harris, and Piwowar (2007), Goldstein, Hotchkiss, and Sirri (2007), and Hendershott and Madhavan (2015).

[11] For recent studies of the core-periphery structure in the corporate bond market, see, for example, Harris (2015) and Di Maggio, Kermani, and Song (2017).

[12] While, to our knowledge, this is the first study of size-discovery mechanisms in swap markets, such trading protocols are widely used in the equity market (in the form of mid-point dark pools) and in the Treasury market (in the form of workups); see, for example, Comerton-Forde and Putniņš (2015) and Fleming and Nguyen (2019).

clients are differentially informed and can signal their "type" to dealers (see, for example, Seppi (1990) and Lee and Wang (2016)). Furthermore, our results on interdealer trading are consistent with models in which an interdealer market emerges to manage inventory risk (see, for example, Atkeson, Eisfeldt, and Weill (2013) and Wang (2016)), as well as with models in which several anonymous trading protocols coexist because of differentially informed order flow (see, for example, Zhu (2014)).

Our evidence suggests that market quality is high in the index CDS market. Whether market fragmentation is welfare improving, however, is controversial in theory and not something we can address empirically.[13]

This paper is related to a large theoretical literature on OTC markets that analyzes the role of dealers and their trading patterns and how they relate to characteristics of clients' liquidity needs (see, for example, Duffie, Gârleanu, and Pedersen (2005), Hugonnier, Lester, and Weill (2015), Neklyudov (2014), Chang and Zhang (2016), Glode and Opp (2016), and Babus and Hu (2017)) as well as to theoretical papers on trading in two-tiered markets (see, for example, Vogler (1997), Viswanathan and Wang (2004), and Dunne, Hau, and Moore (2015)).

The paper is also related to a number of recent studies on how various provisions of the Dodd-Frank Act affect swap market liquidity. Loon and Zhong (2016) show that posttrade transparency and central clearing have a positive effect on liquidity in the index CDS market. Benos, Payne, and Vasios (2020) find that pretrade transparency (the mandate to trade on SEFs) has a positive impact on liquidity in the interest rate swap market. In contrast, we focus on the market structure and transaction costs of index CDSs after the full implementation of the new swap market regulation.[14]

## I. The Index CDS Market

In this section, we describe index CDSs and the structure of the market in which these contracts trade. Furthermore, we discuss regulatory reforms set forth by the Dodd-Frank Act.

### *A. Index CDSs*

A corporate index CDS is a standardized credit derivative contract on a diversified index of companies. Over the life of the contract, the credit protection seller provides default protection on each index constituent and in return receives periodic premium payments according to the "fixed spread" of the contract. At initiation, counterparties exchange an upfront amount equal

[13] Pagano (1989) and Babus and Parlatore (2017) find that liquidity and welfare typically decline with market fragmentation. Glode and Opp (2020), Malamud and Rostek (2017), Babus and Kondor (2018), and Lee and Wang (2016) find instead that welfare can improve with fragmentation under specific conditions.

[14] Using message-level data, Riggs et al. (2018) study the strategic interaction between clients and dealers on D2C SEFs when trading index CDSs.

to the present value of the contract. However, standard market practice is to quote the contract either in terms of "spread" or in terms of "price." The quoted price is one minus the upfront amount per dollar of notional, and the quoted spread—which we refer to as the par spread—is obtained from the upfront using the International Swaps and Derivatives Association (ISDA) CDS Standard Model.[15] We use the spread-quoting convention unless stated otherwise. Typically, contract tenors between one and 10 years can be traded but the five-year tenor is the most liquid.

Twice a year, on the so-called index roll dates in March and September, a new index—or, more precisely, a new series of an index—is launched, with the set of index constituents revised according to credit rating and liquidity criteria.[16] Companies that fail to maintain a credit rating within a specified range, due to either upgrades or downgrades, and companies whose single-name CDSs have deteriorated significantly in terms of their trading activity are replaced by the most actively traded companies that meet the credit rating requirements. Typically, liquidity is concentrated in the most recently launched index series, which is referred to as the on-the-run index. All previously launched index series are referred to as off-the-run indices.

The administrator of the most popular credit indices is Markit. Its benchmark credit indices of investment-grade and high-yield credit risk in North America are CDX.IG and CDX.HY, respectively. The former comprises 125 North American companies with investment-grade credit ratings, while the latter comprises 100 North American companies with noninvestment-grade credit ratings. These indices are the focus of the paper.

### *B. Pre–Dodd-Frank Market Structure*

Index CDSs used to be traded in a relatively opaque two-tiered OTC market. In the D2C segment of the market, dealers provided liquidity to their institutional clients. D2C trades were either negotiated over the phone or executed electronically on trading platforms via name-disclosed RFQs.

In the D2D segment of the market, dealers traded with each other through interdealer brokers. D2D trades were either voice brokered or executed electronically using a range of order book functionalities. Broker intermediation guaranteed that trades were executed anonymously and that access to the interdealer market was restricted to dealers.

[15] In short, using the ISDA CDS Standard Model and assuming a constant recovery (40% for CDX.IG and 30% for CDX.HY), a constant default intensity can be implied from the upfront and the fixed spread. Using this implied intensity and the same model, the quoted spread is then obtained as the fixed spread that would require no upfront payment. Note that when a full term structure of CDS contracts is available, the par spread at a given maturity will differ slightly from the quoted spread because the par spread uses the full term structure of default intensities. For a more in-depth description of index CDSs, including the link between an index CDS and the portfolio of single-name CDSs on the index constituents, see, for example, Junge and Trolle (2015).

[16] An index's series number uniquely determines the reference entities in the index.

### *C. The Dodd-Frank Act and Current Market Structure*

The Dodd-Frank Act tasked the CFTC with regulating the index CDS market in an effort to promote financial stability as well as post- and pretrade transparency. Pursuing these objectives, the CFTC enacted a clearing requirement for index CDSs with standardized contract terms as well as reporting and trade execution requirements.[17]

The reporting requirement mandates real-time trade reporting of all index CDS trades to so-called swap data repositories (SDRs). SDRs publicly disseminate the received transaction data. Dissemination is immediate unless the trade qualifies as a block, in which case dissemination is delayed by at least 15 minutes.[18]

The trade execution requirement mandates that the most liquid index CDSs trade on SEFs via one of two trading functionalities: an order book or an RFQ that is transmitted to at least three other market participants on the SEF.[19] Since the trade execution requirement took effect, trades in five-year on-the-run and immediate off-the-run index CDSs on CDX.IG and CDX.HY have been subject to the requirement.[20] Block trades are exempt from the trade execution requirement.

Implementation of the Dodd-Frank Act provisions for index CDSs was rolled out in stages over a period of about one year. For dealers the reporting requirement took effect on December 31, 2012, and the clearing requirement took effect on March 11, 2013. By the time the first SEFs started operating on October 2, 2013, the trade reporting and clearing requirements were in effect for all market participants. Finally, the trade execution requirement took effect on February 26, 2014. Section I of the Internet Appendix provides additional details concerning the CFTC's implementation of the Dodd-Frank Act provisions.[21]

Through the introduction of SEFs and the requirement that they offer trading in order books, the new regulation had the potential to open the index

[17] See Code of Federal Regulations (CFR), Title 17, Chapter I, Parts 50, 43, and 37 and Section 2(h) of the Commodity Exchange Act (CEA).

[18] Block trades have notional amounts that exceed certain minimum block sizes and are exempt from immediate dissemination to protect liquidity providers in block-sized trades from front running. Minimum block sizes depend on the par spread and contract tenor (see CFR, Title 17, Chapter I, Part 43, Appendix F for details).

[19] The regulatory definition of an order book is relatively broad. Specifically, an order book is a "...trading system or platform in which all market participants in the trading system or platform have the ability to enter multiple bids and offers, observe or receive bids and offers entered by other market participants, and transact on such bids and offers" (see CFR, Title 17, Chapter I, §37.3(a)(3)). For an interim one-year period, it was sufficient to transmit RFQs to at least two other participants.

[20] In addition, trades in five-year on-the-run and immediate off-the-run index CDSs on iTraxx Europe and iTraxx Europe Crossover are subject to the trade execution requirement. iTraxx Europe and iTraxx Europe Crossover are Markit's benchmark credit indices of investment-grade and high-yield credit risk in Europe.

[21] The Internet Appendix may be found in the online version of this article.

CDS market to all-to-all trading.[22] However, several years into the new regulatory regime, the index CDS market remains two-tiered. The D2C segment of the market migrated onto SEFs run by incumbent operators of D2C trading platforms where trades are executed almost exclusively via name-disclosed RFQs.[23] These SEFs—Bloomberg SEF, ICE Swap Trade, MarketAxess SEF, and TW SEF—are collectively referred to as D2C SEFs. The D2D segment of the market migrated onto SEFs run by interdealer brokers where trades are executed via a diverse set of anonymous trading protocols that qualify as order book functionalities for regulatory purposes.[24] These SEFs—GFI SEF, ICAP SEF, tpSEF, and Tradition SEF—are collectively referred to as D2D SEFs.

## II. Data and Identification Algorithms

In this section, we describe the transaction and quote data and the algorithms we use to identify SEFs and package transactions.

### A. Transaction Data

Our empirical analysis is based on transaction data over a two-year period from October 2, 2013, to October 16, 2015. The data come from the three SDRs that disseminate trade reports of index CDS transactions: the Bloomberg Swap Data Repository (BSDR), the Depository Trust & Clearing Corporation Data Repository (DDR), and the Intercontinental Exchange Trade Vault (ICETV). Trade reports contain execution timestamps, transaction prices, and trade sizes up to a cap of at least USD 100 million,[25] and they indicate whether the trade is centrally cleared, whether it features nonstandard (or bespoke) contract terms, and whether it is subject to an end-user exception that exempts the trade from the clearing and trade execution requirements.[26] The trade reports also indicate whether the trade is executed on a SEF, but they do not specify on which one. They also do not specify whether the trade is part of a package, that is, a transaction that involves more than one index CDS or an index CDS and another instrument, such as an index swaption or tranche

[22] Indeed, when discussing the benefits of SEF rules, the CFTC stated that the "...rules provide for an anonymous but transparent order book that will facilitate trading among market participants directly without having to route all trades through dealers." See 78 Federal Register at 33565 (June 4, 2013).

[23] It might seem that the RFQ protocol protects dealers from quote competition by nondealers. However, the regulation stipulates that when a client submits an RFQ, the SEF must return to the requester not only the dealer quotes but also any resting limit orders on the limit order book. This, in principle, enables quote competition by all market participants.

[24] Although trading is anonymous pretrade, most D2D SEFs practice posttrade name give-up whereby anonymously matched traders learn about the identity of their counterparty after the trade is executed.

[25] The actual cap size is the greater of USD 100 million and the minimum block size (see CFR, Title 17, Chapter I, §43.4(h)).

[26] This would be the case if one counterparty is a nonfinancial entity that uses the trade to hedge commercial risks (see Sections 2(h)(7) and 2(h)(8) of the CEA).

swap (both of which are conventionally traded with delta; see below).[27] Fortunately, SEFs and package transactions can be identified from trade reports when the transaction data are restricted to trades that are executed on SEFs. It should be emphasized that limiting the sample to trades executed on SEFs is not restrictive because we focus on trades in the most actively traded five-year on-the-run index CDSs. As of February 26, 2014, trades in these index CDSs are required to be executed on SEFs. In the initial period from October 2, 2013, to February 25, 2014, on-SEF trade execution was not mandatory for these index CDSs but the majority of trades were nonetheless executed on SEFs (see Section V of the Internet Appendix).

### *B. Identification of SEFs*

In devising the SEF identification algorithm, we use SEF-reported trading volumes from Clarus FT.[28] Each of the on-SEF trade reports must have been submitted by one of the eight aforementioned SEFs. Bloomberg SEF submits trade reports to the BSDR, and ICE Swap Trade submits trade reports to the ICETV. The remaining SEFs submit trade reports to the DDR. The SEF submitting the trade report can be identified based on the format of the trade report. Specifically, we associate with each SEF the format of trade reports whose aggregate trade size corresponds to the SEF-reported trading volume over our sample period (see Section II of the Internet Appendix). The SEF on which a trade is executed reveals whether the trade is D2C or D2D.

### *C. Identification of Package Transactions*

We identify four popular types of package transactions: index rolls, curve trades, delta-hedged index swaptions, and delta-hedged index tranche swaps (see Section II of the Internet Appendix). A typical index roll involves an on-the-run and an off-the-run index CDS with the same contract tenor. Protection is sold on one index series and simultaneously bought on the other. Index rolls are popular because many institutional investors like to maintain liquid credit exposure with a relatively constant maturity profile. We identify index rolls as simultaneously executed index CDS trades on the same SEF that have the same contract tenor and reference two different series of the same index.

A typical curve trade involves two index CDSs with different contract tenors.[29] Protection is sold on one contract tenor and simultaneously bought on the other. Curve trades are popular because they are relatively directional (index CDS term structures tend to become flatter when spreads widen and

[27] Other important trade characteristics are not specified in the trade reports. For instance, trade reports do not specify whether the trade is buyer- or seller-initiated, whether it is D2C or D2D, or which trading protocol is used to execute the trade.

[28] Clarus FT is the standard data source for SEF-reported daily trading volumes. In Section III of the Internet Appendix, we describe the Clarus FT data in detail.

[29] The two index CDSs typically reference the same index series, but there also exist curve trades in which the two index CDSs reference different index series.

steeper when spreads contract; see, for example, Erlandsson, Ghosh, and Rennison (2008)) and require less capital outlay than outright index CDS trades. We identify curve trades as simultaneously executed index CDS trades on the same SEF that have different contract tenors and reference the same index (but not necessarily the same index series).

We also account for the fact that index swaptions and tranche swaps are conventionally traded "with delta," that is, together with a delta hedge in the corresponding index CDS. Quotes of index swaptions and tranche swaps incorporate both the delta and the so-called "reference level" at which the delta hedge will be traded. Usually, the reference level is set close to the par spread at which the index CDS trades at the beginning of the trading day (see, for example, Hünseler (2013)), but it may be updated throughout the trading day because of spread movements. For CDX.IG, the reference level is usually set in spread multiples of 0.5 bps.[30] We identify index swaption and tranche swap delta hedges as index CDS trades that have the same underlying index and contract tenor as an index swaption or tranche swap trade. Trade executions must be near simultaneous and notional amounts must be reconcilable with a delta that is quoted on the same trading day.

Index swaptions and tranche swaps can also be traded without delta but usually at less favorable prices that incorporate the dealer's cost of establishing the hedge. Therefore, investors may find it beneficial to trade index swaptions and tranche swaps with delta and unwind the hedge themselves (see, for example, Hünseler (2013)). We identify such delta unwinds as trades with the same transaction price and notional amount as a delta hedge of an index swaption or tranche swap trade that occurs on the same trading day and on the same SEF.

