Journal of Financial Economics 137 (2020) 857–886

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

Swap trading after Dodd-Frank: Evidence from index CDS[☆]

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ARTICLE INFO

Article history:
Received 26 January 2018
Revised 20 August 2019
Accepted 26 August 2019
Available online 19 March 2020

JEL classification:
G14
G18

Keywords:
Dodd-Frank Act
OTC derivatives
Swaps
Swap execution facility
Request for quotes
Auction
Competition
Winner's curse
Relationship

ABSTRACT

The Dodd-Frank Act mandates that certain standard over-the-counter (OTC) derivatives must be traded on swap execution facilities (SEFs). Using message-level data, we provide a granular analysis of dealers' and customers' trading behavior on the two largest dealer-to-customer SEFs for index credit default swaps (CDS). On average, a typical customer contacts few dealers when seeking liquidity. A theoretical model shows that the benefit of competition through wider order exposure is mitigated by a winner's curse problem and dealer-customer relationships. Consistent with the model, we find that order size, market conditions, and customer-dealer relationships are important empirical determinants of customers' choice of trading mechanism and dealers' liquidity provision.

☆ The research presented in this paper is co-authored by Lynn Riggs, a former Commodity Futures Trading Commission (CFTC) economist, Haoxiang Zhu, a former CFTC limited term consultant, and Esen Onur and David Reiffen in their official capacities with the CFTC. The analyses and conclusions expressed in this paper are those of the authors and do not reflect the views of other members of the Office of Chief Economist, other Commission staff, or the Commission itself.

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A previous version of the paper was distributed under the title "Mechanism Selection and Trade Formation on Swap Execution Facilities: Evidence from Index CDS." We thank Bloomberg SEF and Tradeweb SEF for providing data and valuable comments. We thank the National Futures Association (NFA) for sharing their knowledge about the data structure and for their valuable comments. For helpful comments and suggestions, we thank Robert Battalio, Antje Berndt (discussant), Darrell Duffie, Gary Gensler, Alex Gorbenko (discussant), Arie Gozluklu (discussant), Richard Haynes, Mike Penick, Ivana Ruffini, Sayee Srinivasan, Bruce Tuckman, Pierre-Olivier Weill (discussant), and Hongjun Yan (discussant), as well as seminar participants at CFTC, MIT, Midwest Finance Association annual meeting, Conference on Financial Market Design at Georgia State University, Federal Reserve Bank of New York, Federal Reserve Board, Office of the Comptroller of the Currency, Office of Financial Research, University of Melbourne, Australian National University, University of Technology Sydney, University of Sydney, Federal Reserve Bank of Chicago, University of Notre Dame, the 13th Annual Central Bank Conference on the Microstructure of Financial Markets, NYU Stern, Boston College, NBER Market Design meeting, LAEF OTC Market Conference, Federal Reserve Bank of Atlanta Conference on Financial Regulation, University of Colorado Boulder, Harvard-MIT joint workshop on financial economics, Chicago Booth, Arizona State University, Michigan Ross, HEC Paris, Michigan State University, Western Finance Association meeting, University of Delaware, Berkeley Haas, Copenhagen Business School, University of Oxford, and the 2019 RAPS/RCFS conference. We thank Ron Yang of Harvard Business School for excellent research assistance.

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https://doi.org/10.1016/j.jfineco.2020.03.008

1. Introduction

Title VII of the Dodd-Frank Act was designed to, among other objectives, bring transparency into the once-opaque over-the-counter (OTC) derivatives markets, also known as swaps markets. The Act's goal of increased transparency in these markets likely reflected their economic significance. As of June 2017, OTC derivatives markets worldwide had a notional outstanding amount of $542 trillion, according to the Bank for International Settlements (BIS). Key implementation steps related to transparency in Title VII of Dodd-Frank include mandatory real-time reporting of swaps transactions,[1] mandatory central clearing of standardized swaps,[2] and for a subset of liquid, standardized interest rate swaps (IRS) and credit default swaps (CDS), a requirement that all trades must be executed on swap execution facilities (SEFs). According to *SEF Tracker* published by the Futures Industry Association (FIA),[3] SEFs handled about $7 trillion of CDS volume[4] and about $129 trillion of IRS volume in 2017.

This paper provides a granular analysis of SEF trading mechanisms and the associated behavior of market participants after the implementation of Dodd-Frank. A better understanding of post-Dodd-Frank swaps markets is important because of their large size and their central position in the post-crisis regulatory framework in the US and worldwide. It is far from obvious what are the best, or even desirable, market designs for swaps markets. To improve swaps market design, it is useful to understand market participants' behavior in the new, post-Dodd-Frank swap trading environment. Moreover, insights from analyzing swaps trading are also informative for the design of related markets, such as the Treasury and corporate bond markets, which are undergoing their own evolution due to regulatory or technological changes.

Our analysis focuses on index CDS markets. Relative to interest rate swaps (the only other asset class subject to the SEF trading mandate), index CDS are more standardized and have fewer alternatives in futures and cash markets. Specifically, we analyze combined message-level data for index CDS traded on Bloomberg SEF (Bloomberg) and Tradeweb SEF (Tradeweb) in May 2016. These two SEFs specialize in dealer-to-customer (D2C) trades. According to *SEF Tracker*, in May 2016, Bloomberg and Tradeweb were the top two SEFs in the index CDS market, capturing market shares of 71.0% and 13.6%, respectively. Therefore, data from these two SEFs offer a comprehensive view of customer activities in SEF-traded index CDS. Other SEFs are mostly interdealer SEFs where dealers trade with each other, with little customer participation (see Collin-Dufresne et al., 2018).

A critical aspect of a trading mechanism is the degree to which potential trading interest is exposed to the broader market. On both Bloomberg and Tradeweb, customers interested in trading index CDS typically receive indicative quotes from dealers who are available to trade, and then choose one of the following three execution mechanisms:

- Central limit order book (CLOB). Customers may execute against existing orders or post new orders on a mostly transparent order book. As explained in detail in Section 2, CLOBs in swap markets typically have "name give-ups," which reveal the identities of the two counterparties to each other after the trade.
- Request for quote (RFQ). Customers select multiple dealers and request quotes from each, revealing their intended trade size, side, and identity. The RFQ mechanism is thus similar to sealed-bid first-price auctions. Importantly, dealers observe how many other dealers a customer contacts in the RFQ.
- Request for streaming (RFS). Customers observe two-sided quotes from multiple dealers, and can respond to a single dealer's streaming quote, proposing to trade at the dealer's quoted price. If the customer does respond to a quote, he/she reveals the intended trade size, side, and his/her identity. The dealer can accept or reject this request.

In a sense, from CLOB to RFQ to RFS, a customer's detailed order information is progressively exposed to fewer and fewer market participants. The customer's choice is always made conditional on observing indicative streaming quotes, and the customer understands that none of the three mechanisms are anonymous ex post to the eventual counterparty.

The granular message-level data give us a unique opportunity to analyze trading mechanisms and strategic behavior. Our data record the full trade formation process, including customers' inquiries (demand for liquidity), dealers' responses (supply of liquidity), and resulting trades (or lack thereof). In contrast, publicly reported transaction data contain little information about how the trade takes place. In addition, our data contain identifiers for customers and dealers, which allow us to measure or control certain characteristics of these institutions.

A first look at data. Our main analysis focuses on eight CDS contracts that, by Commodity Futures Trading Commission (CFTC) rules, must be transacted on SEFs (see Section 3 for details). Among the three mechanisms mentioned above, we find that the CLOB mechanism has very low trading activity on both SEFs in our sample. Between RFQ and RFS, the RFS mechanism captures over 60% of customer activity in both the number of orders and notional quantity. That is, bilateral trades remain the most popular trading mechanism of index CDS in our sample, although customers are now provided with pre-trade transparency in the form of indicative streaming quotes. Moreover, conditional on using RFQ (e.g., electronic auctions), customers

[1] Beginning in December 2012, certain swaps transactions are required to be reported to Swap Data Repositories (SDRs). At the same time, SDRs started making a limited set of the information about these transactions available to the public. This allowed the public to learn quickly (typically, as little as 15 minutes after the trade) about the transactions that have taken place, including information about the product traded and the price.

[2] Beginning in January 2013, swaps in the most liquid interest rate swaps and index credit default swaps became subject to mandatory central clearing.

[3] The FIA is a trade organization for futures, options, and centrally cleared derivatives markets.

[4] CDS trading on SEFs is predominantly comprised of index CDS, and there is very little single-name CDS trading on SEFs.

request quotes from only about four dealers on average, even though more quotes could be obtained on both platforms. Dealers' response rates in RFQs are high overall but decline in the number of competitors. If a customer contacts 3–5 dealers in an RFQ, the response rate from dealers is about 90%, but the response rate drops to about 80% if the customer contacts more than five dealers in the RFQ.

A model of SEF trading. The salient empirical patterns mentioned above—limited order exposure by customers and variations in dealers' response rates—strongly suggest that competition is not the only consideration when customers trade on SEFs. Because competitiveness is widely viewed as a key yardstick for the health of markets, it is important to understand economic incentives that mitigate the desire to maximize competition on SEFs.

To better understand these incentives and to guide further empirical analysis, we propose and solve a model of SEF trading. We focus on the RFQ mechanism because of its central position in the spectrum of mechanisms. At least in theory, an RFQ to one dealer is similar to the RFS mechanism (bilateral), whereas an RFQ to all available dealers approaches the CLOB mechanism. In the model, the customer first contacts an endogenous number k of dealers in an RFQ process on a dealer-to-customer SEF, and then dealers smooth inventories among themselves on an interdealer SEF. This market segmentation between D2C and interdealer SEFs is realistic (Collin-Dufresne et al., 2018) and, as we discuss shortly, creates a winner's curse problem, which dampens the effect of competition. In addition to the winner's curse, we also incorporate customer-dealer relationship in the model, whereby a customer can freely request a quote from the "relationship" dealer but requesting quotes from each non-relationship dealer incurs an incremental cost.

Both the winner's curse channel and the relationship channel are important for explaining empirical facts in the data. The relationship channel generates an interior solution for the optimal number of dealers requested, and the winner's curse channel generates the comparative statics that we eventually test. For this reason, let us explain briefly the nature and the intuition of the winner's curse.

Suppose that the customer is selling an index CDS and has sent an RFQ to k dealers. In equilibrium, the dealer who wins the RFQ infers that he has the highest value among the k dealers contacted. In our model, a dealer with a lower inventory has a higher valuation of a customer sell order, all else equal. Therefore, the winning dealer infers that the total inventory of all dealers is more likely to be long. This inference about other dealers' positions will lower the price the winning dealer expects to receive when he offloads some of that position in the interdealer market (that is, the conditional expected interdealer price is below the unconditional expected price). This adverse inference reduces dealers' response rates and reduces each participating dealer's bid for the customer's order. On the other hand, a larger k does reduce each participating dealer's market power. Thus, the total effect of k on dealers' quoted spreads (defined as the difference between the dealers' quotes and a benchmark price), conditional on participating, is ambiguous. One prediction that is unambiguous is that dealers' response rate will be decreasing in k.

Within the context of the model, dealers' response rates have the most tractable and unambiguous theoretical predictions: all else equal, a dealer is more likely to respond to an RFQ if the customer's order is larger or nonstandardized, if more dealers are streaming quotes, or if dealers' inventory cost is lower. In contrast, the model's predictions on the customer's choice of order exposure and dealers' quoted spreads generally have ambiguous signs and depend on model parameters. We will present evidence on all these dimensions for empirical relevance, but the tightest link to theory is dealers' response rates.

Empirical results. As in the model, our empirical analysis also primarily focuses on RFQs. Compared to order book trading (exchange markets) and bilateral trading (most OTC markets before the crisis), trading by RFQ in financial markets has a shorter history and hence receives little academic attention, especially in empirical work (also see the literature section). On the other hand, as more fixed-income securities and OTC derivatives move to electronic trading, the RFQ mechanism has emerged as a very important source of liquidity, a flexible middle ground between the two "extremes" of bilateral trading and the equity-like CLOB (or all-to-all) mechanism. Therefore, an empirical analysis of RFQs sheds light not only on the liquidity of OTC derivatives after Dodd-Frank, but also on other fixed-income markets that are undergoing similar transitions due to changes in technology and regulation.

We begin our empirical tests by analyzing the customer's choice of how widely the customer exposes his trading interest. Because the model does not make unambiguous predictions in this regard, we directly go to the data. We exclude the CLOB due to its low activity but analyze both RFQ and RFS mechanisms at this step. We find that a larger trade size significantly reduces the customer's likelihood of choosing RFQ relative to RFS, and, if the customer does choose RFQ, reduces the number of dealers queried in the RFQ. For example, a $22 million increase in notional quantity (close to one standard deviation in the order size in the sample) reduces the probability of initiating an RFQ by about 3.9%. Conditional on the customer sending an RFQ, the same increase in notional quantity reduces the number of contacted dealers by approximately half a dealer, which is fairly substantial given that the average number of dealers queried is just above four. In addition, customers tend to expose their orders to fewer dealers if the trade size is standard or if it is early in the trading day. While these results are not directly predicted by the model, we believe they are still noteworthy because they establish facts that are new to the literature.

Using identifying information for dealers and customers, we also find that customers are more likely to send RFQs to their relationship dealers, that is, their clearing members or dealers with whom they have traded more actively in the last four months, controlling for dealer fixed effects. This evidence supports that customer-dealer relationships play a role in index CDS markets, just like in many other markets without anonymous trading.

Next, we examine dealers' strategic responses to RFQs. Again, on the two SEFs we study, dealers selected for RFQs observe how many other dealers are competing for the order (but not the identities or responses of other dealers).

Our model makes clear predictions about dealers' response rates, especially when combined with the empirical determinants of the number of dealers the customer contacts in an RFQ. As predicted by the model, we find that a dealer's likelihood of responding to an RFQ decreases in the number of dealers selected (suggesting a winner's curse effect), increases in notional quantity (suggesting larger gains from trade), and increases in the number of streaming quotes available before the customer places the order (suggesting it is easier to offload positions in interdealer markets), all controlling for dealer fixed effects. Moreover, for a fixed dealer, having a clearing relationship with the customer increases the dealer's response probability, but a higher trading volume with the customer in the past does not. Customer RFQs are executed more than 90% of the time and are more likely to result in actual trades if order sizes are larger or nonstandard, which is consistent with the interpretation that those orders imply larger gains from trade between customers and dealers.

Finally, we examine dealers' pricing behavior conditional on responding to RFQs, for which the model does not make unambiguous predictions. For on-the-run contracts that account for the vast majority of the sample, the average transaction cost is about 0.2 basis points (bps) for investment grade CDS indices and 0.5–1.1 bps for high yield ones. Using individual dealers' quotes, we find that a higher notional quantity slightly increases dealers' quoted spreads, albeit with a small economic magnitude. Dealers' quotes become more competitive, in the sense of a smaller distance between the best and the second-best quotes, if more dealers are selected in the RFQ or if the number of streaming quotes is higher, but again the economic magnitude is small. The clearing relationship reduces the quoted spread slightly only for investment grade contracts. The customer's final transaction cost does not depend significantly on any other variable in our regressions. Overall, the regressions on quoted spread do not reveal any striking or quantitatively large effect.

Relation to the literature. Our paper contributes to the small but growing literature that analyzes swaps trading after the implementation of Dodd-Frank. Collin-Dufresne et al. (2018) use swap data reported on SDRs to analyze the difference in trading costs between dealer-to-customer (D2C) and interdealer SEFs in the index CDS market. They report that effective spreads are higher on D2C SEFs and that price discovery seems to originate from D2C SEFs. Moreover, Collin-Dufresne et al. (2018) provide an in-depth analysis of mid-market matching and workup, which turn out to account for most trading activity on GFI, an interdealer SEF.

Benos et al. (2016) analyze the impact of the introduction of SEFs on the US interest rate swaps market, using publicly reported interest rate swaps data from swap data repositories (SDRs) and a private data set acquired from a clearinghouse. The authors find that the introduction of SEFs improved liquidity and reduced execution costs for end-users. Related to earlier rules in swaps markets, Loon and Zhong (2016) analyze the effect of public dissemination of swap transactions in the index CDS market. They find evidence of improved liquidity as a result of post-trade transparency. Loon and Zhong (2014) find that the (voluntary) central clearing of single-name CDS reduces counterparty risk, lowers systemic risk, and improves liquidity.

Relative to these studies, our main empirical contribution is the analysis of customers' and dealers' strategic behavior throughout the trade formation process, from the initial customer inquiry to dealers' responses to the final trade confirmation, all with time stamps. The granular data enable us to separately analyze the demand for liquidity (customers' inquiries) and the supply of liquidity (dealers' responses), which would not be possible if only completed transactions were observed. Moreover, identity information in the data allows us to study how customer-dealer relationships affect the trade formation process. Overall, equipped with the granular data, we can ask economic questions that are distinct from the papers mentioned above.

Our study also contributes to the understanding of new electronic trading mechanisms in fixed-income markets, in particular the RFQ mechanism. Hendershott and Madhavan (H&M, 2015) compare voice trading versus electronic RFQs in US corporate bond markets. In their data, customers typically request quotes from 25 or more bond dealers, and dealers' response rates are generally between 10% and 30%. Like H&M, we find that the number of dealers queried in RFQs decreases in trade size but dealers' response rates increase in trade size. But beyond H&M, we show that dealers' response rates depend on intraday market conditions such as the number of streaming quotes as well as stable variables such as customer-dealer clearing relationships and customer types. In addition, H&M find that RFQs are used more frequently for more liquid bonds and are associated with lower transaction costs. We do not find evidence that the degree of order exposure is significantly correlated with transaction cost in the index CDS market, possibly because the CDS indices we examine are already highly liquid and generally have low transaction costs (see also Collin-Dufresne et al., 2018). Finally, another key contribution of our paper is the model. While H&M discuss dealers' inventory premium and information leakage, these notations do not have a microfoundation in their analysis. In contrast, we provide a microfoundation for the winner's curse in a model of segmented SEF trading, which produces additional empirical predictions that are confirmed in the data.

The winner's curse problem in our model is related to but different from the risk of information leakage modeled by Burdett and O'Hara (1987). In their model, a seller of a block of shares contacts multiple potential buyers sequentially. The sequential nature of search implies that a contacted potential buyer may subsequently short the stock and thereby drive down the stock price. In our model, by contrast, the customer contacts multiple dealers simultaneously and the customer's order flow is not driven by superior fundamental information.

A number of papers have studied the effect of relationships on trading behavior in OTC markets. Using enhanced Trade Reporting and Compliance Engine (TRACE) data in corporate bond markets, Di Maggio et al. (2017) find that dealers offer lower spread to counterparties with stronger prior trading relations, and this pattern is magnified during stressful periods as measured by a higher VIX (the CBOE volatility index for S&P 500). Using data on transactions of insurance companies in corporate bond markets, Hendershott et al. (2016) find that larger insurers use more dealers and also have lower transaction costs. Their interpretation, also modeled formally, is that the value of future business with large insurers provides strong incentives for dealers to offer better prices. Using regulatory CFTC data, Haynes and McPhail (2019) find that customers in index CDS markets who trade with more dealers and have connections to more active dealers incur lower price impact. In single-name CDS markets, Iercosan and Jiron (2017) find that, consistent with bargaining power, a customer's transaction cost is lower if the customer is more important for the dealer or if the dealer is less important for the customer in terms of past transactions. While all these studies focus on past trading relationships, our evidence highlights the importance of clearing relationships: customers send more RFQs to their clearing dealers and their clearing dealers are more likely to respond. However, we do not find evidence that clearing relationships or past trading relationships have a significant impact on transaction costs. This is possibly due to our short sample and because SEF-traded CDS indices already have high liquidity and low transaction costs on average.

2. SEF trading mechanisms

In this section, we briefly describe SEF trading mechanisms, focusing on index CDS markets. Detailed descriptions of the trading mechanisms used on each SEF can be found on the web sites of Bloomberg SEF and Tradeweb SEF.[5]

Under CFTC rules, a SEF must offer a central limit order book (CLOB) where buy and sell quotes for various sizes can be observed by traders. SEFs also offer other ways of executing a trade such as RFQ and RFS, as we discuss in detail below. The two SEFs examined in this study, Bloomberg and Tradeweb, are similar in that the vast majority of trading is executed via electronic RFQ and RFS but differ slightly in the implementation of these execution mechanisms. Fig. 1 provides a stylized representation of the trading process on these two SEFs.

On either SEF, the customer typically starts by choosing to initiate RFS for the contract(s) he or she might be interested in trading.[6] That indication of interest automatically transmits a request for streaming (RFS) message to dealers who make markets in that contract and have agreed to stream quotes to the customer. As a result of the RFS, the customer receives a stream of two-way indicative quotes from those dealers. (Dealers have the choice of not streaming quotes to a specific customer.) The customer also observes the resting orders on the CLOB, which are firm. At this point, the customer has essentially three choices: responding to one of the RFS quotes, initiating a request for quote (RFQ), or interacting with the order book (CLOB).