### *D. Descriptive Statistics of On-SEF Trades*

Table I displays descriptive statistics for the enriched transaction data that allow us to distinguish between D2C and D2D trades and between outright trades and package transactions. Descriptive statistics are computed separately for D2C and D2D trades in CDX.IG (Panels A1 and A2, respectively) and CDX.HY (Panels B1 and B2, respectively) and, within these broad categories of trades, they are computed separately for trades executed on a given SEF.

The index CDS market is characterized by relatively few trades in very large sizes. For CDX.IG, there are 114 D2C trades and 24 D2D trades per day, on average, and the median trade size is USD 50 million in both segments. For CDX.HY, there are somewhat more trades (164 D2C trades and 27 D2D trades per day, on average), but the median trade size is smaller (USD 10 million in both segments) because of the significantly higher volatility of high-yield contracts.

[30] Because CDX.HY is price-quoted instead of spread-quoted, the reference level is usually set in price multiples of 0.125%.

**Table I**

**Descriptive Statistics for On-SEF Index CDS Trades**

The table shows descriptive statistics for on-SEF dealer-to-client (D2C) and dealer-to-dealer (D2D) index CDS trades in CDX.IG and CDX.HY by SEF. Trds is the number of trades per day, computed as the total number of trades divided by the number of trading days in the sample period, 511. Sz is median trade size. Vlm is daily volume, computed as the aggregate notional amount divided by the number of trading days in the sample period (ActVlm is actual daily volume computed equivalently using daily volumes reported by SEFs). 5Y (OTR) is the percentage of trades in five-year (on-the-run) index CDSs. Bspk is the percentage of trades with bespoke contract terms. Clrd is the percentage of cleared trades. Blck is the percentage of trades that qualify as block trades. Cppd is the percentage of trades that are disseminated with capped notional amounts. Crv (Rll) is the percentage of the aggregate notional amount that is identified as being part of curve trades (index rolls). Swptn (Trnch) is the percentage of the aggregate notional amount that is identified as index swaption (index tranche swap) delta hedges. The sample period is October 2, 2013, to October 16, 2015. The sample comprises 58,224 (12,397) and 83,773 (13,585) D2C (D2D) trades in CDX.IG and CDX.HY, respectively.

| | | USD MM | | % of Trds | | | | | | % of Vlm | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| SEF | Trds | Sz | Vlm (ActVlm) | 5Y | OTR | Bspk | Clrd | Blck | Cppd | Crv | Rll | Swptn | Trnch |
| Panel A1: CDX.IG Dealer-To-Client | | | | | | | | | | | | | |
| Bloomberg SEF | 95 | 50 | 5,394 (7,681) | 99.7 | 93.5 | 0.0 | 100.0 | 20.1 | 19.4 | 0.1 | 4.5 | 0.0 | — |
| ICE Swap Trade | 3 | 44 | 154 (318) | 98.0 | 90.1 | 0.0 | 84.1 | 27.2 | 32.5 | 0.1 | 0.0 | 16.9 | 6.5 |
| MarketAxess SEF | 5 | 37 | 282 (533) | 99.0 | 89.7 | 0.0 | 100.0 | 25.0 | 26.1 | 0.2 | 13.1 | 0.6 | — |
| TW SEF | 11 | 50 | 605 (1,310) | 98.9 | 84.8 | 0.0 | 100.0 | 28.4 | 31.5 | 0.0 | 7.3 | — | — |
| Total | 114 | 50 | 6,434 (9,843) | 99.6 | 92.4 | 0.0 | 99.6 | 21.3 | 21.2 | 0.1 | 5.0 | 0.4 | 0.2 |
| Panel A2: CDX.IG Dealer-To-Dealer | | | | | | | | | | | | | |
| GFI Swaps Exchange | 17 | 50 | 773 (808) | 96.1 | 91.6 | 0.7 | 99.3 | 0.0 | 3.9 | 4.7 | 16.9 | 3.2 | 1.9 |
| ICAP SEF | 1 | 25 | 58 (71) | 75.8 | 71.2 | 0.0 | 94.9 | 0.0 | 9.7 | 0.0 | 0.0 | 7.4 | 51.8 |
| tpSEF | 6 | 50 | 351 (445) | 94.8 | 86.9 | 0.0 | 96.0 | 2.2 | 14.1 | 4.7 | 21.9 | 1.7 | 0.0 |
| Tradition SEF | 0 | 79 | 19 (30) | 78.7 | 63.8 | 0.0 | 72.4 | 0.0 | 27.6 | 0.0 | 0.0 | 61.6 | 35.0 |
| Total | 24 | 50 | 1,201 (1,354) | 94.8 | 89.3 | 0.5 | 98.0 | 0.5 | 6.8 | 4.4 | 17.3 | 3.9 | 4.3 |

(*Continued*)

**Table I**—*Continued*

| SEF | Trds | USD MM | | % of Trds | | | | | | % of Vlm | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Sz | Vlm (ActVlm) | 5Y | OTR | Bspk | Clrd | Blck | Cppd | Crv | Rll | Swptn | Trnch |
| Panel B1: CDX.HY Dealer-To-Client | | | | | | | | | | | | | |
| Bloomberg SEF | 140 | 10 | 2,583 (2,840) | 100.0 | 93.9 | 0.0 | 100.0 | 17.8 | 1.4 | 0.0 | 7.8 | 0.0 | — |
| ICE Swap Trade | 3 | 5 | 68 (77) | 99.7 | 87.9 | 0.0 | 91.0 | 28.3 | 7.2 | 0.0 | 0.1 | 9.9 | 6.5 |
| MarketAxess SEF | 6 | 10 | 138 (150) | 99.9 | 90.8 | 0.0 | 100.0 | 24.5 | 3.9 | 0.0 | 12.1 | 0.2 | — |
| TW SEF | 15 | 16 | 434 (639) | 100.0 | 87.0 | 0.0 | 100.0 | 35.8 | 9.9 | 0.0 | 15.9 | — | — |
| Total | 164 | 10 | 3,224 (3,705) | 100.0 | 93.0 | 0.0 | 99.8 | 19.9 | 2.3 | 0.0 | 8.9 | 0.2 | 0.1 |
| Panel B2: CDX.HY Dealer-To-Dealer | | | | | | | | | | | | | |
| GFI Swaps Exchange | 17 | 10 | 209 (211) | 99.9 | 94.1 | 0.7 | 99.2 | 0.0 | 0.9 | 0.0 | 21.1 | 4.2 | 0.5 |
| ICAP SEF | 1 | 10 | 17 (25) | 98.6 | 68.9 | 0.0 | 87.8 | 0.0 | 0.7 | 0.0 | 0.0 | 13.1 | 45.8 |
| tpSEF | 8 | 10 | 147 (157) | 99.6 | 89.1 | 0.0 | 96.2 | 2.7 | 2.6 | 0.0 | 26.1 | 1.0 | 0.0 |
| Tradition SEF | 0 | 20 | 6 (8) | 95.0 | 68.3 | 0.0 | 79.2 | 0.0 | 1.0 | 0.0 | 0.0 | 49.6 | 36.8 |
| Total | 27 | 10 | 380 (402) | 99.7 | 91.5 | 0.4 | 97.8 | 0.9 | 1.4 | 0.0 | 21.7 | 4.1 | 3.0 |

Trading volumes are large. The average daily D2C trading volumes are USD 9.843 billion for CDX.IG and USD 3.705 billion for CDX.HY. The corresponding D2D trading volumes are USD 1.354 billion and USD 0.402 billion.[31] These averages appear in parentheses in the table because they are based on SEF-reported daily trading volumes from Clarus FT instead of transaction data. They cannot be reproduced with transaction data because trade reports contain capped trade sizes. Indeed, the table shows that the fraction of D2C (D2D) trades that are disseminated with capped notional amounts is 21.2% (6.8%) for CDX.IG and 2.3% (1.4%) for CDX.HY.[32] As a consequence, average daily trading volumes based on transaction data are biased downward.[33]

The vast majority of trades are in the five-year contract tenor and around 90% of trades are in on-the-run index CDSs. Almost all trades have standardized contract terms and are centrally cleared.[34] The fact that there are virtually no D2D block trades, whereas about 20% of D2C trades are blocks, is consistent with the use of order book functionalities on D2D SEFs. This is because block-sized trades that are executed via an order book functionality do not qualify as block trades. Outright trades account for most of the trading volume and among package transactions, index rolls are most popular.

We focus on analyzing transaction costs of outright trades in five-year on-the-run index CDSs. These trades account for 88.5% and 84.6% of D2C trading

[31] D2D trading accounts for 10% (for CDX.HY) to 12% (for CDX.IG) of total volume in the index CDS market. The ISDA 2014 estimates that, in the case of interest rate swaps, D2D trading accounts for 35% of total volume. However, the ISDA argues that as much as two-thirds of D2D trading is due to nonprice-forming trades, such as amendments, novations, and terminations, all of which are excluded from our sample. This brings the ISDA's estimate for interest rate swaps more in line with our estimate for index CDSs.

[32] In comparison to trades in CDX.IG, the percentage of trades that are disseminated with capped notional amounts is lower for trades in CDX.HY because the latter tend to be of smaller size (in absolute terms and relative to the cap). The median size of trades in CDX.IG is five times that of trades in CDX.HY, but caps typically differ by USD 10 million only (for trades in CDX.IG the cap is typically USD 110 million, and for trades in CDX.HY the cap is typically USD 100 million).

[33] Actual volumes allow us to impute the extent to which the size of trades that are disseminated with capped notional amounts exceeds the cap on average. For instance, the size of D2C trades in CDX.IG that are disseminated with capped notional amounts exceeds the cap by USD 141.13 ($= 511 \times (9,843 - 6,434)/(0.212 \times 58,224)$) million, on average (511 is the number of trading days in the sample period). Most of these trades are capped at USD 110 million, suggesting that, conditional on being capped, the average size of D2C trades in CDX.IG is approximately USD 250 million. Similarly, conditional on being capped, the average size of D2D trades in CDX.IG is approximately USD 200 million. For CDX.HY, most trades are capped at USD 100 million and, conditional on being capped, the average sizes of D2C and D2D trades in CDX.HY are approximately USD 225 million and USD 160 million, respectively.

[34] Loon and Zhong (2016) find that bespoke contract terms, central clearing, and a counterparty that qualifies as an end-user are trade characteristics that significantly affect transaction costs of index CDSs. These characteristics cannot be a main driver of potential transaction cost differences between D2C and D2D trades because the vast majority of both D2C and D2D trades are nonbespoke and centrally cleared, and there are few end-user exempt trades in our sample (there are no such trades after February 10, 2014).

volume in CDX.IG and CDX.HY, respectively, and 67.2% and 63.5% of D2D trading volume. For all other trade types, there are either too few trades or too few quotes to reliably measure transaction costs.

### *E. Quote Data*

The quote data come from Markit and GFI. Markit intraday bid and offer quotes are composites of indicative quotes that dealers provide to their clients via electronic messages known as "dealer runs." Markit updates the quotes whenever a dealer sends out a new message. The Markit mid-quote constitutes the main real-time reference of the index level in the D2C segment. It is available to all clients through standard data providers.

GFI intraday bid and offer quotes represent executable prices in the interdealer market. The quotes are the best prices at which protection can be sold or bought on the limit order book of the GFI SEF. Virtually all dealers are active on the GFI SEF as it is the main D2D SEF in terms of both number of trades and trading volume (see Table I).

Figure 1 displays time series of mid-quotes, averaged daily. For both indices, the Markit and GFI mid-quotes are visually indistinguishable. The average index level over the sample period is 68.2 bps for CDX.IG and 346.2 bps for CDX.HY. CDX.HY is more volatile than CDX.IG: the standard deviation of daily changes is 1.46 bps for CDX.IG and 7.95 bps for CDX.HY.

On average, there are 448 and 396 Markit quotes per day for CDX.IG and CDX.HY, respectively, and 1,094 and 864 GFI quotes. Quoting is continuous during New York trading hours, with 97% of Markit quotes and virtually all GFI quotes being made between 7:00 a.m. and 5:00 p.m. New York time. During this part of the day, Markit quotes are updated, on average, every 79 seconds for CDX.IG and every 89 seconds for CDX.HY. GFI quotes for CDX.IG and CDX.HY are updated every 29 and 37 seconds, respectively.

Figure 2 plots transaction prices and mid-quotes on a representative trading day—May 6, 2015—for the five-year index CDS contract on the then on-the-run series of CDX.IG. There are 165 trades, 405 Markit quotes, and 739 GFI quotes on this trading day. The two mid-quotes move in lockstep during the trading day. The few deviations that occur are small and transitory.

Most striking are the trades at 64 bps and 66 bps that appear to be outliers in comparison to the other trades, which tend to be relatively close to both mid-quotes. These trades are classified as delta hedges of index swaption trades by our identification algorithm for package transactions. The transaction prices on the index CDS legs of package transactions generally do not reflect the par spread at which outright trades are executed because packages are quoted either in relative terms (index rolls and curve trades) or along with a nonprice-forming quote for the delta hedge (delta-hedged index swaptions and tranche swaps). It is because of this difference in the pricing of outright trades and package transactions that it is important to isolate the outright trades.

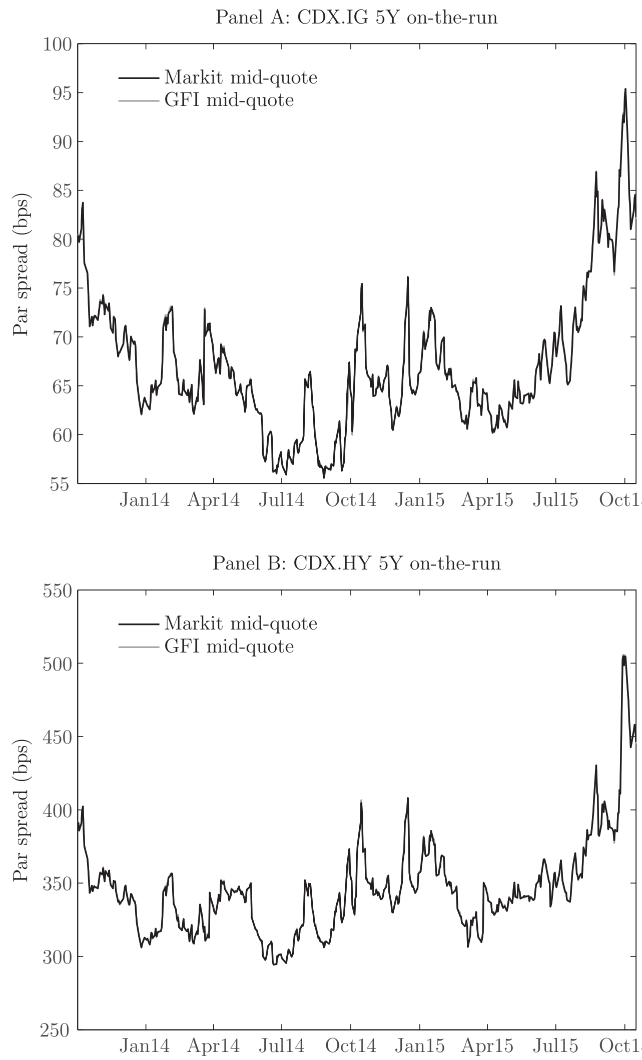



**Figure 1. Daily mid-quotes**. Panels A and B show daily sample means of mid-quotes for five-year on-the-run index CDSs on CDX.IG and CDX.HY, respectively. Quotes are in terms of par spreads and expressed in basis points. The sample period is October 2, 2013, to October 16, 2015. The sample comprises 223,324 (546,916) and 197,042 (431,894) Markit (GFI) quotes for five-year on-the-run index CDSs on CDX.IG and CDX.HY, respectively.