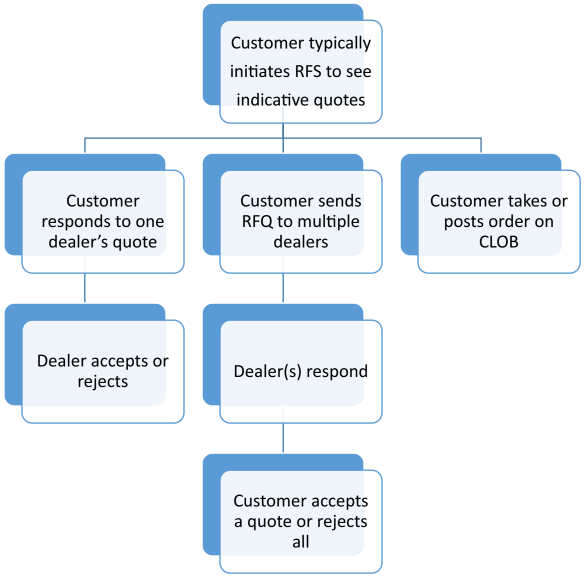

Fig. 1. Representation of the trading process for index CDS on Bloomberg and Tradeweb SEFs. We refer to the customer choices in the three columns as RFS, RFQ, and CLOB, respectively.

The customer's first option is to respond to the stream of indicative quotes by selecting a *single* quote and informing that dealer about the side of the transaction (i.e., buy or sell), the associated quantity, and the customer's identity. At that point, the dealer has the choice to accept or reject the order. If the dealer accepts, the trade occurs; and if the dealer rejects, the transaction is not executed. This is quite similar to the "last look" option in FX (foreign exchange) markets.

The customer's second option is to send an RFQ. The RFQ process is essentially an electronic, sealed-bid, first-price auction. As in an auction, price inquiries can be sent to a set of dealers chosen by the customer. CFTC rules mandate that for swaps that are subject to the SEF mandatory trading rule (known as the "made available to trade" or "MAT" mandate) at least three different dealers must be contacted for each RFQ. (Bloomberg SEF sets an upper bound of five dealers in a single RFQ, whereas Tradeweb does not set a limit.[7]) In the RFQ mechanism, the customer reveals his identity, the size of the potential transaction, and whether he or she is buying or selling. Each contacted dealer observes how many other dealers are contacted in the RFQ. The dealers who have received an inquiry can then choose to respond. In some cases, the dealer can choose to send either a firm or an indicative quote, but generally dealers send firm quotes. When a firm quote is sent, the quote has a clock that counts down (generally 30 seconds), during which time the quote is firm and the dealer cannot update their quote. The customer can select

[5] Bloomberg SEF: https://data.bloomberglp.com/professional/sites/10/Rulebook-Clean.pdf. Tradeweb SEF: http://www.tradeweb.com/uploadedFiles/Exhibit%20M-1%20TW%20SEF%20Rulebook.pdf. Both files were accessed on June 23, 2017.

[6] Customers may choose to go to RFQ directly, but they typically choose to initiate RFS since it provides valuable information.

[7] According to Fermanian et al. (2016), in European corporate bond markets, Bloomberg Fixed Income Trading sets a limit of up to six dealers in a single RFQ.

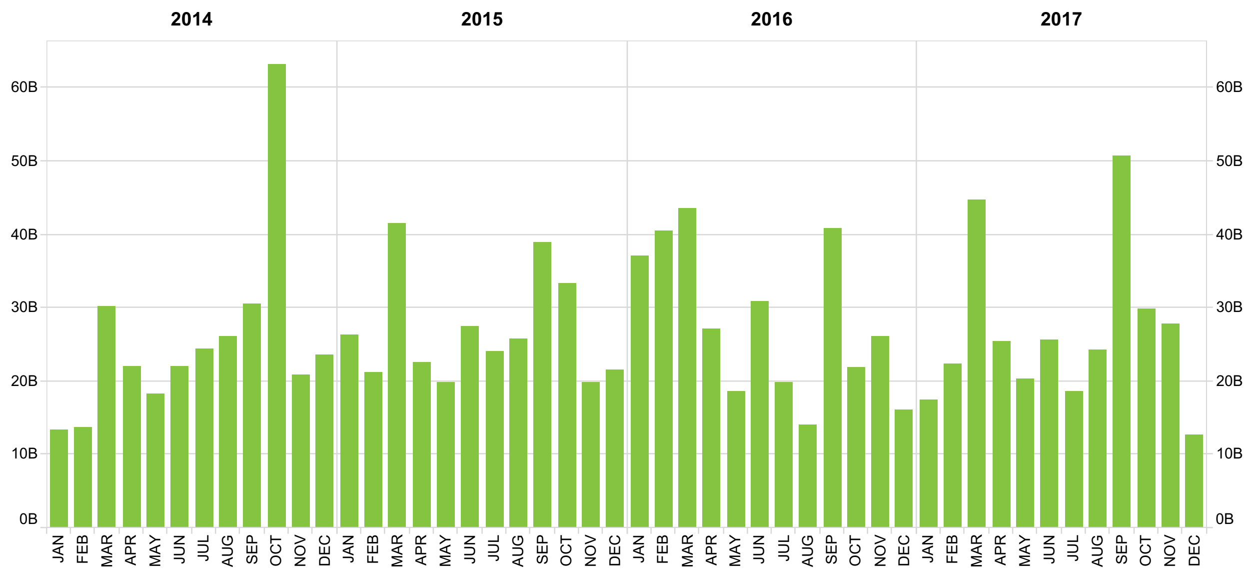

Fig. 2. SEF daily trading volume of index CDS in $ billion. Source: Futures Industry Association, https://fia.org/node/1834/.

one of the available quotes. If the customer selects a firm quote, the trade is completed, and other dealers are notified that their quotes were not selected. If the customer selects an indicative quote, the dealer has the option to accept or reject the order. If the customer does not choose any of the quotes, they will expire and no transaction occurs.

Finally, the customer may use the CLOB, by either taking one of the firm orders on the CLOB (aggressive side), at the size and price of the existing order, or posting their own firm order on the CLOB (passive side) and waiting for another trader to take it. Different from order books in equity and futures markets, order books in swaps markets typically have "post-trade name give-ups." The Commodity Futures Trading Commission (2018a) defines post-trade name give-up as "the practice of disclosing the identity of each swap counterparty to the other after a trade has been matched anonymously."

To summarize, customers on D2C SEFs for index CDS receive some degree of pre-trade transparency through indicative streaming quotes and the CLOB when it is active. To trade, customers may respond to a single dealer's streaming quotes (labeled as RFS for short), run an auction (RFQ), or use the order book (CLOB). Note that even if the customer chooses RFQ or CLOB, he still observes the streaming quotes. Thus, the main difference between the three mechanisms is not the information received by the customer, but how widely the customer chooses to reveal his order information. As discussed above, none of the three mechanisms are anonymous after the trade happens.

3. Data and summary statistics

3.1. A first look at SEF trading activity of index CDS

Index CDS is an important derivative class that is, for the most part, subject to the CFTC's SEF trading rules since February 2014. Fig. 2 shows the average daily trading volume of index CDS in $ billions by month, from January 2014 to December 2017. These data are publicly available from the Futures Industry Association and only cover US-registered SEFs. Throughout the four years, the daily trading volume of index CDS is about $30 billion. Generally speaking, March and September have the highest average daily volume as the major CDS indices are reconstituted and investors roll their index CDS positions from one series to the next during this time.

To understand usual investor and dealer behaviors, it is desirable to avoid the index-rolling periods as trading during these periods may not be generalizable to other periods. For example, Collin-Dufresne et al. (2018) find that the transaction prices of package trades like these tend to be abnormal and look like outliers. For this reason, we pick a non-roll month, May 2016, as our sample period for the empirical analysis.

Table 1 shows more details of index CDS trading activity in May 2016, broken down by SEF, currency, and index. Over the 21 trading days of this month, the average daily trading volume of index CDS is $18.6 billion. Bloomberg and Tradeweb have market shares of 71.0% and 13.6%, respectively. About 69% of the SEF trading activity is on USD indices, and the remainder is on EUR indices. CFTC rules require the on-the-run and the first off-the-run series of 5-year CDX.NA.IG, CDX.NA.HY, iTraxx Europe, and iTraxx Europe Crossover to be executed on SEFs.[8] While other CDS indices are permitted (but not required) to be traded on SEFs, we observe that CDX.NA.IG, CDX.NA.HY, iTraxx Europe, and iTraxx Europe Crossover have a combined

[8] All four indices are corporate indices administered by Markit Indices Limited. The CDX North American Investment Grade (CDX.NA.IG) and iTraxx Europe indices are composed of entities with investment grade credit ratings in North America and Europe, respectively. The CDX North American High Yield (CDX.NA.HY) index is composed of North American entities with high yield credit ratings. The iTraxx Crossover index is composed of European entities with non-investment grade credit ratings.

Table 1
Daily SEF trading volume in index CDS in May 2016.
Source: Futures Industry Association.

By SEF	Average daily volume ($ mil)	Market share (%)
Bloomberg	$13,194	71.0
TW	$2,517	13.6
GFI	$945	5.1
Tullett Prebon	$931	5.0
ICE	$385	2.1
MarketAxess	$297	1.6
ICAP	$152	0.8
BGC	$116	0.6
Tradition	$39	0.2
Total	$18,576	100.0
By currency	Average daily volume ($ mil)	Market share (%)
USD	$12,799	68.9
EUR	$5,774	31.1
JPY	$3	0.0
Total	$18,576	100.0
By CDS index (top 10 only)	Average daily volume ($ mil)	Market share (%)
CDX.NA.IG	$9,128	49.1
iTraxx Europe	$3,893	21.0
CDX.NA.HY	$3,094	16.7
iTraxx Europe Crossover	$929	5.0
iTraxx Europe Senior Financials	$729	3.9
CDX.EM	$453	2.4
iTraxx Europe-Option	$210	1.1
CDX.NA.IG-Option	$68	0.4
CDX.NA.HY-Option	$16	0.1
iTraxx Europe Sub Financials	$15	0.1
Total	$18,533	99.8

volume share of about 92%. Moreover, the two investment grade indices, CDX.NA.IG and iTraxx Europe, have total volume about 3–4 times that of the two high yield indices, CDX.NA.HY and iTraxx Europe Crossover.

3.2. Main data set: Message-level data from Bloomberg and Tradeweb

The primary data set we use in this paper is message-level data from Bloomberg and Tradeweb from May 2016. These two venues specialize in customer-to-dealer trades and, as shown above, account for about 85% of all SEF trading volume in index CDS in our sample period. For each message, the data include the message type (e.g., request for quote or response to request), parties to the trade, the specific CDS index being traded, a buy/sell indicator, price, notional quantity, date, time, and other relevant trade characteristics. The messages related to a given request or order are grouped together with a unique identifier. We refer to the group of related messages as a "session."

We filter our message data based on the following criteria:

- We restrict the sample to MAT contracts, i.e., the on-the-run and the first off-the-run series with a 5-year tenor in CDX.NA.IG, CDX.NA.HY, iTraxx Europe, and iTraxx (Europe) Crossover. By CFTC rules, non-MAT contracts are not required to be traded on SEFs, and if they trade on a SEF, they are not subject to the CFTC's requirement of sending RFQs to at least three dealers.
- Among MAT contracts, we also exclude orders whose sizes are above the contract-specific minimum block sizes.[9] By CFTC rules, block-sized trades are not required to be executed on SEFs; nor are they subject to the "RFQ to minimum three" rule (if they do trade on a SEF by RFQ). Hence, the regulatory environment is substantially different for block size and less-than-block size trades.
- We also exclude strategies and orders that are exempted from the "RFQ to three" requirement. In our data, these types of orders include packages such as index rolls (selling an off-the-run index CDS and simultaneously buying the on-the-run index).

While it is undesirable to lose data, the filtering is done to make sure that all customer orders in the final sample are required to be executed on SEFs. The complementary question of how investors determine where to execute "permitted" trades,[10] on SEF or off SEF, is for a different study.

Table 2 below shows the number of transactions and aggregate notional amount traded via RFQ, RFS, and CLOB in our sample. We observe that RFS is the most popular transaction mechanism, followed by RFQ. CLOBs only account for 3% of transactions and 2.5% of notional amounts.

The low level of activity on CLOBs could be due to post-trade name give-ups, as discussed earlier. When swaps were not centrally cleared, name give-up helped the swaps

[9] In our sample, the smallest sizes of block trades are 110 million USD for CDX.NA.IG, 28 million USD for CDX.NA.HY, 99 million EUR for iTraxx Europe, and 26 million EUR for iTraxx Crossover.

[10] By CFTC rules, "permitted" trades refer to trades that can, but are not required, to be executed on SEFs.

Table 2
Transaction volume and count by trade mechanism.
The sample includes index CDS trades on Bloomberg and Tradeweb in May 2016 that satisfy the following filtering criteria: MAT contracts, size below minimum block sizes, and not exempted from the "RFQ to three" requirement.

	RFQ	RFS	CLOB
Notional quantity ($mil)	55,976	113,545	4,468
Number of transactions	2,943	5,079	250

counterparties manage counterparty credit risk. But such credit risk is now insulated by the clearinghouse because many standard OTC derivatives, including the index CDS that we consider, became centrally cleared after the financial crisis. For this reason, some buy-side investors have argued that post-trade name give-up no longer serves credit-risk purposes, but instead leads to information leakage, discourages the use of CLOBs, and bifurcates liquidity into a dealer-to-dealer (D2D) segment and a dealer-to-customer (or dealer-to-client, D2C) segment (see Managed Fund Association, 2015). The Commodity Futures Trading Commission (2018b) also states, in footnote 976 of its proposed rule, that "The Commission notes that additional factors, such as the use of name give-up and the lack of certain trading features, may have also contributed to the limited use of Order Books." Recently, the Commodity Futures Trading Commission (2018a) has requested comments on name give-ups but has not yet made its determination.

Because of the low level of activity on CLOBs in the D2C SEFs in our sample period, we exclude CLOB messages from our analysis and focus on RFQ and RFS. In the final sample, we have 8410 sessions and $177.602 billion notional value, or 400 customer orders and $8.46 billion notional value per day, including both RFS and RFQ. Note that these numbers refer to the initial customer orders, so they are larger than the final transaction numbers shown in Table 2. The $177.602 billion notional value in customer orders and the $169.521 billion notional value in final trades imply that 95.5% of notional amount requested by customers through RFQ and RFS results in trades.

Table 3 shows the summary statistics of key variables that we use in the empirical analysis. Panel A shows the summary statistics of all RFQ and RFS sessions, whereas Panel B restricts to RFQs since they are the focus of a substantial part of our paper. In each panel, we report the summary statistics for all indices as well as separately for investment grade (IG, including CDX.NA.IG and iTraxx Europe) and high yield (HY, including CDX.NA.HY and iTraxx Crossover).

RFQ and RFS sessions—Across all eight indices, the notional quantity has a mean of $21 million, while IG indices have a mean of $34.8 million.[11] Order size is the most salient difference between HY and IG in our sample.

For each contract, a few notional quantities occur with very high frequency in the data, and we label them as "standard" quantities.[12] On average, more than 60% of the trades are in those standard quantities, and this number is comparable between IG and HY. When a customer sends out an RFQ or RFS inquiry, about 17.5 streaming quotes are available on the index. Slightly less than 30% of the sessions occur in the last four hours of active trading for the day. Customer buys and sells are balanced.

The message-level data also contain identity information of the customer, enabling us to disaggregate the activity by customer type. The most active customer type is hedge fund/proprietary trading firm/private equity firm (HF/PTF/PE), representing 60% of the sessions, with a slightly higher fraction in HY indices. Asset manager is the second most active customer type, accounting for 24% of the sessions, but with a slightly higher share in IG indices. In about 7% of the sessions, the customer (quote seeker) is in fact a dealer (market maker), in the sense that the quote seeker has provided quotes to customers in other sessions. Only 6% of the sessions are initiated by banks or brokers who are not market makers. The remaining 2% of orders come from other customer types (including non-financial corporations, insurance companies, and pension funds, among others). We also calculate the share of these customer types in terms of notional quantity, and the results are very similar (not reported).

Only RFQ sessions—On average, customers select RFQ 36% ($=3031/8410$) of the time (the remaining 64% goes to RFS). Compared with the full sample with both RFQ and RFS sessions (Panel A of Table 3), RFQ sessions display the following features:

- The average size of RFQ orders is $18.3 million, smaller than RFS (but standard deviation is similar, at $21 million). IG RFQ orders are about three times as large as HY RFQ orders.
- Only 41% of RFQ orders are of standard size, lower than the full sample, with HY slightly higher.
- The number of streaming quotes right before the session is similar between RFQ and RFS sessions.
- 30% of RFQ orders are sent during the last four hours of active trading, similar to RFS orders.
- For RFQ, asset manager is the most active customer type, accounting for 49% of the orders. Hedge fund/proprietary trading firm/private equity firm is the second most active customer type, accounting for 39% of RFQ orders.
- Conditional on selecting RFQ, a customer on average queries 4.1 dealers and receives 3.6 responses, implying an overall response rate of nearly 90%. About 92% of the RFQ sessions result in trades.[13] All these statistics are similar between IG and HY.

[11] The average order size in our sample is smaller than that reported in Haynes and McPhail (2019) due to different methodologies in constructing the data sample. Haynes and McPhail (2019) remove block trades by using a self-reported block flag in the trade repository data, whereas we use the contract-specific minimum block size as a cutoff. For example, a large trade that is above the minimum block size but not self-reported as such would be in the sample of Haynes and McPhail (2019), but not in our sample. Moreover, Haynes and McPhail (2019) remove all trades with notional size less than $5 million, whereas we do not impose a lower bound on the order size.

[12] For CDX.NA.IG, standard sizes include 10, 20, 25, 50, and 100 million USD notional. For CDX.NA.HY, standard sizes include 5, 10, 15 and 25 million USD. For iTraxx Europe, standard sizes include 10, 20, 25, and 50 million EUR. For iTraxx Crossover, standard sizes include 3, 5, 10, 15, and 20 million EUR.

[13] About 93% of RFS sessions result in trade (unreported).

Table 3
Mean and standard deviation (SD) of key empirical variables.
The top half shows the summary statistics for all RFQ and RFS sessions, and the bottom half shows only RFQ sessions. The sample is described in Table 2, after suppressing trades that occurred on CLOBs.

Panel A: RFQ and RFS						
# Customer orders	All 8410		IG 3860		HY 4550	
	Mean	SD	Mean	SD	Mean	SD
Notional quantity ($mil)	21.12	22.03	34.81	25.59	9.51	6.90
Standard quantity (0/1)	0.64	0.48	0.60	0.49	0.67	0.47
# Streaming quotes	17.56	7.19	16.30	5.95	18.56	7.93
Last 4 hours of trading (0/1)	0.27	0.45	0.27	0.45	0.28	0.45
Customer buys protection (0/1)	0.50	0.50	0.50	0.50	0.49	0.50
Customer is asset manager (0/1)	0.24	0.43	0.28	0.45	0.21	0.40
Customer is HF/PTF/PE (0/1)	0.60	0.49	0.54	0.50	0.66	0.48
Customer is bank/broker (0/1)	0.06	0.24	0.09	0.28	0.05	0.21
Customer is dealer (0/1)	0.07	0.26	0.07	0.26	0.08	0.27
Customer is other (0/1)	0.02	0.15	0.03	0.17	0.02	0.12
Customer selects RFQ (0/1)	0.36	0.48	0.37	0.48	0.35	0.48
Panel B: RFQ Only						
# Customer orders	All 3031		IG 1427		HY 1604	
	Mean	SD	Mean	SD	Mean	SD
Notional quantity ($mil)	18.28	21.32	28.86	26.35	8.88	7.31
Standard quantity (0/1)	0.41	0.49	0.36	0.48	0.47	0.50
# Streaming quotes	17.18	7.16	15.96	5.66	18.27	8.13
Last 4 hours of trading (0/1)	0.30	0.46	0.30	0.46	0.30	0.46
Customer buys protection (0/1)	0.51	0.50	0.51	0.50	0.52	0.50
Customer is asset manager (0/1)	0.49	0.50	0.52	0.50	0.46	0.50
Customer is HF/PTF/PE (0/1)	0.39	0.49	0.35	0.48	0.42	0.49
Customer is bank/broker (0/1)	0.06	0.24	0.07	0.26	0.05	0.22
Customer is dealer (0/1)	0.04	0.20	0.03	0.16	0.05	0.23
Customer is other (0/1)	0.02	0.15	0.03	0.17	0.01	0.12
# Dealers queried in RFQ	4.12	1.35	4.02	1.19	4.21	1.48
# Dealers' responses in RFQ	3.64	1.36	3.57	1.14	3.70	1.52
Response rate in RFQ	0.89	0.19	0.90	0.18	0.88	0.20
Order results in trade in RFQ (0/1)	0.92	0.27	0.91	0.29	0.93	0.26

Fig. 3 provides more details on the number of dealers contacted and dealers' response rates in RFQs. The top plot of Fig. 3 reports the probability distribution of the number of dealers contacted. The probability masses add up to one, although we separately label IG and HY indices. Customers most frequently request quotes from three dealers, which happens in about 45% of the RFQ sessions, followed by five dealers, which happens in slightly less than 30% of the RFQ sessions. Customers rarely select more than five dealers for their RFQs. The bottom plot of Fig. 3 reports dealers' response statistics in RFQs. The overall pattern is that response rates are high but decrease in the number of dealers requested. The response rate is about 90% if the customer requests quotes from three to five dealers, but the response rate decreases to about 80% if the customer requests quotes from six or more dealers. These patterns are broadly similar between IG and HY.