## III. Transaction Costs

We now compare transaction costs and price impacts across D2C and D2D trades. We also control for differences in trade characteristics and market conditions under which trades are executed.

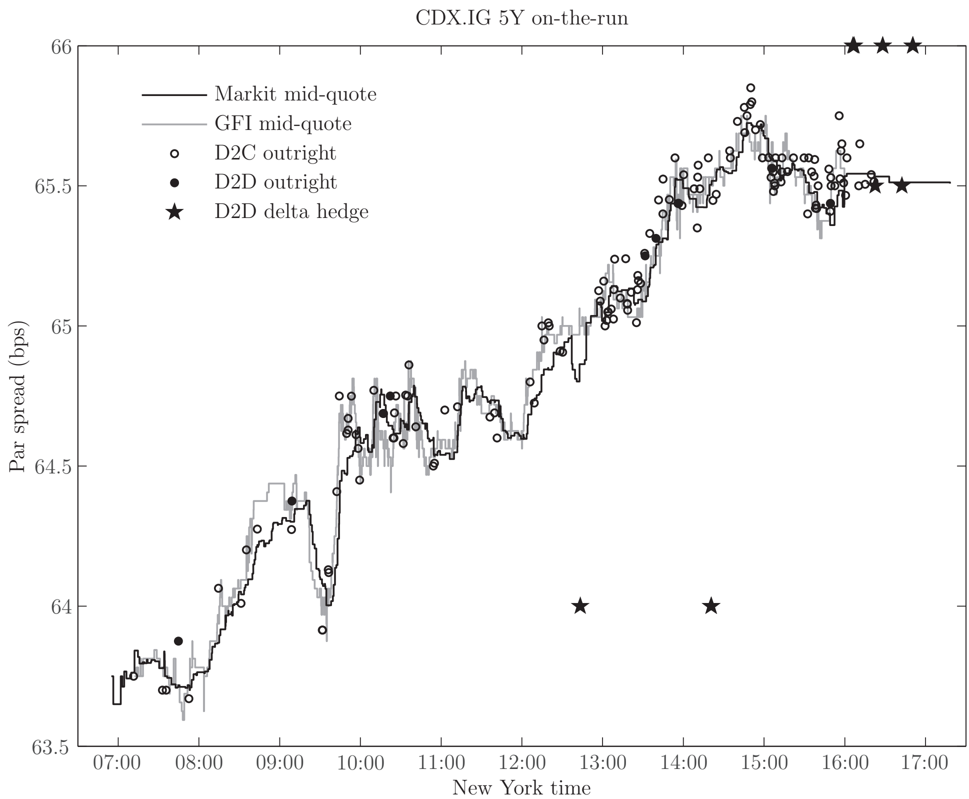



**Figure 2. Transaction prices and mid-quotes on May 6, 2015**. The figure shows transaction prices and mid-quotes for the five-year index CDS contract on series 24 of CDX.IG on May 6, 2015. Circles indicate outright trades and stars indicate delta hedges of index swaption trades. Unfilled symbols indicate dealer-to-client (D2C) trades and filled symbols indicate dealer-to-dealer (D2D) trades. The black line is the mid-quote based on Markit intraday composite quotes and the gray line is the mid-quote based on inside quotes on the limit order book of the GFI Swaps Exchange. Both transaction prices and quotes are in terms of par spreads and expressed in basis points (bps). Series 24 of CDX.IG was on-the-run on May 6, 2015.

## A. Transaction Cost Decomposition

We measure the cost of a transaction by the effective half-spread with respect to the mid-quote in the relevant market segment. For a D2C trade, the effective half-spread is with respect to the Markit mid-quote, and for a D2D trade, it is with respect to the GFI mid-quote. We further decompose the effective half-spread into a price impact and a realized half-spread, which measures the cost of a transaction after taking price impact into account. Specifically, let $\tau$ indicate whether the trade is D2C or D2D. Then

$$\underbrace{q_t(p_t - m_t^\tau)}_{=\text{EffcSprd}_t} = \underbrace{q_t(p_t - m_{t+\Delta}^\tau)}_{=\text{RlzdSprd}_t} + \underbrace{q_t(m_{t+\Delta}^\tau - m_t^\tau)}_{=\text{PrcImp}_t}, \quad \tau \in \{\text{D2C}, \text{D2D}\}, \tag{1}$$

where $p_t$ is the transaction price, $m_t^{\mathrm{D2C}}$ and $m_t^{\mathrm{D2D}}$ are the latest Markit and GFI mid-quotes, respectively, in the 15-minute period prior to trade execution, and $m_{t+\Delta}^{\mathrm{D2C}}$ and $m_{t+\Delta}^{\mathrm{D2D}}$ are the respective mid-quotes that prevail 15 minutes after trade execution. Trade direction, $q_t$, is inferred by the Lee and Ready (1991) algorithm and equals $+1$ ($-1$) in the case of protection-buyer-initiated (protection-seller-initiated) trades.[35]

Measuring price impact by trade-induced mid-quote changes is standard in empirical market microstructure, but the definition becomes ambiguous when there is no consolidated quote. Ultimately, all quotes should be driven by a common efficient price, with potential differences in the measurement of price impact being due to temporary deviations between mid-quotes. The cointegrated VAR model that we estimate in Section IV filters out the temporary deviations by taking into account the dynamic interactions between trades and mid-quotes across the two market segments.

### *B. Transaction Costs across Market Segments*

Figure 3 shows daily averages of effective half-spreads for D2C and D2D trades. For both indices, D2C trades have consistently higher effective half-spreads than D2D trades. The overall level of transaction costs is low relative to the par spreads at which the index CDSs trade; see Figure 1.

Table II displays average effective half-spreads, realized half-spreads, and price impacts by market segment. The results confirm the impression from Figure 3. For CDX.IG, average effective half-spreads for D2C and D2D trades are 0.138 bps and 0.098 bps, respectively, with the difference of 0.040 bps statistically significant. The corresponding figures for CDX.HY are 0.676 bps and 0.494 bps, with the difference of 0.181 bps again statistically significant.

These transaction cost differentials are due to D2C trades having a higher price impact than D2D trades. For CDX.IG, average price impacts for D2C and D2D trades are 0.102 bps and 0.060 bps, respectively, with the difference of 0.042 bps statistically significant. The corresponding figures for CDX.HY are 0.492 bps and 0.247 bps, with the difference of 0.246 bps again being statistically significant. After taking price impact into account, D2C trades have, if anything, lower transaction costs (as measured by realized half-spreads) than D2D trades.

Table II also displays results for four trade-size intervals that roughly correspond to the quartiles of the trade-size distribution for each index. For all trade sizes, effective half-spreads and price impacts of D2C trades are significantly higher than those of D2D trades. Realized half-spreads of D2C trades are lower than those of D2D trades (except for small trade sizes in CDX.IG).

Note that transaction costs of D2C trades increase with trade size, in contrast to evidence from other dealer markets, such as the corporate and

[35] Following Lee and Ready (1991), we sign trades at the mid-quote by a tick test. For a D2C trade the tick test is applied to the sequence of D2C trades, and for a D2D trade it is applied to the sequence of D2D trades.

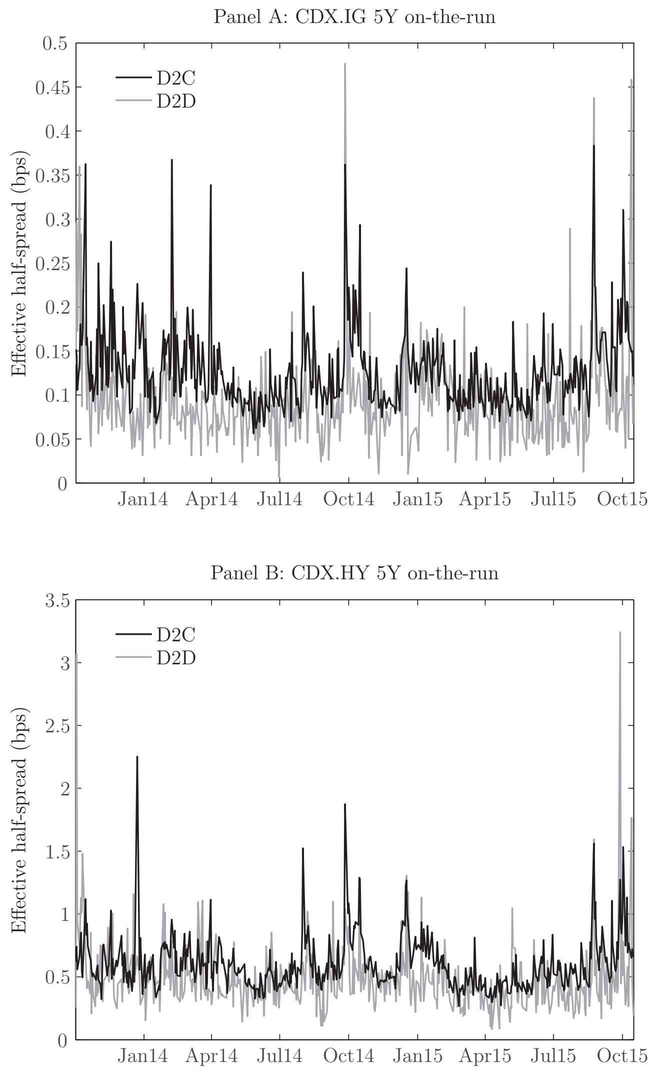



**Figure 3. Daily transaction costs by market segment**. Panels A and B show daily sample means of effective half-spreads for outright dealer-to-client (D2C) and dealer-to-dealer (D2D) trades in five-year on-the-run index CDSs on CDX.IG and CDX.HY, respectively. The effective half-spread is defined as $q_t \times (p_t - m_t^\tau)$, where $\tau$ indicates whether the trade is D2C or D2D, $p_t$ is the transaction price, and $m_t^{\text{D2C}}$ and $m_t^{\text{D2D}}$ are the latest Markit and GFI mid-quotes, respectively, in the 15-minute period prior to trade execution. Both transaction prices and quotes are in terms of par spreads and expressed in basis points (bps). Trade direction, $q_t$, is inferred by the Lee and Ready (1991) algorithm. The sample period is October 2, 2013, to October 16, 2015. The sample comprises 51,237 (9,132) and 73,115 (10,658) outright D2C (D2D) trades in five-year on-the-run index CDSs on CDX.IG and CDX.HY, respectively.

**Table II**

**Transaction Costs and Price Impacts by Market Segment**

Panels A and B show sample means of effective half-spreads (EffcSprd), realized half-spreads (RlzdSprd), and price impacts (PrcImp) for outright dealer-to-client (D2C) and dealer-to-dealer (D2D) trades in five-year on-the-run index CDSs on CDX.IG and CDX.HY, respectively. Sample means are computed separately by quartiles of the trade-size distribution and in total. EffcSprd is defined as $q_t \times (p_t - m_t^{\tau})$, where $\tau$ indicates whether the trade is D2C or D2D, $p_t$ is the transaction price, and $m_t^{\mathrm{D2C}}$ and $m_t^{\mathrm{D2D}}$ are the latest Markit and GFI mid-quotes, respectively, in the 15-minute period prior to trade execution. RlzdSprd is defined as $q_t \times (p_t - m_{t+\Delta}^{\tau})$, where $m_{t+\Delta}^{\mathrm{D2C}}$ and $m_{t+\Delta}^{\mathrm{D2D}}$ are the respective mid-quotes that prevail 15 minutes after trade execution. PrcImp is defined as $q_t \times (m_{t+\Delta}^{\tau} - m_t^{\tau})$. Both transaction prices and quotes are in terms of par spreads and expressed in basis points. Trade direction, $q_t$, is inferred by the Lee and Ready (1991) algorithm. Trade size is in USD million. $^{**}$ and $^{*}$ denote rejection of a regression-based $t$-test for the null hypothesis that D2C and D2D sample means are identical at the 1% and 5% level, respectively, with inference based on the Newey and West (1987) estimate of the covariance matrix of coefficient estimates. The sample period is October 2, 2013, to October 16, 2015. The sample comprises 51,237 (9,132) and 73,115 (10,658) outright D2C (D2D) trades in five-year on-the-run index CDSs on CDX.IG and CDX.HY, respectively.

| | Dealer-To-Client | | | Dealer-To-Dealer | | | D2C-D2D | | |
|---|---|---|---|---|---|---|---|---|---|
| Trade Size | Effc Sprd | Rlzd Sprd | Prc Imp | Effc Sprd | Rlzd Sprd | Prc Imp | Effc Sprd | Rlzd Sprd | Prc Imp |
| Panel A: CDX.IG | | | | | | | | | |
| $\leq$25 | 0.122 | 0.036 | 0.086 | 0.088 | 0.032 | 0.056 | 0.034$^{**}$ | 0.004 | 0.030$^{**}$ |
| 25–50 | 0.132 | 0.026 | 0.106 | 0.106 | 0.030 | 0.076 | 0.026$^{**}$ | −0.004 | 0.030$^{**}$ |
| 50–100 | 0.143 | 0.025 | 0.118 | 0.114 | 0.079 | 0.034 | 0.029$^{**}$ | −0.055$^{**}$ | 0.084$^{**}$ |
| > 100 | 0.171 | 0.057 | 0.114 | 0.148 | 0.146 | 0.002 | 0.023 | −0.089$^{**}$ | 0.112$^{**}$ |
| Total | 0.138 | 0.036 | 0.102 | 0.098 | 0.038 | 0.060 | 0.040$^{**}$ | −0.002 | 0.042$^{**}$ |
| Panel B: CDX.HY | | | | | | | | | |
| $\leq$ 5 | 0.604 | 0.179 | 0.424 | 0.433 | 0.256 | 0.178 | 0.171$^{**}$ | −0.076$^{*}$ | 0.247$^{**}$ |
| 5–10 | 0.637 | 0.137 | 0.500 | 0.523 | 0.220 | 0.303 | 0.114$^{**}$ | −0.084$^{**}$ | 0.198$^{**}$ |
| 10–25 | 0.701 | 0.134 | 0.566 | 0.506 | 0.291 | 0.215 | 0.195$^{**}$ | −0.156$^{**}$ | 0.351$^{**}$ |
| > 25 | 0.804 | 0.316 | 0.489 | 0.620 | 0.417 | 0.203 | 0.184$^{**}$ | −0.101 | 0.286$^{**}$ |
| Total | 0.676 | 0.183 | 0.492 | 0.494 | 0.248 | 0.247 | 0.181$^{**}$ | −0.064$^{**}$ | 0.246$^{**}$ |

municipal bond markets, where transaction costs typically decrease with trade size; see, for example, Bessembinder, Maxwell, and Venkataraman (2006), Edwards, Harris, and Piwowar (2007), Goldstein, Hotchkiss, and Sirri (2007), Harris and Piwowar (2006), and Green, Hollifield, and Schürhoff (2007). This likely reflects structural differences between markets: the index CDS market is purely institutional with professional investors trading in large sizes, while there is significant retail participation in bond markets with relatively unsophisticated clients trading in small sizes with dealers who can exert market power. The price impact of D2C trades also increases with trade size, but only up to the third quartile of the trade-size distribution. The lower price impact of block-sized trades in the fourth quartile of the trade-size distribution is consistent with block trade provisions that aim to mitigate the price impact of block-sized trades.