The summary statistics so far are at the session level. Table 4 shows summary statistics of dealers' and customers' activity. In our sample, there are 20 dealers and 287 customers (including dealers who act as quote seekers). A salient pattern arising from Table 4 is that most customers interact with relatively few dealers. The median customer contacts only six out of the 20 dealers and trades with four. The median dealer contacts 76 customers and trades with 54. The fact that the mean activity for both customers and dealers is greater than the median suggests a right-skewed distribution, that is, some dealers and some customers seem to be much more active than others.

3.3. Relationship between customers and dealers

An important aspect of non-anonymous trading is the "relationship" between customers and dealers. We construct two proxies.

The first proxy is clearing relationship. All MAT contracts in our sample are subject to the mandatory clearing requirement of Dodd-Frank. However, most market participants are not direct members of derivatives clearinghouses. Instead, they rely on their clearing agents, who are direct members of clearinghouses, to get access to clearing and therefore satisfy the clearing mandate. For a fee, the clearing member helps the customer manage margin and collateral as a normal part of a cleared derivative trade, and

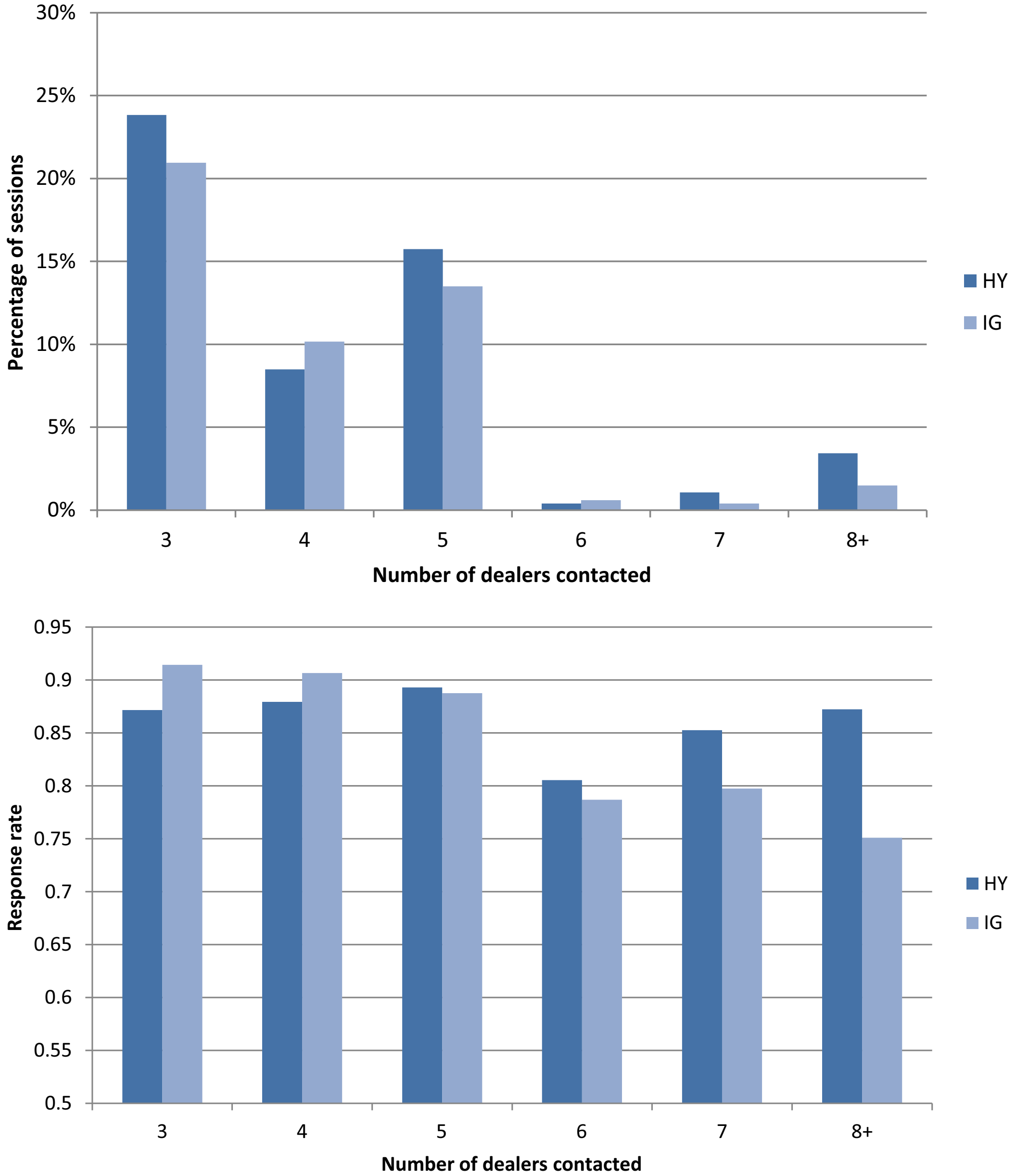

Fig. 3. Number of dealers queried and dealers' response rate in RFQs. The top plot shows the probability distribution of the number of dealers contacted, where the masses add up to one. In the bottom plot, the *x*-axis shows the number of dealers contacted and the *y*-axis shows the response rate. The data sample is described in Table 3, restricted to RFQs.

also contributes to the clearinghouse's default fund on behalf of the customer. These important functions make the clearing member somewhat "special" to the customer relative to other dealers who are not affiliated with the customer's clearing member.

Indeed, the Joint FSB-BCBS-CPMI-IOSCO Report (2018),[14] for which one of the authors acted as an academic expert, finds evidence about asymmetric bargaining positions in the clearing of derivatives. Survey data from a large clearinghouse indicate that 50% of clients have exactly one clearing member, and 30% two (see Fig. C.8 of the joint report). Moreover, clearing members typically give clients a notice period of 1–3 months before off-boarding (i.e., firing) the clients, but the time required to find a new clearing agent is 4–6 months (see Fig. E.5 of the joint report). These facts point to the strong bargaining power of dealers in OTC derivatives where clearing is essential. In addition, two recent class lawsuits in OTC derivatives alleged that, among other things, some dealer banks used their

[14] The report is published jointly by the Financial Stability Board (FSB), the Basel Committee on Banking Supervision (BCBS), the Committee on Payments and Market Infrastructures (CPMI), and the International Organization of Securities Commissions (IOSCO).

Table 4
Characteristics of dealers and customers in RFQ and RFS sessions.
The data sample is described in Table 3. In addition, a dealer is defined as a counterparty that has ever responded to an RFQ or an RFS in the sample, and all other counterparties are customers.

Dealers (total 20)	Mean	Std. dev.	Median
Market share (dealer's trade volume/total)	5.00%	5.44%	3.23%
Total number of trades	391.7	416.3	286
Number of unique customers traded with	68.1	60.9	54
Number of unique customers interacted with	95.9	82.2	76
Customers* (total 287)	**Mean**	**Std. dev.**	**Median**
Market share (customer's trade volume/total)	0.35%	0.99%	0.05%
Total number of trades	27.3	70.2	6
Number of unique dealers traded with	4.7	3.5	4
Number of unique dealers interacted with	6.7	3.4	6

*Including dealers that request quotes from other dealers

unique positions as clearing members to discourage customers from using multilateral trading mechanisms in centrally cleared OTC derivatives (see Chang, 2016).

For each customer c and dealer d, we say c and d have a clearing relationship if customer c's clearing member and dealer d are the same firm or affiliated through the same bank holding company. In our sample, the vast majority of customers (over 85% of them) use a single clearing member. (Different customers tend to use different clearing members, but any given customer tends to use a single clearing member.)

The second proxy of relationship is past trading activity between a customer and a dealer. To construct this proxy, we supplement our message-level data with transaction-level regulatory data that were made available to the CFTC as a result of the Dodd-Frank Act. This complementary data set has information on every trade that is in the CFTC's jurisdiction, including the identifier of each counterparty. We focus on all index CDS trades (including non-MAT contracts and block trades) from January to April 2016, the four months leading up to our sample of May 2016 data. Using counterparty identifiers, we calculate the total number of transactions and the total amount of notional traded for each customer-dealer pair. These statistics are further used to construct relationship variables that we describe in more detail later.

4. A model of SEF trading and implications

The summary statistics presented in the previous section show substantial heterogeneity in how customers expose their orders to dealers and how dealers respond to customers' requests. In particular, customers restrict their order exposure to relatively few dealers, especially for larger trades. Conversely, while dealers' response rates are high, they are not 100%.

The primary objective of this section is to formally propose, by building and solving a parsimonious model, two relevant economic forces that could potentially explain the customers' and dealers' behavior throughout the trade formation process—the winner's curse and the customer-dealer relationship.

- The winner's curse problem is faced by dealers when bidding in an RFQ. In practice, the RFQ is indivisible, which implies that the dealer who wins the customer's order on a D2C SEF may need to subsequently lay off unwanted positions on an interdealer SEF. Appendix C presents evidence that on days for which a dealer makes trades on either D2C SEFs or D2D SEFs (or both), the trading directions in the two segments are opposite in about one-third of the dealer-day observations. This fraction is slightly higher (38%) if the absolute value of a dealer's trades in D2C SEFs for a particular contract is larger than the average across all 21 days in our sample for the dealer and the contract. This evidence suggests that offloading part of a D2C trade in the D2D segment is an important feature of the data. Therefore, when bidding for the customer's order in an RFQ, dealers are acutely concerned with the expected interdealer price and the speed at which dealers can lay off their unwanted positions. This concern gives rise to the winner's curse.
- The relationship between customers and dealers is motivated by the clearing relationship, and modeled as an overlay of costly solicitation of quotes from dealers who are not the customer's clearing agent.

Winner's curse and relationship are not the only possible reasons behind limited order exposure. Appendix D discusses front-running as another potential explanation, but the evidence presented there suggests that the front-running hypothesis has little empirical support in our setting.

4.1. Model primitives

Time is continuous, $t \in [0, \infty)$. The payoff of a traded asset is realized at some exponentially distributed time with arrival intensity r, that is, with mean waiting time $1/r$. The realized asset payoff has a mean of v. Everyone is risk neutral.

At time $t = 0$, a customer arrives to the dealer-to-customer (D2C) SEF with a demand $-y$, or supply y. There are n dealers on the SEF, and the customer endogenously chooses $k \in \{1, 2, 3, \ldots, n\}$ dealers and sends an RFQ to them. One of the n dealers is the customer's clearing member, and adding the clearing member to the RFQ is costless for the customer. Contacting each additional dealer who is not his clearing member, however, incurs a cost of cy for the customer, where c is a constant and $y > 0$ is the order size. This cost could come from duplicated back-office operations with multiple dealers or from the implicit relationship cost of giving the trade to a dealer other than the customer's clearing member. This assumption of costly addition of dealers in RFQs is not used for most of the analysis and is only invoked in Section 4.4.