### C. Controlling for Trade Characteristics and Market Conditions

Potential explanations for differences in average transaction costs and price impacts of D2C and D2D trades are that trade characteristics are different or that trades are executed under different market conditions. Therefore, we separately regress the effective half-spread, the realized half-spread, or the price impact of a trade on trade-size dummies, their interactions with the negative of a D2D dummy (negation is for comparability with Table II), an additional trade characteristic, and control variables for the market conditions prevailing at trade execution.

The additional trade characteristic is a dummy variable for trades at the reference levels of index swaption and tranche swap trades that accounts for potentially unidentified delta hedges.[36] The control variables for market conditions include the bid-offer spreads of the latest Markit and GFI quotes, the end-of-day composite par spread, and the end-of-day implied volatility of the at-the-money three-month option on the index CDS. The control variables are stated in deviations from their sample means for comparability with Table II.

Table III displays the regression results. The main variables of interest are the interactions with the negative of the D2D dummy, which are the regression-implied equivalents of the differences in Table II. Differences in effective half-spreads and price impacts of D2C and D2D trades remain statistically significant, although controlling for trade characteristics and market conditions reduces the magnitudes somewhat. As in Table II, differences in price impacts fully explain differences in transaction costs.

The estimated regression coefficients further show that transaction costs and price impacts increase with bid-offer spreads and implied volatility. In addition, trades with reference-level transaction prices are more expensive.

Section VII of the Internet Appendix shows that our results are robust to using an alternative client mid-quote from Credit Market Analysis, restricting the sample to the period when trading on SEFs is mandatory, and computing price impacts and realized half-spreads over longer periods of time.

## IV. The Dynamics of Trades and Quotes

We now consider a cointegrated VAR model in the spirit of Hasbrouck (1995), which provides a robust and flexible tool to study the dynamic interactions between trades and quotes in cases in which more than one quote is relevant to the analysis. The model allows us to measure the information content of D2C and D2D trades and to quantify their relative importance for price discovery.

[36] One reason for unidentified delta hedges is that we only identify delta hedges of on-SEF index swaption and tranche swap trades, but neither swaptions nor tranche swaps have to be traded on SEFs. Nevertheless, the delta hedges of off-SEF index swaption and tranche swap trades would typically be executed on SEFs to satisfy other regulatory requirements.

**Table III**

**Regressions Controlling for Trade Characteristics and Market Conditions**

The table shows OLS estimates of regression specifications that control for selection bias in the comparison of effective half-spreads (EffcSprd), realized half-spreads (RlzdSprd), and price impacts (PrcImp) across outright dealer-to-client (D2C) and dealer-to-dealer (D2D) trades in five-year on-the-run index CDSs on CDX.IG and CDX.HY ($t$-statistics based on Newey and West (1987) standard errors are shown in parentheses). EffcSprd, RlzdSprd, and PrcImp are defined in Table II. The explanatory variables include dummy variables for small- (SMLL), medium- (MDM), large- (LRG), and block-sized (BLCK) trades (cutoffs for trade-size dummies are the quartiles of the trade-size distribution—USD 25, USD 50, and USD 100 MM for CDX.IG and USD 5, USD 10, and USD 25 MM for CDX.HY), their interactions with the negative of a dummy variable for D2D trades (D2D), a dummy variable for trades with transaction prices at typical reference levels (RFRNC; par spread multiples of 0.5 bps for CDX.IG and price multiples of 0.125% for CDX.HY), the bid-offer spreads of the latest Markit (BASD2C) and GFI (BASD2D) quotes for the five-year on-the-run index CDS, the end-of-day composite spread for the five-year on-the-run index CDS (SPRD), and the end-of-day implied volatility of three-month at-the-money swaptions on the five-year on-the-run index CDS (VLTLTY). Continuous explanatory variables are demeaned. $^{**}$ and $^{*}$ denote statistical significance at the 1% and 5% level, respectively. The sample period is October 2, 2013 to October 16, 2015. The sample comprises 49,425 (9,036) and 70,628 (10,328) outright D2C (D2D) trades in five-year on-the-run index CDSs on CDX.IG and CDX.HY, respectively.

| | CDX.IG | | | CDX.HY | | |
|---|---|---|---|---|---|---|
| | EffcSprd | RlzdSprd | PrcImp | EffcSprd | RlzdSprd | PrcImp |
| SMLL | 0.117$^{**}$ | 0.031$^{**}$ | 0.086$^{**}$ | 0.591$^{**}$ | 0.164$^{**}$ | 0.427$^{**}$ |
| | (69.04) | (13.33) | (30.73) | (77.91) | (16.45) | (31.63) |
| SMLL×(−D2D) | 0.023$^{**}$ | 0.005 | 0.018$^{**}$ | 0.138$^{**}$ | −0.081$^{*}$ | 0.219$^{**}$ |
| | (7.22) | (0.80) | (3.05) | (7.07) | (−2.12) | (6.02) |
| MDM | 0.124$^{**}$ | 0.021$^{**}$ | 0.103$^{**}$ | 0.602$^{**}$ | 0.118$^{**}$ | 0.484$^{**}$ |
| | (73.18) | (8.11) | (31.37) | (76.13) | (11.62) | (34.13) |
| MDM×(−D2D) | 0.011$^{**}$ | −0.005 | 0.016$^{*}$ | 0.056$^{**}$ | −0.093$^{**}$ | 0.149$^{**}$ |
| | (3.76) | (−0.68) | (2.39) | (3.98) | (−3.36) | (5.14) |
| LRG | 0.134$^{**}$ | 0.020$^{**}$ | 0.114$^{**}$ | 0.661$^{**}$ | 0.113$^{**}$ | 0.548$^{**}$ |
| | (65.00) | (6.73) | (31.67) | (66.72) | (8.77) | (28.37) |
| LRG×(−D2D) | 0.018$^{**}$ | −0.052$^{**}$ | 0.070$^{**}$ | 0.145$^{**}$ | −0.164$^{**}$ | 0.309$^{**}$ |
| | (3.17) | (−4.58) | (6.98) | (6.94) | (−3.66) | (6.89) |
| BLCK | 0.160$^{**}$ | 0.050$^{**}$ | 0.110$^{**}$ | 0.781$^{**}$ | 0.287$^{**}$ | 0.494$^{**}$ |
| | (65.29) | (13.61) | (26.56) | (68.15) | (20.08) | (28.28) |
| BLCK×(−D2D) | 0.009 | −0.088$^{**}$ | 0.097$^{**}$ | 0.129$^{**}$ | −0.098 | 0.227$^{**}$ |
| | (0.59) | (−3.77) | (6.01) | (2.59) | (−1.04) | (3.00) |
| RFRNC | 0.020$^{**}$ | 0.031$^{**}$ | −0.010$^{*}$ | 0.113$^{**}$ | 0.154$^{**}$ | −0.041 |
| | (7.92) | (6.29) | (−2.24) | (6.14) | (5.57) | (−1.66) |
| BASD2C | 0.381$^{**}$ | −0.029 | 0.410$^{**}$ | 0.270$^{**}$ | 0.029 | 0.242$^{**}$ |
| | (7.11) | (−0.49) | (4.17) | (10.23) | (0.91) | (5.15) |
| BASD2D | 0.039$^{**}$ | 0.027$^{*}$ | 0.011 | 0.037$^{**}$ | 0.026$^{**}$ | 0.012 |
| | (4.41) | (2.24) | (0.75) | (5.22) | (3.01) | (1.00) |
| SPRD/100 | 0.016 | 0.107$^{**}$ | −0.091 | 0.069$^{*}$ | 0.052 | 0.017 |
| | (0.60) | (2.63) | (−1.76) | (2.16) | (1.68) | (0.33) |
| VLTLTY | 0.197$^{**}$ | −0.169$^{**}$ | 0.365$^{**}$ | 1.285$^{**}$ | −0.521$^{**}$ | 1.805$^{**}$ |
| | (6.39) | (−3.93) | (6.18) | (7.53) | (−2.95) | (6.21) |
| $N$ | 58,461 | 58,461 | 58,461 | 80,956 | 80,956 | 80,956 |

### A. Cointegrated VAR Model and Estimation

We estimate the error correction form of the cointegrated VAR model in event time, with $t$ indexing the $t$-th revision of client quotes.[37] Specifically,

$$\Delta m_t^{\mathrm{D2C}} = \lambda_1 z_{t-1} + \sum_{j=1}^{20} \alpha_j \Delta m_{t-j}^{\mathrm{D2C}} + \sum_{j=0}^{20} \beta_j \Delta m_{t-j}^{\mathrm{D2D}} + \sum_{j=0}^{20} \gamma_j x_{t-j}^{\mathrm{D2C}} + \sum_{j=0}^{20} \delta_j x_{t-j}^{\mathrm{D2D}} + \epsilon_{m,t}^{\mathrm{D2C}}, \tag{2a}$$

$$\Delta m_t^{\mathrm{D2D}} = \lambda_2 z_{t-1} + \sum_{j=1}^{20} \zeta_j \Delta m_{t-j}^{\mathrm{D2C}} + \sum_{j=1}^{20} \eta_j \Delta m_{t-j}^{\mathrm{D2D}} + \sum_{j=0}^{20} \theta_j x_{t-j}^{\mathrm{D2C}} + \sum_{j=0}^{20} \kappa_j x_{t-j}^{\mathrm{D2D}} + \epsilon_{m,t}^{\mathrm{D2D}}, \tag{2b}$$

$$x_t^{\mathrm{D2C}} = \lambda_3 z_{t-1} + \sum_{j=1}^{20} \nu_j \Delta m_{t-j}^{\mathrm{D2C}} + \sum_{j=1}^{20} \xi_j \Delta m_{t-j}^{\mathrm{D2D}} + \sum_{j=1}^{20} \pi_j x_{t-j}^{\mathrm{D2C}} + \sum_{j=1}^{20} \rho_j x_{t-j}^{\mathrm{D2D}} + \epsilon_{x,t}^{\mathrm{D2C}}, \tag{2c}$$

$$x_t^{\mathrm{D2D}} = \lambda_4 z_{t-1} + \sum_{j=1}^{20} \phi_j \Delta m_{t-j}^{\mathrm{D2C}} + \sum_{j=1}^{20} \chi_j \Delta m_{t-j}^{\mathrm{D2D}} + \sum_{j=0}^{20} \psi_j x_{t-j}^{\mathrm{D2C}} + \sum_{j=1}^{20} \omega_j x_{t-j}^{\mathrm{D2D}} + \epsilon_{x,t}^{\mathrm{D2D}}, \tag{2d}$$

where the first term on the right-hand side of each equation is the error correction term, $z_t = m_t^{\mathrm{D2C}} - m_t^{\mathrm{D2D}}$ is the cointegrating relation, and $x_t^{\mathrm{D2C}}$ and $x_t^{\mathrm{D2D}}$ are D2C- and D2D-trade–related variables, respectively, which count the number of signed D2C and D2D trades that occur between the $t-1^{\mathrm{th}}$ and $t^{\mathrm{th}}$ revision of client quotes (i.e., $x_t^{\mathrm{D2C}}$ and $x_t^{\mathrm{D2D}}$ are sums of the above trade direction indicators, $q_u$, with $u$ between the calendar time of the $t-1^{\mathrm{th}}$ and $t^{\mathrm{th}}$ revision of client quotes). The error terms, $\epsilon_{m,t}^{\mathrm{D2C}}$, $\epsilon_{m,t}^{\mathrm{D2D}}$, $\epsilon_{x,t}^{\mathrm{D2C}}$, and $\epsilon_{x,t}^{\mathrm{D2D}}$, are uncorrelated because we resolve contemporaneous effects by including contemporaneous variables in equations (2a), (2b), and (2d).[38] Intuitively, the D2C-trade–related variable may contemporaneously affect the D2D-trade–related variable when dealers immediately offload inventory in the interdealer market. The D2D-trade–related variable may contemporaneously affect the GFI mid-quote directly when a trade in the limit order book of the GFI SEF depletes depth at the inside quote or indirectly when dealers immediately adjust their limit orders in response to D2D trades. Adjustment of limit orders is also

[37] Below, the error correction form is referred to as the vector error correction model (VECM).

[38] Moreover, error terms are assumed to be serially uncorrelated and homoskedastic.

how the D2C-trade–related variable may contemporaneously affect the GFI mid-quote. Finally, the D2C- and D2D-trade–related variables may contemporaneously affect the Markit mid-quote when dealers immediately revise client quotes in response to trades, and the GFI mid-quote may contemporaneously affect the Markit mid-quote when dealers set client quotes relative to the mid-quote in the interdealer market.

Cointegration in the present framework captures the idea that supply and demand imbalances in the two segments of the market may lead to temporary deviations between mid-quotes, but that an unobservable efficient price, $m_t$, that is common to both market segments, ultimately drives mid-quotes. This is clearly seen from the vector moving average (VMA) or Granger representation of the cointegrated VAR model. In our case, it is given by

$$m_t^{\mathrm{D2C}} = m_t + a(L)\epsilon_{m,t}^{\mathrm{D2C}} + b(L)\epsilon_{m,t}^{\mathrm{D2D}} + c(L)\epsilon_{x,t}^{\mathrm{D2C}} + d(L)\epsilon_{x,t}^{\mathrm{D2D}}, \tag{3a}$$

$$m_t^{\mathrm{D2D}} = m_t + e(L)\epsilon_{m,t}^{\mathrm{D2C}} + f(L)\epsilon_{m,t}^{\mathrm{D2D}} + g(L)\epsilon_{x,t}^{\mathrm{D2C}} + h(L)\epsilon_{x,t}^{\mathrm{D2D}}, \tag{3b}$$

$$n_t^{\mathrm{D2C}} = y_{2,t} + k(L)\epsilon_{m,t}^{\mathrm{D2C}} + l(L)\epsilon_{m,t}^{\mathrm{D2D}} + p(L)\epsilon_{x,t}^{\mathrm{D2C}} + q(L)\epsilon_{x,t}^{\mathrm{D2D}}, \tag{3c}$$

$$n_t^{\mathrm{D2D}} = y_{3,t} + r(L)\epsilon_{m,t}^{\mathrm{D2C}} + u(L)\epsilon_{m,t}^{\mathrm{D2D}} + v(L)\epsilon_{x,t}^{\mathrm{D2C}} + w(L)\epsilon_{x,t}^{\mathrm{D2D}}, \tag{3d}$$

where $n_t^\tau = \sum_{s=1}^t x_s^\tau,\ \tau \in \{\mathrm{D2C},\ \mathrm{D2D}\}$, is the aggregate number of signed $\tau$ trades between the first and $t^{\mathrm{th}}$ revision of client quotes, $a(L), b(L), \ldots, w(L)$ are polynomial lag operators whose coefficients $a_j,\ b_j,\ \ldots,\ w_j,\ j = 0, 1, \ldots,$ converge to zero for $j \to \infty$, and $y_t = (m_t,\ y_{2,t},\ y_{3t})'$ is a three-dimensional random walk with initial value $y_0 = ((m_0^{\mathrm{D2C}} + m_0^{\mathrm{D2D}})/2,\ 0,\ 0)'$ and innovation $\Delta y_t = \Psi\epsilon_t$. The $3 \times 4$ matrix $\Psi$ plays an important role in characterizing price impact and studying the role of trades in the price discovery process, and it is explicitly given in terms of VECM parameters.[39]

In the spirit of Hasbrouck (1991a), we measure the information content of D2C and D2D trades by the permanent price impact of shocks to the trade-related variables. It immediately follows from equation (3a) that the impact of a single protection-buyer–initiated D2C trade on the Markit mid-quote is

$$\sum_{j=0}^{n} \mathbb{E}\Big[\Delta m_{t+j}^{\mathrm{D2C}} | \mathrm{D2C}_t\Big] = \mathbb{E}\Big[m_{t+n}^{\mathrm{D2C}} | \mathrm{D2C}_t\Big] - m_{t-1}^{\mathrm{D2C}} = \Psi_{13} + c_n \tag{4}$$

[39] Specifically, let $\tilde{\beta}$ be the cointegration vector satisfying $z_t = (m_t^{\mathrm{D2C}},\ m_t^{\mathrm{D2D}},\ n_t^{\mathrm{D2C}},\ n_t^{\mathrm{D2D}})\tilde{\beta}$ and let $\lambda = (\lambda_1,\ \lambda_2,\ \lambda_3,\ \lambda_4)'$. Then $\Psi = (\lambda_\perp' \Gamma \tilde{\beta}_\perp)^{-1}\lambda_\perp'$, where $\lambda_\perp$ and $\tilde{\beta}_\perp$ span the null spaces of $\lambda'$ and $\tilde{\beta}'$, respectively, and $\Gamma = I - \sum_{j=0}^{20} \Gamma_j$, where $I$ is the identity matrix and the $\Gamma_j$ are the autoregressive coefficient matrices of the VECM.

after $n+1$ revisions of client quotes, where $\mathrm{D2C}_t = \{\epsilon_{x,t}^{\mathrm{D2C}} = 1,\ \epsilon_{m,t}^{\mathrm{D2C}} = \epsilon_{m,t}^{\mathrm{D2D}} = \epsilon_{x,t}^{\mathrm{D2D}} = 0,\ \epsilon_{m,s}^{\mathrm{D2C}} = \epsilon_{m,s}^{\mathrm{D2D}} = \epsilon_{x,s}^{\mathrm{D2C}} = \epsilon_{x,s}^{\mathrm{D2D}} = 0,\ s < t\}$ denotes an isolated unit-sized shock of the D2C-trade–related variable.[40] Similarly, it follows from equation (3b) that the impact of the trade on the GFI mid-quote is

$$\sum_{j=0}^{n} \mathbb{E}\left[\Delta m_{t+j}^{\mathrm{D2D}} | \mathrm{D2C}_t\right] = \mathbb{E}\left[m_{t+n}^{\mathrm{D2D}} | \mathrm{D2C}_t\right] - m_{t-1}^{\mathrm{D2D}} = \Psi_{13} + g_n \tag{5}$$

after $n+1$ revisions of client quotes. Consequently, the trade has the same permanent price impact on both quotes, which is given by

$$\Psi_{\mathrm{D2C}} = \lim_{n\to\infty} \sum_{j=0}^{n} \mathbb{E}\left[\Delta m_{t+j}^{\mathrm{D2C}} | \mathrm{D2C}_t\right] = \lim_{n\to\infty} \sum_{j=0}^{n} \mathbb{E}\left[\Delta m_{t+j}^{\mathrm{D2D}} | \mathrm{D2C}_t\right] = \Psi_{13}. \tag{6}$$

Similarly, the permanent price impact of a single protection-buyer–initiated D2D trade is $\Psi_{\mathrm{D2D}} = \Psi_{14}$.

The above is based on the more general idea that efficient price innovations—which are permanently incorporated into prices—reflect information. Hasbrouck (1991b) shows that the variance of efficient price innovations, $\sigma_{\Delta m}^2$, can be explicitly expressed in terms of error term variances and VECM parameters. Specifically,

$$\sigma_{\Delta m}^2 = \underbrace{(\Psi_{11})^2 \sigma_{m,\mathrm{D2C}}^2 + (\Psi_{12})^2 \sigma_{m,\mathrm{D2D}}^2}_{\text{trade-unrelated}} + \underbrace{(\Psi_{13})^2 \sigma_{x,\mathrm{D2C}}^2}_{\text{D2C-trade-related}} + \underbrace{(\Psi_{14})^2 \sigma_{x,\mathrm{D2D}}^2}_{\text{D2D-trade-related}}, \tag{7}$$

where $\sigma_{m,\tau}^2 = \mathbb{V}(\epsilon_{m,t}^{\tau})$ and $\sigma_{x,\tau}^2 = \mathbb{V}(\epsilon_{x,t}^{\tau})$, $\tau \in \{\mathrm{D2C},\ \mathrm{D2D}\}$. Equation (7) decomposes efficient price innovations into three mutually orthogonal components, namely, a trade-unrelated component with variance given by the sum of the first two terms on the right-hand side of equation (7), and two trade-related components with variances given by the third and fourth terms. The first trade-related component is associated with D2C trades and the second with D2D trades. Equation (7) is the basis for measuring contributions to price discovery by Hasbrouck's (1991b) $R^2$, which expresses each component's variance as a fraction of $\sigma_{\Delta m}^2$. The trade-unrelated component is not further broken down into Hasbrouck's (1995) information shares because informational attribution to market segments is elusive when the same dealers set prices in both segments of the market.

We estimate the VECM using all revisions of client quotes (as captured by updates of Markit intraday composite quotes) between 7:00 a.m. and 5:00 p.m. New York time for which both mid-quotes are available at the beginning of the period that spans the quote revision. We exclude a few intraday periods during

[40] A single protection-buyer–initiated D2C trade is not the only event that gives rise to a unit-sized shock of the D2C-trade–related variable. For instance, two protection-buyer–initiated D2C trades and one protection-seller–initiated D2C trade between the $t-1^{\text{th}}$ and $t^{\text{th}}$ revisions of client quotes also result in a unit-sized shock of the D2C-trade–related variable.

which Markit quotes are stale.[41] Finally, we winsorize mid-quote changes at the 0.1% and 99.9% quantiles of their distribution.

### *B. Results*

Panels A1 and A2 of Table IV display VECM coefficient estimates for CDX.IG and CDX.HY, respectively. The results are similar for both indices and therefore our discussion focuses on CDX.IG. First, consider the adjustment coefficients. Both mid-quotes adjust against deviations from the long-run equilibrium relationship. Moreover, the significant adjustment coefficients in equations (2c) and (2d) suggest that there is also trading against those deviations, with D2C and D2D trades occurring in opposite directions. D2C trades tend to be protection seller initiated when the Markit mid-quote is high relative to the GFI mid-quote and protection buyer initiated when the Markit mid-quote is relatively low.

Next, consider how trades affect mid-quotes. The positive and significant coefficients on the contemporaneous trade-related variables in equations (2a) and (2b) show that, on average, dealers immediately raise quotes in response to protection-buyer–initiated trades. For both mid-quotes, the immediate price impact of D2C trades is higher than that of D2D trades. The coefficients on the lagged trade-related variables are generally positive (for brevity, the table only reports sums of autoregressive coefficients and the corresponding $t$-statistics), indicating that mid-quotes are raised further in subsequent revisions.

Finally, consider the dynamics of trades. The generally positive coefficients on the lagged D2C-trade–related (D2D-trade–related) variables in equation (2c) (equation (2d)) indicate positively autocorrelated trades, a pervasive feature in financial markets.[42] More interestingly, the coefficients on the lagged D2C-trade–related variable in equation (2d) are generally positive. Furthermore, bivariate Granger causality tests show that D2C- and D2D-trade–related variables are characterized by one-way Granger causality from D2C trades to D2D trades (see Table IA.XIV of the Internet Appendix). This is consistent with inventory management taking place in the interdealer market.[43]

Figure 4 displays the model-implied price impacts of D2C and D2D trades. Specifically, Panels A and C show how the Markit mid-quote changes following a single protection-buyer–initiated D2C or D2D trade, while Panels B and D show how the GFI mid-quote changes. Price impact unfolds in a distinct manner across mid-quotes but ultimately converges to the same permanent price impact. The price impact is higher for D2C trades and largely permanent.

[41] During these periods there are typically no quotes for CDX.IG or CDX.HY, suggesting technical disruptions to Markit's quote-generating process.

[42] Positive autocorrelation of trades could stem, for instance, from order splitting or correlation in trading strategies across agents. In comparison to anonymous limit order book markets, there is less of a rationale for order splitting in OTC markets (at least for D2C trades, which are typically not executed anonymously).

[43] In addition, dealers have told us that CDX positions are often hedged using other liquid instruments, such as S&P 500 futures.

## Table IV
## VECM Estimates

The table shows coefficient estimates of event-time vector error correction models (VECMs) for Markit and GFI mid-quote changes ($\Delta m_t^{\mathrm{D2C}}$ and $\Delta m_t^{\mathrm{D2D}}$, respectively) and sums of signed dealer-to-client (D2C) and dealer-to-dealer (D2D) trades that occur between events ($x_t^{\mathrm{D2C}}$ and $x_t^{\mathrm{D2D}}$, respectively). Revisions of client quotes (as captured by updates of Markit quotes) constitute events. Panels A1 and A2 show VECM coefficient estimates ($t$-statistics based on OLS standard errors are shown in parentheses). Coefficient estimates of contemporaneous variables are separated from coefficient estimates of lagged variables, with sums of the latter reported in columns that show sums of lagged variables. Panel B shows permanent price impact estimates ($t$-statistics based on OLS standard errors are shown in parentheses; details of the standard error computation are contained in Section VI of the Internet Appendix) as captured by the model-implied long-run cumulative quote change (in basis points) in response to a single protection-buyer–initiated D2C trade or a single protection-buyer–initiated D2D trade, as well as the difference in permanent price impacts of D2C and D2D trades. Panel C shows a model-implied variance decomposition of efficient price innovations into trade-related and trade-unrelated components (in percent of the variance of efficient price innovations). Quotes are in terms of par spreads, and trade direction used to sign trades is inferred by the Lee and Ready (1991) algorithm. The sample period is October 2, 2013, to October 16, 2015. The sample comprises 212,103 and 183,861 client-quote revisions for CDX.IG and CDX.HY, respectively.

| | $z_{t-1}$ | $\sum_{j=1}^{20} \Delta m_{t-j}^{\mathrm{D2C}}$ | $\Delta m_t^{\mathrm{D2D}}$ | $\sum_{j=1}^{20} \Delta m_{t-j}^{\mathrm{D2D}}$ | $x_t^{\mathrm{D2C}}$ | $\sum_{j=1}^{20} x_{t-j}^{\mathrm{D2C}}$ | $x_t^{\mathrm{D2D}}$ | $\sum_{j=1}^{20} x_{t-j}^{\mathrm{D2D}}$ |
|---|---|---|---|---|---|---|---|---|
| Panel A1: CDX.IG | | | | | | | | |
| $\Delta m_t^{\mathrm{D2C}}$ | −0.037 | −0.116 | 0.111 | 0.587 | 0.005 | 0.010 | 0.001 | 0.001 |
| | (−50.35) | (−9.86) | (100.10) | (47.77) | (43.63) | (23.09) | (6.15) | (1.21) |
| $\Delta m_t^{\mathrm{D2D}}$ | 0.029 | 0.240 | | −0.119 | 0.019 | 0.005 | 0.002 | 0.014 |
| | (20.31) | (10.43) | | (−4.96) | (93.46) | (5.72) | (4.33) | (8.62) |
| $x_t^{\mathrm{D2C}}$ | −0.231 | −0.889 | | 3.485 | | 0.222 | | −0.001 |
| | (−15.56) | (−3.71) | | (13.92) | | (25.06) | | (−0.05) |
| $x_t^{\mathrm{D2D}}$ | 0.069 | 0.293 | | −0.583 | 0.002 | 0.012 | | 0.144 |
| | (8.75) | (2.32) | | (−4.42) | (2.00) | (2.64) | | (16.73) |
| Panel A2: CDX.HY | | | | | | | | |
| $\Delta m_t^{\mathrm{D2C}}$ | −0.038 | −0.189 | 0.099 | 0.613 | 0.022 | 0.045 | 0.005 | −0.001 |
| | (−46.43) | (−14.43) | (89.75) | (45.71) | (45.92) | (23.89) | (4.69) | (−0.19) |
| $\Delta m_t^{\mathrm{D2D}}$ | 0.040 | 0.264 | | −0.335 | 0.097 | 0.026 | −0.003 | 0.041 |
| | (23.09) | (9.56) | | (−11.87) | (97.58) | (6.56) | (−1.27) | (4.76) |
| $x_t^{\mathrm{D2C}}$ | −0.065 | −0.372 | | 1.004 | | 0.275 | | −0.004 |
| | (−15.97) | (−5.72) | | (15.14) | | (29.81) | | (−0.19) |
| $x_t^{\mathrm{D2D}}$ | 0.015 | 0.043 | | −0.140 | −0.002 | 0.008 | | 0.166 |
| | (8.50) | (1.49) | | (−4.75) | (−2.22) | (1.96) | | (18.43) |