While the customer's choice here seems to be narrowly confined to the RFQ protocol, the model is in fact more general because responding to a single dealer's streaming quotes is conceptually similar to setting $k = 1$ and posting the order to the CLOB is conceptually similar to setting $k = n$.

As in practice, only the k selected dealers observe the customer's supply y, and the k selected dealers also observe k. The dealers' decision is whether to respond to the RFQ and, if so, at what price. We assume that the customer has a reservation price $\underline{p}$ that depends on y, and this reservation price is observable to all dealers. The customer picks the best price and sells the entire supply y to the winning dealer. As a tie-breaking rule, a dealer does not respond to the RFQ if the probability of winning the order is zero. Again, as in practice, this RFQ behaves like an indivisible, first-price auction.

Once the D2C trade takes place, the n dealers trade among themselves in a different interdealer (D2D) SEF. We denote by z_i the inventory of the asset held by dealer i at time 0 before the D2C trade, where $\{z_i\}$ are independent and identically distributed (i.i.d.) with cumulative distribution function $F : (-\infty, \infty) \mapsto [0, 1]$ and mean zero. We denote the total inventory held by dealers before the D2C trade by $Z \equiv \Sigma_i z_i$. Immediately after the D2C trade, any dealer i who does not win the D2C trade enters interdealer trading with an inventory $z_{i0} = z_i$, whereas the dealer j who wins the D2C trade enters interdealer trading with the inventory $z_{j0} = z_j + y$. For any generic $t > 0$, we denote the inventory of dealer i at time t by z_{it}. The instantaneous flow cost of dealer i for holding the inventory z_{it} is $0.5\lambda z_{it}^2$, where $\lambda > 0$ is a commonly known constant. For simplicity, dealers receive no further inventory shocks after the D2C trade, so the total inventory held by dealers during D2D trading is $Z_t = Z + y$ for $t \geq 0$. At any time, a dealer's inventory is his private information.

The trading protocol on the D2D SEF is periodic double auctions, as in Du and Zhu (2017) and Duffie and Zhu (2017). Specifically, the double auctions are held at clock times $t \in \{0, \Delta, 2\Delta, \ldots\}$, where $\Delta > 0$ is a constant that represents the "speed" of the interdealer SEF. For instance, continuous interdealer trading implies $\Delta = 0$. In the double auction at time t, each dealer i submits a demand schedule $x_{it}(p)$. The equilibrium price at time t, p_t, is determined by

$$\sum_i x_{it}(p_t) = 0. \tag{1}$$

The continuation value of dealer i at some time $t = \ell\Delta > 0$, right before the double auction at time t, is given recursively by

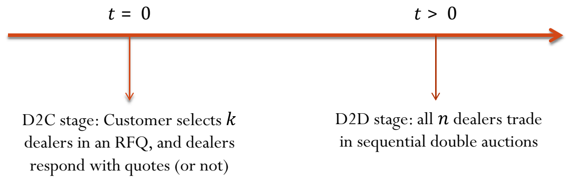

Fig. 4. Time line of the model.

$$V_{it} = -x_{it}p_t - 0.5\lambda(x_{it} + z_{it})^2 \frac{1 - e^{-r\Delta}}{r} + (1 - e^{-r\Delta})(x_{it} + z_{it})v + e^{-r\Delta} E_t[V_{i,t+\Delta}]. \tag{2}$$

Here, the first term is the payment made to purchase x_{it} units at price p_t; the second term is the expected delay cost incurred between time $t = \ell\Delta$ and the payoff time; the third term is the expected value of the asset if it pays off before the next double auction; and the final term is the continuation value if the asset payoff is not realized by the next double auction. Each dealer i's strategy $x_{it}(\cdot)$ maximizes $E_t[V_{it}]$, taking all other dealers' strategies as given.

The time line of the model is summarized in Fig. 4. We will solve it by backward induction, from the D2D SEF to the D2C SEF.

4.2. Equilibrium on the interdealer SEF

This model of interdealer trading was solved in Du and Zhu (2017) and Duffie and Zhu (2017), as summarized in the next proposition.

Proposition 1 (Du and Zhu, 2017; Duffie and Zhu, 2017). *The following strategies constitute an equilibrium in the interdealer SEF. In the double auction at time t, each dealer i submits the demand schedule*

$$x_{it}(p) = a\left(v - p - \frac{\lambda}{r} z_{it}\right), \tag{3}$$

where

$$a = \frac{r}{\lambda} \frac{2(n-2)}{(n-1) + \frac{2e^{-r\Delta}}{1-e^{-r\Delta}} + \sqrt{(n-1)^2 + \frac{4e^{-r\Delta}}{(1-e^{-r\Delta})^2}}}. \tag{4}$$

The equilibrium price is

$$p_t = v - \frac{\lambda}{nr} Z_t. \tag{5}$$

These strategies are ex post optimal, in that they remain an equilibrium even if the traders receive some information about each other's inventories.

Moreover, the continuation value of each trader i conditional on Z_0 is

$$V_{i,0+} = \mathcal{V}(z_{i0}, Z_0) = \left[v\frac{Z_0}{n} - \frac{\lambda}{r}\left(\frac{Z_0}{n}\right)^2\right] + \left(v - \frac{\lambda}{r}\frac{Z_0}{n}\right)\left(z_{i0} - \frac{Z_0}{n}\right) - \frac{0.5\lambda}{r}\frac{1 - a\lambda/r}{n-1}\left(z_{i0} - \frac{Z_0}{n}\right)^2. \tag{6}$$

The continuation value function $\mathcal{V}(\cdot,\cdot)$ will serve as the "terminal value" when dealers solve their optimal strategy in the D2C SEF, which we turn to next.

4.3. D2C SEF: Dealers' optimal bidding strategy

Without loss of generality, we will consider $y > 0$, that is, the customer is selling the asset and the dealers are buying it. The selected dealers in the RFQ are labeled as dealer 1, 2, 3, ..., k. Upon receiving the RFQ, dealer i's value immediately changes to $\mathcal{V}(z_i, Z+y)$, and if dealer i wins the quantity y_t, his value changes to $\mathcal{V}(z_i+y, Z+y)$. Thus, by winning the RFQ, the increase in value to dealer i is

$$U_i \equiv \mathcal{V}(z_i+y, Z+y) - \mathcal{V}(z_i, Z+y)$$
$$= \underbrace{\upsilon y - \frac{\lambda}{r}\frac{y^2}{n} - \frac{0.5\lambda C}{r}\frac{n-2}{n}y^2}_{A_1,\text{ dependent on } y \text{ but observed by all dealers in RFQ}}$$
$$- \underbrace{\frac{\lambda(1-C)}{nr}}_{A_2,\text{ "winner's curse"}} Zy - \underbrace{\frac{\lambda C}{r}}_{B,\text{ "private value"}} z_i y, \tag{7}$$

where

$$C = \frac{1-a\lambda/r}{n-1}. \tag{8}$$

There is a common component and a private component for U_i. For instance, if $y > 0$, a dealer who is short inventory benefits more from winning this customer order (last term). In addition, if $y > 0$, the more negative is the total inventory Z of all dealers, the more attractive it is for each dealer to win the customer's sell order (middle term). This is because a more negative total inventory implies that the interdealer price will be higher later, so it would be more advantageous to acquire the inventory from the customer.

Dealer i's increased value of winning the RFQ can be rewritten as

$$U_i = A_1 - A_2 Z_{-i} y - (A_2+B) z_i y, \tag{9}$$

where $Z_{-i} = Z - z_i$.

Dealer i's profit of bidding p is

$$\pi_i = (U_i - py)1(win), \tag{10}$$

$$E[\pi_i] = (A_1 - A_2 y E[Z_{-i} \mid win] - (A_2+B) z_i y - py) P(win). \tag{11}$$

Recall that the inventories $\{z_j\}$ have zero mean, so $E[Z_{-i} \mid win] = E[Z^k_{-k} \mid win]$, where $Z^k_{-i} \equiv \sum_{j\neq i, 1\leq j\leq k} z_j$.

We conjecture the following equilibrium:

- There is some inventory threshold z^* (which depends on k) such that dealer i responds to the RFQ if and only if $z_i < z^*$. (Recall that, by the tie-breaking rule, a dealer does not respond if he has zero probability of winning the RFQ.)
- Each dealer uses a downward-sloping bidding function $\beta(\,\cdot\,)$: $z_i \mapsto \beta(z_i)$, where $\beta(z_i)$ denotes the per-notional price. So the total price paid conditional on winning the RFQ is $\beta(z_i)y$.

Under the conjectured strategy, conditional on responding to the RFQ, dealer i wins the RFQ if and only if $z_i < \min_{j\neq i, 1\leq j\leq k} z_j$. Thus, a dealer whose inventory is just below z^* should receive zero expected profit, i.e.,

$$0 = \left(A_1 - A_2 y E\left[Z^k_{-i} \mid \min_{j\neq i} z_j > z^*\right]\right.$$
$$\left. - (A_2+B) z^* y - \beta(z^*) y\right) P\left(\min_{j\neq i} z_j > z^*\right)$$
$$= \left(A_1 - A_2 y (k-1) E\left[z_j \mid z_j > z^*\right]\right.$$
$$\left. - (A_2+B) z^* y - \underline{p} y\right)(1-F(z^*))^{k-1}. \tag{12}$$

Here, the dealer at z^* bids the customer's reservation price $\underline{p}$ because he wins if and only if no other dealer responds, in which case he, as the only dealer responding, would bid the customer's reservation price. By Eq. (12), the cutoff z^* is given by

$$0 = \frac{A_1}{y} - A_2(k-1)E[z_j \mid z_j > z^*]$$
$$- (A_2+B)z^* - \underline{p} \equiv \Gamma(y, z^*). \tag{13}$$

Since A_2 and B are both positive, the function $\Gamma(y, z^*)$ is decreasing in z^*. As z^* increases from $-\infty$ to $+\infty$, $\Gamma(y, z^*)$ decreases from $+\infty$ to $-\infty$. Thus, there is a unique, finite z^* that solves Eq. (13).

For a generic $z_i < z^*$, the expected gross profit of bidding p (per unit notional) is

$$E[\pi_i] = \left(A_1 - A_2 y (k-1) E[z_j \mid \beta(z_j) < p]\right.$$
$$\left. - (A_2+B) z_i y - py\right) P(\max_{j\neq i} \beta(z_j) < p)$$
$$= \left(A_1 - A_2 y (k-1) E[z_j \mid z_j > \beta^{-1}(p)]\right.$$
$$\left. - (A_2+B) z_i y - py\right)(1 - F(\beta^{-1}(p)))^{k-1}. \tag{14}$$

By the usual first-order approach, we can solve, for all $z_i < z^*$,

$$\beta(z_i) = \frac{A_1}{y} - (A_2+B)z_i - \underbrace{(A_2+B)\frac{\int_{u=z_i}^{z^*}(1-F(u))^{k-1}du}{(1-F(z_i))^{k-1}}}_{\text{Market power}}$$
$$- \underbrace{A_2(k-1)E[z_j \mid z_j > z_i]}_{\text{Winner's curse}}. \tag{15}$$

It is easy to verify that $\beta(z_i)$ is decreasing in z_i, as conjectured.

The bidding strategy in Eq. (15) combines two important incentives: competition and winner's curse. As is standard in auction theory, the term involving the integral represents a dealer's "market power" (also known as "bid shading"). A higher number of dealers k reduces a dealer's market power. On the other hand, a higher k linearly increases the winner's curse problem, which is shown in the last term of Eq. (15). Intuitively, dealer i's winning of the RFQ implies that all other invited dealers' inventories are more positive than dealer i's (recall the customer is selling). This inference, in turn, implies that the interdealer price after the D2C trade tends to be lower. Given this more attractive outside option, dealer i would not want to bid a high price. Put differently, bidding a high price would subject dealer i to the winner's curse, in the sense that he could have purchased the asset in the interdealer market at a lower price.

We summarize the equilibrium in the following proposition.

Proposition 2. Suppose that the customer selects k dealers in the RFQ and the customer's supply of the asset is $y > 0$ in notional amount. There exists a unique threshold inventory level z^* such that dealer i responds to the RFQ if and only if $z_i < z^*$, where z^* is implicitly given by Eq. (13). Moreover, conditional on responding to the RFQ, dealer i's responding price (per unit notional) is given by Eq. (15).

The RFQ equilibrium of Proposition 2 takes as given the customer's choice of k. At this point, we can prove the following comparative statics in terms of partial derivatives.

Proposition 3. Suppose that the interdealer market is open continuously ($\Delta = 0$).[15] All else equal, conditional on receiving an RFQ, a dealer's probability of responding to the RFQ:

- *decreases in k, the number of dealers included in the RFQ;*
- *increases in n, the number of active dealers in the market;*
- *decreases in λ, the cost of holding inventory; and*
- *increases in $|v - \underline{p}|$, the gain from trade between the customer and dealers.*[16]

If, in addition, $\partial\Gamma/\partial y > 0$ (i.e., the customer's reservation price decreases faster in quantity than dealers' values do), then all else equal, a dealer's response probability to the RFQ and the quoted spread both increase in notional size.

Proof. See Appendix A. □

Note that these comparative statics refer to partial derivatives. For example, the prediction $\partial z^*/\partial k < 0$ says holding fixed all primitive model parameters such as y, n, λ and $\underline{p}$, a higher k reduces each contacted dealer's response probability. By varying k but holding all else fixed, we recognize that the customer's actual choice of k may not be completely explained by these primitive model parameters. For instance, the relationship between customers and dealers could be one such orthogonal consideration. Likewise, a customer's firm may have specific guidelines on how many bids a trader must obtain before executing a trade. These other idiosyncratic determinants of k are unobservable to us. In this sense, we could view the observed k as the sum

$$k = k^* + \epsilon, \tag{16}$$

where k^* is the theoretical optimal number of dealers contacted if the customer only cares about the primitive model parameters such as trade size and market conditions, and ϵ is the orthogonal residual that is a proxy for relationship or institutional constraint. Therefore, given the residual variation in observed k caused by ϵ, taking the partial derivative with respect to k is still a valid exercise.

Likewise, when considering how the response probability $F(z^*)$ depends on, say, notional size y, $\partial z^*/\partial y$ in Proposition 3 only takes into account the direct effect of y on the response probability and not the indirect effect of y on z^* through its effect on k^*. These partial derivatives are nonetheless very useful. Later, we combine Proposition 3 and the empirical patterns reported in Section 6 to derive the total derivatives $dz^*/d\bullet$ that we test in Section 7.

The intuition of Proposition 3 comes from the winner's curse problem. As we discuss near Eq. (15), if a dealer wins the RFQ against more competitors, he infers a worse interdealer price when he tries to lay off the position. This adverse inference reduces the dealer's incentive to bid in the RFQ. In addition, because the winning dealer also incurs inventory cost and price impact cost when laying off the position in the interdealer SEF, he is less likely to participate in the RFQ if these costs are higher, which happens if fewer dealers are present in sharing inventory (smaller n) or if the inventory holding cost is higher (larger λ).

The parameter $|v - \underline{p}|$ can be viewed as a proxy for gains from trade, or the urgency of the customer's order. A larger gain from trade increases dealers' response rate. Likewise, under the condition $\partial\Gamma/\partial y > 0$, gains from trade between dealers and the customer increase in y, so dealers' response rate increases in y. At the same time, a larger gain from trade implies that dealers can capture a larger absolute profit, hence a worse response price $\beta(\,\cdot\,)$; at the same time, the customer is still willing to take this worse price because the cost of not trading, or the reservation price $\underline{p}$, is worse still.

4.4. D2C SEF: The customer's optimal choice of order exposure

The final step is to solve the customer's optimal degree of order exposure, or k. Due to the cost for getting quotes from non-clearing members, the customer solves

$$\max_k \left\{ \max_{1 \le j \le k} \beta(z_j) - cy(k-1) \right\}, \tag{17}$$

where $\beta(z_j)$ is equal to the equilibrium bid if $z_j \le z^*$ and $\underline{p}$ if $z_j > z^*$. We have not been able to derive analytical comparative statics of k^* with respect to primitive model parameters, but the model can be solved numerically.

We stress that some kind of explicit cost is needed to generate an interior solution for k^*, at least in our model framework. If we set $c = 0$, the model tends to produce a corner solution, $k^* = n$, despite the winner's curse. The intuition is that the "strongest" dealer, whose inventory level is close to the lower bound of the distribution, faces little winner's curse because

$$\lim_{z_i \to -\infty} E\left[z_j \mid z_j > z_i\right] = E\left[z_j\right] = 0. \tag{18}$$

Hence, the customer may still want to include as many dealers as possible to maximize the chance of reaching this strong type. A corner solution like this is clearly counterfactual (see Table 3). An explicit cost of adding dealers, as motivated by clearing relationship, is a simple way

[15] The result that z^* decreases in k is valid for any Δ. For other primitive parameters, working with $\Delta = 0$ (a continuous interdealer market) simplifies the calculation. A continuous interdealer market is also realistic.

[16] If the customer is selling, as in the model, we expect $\underline{p} < v$, so a higher $\underline{p}$ leads to a lower response probability. If the customer is buying, then by symmetry, we expect $\underline{p} > v$, so a lower $\underline{p}$ leads to a lower response probability.

to obtain an interior solution of k^*. There are, of course, other modeling approaches to generate an interior k^*. For example, one can adapt the costly participation model of Menezes and Monteiro (2000) in the SEF setting, where the cost is paid by the dealers rather than the customer. That model can also be solved with similar comparative statics.[17]

We also stress that although the winner's curse is insufficient to generate an interior k^* by itself, it is flexible enough to generate interesting variations in k^* if k^* is already interior. Moreover, the severity of the winner's curse depends on high-frequency market conditions such as the cost of holding inventory, whereas relationship is a highly persistent variable. In this sense, the winner's curse and the customer-dealer relationship operate in different dimensions.

Appendix B illustrates the numerical solutions of our model under reasonable parameters. The model-implied solutions can match a few key summary statics as well as key comparative statics we find in the next three sections.

5. Empirical strategy

In the previous section we have laid out a model and derived its implications. In particular, Proposition 3 makes the following predictions on the response probability of dealers in terms of partial derivatives (under stated conditions):

$$\frac{\partial z^*}{\partial y} > 0, \quad \frac{\partial z^*}{\partial |v - \underline{p}|} > 0, \quad \frac{\partial z^*}{\partial n} > 0, \quad \frac{\partial z^*}{\partial \lambda} < 0, \quad \frac{\partial z^*}{\partial k} < 0. \tag{19}$$

To take these predictions into the data, however, we need to derive the predictions in terms of total derivatives, such as $\frac{dz^*}{dy}$. The difference between the partial derivatives and the total derivatives comes from the customer's endogenous choice of k, the number of dealers requested. The following equations spell out such dependence.

$$\frac{dz^*}{dy} = \underbrace{\frac{\partial z^*}{\partial k}}_{<0,\text{ in theory}} \underbrace{\frac{\partial k}{\partial y}}_{\text{ambiguous}} + \underbrace{\frac{\partial z^*}{\partial y}}_{>0,\text{ in theory}}, \tag{20}$$

$$\frac{dz^*}{d|v - \underline{p}|} = \underbrace{\frac{\partial z^*}{\partial k}}_{<0,\text{ in theory}} \underbrace{\frac{\partial k}{\partial |v - \underline{p}|}}_{\text{ambiguous}} + \underbrace{\frac{\partial z^*}{\partial |v - \underline{p}|}}_{>0,\text{ in theory}}, \tag{21}$$

$$\frac{dz^*}{dn} = \underbrace{\frac{\partial z^*}{\partial k}}_{<0,\text{ in theory}} \underbrace{\frac{\partial k}{\partial n}}_{\text{ambiguous}} + \underbrace{\frac{\partial z^*}{\partial n}}_{>0,\text{ in theory}}, \tag{22}$$

$$\frac{dz^*}{d\lambda} = \underbrace{\frac{\partial z^*}{\partial k}}_{<0,\text{ in theory}} \underbrace{\frac{\partial k}{\partial \lambda}}_{\text{ambiguous}} + \underbrace{\frac{\partial z^*}{\partial \lambda}}_{<0,\text{ in theory}}. \tag{23}$$

[17] We do not show the results here but make them available upon request.

As we can see, the main challenge is that the partial derivatives of k, $\frac{\partial k}{\partial \bullet}$, do not have analytically proven signs in the model (labeled as "ambiguous" in the equations above).

Therefore, our empirical test of the theory consists of two steps. First, we check the sign of $\frac{\partial k}{\partial \bullet}$ directly in the data (in Section 6). Second, we plug the empirical signs of $\frac{\partial k}{\partial \bullet}$ into Eqs. (20)–(23), and test the total derivatives $\frac{dz^*}{d\bullet}$ in Section 7. Besides the predictions on response rates, we will also explore transaction costs in Section 8 for their empirical relevance, although, again, the model does not make unambiguous predictions about dealers' quoted prices.

6. Customers' choice of order exposure

Our empirical tests begin with the customer's choice of order exposure. Specifically, we analyze three decisions made by the customer:

- Under what conditions does the customer select RFQ versus RFS?
- Conditional on using RFQ, what determines the number of dealers the customer contacts?
- Conditional on using RFQ, how does the customer's choice of dealers relate to the customer-dealer relationship?