Panel B: Permanent Price Impact

| | CDX.IG | | | CDX.HY | | |
|---|---|---|---|---|---|---|
| | D2C | D2D | D2C − D2D | D2C | D2D | D2C − D2D |
| $\Psi$ | 0.042 | 0.019 | 0.023 | 0.185 | 0.039 | 0.146 |
| | (34.63) | (9.07) | (9.44) | (37.84) | (3.87) | (13.19) |

Panel C: Price Discovery

| | CDX.IG | | | CDX.HY | | |
|---|---|---|---|---|---|---|
| | D2C | D2D | Trade-Unrelated | D2C | D2D | Trade-Unrelated |
| $R^2$ | 15.07 | 0.87 | 84.07 | 21.12 | 0.18 | 78.70 |

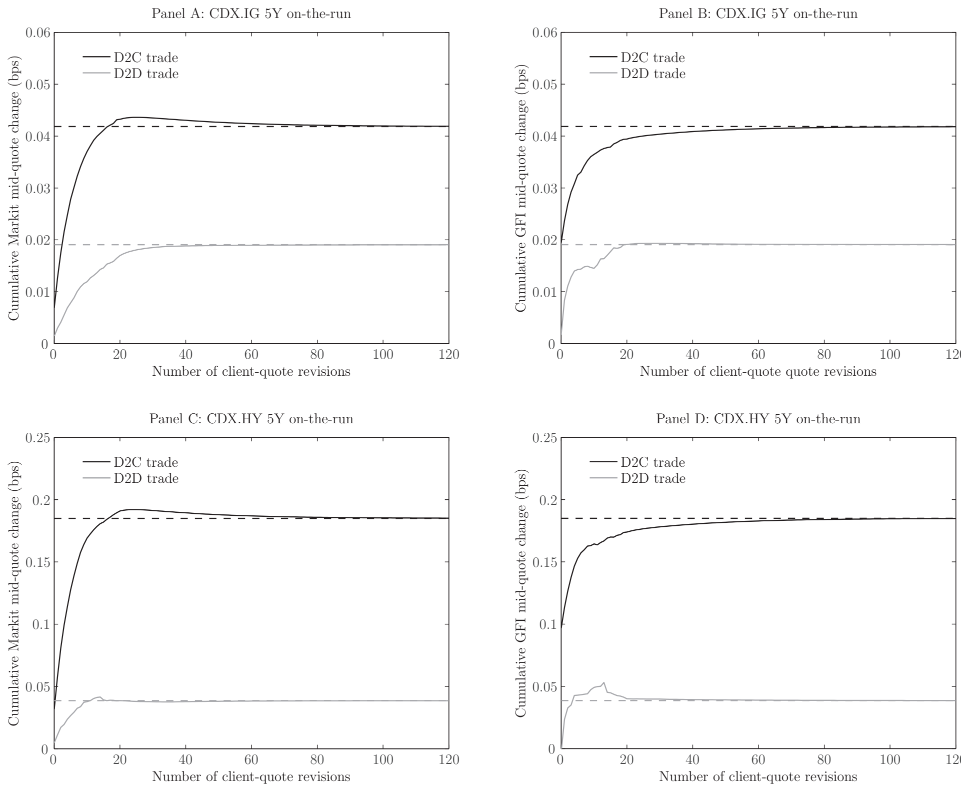



**Figure 4. Price impacts by market segment**. The panels show cumulative changes of Markit (Panels A and C) and GFI (Panels B and D) mid-quotes in response to a single protection-buyer-initiated dealer-to-client (D2C) trade (solid black lines) or a single protection-buyer–initiated dealer-to-dealer (D2D) trade (solid light gray lines). The trades are outright five-year on-the-run index CDS trades in CDX.IG (Panels A and B) and CDX.HY (Panels C and D). Cumulative quote changes are implied by event-time vector error correction models for Markit and GFI mid-quote changes and sums of signed D2C and D2D trades that occur between events. Revisions of client quotes (as captured by updates of Markit quotes) constitute events. Dashed horizontal lines mark permanent price impacts as captured by the long-run cumulative quote change. Quotes are in terms of par spreads and expressed in basis points (bps). The sample period is October 2, 2013, to October 16, 2015. The sample comprises 212,103 and 183,861 client-quote revisions for CDX.IG and CDX.HY, respectively.

Panel B of Table IV displays the permanent price impact of a trade and formally rejects the hypothesis of identical permanent price impacts of D2C and D2D trades.

Asymmetric information entails a permanent price impact, while inventory control entails a transient price impact. For both indices, we observe a small transient component in the change of the Markit mid-quote in response to a D2C trade, consistent with the quote revision mechanism in standard inventory control models. However, the overall quote revision is dominated by the permanent price impact, which points to clients trading on information.

Clients could, for instance, have private information about the credit risk of certain index constituents (see, for example, Acharya and Johnson (2007) and Ivashina and Sun (2011)) or have an advantage over dealers in interpreting public information in relation to the aggregate credit risk in the economy. The lower permanent price impact of D2D trades indicates that dealers use the interdealer market mainly for inventory management. It also follows that D2C trades play a more important role in the price discovery process than D2D trades. Indeed, Panel C of Table IV shows that D2C trades account for a much higher proportion of the efficient price variance than D2D trades.

Section VII of the Internet Appendix shows that our results are robust to using an alternative client mid-quote, restricting the sample to the period in which trading on SEFs is mandatory, and estimating alternative specifications of the cointegrated VAR model.

## V. Segmentation of Interdealer Order Flow

Trading in the interdealer market is anonymous, with dealers using a variety of trading protocols that differ in their degree of immediacy. This may lead to a segmentation of the interdealer order flow (see, for example, Zhu (2014) and Menkveld, Yueshen, and Zhu (2017)). To explore the variation in transaction costs and price impacts across trading protocols, we focus on the GFI SEF, for which we can identify the trading protocol used for each trade.[44] In addition to a standard limit order book (and voice-brokered RFQs), this SEF offers two size-discovery trading protocols—mid-market matching and workup—where the price at which orders are matched is known and fixed, but execution is uncertain because the size that can be matched is not visible to traders (see, for example, Duffie and Zhu (2017)).

### A. Size-Discovery Trading Protocols

For five-year on-the-run index CDSs, the GFI SEF offers continuous mid-market matching.[45] At any point in time, market participants can submit size orders for matching at a "mid-market level" and any opposing interest immediately results in a trade. The mid-market level is fixed by a GFI broker and is virtually always between the inside quotes on the limit order book, but is usually different from the mid-quote. The mid-market level is displayed on the trading screen that shows the limit order book, and the color in which the mid-market level is displayed indicates whether there is interest for matching. The direction and size of interest are not displayed, but market participants know that interest must be at least of a minimum size.[46]

[44] Focusing on trades executed on the GFI SEF is not restrictive because it is the main D2D SEF. Other D2D SEFs also offer size-discovery trading protocols, but the data are not readily available.

[45] For less frequently traded index CDSs, the GFI SEF offers periodic matching sessions, which we discuss briefly in Section III of the Internet Appendix.

[46] Current minimum sizes are USD 25 million for CDX.IG and USD 10 million for CDX.HY.

A workup session on the GFI SEF is initiated by a trade in the limit order book. During the session, the parties to the initiating trade and other market participants joining the trade can work up the size of the trade by submitting size orders that, in the case of a match, result in trades at the transaction price of the initiating trade. The initiator and liquidity provider of the initiating trade enjoy a 10-second exclusivity period during which they are the only market participants that can work up the trade size. The exclusivity period is followed by a public period during which other market participants can join the trade. The public period lasts for at least 30 seconds, with any workup during the public period automatically extending the workup session. The session terminates 40 seconds after the initiating trade or, if it is extended, 30 seconds after the last workup. In contrast to continuous mid-market matching, the direction and size of interests are on display.

### *B. Data and Identification of Mid-Market Matches and Workups*

We obtain additional data from GFI on the mid-market levels for continuous matching. On average, there are 132 and 151 mid-market levels per day for CDX.IG and CDX.HY, respectively. Together with the GFI bid and offer quote data, these data allow us to identify whether trades were executed in the limit order book (i.e., at the best bid or offer), via mid-market matching (i.e., at the mid-market level), or using the workup protocol (i.e., at the transaction price of an initiating trade in the limit order book and before the respective workup session timed out; see Section IV of the Internet Appendix). Trades that satisfy none of the above are subsumed into their own category. Some of these trades are voice-brokered RFQs.

Table V shows the fraction of trades and the fraction of trading volume on the GFI SEF that are executed via the different trading protocols. For CDX.IG and CDX.HY, trades in the limit order book account for 19.2% and 15.8% of trading volume, mid-market matching accounts for 52.2% and 58.7%, and the workup protocol accounts for 19.9% and 15.5%.[47] Together, size-discovery trading protocols account for more than 70% of trading volume.[48]

### *C. Transaction Costs across Trading Protocols*

Table VI displays average effective half-spreads, realized half-spreads, and price impacts by trading protocol.[49] For both indices and all trade sizes,

[47] About half of the trades in the limit order book are subsequently worked up.

[48] The fraction of trades with unidentified trading protocol is higher in terms of volume than in terms of trades, indicating that these trades tend to be relatively large. Indeed, the trading protocol of most block-sized trades is not identified. As mentioned above, some of the trades with unidentified trading protocol are voice-brokered RFQs. Thus, voice brokers' ability to match dealers with offsetting inventory imbalances may explain why block-sized D2D trades have essentially no price impact (see Table II).

[49] We do not report results for trade-size intervals with less than 10 trades. As for D2D trades in the previous sections, half-spreads and price impacts are with respect to the GFI mid-quote. We note that only 9.55% of the mid-market matches take place at the GFI mid-quote.

**Table V**

**Percentage of Trades and Volume by Trading Protocol**

Panels A and B show percentages of trades and trading volume by trading protocol for outright trades in five-year on-the-run index CDSs on CDX.IG and CDX.HY, respectively, that are executed on the GFI Swaps Exchange. The sample period is October 2, 2013, to October 16, 2015. The sample comprises 7,049 and 7,414 outright trades in five-year on-the-run index CDSs on CDX.IG and CDX.HY, respectively.

| Trading Protocol | % of Trds | % of Vlm |
|---|---|---|
| | Panel A: CDX.IG | |
| Limit order book | 19.1 | 19.2 |
| Workup protocol | 18.4 | 19.9 |
| Mid-market matching | 54.8 | 52.2 |
| Unidentified protocol | 7.7 | 8.8 |
| | Panel B: CDX.HY | |
| Limit order book | 15.3 | 15.8 |
| Workup protocol | 16.0 | 15.5 |
| Mid-market matching | 61.4 | 58.7 |
| Unidentified protocol | 7.3 | 10.0 |

average transaction costs and price impacts of trades in the limit order book are relatively high and even exceed those of D2C trades reported in Table II.[50] For instance, for CDX.IG trades in the USD 25 to 50 million trade-size interval, the average effective half-spread and price impact are 0.134 bps and 0.153 bps, respectively, in comparison to 0.132 bps and 0.106 bps for D2C trades.

Next, we compare mid-market matches with trades in the limit order book. For both indices and all trade sizes, mid-market matches have significantly lower average transaction costs and price impacts than trades in the limit order book. For instance, for CDX.IG trades in the USD 25 to 50 million trade-size interval, the average effective half-spread and price impact are 0.059 bps and 0.040 bps, respectively. That transaction costs are lower for mid-market matches is not surprising because the mid-market level is usually set somewhere between the inside quotes on the limit order book. That price impacts are lower for mid-market matches indicates a partial segmentation of the order flow, with a higher proportion of uninformed trades being executed via mid-market matching (below we show that the difference in price impact also applies to the permanent component). This is consistent with Zhu's (2014) model of strategic venue selection by informed and liquidity traders. In his model, traders optimally choose between sending orders to a mid-point dark pool (roughly equivalent to continuous mid-market matching) and executing against limit orders. Sending an order to a dark pool involves a trade-off

[50] At the same time, for each index the average effective half-spread is significantly lower than the average GFI bid-offer half-spread, which is 0.303 bps for CDX.IG and 1.649 bps for CDX.HY. That is, dealers are more likely to trade in the limit order book when bid-offer spreads are relatively narrow.

**Table VI**

**D2D Transaction Costs and Price Impacts by Trading Protocol**

Panels A and B show sample means of effective half-spreads (EffcSprd), realized half-spreads (RlzdSprd), and price impacts (PrcImp) of outright trades in five-year on-the-run index CDSs on CDX.IG and CDX.HY, respectively, that are executed on the GFI Swaps Exchange. Sample means are computed separately for trades in the limit order book, workups, and mid-market matches. EffcSprd is defined as $q_t \times (p_t - m_t^{\mathrm{D2D}})$, where $p_t$ is the transaction price and $m_t^{\mathrm{D2D}}$ is the latest GFI mid-quote in the 15-minute period prior to trade execution. RlzdSprd is defined as $q_t \times (p_t - m_{t+\Delta}^{\mathrm{D2D}})$, where $m_{t+\Delta}^{\mathrm{D2D}}$ is the GFI mid-quote that prevails 15 minutes after trade execution. PrcImp is defined as $q_t \times (m_{t+\Delta}^{\mathrm{D2D}} - m_t^{\mathrm{D2D}})$. Both transaction prices and quotes are in terms of par spreads and expressed in basis points. Trade direction, $q_t$, is inferred by the Lee and Ready (1991) algorithm. Trade size is in USD million. $^{**}$ and $^{*}$ denote rejection of a regression-based $t$-test for the null hypothesis that sample means are identical to those of trades in the limit order book at the 1% and 5% level, respectively, with inference based on the Newey and West (1987) estimate of the covariance matrix of coefficient estimates. Cells of categories with less than 10 trades are left blank and $t$-tests are conducted if there are at least 10 trades in each of the two categories with respect to which the null hypothesis is formulated. The sample period is October 2, 2013, to October 16, 2015. The sample comprises 1,333 (1,290) [3,782] and 1,124 (1,172) [4,473] outright trades in the limit order book (workups) [mid-market matches] in five-year on-the-run index CDSs on CDX.IG and CDX.HY, respectively.

| | Effc Sprd | | | Rlzd Sprd | | | Prc Imp | | |
|---|---|---|---|---|---|---|---|---|---|
| Trade Size | Order book | Workup | Mid Match | Order book | Workup | Mid Match | Order book | Workup | Mid Match |
| | | | | Panel A: CDX.IG | | | | | |
| ≤25 | 0.128 | 0.129 | 0.052$^{**}$ | −0.023 | −0.015 | 0.016$^{**}$ | 0.150 | 0.144 | 0.036$^{**}$ |
| 25–50 | 0.134 | 0.133 | 0.059$^{**}$ | −0.019 | −0.026 | 0.020$^{**}$ | 0.153 | 0.159 | 0.040$^{**}$ |
| 50–100 | 0.179 | 0.129 | 0.065$^{**}$ | −0.009 | −0.005 | 0.041 | 0.188 | 0.134 | 0.024$^{*}$ |
| >100 | | 0.116 | 0.054 | | −0.119 | 0.033 | | 0.236 | 0.021 |
| | | | | Panel B: CDX.HY | | | | | |
| ≤5 | | 0.666 | 0.266 | | 0.054 | 0.130 | | 0.612 | 0.136 |
| 5–10 | 0.707 | 0.716 | 0.294$^{**}$ | 0.024 | 0.080 | 0.113 | 0.683 | 0.636 | 0.181$^{**}$ |
| 10–25 | 1.043 | 0.717$^{**}$ | 0.292$^{**}$ | 0.010 | −0.174 | 0.104 | 1.032 | 0.891 | 0.188$^{**}$ |
| > 25 | | | 0.304 | | | −0.376 | | | 0.679 |

between price improvement and the risk of no execution. In equilibrium, liquidity traders prefer the dark pool, while informed traders prefer the certainty of executing against limit orders.

We also compare workups with trades in the limit order book. For small- and medium-sized trades, there are no significant differences in transaction costs. This is to be expected because a workup is executed at the price of the initiating trade in the limit order book. There are also no significant differences in price impacts. Because the duration of a workup session is much shorter than the 15-minute period over which price impact is measured, the price impact of a workup will include most of the price impact of the initiating trade. The result therefore indicates that the additional price impact of a workup is close to zero.[51] Note, however, that transaction costs and price impacts of large workups are lower than those of large trades in the limit order book and similar to those of small- and medium-sized trades in the limit order book, underscoring how the workup protocol helps contain the cost and price impact of interdealer trading.

To further explore differences in price impact across trading protocols, we extend the VECM in Section IV by using separate D2D-trade–related variables for trades in the limit order book, mid-market matches, and workups. A residual category comprises trades with unidentified trading protocol that are executed on the GFI SEF as well as trades that are executed on other D2D SEFs. We resolve contemporaneous effects between the D2D-trade–related variables by allowing the residual D2D trades to contemporaneously affect the other D2D-trade–related variables, mid-market matches to contemporaneously affect trades in the limit order book and workups, and trades in the limit order book to contemporaneously affect workups. With the exception of the relation between trades in the limit order book and workups, which is determined by the design of the workup trading protocol, the imposed contemporaneous relations among the remaining pairs of D2D-trade–related variables do not affect our results because pairwise contemporaneous correlations are negligible.

Figure 5 shows the model-implied price impacts, which are consistent with Table VI. For both indices, a trade in the limit order book has a high permanent price impact, which exceeds that of a D2C trade. A mid-market match has a significantly lower permanent price impact than a trade in the limit order book. Finally, the cointegrated VAR model separates the price impact of a workup from that of the initiating trade in the limit order book, with workups having very little price impact at any horizon. The finding that a workup has a much lower price impact than the initiating trade in the limit order book is consistent with evidence from the interdealer Treasury market reported in Fleming and Nguyen (2019).

Taken together, these results show that the low average transaction cost and price impact of D2D trades reported in Sections III and IV is due to the frequent use of size-discovery trading protocols that attract liquidity-motivated trades.

If most clients trade via RFQ on the D2C platforms because they seek immediacy, a natural question that arises is why wouldn't they trade at the executable quotes on the limit order books of the D2D platforms? We next analyze the price improvements that clients obtain by trading via RFQ instead of hitting executable D2D limit orders.

[51] This is confirmed by comparing the average price impact of trades in the limit order book that are subsequently worked up with the average price impact of those that are not. For both indices, the average price impacts of worked-up and non–worked-up trades in the limit order book are not significantly different.

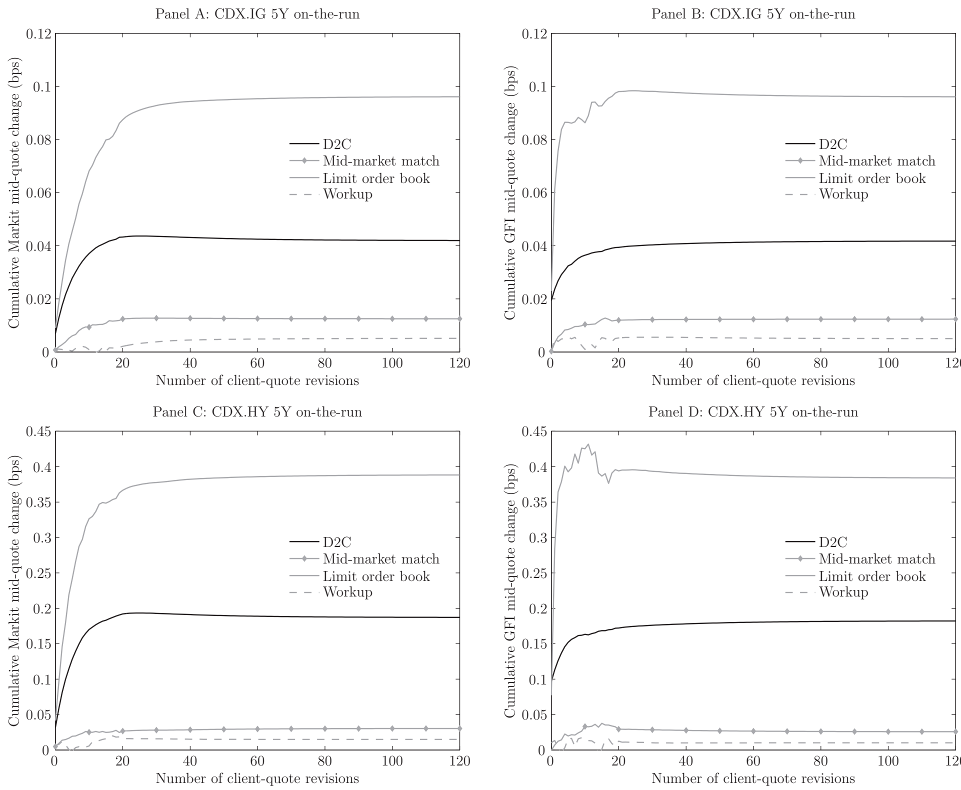



**Figure 5. Price impacts by trading protocol**. The panels show cumulative changes of Markit (Panels A and C) and GFI (Panels B and D) mid-quotes in response to a single protection-buyer–initiated dealer-to-client (D2C) trade (solid black lines) or a single protection-buyer–initiated dealer-to-dealer (D2D) mid-market match (marked solid light gray lines), trade in the limit order book (solid light gray lines), or workup (dashed light gray lines). The trades are outright five-year on-the-run index CDS trades in CDX.IG (Panels A and B) and CDX.HY (Panels C and D). Cumulative quote changes are implied by event-time vector error correction models for Markit and GFI mid-quote changes and sums of signed D2C and D2D trades that occur between events, with separate sums for mid-market matches, trades in the limit order book, workups (all of which are executed on the GFI Swaps Exchange), and the remaining D2D trades (which are executed either on the GFI Swaps Exchange by an unidentified trading protocol or on another interdealer broker SEF). Revisions of client quotes (as captured by updates of Markit quotes) constitute events. Quotes are in terms of par spreads and expressed in basis points (bps). The sample period is October 2, 2013, to October 16, 2015. The sample comprises 212,103 and 183,861 client-quote revisions for CDX.IG and CDX.HY, respectively.

## VI. Price Improvement of Client Trades

An important measure of execution quality is whether clients obtain the best available price at any given moment. For corporate bonds, Harris (2015) finds that clients often trade at prices that are inferior to the best contemporaneous

**Table VII**
**Price Improvements of Dealer-to-Client Trades**

The table shows descriptive statistics of price improvements for outright dealer-to-client (D2C) trades in five-year on-the-run index CDSs on CDX.IG and CDX.HY. Price improvements are with respect to inside quotes on the limit order book of the GFI Swaps Exchange. Price improvement is defined as $o_t^{\mathrm{D2D}} - p_t$ if $q_t = 1$, and $p_t - b_t^{\mathrm{D2D}}$ if $q_t = -1$, where $p_t$ is the transaction price and $b_t^{\mathrm{D2D}}$ and $o_t^{\mathrm{D2D}}$ are the latest GFI bid and offer quotes, respectively, in the 15-minute period prior to trade execution. Both transaction prices and bid and offer quotes are in terms of par spreads and expressed in basis points. Trade direction, $q_t$, is inferred by the Lee and Ready (1991) algorithm. The sample period is October 2, 2013, to October 16, 2015. The sample comprises 49,425 and 70,628 outright D2C trades in five-year on-the-run index CDSs on CDX.IG and CDX.HY, respectively.

| | CDX.IG | CDX.HY |
|---|---|---|
| Mean | 0.229 | 1.291 |
| Standard deviation | 0.168 | 0.838 |
| 25th | 0.166 | 0.924 |
| Median | 0.235 | 1.317 |
| 75th | 0.307 | 1.645 |
| % price improvement > 0 | 95.8 | 96.4 |
| % within bid-offer spread | 95.3 | 96.1 |

executable quotes available to dealers elsewhere in the market.[52] To investigate execution quality for index CDSs, we compare D2C transaction prices to the contemporaneous inside quotes on the limit order book of the GFI SEF.

The price improvement of a D2C trade vis-à-vis resting limit orders is defined as $o_t - p_t$ if $q_t = 1$, and $p_t - b_t$ if $q_t = -1$, where $b_t$ and $o_t$ are the latest inside bid and offer quotes, respectively, in the 15-minute period prior to trade execution. A negative price improvement represents a trade-through, that is, the client would have obtained better execution by sending a marketable order to the GFI limit order book. Table VII shows that price improvements are large and almost always positive.[53] The average price improvements are 0.229 bps for CDX.IG and 1.291 bps for CDX.HY, with the price improvements strictly positive for 95.8% and 96.4% of the trades in CDX.IG and CDX.HY, respectively. The table also shows that, for a very high percentage of trades, transaction prices are strictly within the bid-offer spread, namely for 95.3% of CDX.IG trades and for 96.1% of CDX.HY trades. This shows that our results are not sensitive to the signing of D2C trades.

[52] Similarly, Bjønnes, Kathitziotis, and Osler (2016) find that most D2C trades in the spot FX market exhibit a positive markup relative to the inside quotes in the interdealer market. However, Dunne, Hau, and Moore (2015) find that most D2C trades in the European government bond market occur within the interdealer bid-offer spread.

[53] Our analysis assumes that the entire D2C trade could be executed at the inside quotes. For a large trade, this is unlikely to be true, in which case we underestimate the actual price improvement. As such, the average price improvements and the likelihood of price improvements being positive reported in Table VII are downward biased. Unfortunately, the GFI data do not include depth, which precludes a more accurate computation of price improvements.

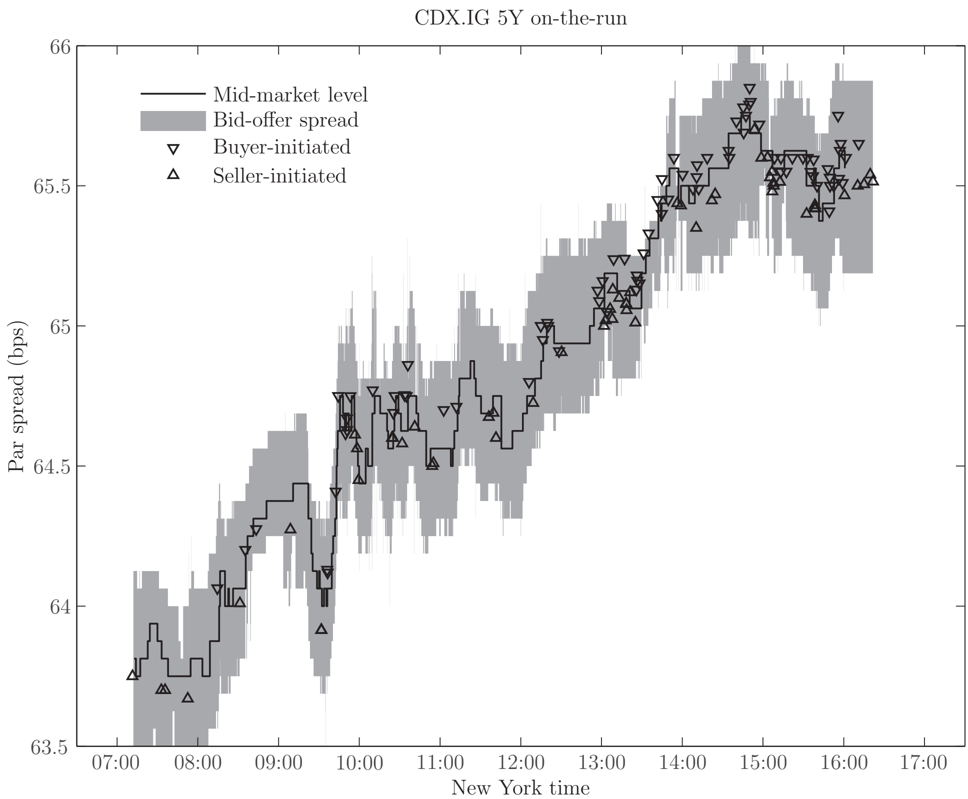



**Figure 6. Dealer-to-client trades and interdealer bid-offer spread on May 6, 2015**. The figure shows transaction prices of outright dealer-to-client trades, the mid-market level, and the bid-offer spread on the limit order book of the GFI Swaps Exchange for the five-year index CDS contract on series 24 of CDX.IG on May 6, 2015. Downward-pointing triangles indicate protection-buyer-initiated trades and upward-pointing triangles indicate protection-seller–initiated trades. The black line is the mid-market level. The gray area is spanned by the best bid and offer on the limit order book of the GFI Swaps Exchange. Transaction prices, the mid-market level, and bid and offer quotes are in terms of par spreads and expressed in basis points (bps). Series 24 of CDX.IG was on-the-run on May 6, 2015.

As an illustration, Figure 6 displays transaction prices of D2C trades in CDX.IG on May 6, 2015—the representative trading day from Figure 2—along with the bid-offer spread on the GFI limit order book. Most D2C trades are executed at prices strictly within the bid-offer spread (135, or 97.1% of the 139 D2C trades) and close to the mid-market level. Price improvements from the inside quotes are substantial (0.224 bps, on average).

The price improvements in Table VII are sizeable in relation to the average transaction costs of D2C trades reported in Table II. The magnitudes of the price improvements mainly reflect the wide bid-offer spreads on the GFI limit order book. However, an additional factor is the relation between Markit and

GFI quotes around trade execution, with the side on which trades occur typically being favorably priced in the D2C segment of the market. This is evident from Figure 7, which shows the average Markit and GFI quotes just prior to execution of protection-buyer–initiated (Panel A) and protection-seller-initiated (Panel B) D2C trades in CDX.IG (a similar pattern holds for CDX.HY; see Figure IA8 of the Internet Appendix).

Panel A shows that for buyer-initiated trades, the Markit offer is significantly lower than the GFI offer, whereas the Markit bid is roughly equal to the GFI bid. Consequently, the Markit mid-quote is below the GFI mid-quote, and thus the average price improvement (0.230 bps) is actually larger than what one obtains when subtracting the average transaction cost (0.132 bps) from the average GFI bid-offer half-spread (0.302 bps). Panel B is a mirror image of Panel A; for seller-initiated trades, the Markit mid-quote is above the GFI mid-quote, and thus the average price improvement (0.229 bps) is again larger than what one obtains when subtracting the average transaction cost (0.135 bps) from the average GFI bid-offer half-spread (0.300 bps).[54]

The relative positioning of Markit and GFI quotes is qualitatively consistent with inventory management by dealers. When dealers are net long (short) inventory, we would expect them to reduce the quoted D2C offer (increase the quoted D2C bid) to trigger client buy (sell) orders. At the same time, we would expect the mid-market level on the GFI SEF to be lower (higher) than the GFI mid-quote, reflecting selling (buying) pressure among dealers. This is, indeed, what we observe in the figure.

## VII. Dispersion in Client Transaction Costs

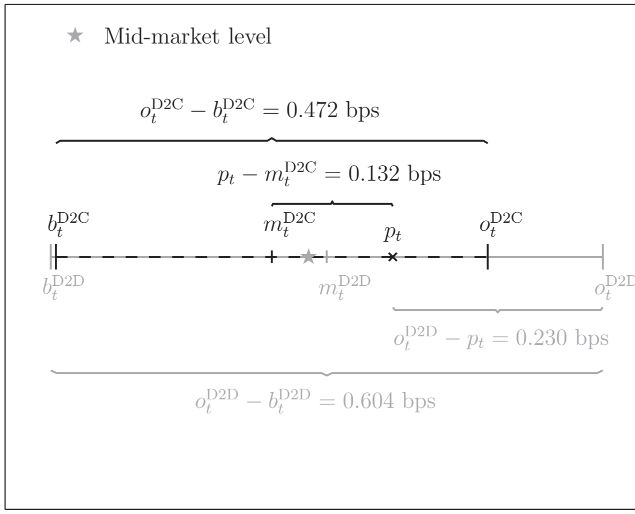
Trading in the D2C segment is not anonymous, as clients disclose their identities to the dealers from whom they request quotes. This allows dealers to price discriminate according to features other than observable trade characteristics. We quantify the dispersion in transaction costs of client trades and provide suggestive evidence on which types of clients benefit from the nonanonymity.

For each of the trade-size intervals from Table II, we sort D2C trades into quartiles based on the effective half-spread. Table VIII shows the average effective half-spread for each quartile. For both indices and all trade sizes, we observe significant dispersion in transaction costs of client trades. Take, for instance, CDX.IG trades in the USD 25 to 50 million trade-size interval. The average transaction cost is 0.132 bps (see Table II), but it varies from 0.025 bps in the first quartile to 0.294 bps in the fourth quartile.

Next, we turn to the possible drivers of the dispersion in transaction costs. While Section IV shows that the average client trade appears to be informed,

[54] Note that the average transaction cost of D2C CDX.IG trades reported in Table II (0.138 bps) is slightly higher than the numbers in Figure 7. The reason is that Figure 7 requires both Markit and GFI quotes to be available within 15 minutes prior to trade execution, while Table II requires only Markit quotes to be available.

Panel A: CDX.IG 5Y on-the-run protection-buyer-initiated




Panel B: CDX.IG 5Y on-the-run protection-seller-initiated

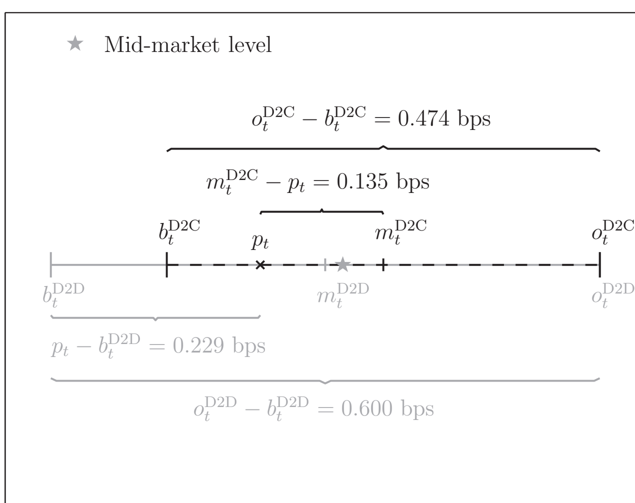



**Figure 7. Relation among quotes at execution of dealer-to-client trades**. Panels A and B show the average relation among Markit and GFI quotes at execution of protection-buyer- and protection-seller–initiated dealer-to-client (D2C) trades, respectively, in five-year on-the-run index CDSs on CDX.IG. $p_t$ is the transaction price, $b_t^{D2C}$ and $b_t^{D2D}$ are the latest Markit and GFI bid quotes, respectively, in the 15-minute period prior to trade execution, $o_t^{D2C}$ and $o_t^{D2D}$ are the latest offer quotes, and $m_t^{D2C}$ and $m_t^{D2D}$ are the corresponding mid-quotes. The dashed black lines mark the spread between Markit bid and offer quotes and the gray lines mark the spread between the GFI bid and offer quotes. The gray star is the mid-market level that prevails at trade execution. The sample period is October 2, 2013, to October 16, 2015. The sample comprises 24,288 (24,767) outright protection-buyer–initiated (protection-seller–initiated) D2C trades in five-year on-the-run index CDSs on CDX.IG.

**Table VIII**

**D2C Transaction Costs and Price Impacts by Effective Half-Spread Quartiles**

Panels A and B show sample means of effective half-spreads (EffcSprd), realized half-spreads (RlzdSprd), and price impacts (PrcImp) by EffcSprd quartiles for outright dealer-to-client (D2C) trades in five-year on-the-run index CDSs on CDX.IG and CDX.HY, respectively. Sample means are computed separately by quartiles of the trade-size distribution with EffcSprd quartiles being determined per quartile of the trade-size distribution. EffcSprd is defined as $q_t \times (p_t - m_t^{\mathrm{D2C}})$, where $p_t$ is the transaction price and $m_t^{\mathrm{D2C}}$ is the latest Markit mid-quote in the 15-minute period prior to trade execution. RlzdSprd is defined as $q_t \times (p_t - m_{t+\Delta}^{\mathrm{D2C}})$, where $m_{t+\Delta}^{\mathrm{D2C}}$ is the Markit mid-quote that prevails 15 minutes after trade execution. PrcImp is defined as $q_t \times (m_{t+\Delta}^{\mathrm{D2C}} - m_t^{\mathrm{D2C}})$. Both transaction prices and quotes are in terms of par spreads and expressed in basis points. Trade direction, $q_t$, is inferred by the Lee and Ready (1991) algorithm. Trade size is in USD million. $^{**}$ and $^{*}$ denote rejection of a regression-based $t$-test for the null hypothesis that Q1 and Q4 sample means are identical at the 1% and 5% level, respectively, with inference based on the Newey and West (1987) estimate of the covariance matrix of coefficient estimates. The sample period is October 2, 2013, to October 16, 2015. The sample comprises 51,237 and 73,115 outright D2C trades in five-year on-the-run index CDSs on CDX.IG and CDX.HY, respectively.

| | Effc Sprd | | | | Rlzd Sprd | | | | Prc Imp | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Trade Size | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 |
| Panel A: CDX.IG | | | | | | | | | | | | |
| ≤25 | 0.022 | 0.066 | 0.121 | 0.278** | 0.005 | 0.027 | 0.038 | 0.074** | 0.017 | 0.040 | 0.083 | 0.204** |
| 25–50 | 0.025 | 0.075 | 0.134 | 0.294** | 0.013 | 0.020 | 0.024 | 0.046** | 0.012 | 0.055 | 0.110 | 0.248** |
| 50–100 | 0.029 | 0.084 | 0.146 | 0.313** | 0.013 | 0.019 | 0.024 | 0.043** | 0.017 | 0.065 | 0.122 | 0.270** |
| >100 | 0.033 | 0.096 | 0.167 | 0.388** | 0.013 | 0.030 | 0.042 | 0.143** | 0.020 | 0.066 | 0.124 | 0.245** |
| Panel B: CDX.HY | | | | | | | | | | | | |
| ≤5 | 0.108 | 0.338 | 0.621 | 1.350** | 0.044 | 0.121 | 0.199 | 0.354** | 0.064 | 0.216 | 0.422 | 0.996** |
| 5–10 | 0.120 | 0.365 | 0.656 | 1.407** | 0.006 | 0.104 | 0.156 | 0.280** | 0.114 | 0.261 | 0.499 | 1.127** |
| 10–25 | 0.135 | 0.402 | 0.705 | 1.560** | 0.028 | 0.112 | 0.127 | 0.271** | 0.107 | 0.290 | 0.578 | 1.289** |
| >25 | 0.158 | 0.456 | 0.787 | 1.816** | 0.082 | 0.167 | 0.247 | 0.767** | 0.076 | 0.288 | 0.541 | 1.049** |

the client base in the index CDS market is diverse, ranging from agents who use index CDSs mainly for speculation to those who use them mainly for hedging purposes. Traditional models of nonanonymous trading generally predict that nonanonymity benefits the least informed clients who can signal their lack of information to dealers (based on their business type, past trading history, etc.) and pay lower transaction costs; see, for example, Seppi (1990), Benveniste, Marcus, and Wilhelm (1992), and Desgranges and Foucault (2005). In contrast, more recent models that emphasize search frictions and networks predict that clients with more bargaining power vis-à-vis dealers or with more repeat business pay lower transaction costs; see, for example, Duffie, Gârleanu, and Pedersen (2005) and Hendershott et al. (2017).[55]

To distinguish between these different explanations, we investigate how price impact and dealer profits (i.e., realized half-spreads) vary across transaction cost quartiles. If dealers price discriminate according to the likely information content of trades, price impact should increase across transaction-cost quartiles, while if dealers price discriminate according to clients' bargaining power and/or the value of repeat transactions, realized half-spreads should increase across transaction-cost quartiles. Table VIII shows the average realized half-spread and price impact for each transaction-cost quartile. For both indices and all trade sizes, we see that price impacts and realized half-spreads increase across transaction-cost quartiles, with all differences between the fourth and first quartiles statistically significant. However, economically the variation in price impacts dominates the variation in realized half-spreads. Take, again, CDX.IG trades in the USD 25 to 50 million trade-size interval. The price impact increases from 0.012 bps in the first quartile to 0.248 bps in the fourth quartile, while realized half-spreads only increase from 0.013 bps to 0.046 bps. This provides suggestive evidence that the dispersion in transaction costs is driven largely by variation in the perceived information content of trades, that is, the least-informed clients benefit from the nonanonymous RFQ trading protocol.[56]

## VIII. Conclusion

Using transaction data, we study the market structure and transaction costs of index CDSs after the implementation of the Dodd-Frank Act. Despite a regulatory effort to promote all-to-all trading, a two-tiered market structure persists with dealer-to-client (D2C) trades and interdealer (D2D) trades taking place on distinct trading platforms. Aggregate trading volume is high, but the client order flow comprises relatively few trades of large size. Overall

[55] Obviously, the different explanations are not mutually exclusive.

[56] Consistent, several empirical studies of equity markets find that nonanonymity benefits uninformed traders; see, for example, Theissen (2003), Bessembinder and Venkataraman (2004), and Linnainmaa and Saar (2012). In contrast, empirical studies of OTC markets typically attribute dispersion in transaction costs to variation in clients' bargaining power and/or the value of repeat transactions; see, for example, Harris (2015), O'Hara, Wang, and Zhou (2018), and Hendershott et al. (2017) for recent studies of the corporate bond market.

transaction costs are low; transaction costs are higher for D2C than D2D trades, but the difference is due to higher price impact of D2C trades instead of higher dealer profits. Price impact is largely permanent and price discovery occurs predominantly in the D2C segment suggesting that clients trade on information. Trading in the D2D segment is anonymous and takes place via protocols that differ in their degree of immediacy. This gives rise to a segmentation of the interdealer order flow, where liquidity-motivated trades are executed via low-cost, low-immediacy trading protocols (mid-market matching and workups). Clients, who seek immediacy, have no incentive to trade on the D2D platforms since D2C prices almost always improve upon contemporaneous executable interdealer quotes. Trading in the D2C segment is nonanonymous and takes place via RFQ; D2C trades with higher transaction costs also exhibit higher price impact, suggesting that dealers price discriminate based on the perceived information content of trades.

Taken together, our results suggest that market quality is high in the index CDS market and that the current market structure is a consequence of client trade characteristics: relatively infrequent, large in size, and differentially informed.

We emphasize that our analysis is limited to characterizing the current market structure and does not allow for comparison with an all-to-all market structure.[57] However, if all-to-all trading were to take the form of a single limit order book, in which case the market-clearing price would reflect a pooling of adverse selection risk, our results suggest that this would benefit informed traders at the expense of uninformed traders. Our results also suggest that anonymous all-to-all trading would not be a stable equilibrium, because the least informed clients would have an incentive to trade nonanonymously off-exchange.

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[57] Transaction costs in an all-to-all structure would obviously depend on a multitude of factors such as the set of available trading protocols, the extent of liquidity provision by clients, and changes to the composition of the order flow.

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## Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

**Appendix S1**: Internet Appendix.
**Replication code.**