Not only are these choices interesting in their own right, they are also part of the test of the dealers' response rates, as explained above.

6.1. RFQ or RFS?

We denote a contract by i and a day by t. On each day and for each contract, there are potentially multiple sessions, where we denote the session number by m. (Recall a session may or may not result in a trade.)

We run a logistic regression of the following form:

$$P(y_{itm} = 1) = \frac{e^{\beta' X_{itm}}}{1 + e^{\beta' X_{itm}}}, \tag{24}$$

where y_{itm} takes the value of one if the mth session of contract i on day t is the customer's initiation of an RFQ, and zero otherwise (i.e., if the customer uses RFS by responding to a streaming quote). The vector X_{itm} includes the following:

- The notional quantity in millions USD. This corresponds to y in the model of Section 4.
- A dummy variable equal to one if the notional value is a standard size, and zero otherwise. The standard size dummy may be viewed as a proxy for gains from trade between the customer and the dealers, or $|v - \underline{p}|$ in the model. For example, trades of nonstandard sizes are less liquid by definition, so customers seeking to trade such sizes may have particular hedging needs, which implies a higher gain from trade between the customer and dealers.
- The number of streaming quotes right before the session. This could be a proxy for how many dealers are actively trading in this contract, or n in the model.

Table 5
Logistic regression of RFQ dummy as left-hand variable.
All estimates are marginal effects. t-statistics are in parentheses (* for $p < 0.05$, ** for $p < 0.01$, and *** for $p < 0.001$, where p is the p-value). The data sample is described in Table 3. The right-hand variables are defined right after Eq. (24).

	(1) ALL	(2) IG	(3) HY
Quantity in millions USD	-0.00177**	-0.00200***	0.00226
	(-3.15)	(-3.77)	(1.54)
Quantity is standardized (0/1)	-0.183***	-0.228***	-0.141***
	(-11.68)	(-11.78)	(-5.92)
# Streaming quotes	0.000811	0.000246	0.00103
	(0.87)	(0.14)	(0.89)
Last 4 hours of trading (0/1)	0.0319	0.0423*	0.0215
	(1.62)	(1.98)	(0.76)
Customer is buyer (0/1)	0.0222	-0.0140	0.0538***
	(1.36)	(-0.56)	(3.47)
Customer is asset manager (0/1)	0.371***	0.220***	0.642***
	(6.57)	(3.55)	(6.49)
Customer is HF/PTF/PE (0/1)	-0.0141	-0.0717	0.152
	(-0.26)	(-1.19)	(1.47)
Customer is bank/broker (0/1)	0.0348	-0.0825	0.294**
	(0.59)	(-1.27)	(2.76)
Customer is dealer (0/1)	-0.0129	-0.191*	0.241
	(-0.16)	(-2.12)	(1.95)
Observations	8399	3854	4545
Pseudo (R^2)	0.2936	0.3151	0.2933

- A dummy variable equal to one if the session was in the last four hours of active trading, and zero otherwise. Presumably, toward the end of the main trading hours, traders become more anxious to finish intended transactions to avoid keeping undesired inventory overnight. Therefore, this dummy could be viewed as a proxy for λ (inventory cost) in the model.
- A dummy variable equal to one if the customer is buying protection, and zero otherwise.
- A dummy variable equal to one if the customer is an asset manager, and zero otherwise.
- A dummy variable equal to one if the customer is a hedge fund/proprietary trading firm/private equity firm, and zero otherwise.
- A dummy variable equal to one if the customer is a bank or broker (but not a market maker), and zero otherwise.
- A dummy variable equal to one if the customer is a dealer (market maker) itself, and zero otherwise.
- A dummy variable for each of the trading days of the month.
- A dummy variable for each of the MAT contracts.
- A dummy variable for Bloomberg SEF.

Many of the dummy variables can be interpreted as control variables that absorb some heterogeneity in the data on which our model sheds little light. For example, different types of customers may have different reservation values, but we have no prior on the sign of the coefficients of these dummy variables.

Table 5 reports the results of regression (24). Column 1 pools all contracts, while column (2) and (3) examine IG and HY indices separately. All reported results are marginal effects, i.e., $\partial P(y_{itm} = 1 \mid X_{itm})/\partial x_{itm}$. In all regressions in this paper, robust standard errors are clustered by day to account for correlations of errors among trades on the same day. Point estimates of the contract, day, and SEF fixed effects are omitted from the tables.

The coefficient on quantity is negative and significant in the pooled regression. The estimated marginal effect of notional quantity of -0.00177 means that a \$22 million increase in notional quantity, which is approximately one standard deviation of notional quantities in the sample (see Table 3), reduces the probability of initiating an RFQ by 3.9% ($= 0.00177 \times 22$). A comparison between columns 2 and 3 suggests that this effect of quantity mainly comes from IG, whereas the coefficient for HY is statistically insignificant.

The regression also shows that standard notional sizes are less likely to be executed by RFQ than RFS. By Column 1, if a customer inquiry has a standard notional size, the probability of using RFQ declines by 18.3%, which is large statistically and economically. As discussed above, a possible interpretation is that standard sizes are less likely to be submitted by customers with idiosyncratic hedging needs, so gains from trade between customers and dealers are smaller from the outset. Since the winner's curse problem is more severe on these trades (see Proposition 3), the customer internalizes it and chooses RFS more often. A related yet different interpretation is that it is more difficult for customers to estimate prices for nonstandard sizes, so it is more useful to request a few more quotes for those trades through RFQ.

The coefficients on notional size and standardized size are consistent with the observation from Table 3 that RFQs are smaller and are less likely to have standardized sizes, compared to the full sample with both RFQ and RFS.

The number of streaming quotes and the time of day do not seem to be significant determinants for the choice between RFQ and RFS. That said, for IG, customers are

Table 6
Number of dealers requested in RFQs, fitted to a Poisson distribution.
Reported estimates are marginal effects. t-statistics are in parentheses (* for $p < 0.05$, ** for $p < 0.01$, and *** for $p < 0.001$, where p is the p-value). The data sample is described in Table 3, restricted to RFQs. The right-hand variables are defined right after Eq. (24).

	(1) ALL	(2) IG	(3) HY
Quantity in millions USD	-0.0214***	-0.0182***	-0.0518***
	(-7.79)	(-7.30)	(-5.45)
Quantity is standardized (0/1)	0.0680	0.538***	-0.139
	(0.63)	(3.65)	(-1.00)
# Streaming quotes	-0.00342	-0.0161	-0.00115
	(-0.59)	(-1.37)	(-0.18)
Last 4 hours of trading (0/1)	0.223**	0.451***	0.0521
	(2.69)	(4.04)	(0.50)
Customer is buyer (0/1)	-0.0195	-0.102	-0.00497
	(-0.19)	(-0.86)	(-0.04)
Customer is asset manager (0/1)	1.376*	0.862	2.169**
	(2.32)	(1.55)	(3.11)
Customer is HF/PTF/PE (0/1)	0.406	0.135	1.039
	(0.67)	(0.24)	(1.37)
Customer is bank/broker (0/1)	0.986	-0.119	2.102**
	(1.41)	(-0.16)	(2.83)
Customer is dealer (0/1)	2.233***	1.446**	3.116***
	(3.82)	(2.93)	(4.05)
Observations	3028	1425	1603
Pseudo (R^2)	0.1535	0.1578	0.1675

marginally more likely to choose RFQ in the last four hours of active trading. As discussed above, the last four hours of active trading may be associated with a higher λ, or higher inventory cost. In this situation, dealers are less strategic in interdealer trading (see Proposition 1), so the winning dealer has an easier time offloading his position to other dealers, which implies a less severe winner's curse. This in turn encourages the customer to use RFQ.

Across customer types, asset managers are significantly more likely to choose RFQ, relative to the omitted category "Other" (which consists of pensions, insurance companies, sovereign wealth funds, and nonfinancial corporations, among others). The point estimate on this coefficient in the pooled regression is 37.1%, which is very large economically. The estimate for IG is 22.0% and the estimate for HY is 64.2%. Since the overall probability of choosing RFQ over RFS is about 36% for both IG and HY, these magnitudes are very large. One possible explanation is that asset managers are essentially intermediaries and they have a fiduciary duty of delivering best execution for their clients. None of the other customer types have a clear-cut preference for RFQ or RFS, at least in the pooled regression.

6.2. How many dealers to select in an RFQ?

Our next step is to analyze how many dealers are selected in an RFQ, conditional on the customer choosing RFQ rather than RFS. The trade-off here is similar to that in the previous section—selecting an additional dealer brings in more competition but also increases the winner's curse problem. We therefore use the same right-hand-side variables and expect qualitatively similar results to the RFQ versus RFS choice.

Because the left-hand-side variable is an integer, we use a Poisson regression to estimate the effect of the variables of interest on the number of requests sent. In addition, due to the "minimum three" requirement on MAT contracts, we fit the number of dealers requested in an RFQ to a Poisson distribution left-truncated at three. Specifically, let y_{itm} be the number of selected dealers in an RFQ, which is at least three in all RFQ sessions in our sample. Then, the conditional probability of observing y_{itm} events given that $y_{itm} \geq 3$ is given by the following equation:

$$P(Y = y_{itm} \mid Y \geq 3, X_{itm}) = \frac{e^{-\lambda}\lambda^{y_{itm}}}{y_{itm}!} \cdot \frac{1}{P(Y \geq 3 \mid X_{itm})}, \tag{25}$$

where λ is the mean of the Poisson distribution without truncating. The log-likelihood function is derived from the conditional probability. Again, X_{itm} is the same vector of covariates as in the previous section. As before, we convert all estimates into marginal effects, that is, the number of additional dealers selected if a covariate increases by one unit.

Table 6 reports marginal effects from fitting the truncated Poisson model (25). Column (1) shows the pooled regression with all indices, whereas columns (2) and (3) provide the results for IG and HY separately.

As is the case with the choice between RFQ and RFS in the previous section, a customer wishing to trade a larger notional quantity exposes his order to fewer dealers. In column (1), the point estimate of the marginal effect is -0.0214. A \$21 million increase in the notional size—one standard deviation of notional size conditional on RFQ—reduces the number of dealers requested by about 0.45, which is economically significant since the average number of dealers queried in RFQs is just over 4.

Conditional on using RFQ, customers contact 0.22 additional dealers on average if the RFQ is sent in the last four hours of active trading. Again, the intuition is that dealers are less strategic toward the end of the day, which reduces the winner's curse problem. Standardized quantity, however, is not statistically significant for the full sample.

Also consistent with the RFQ versus RFS regression, asset managers prefer more competitors for their business, selecting 1.4 additional dealers on average relative to the "Other" category, and this effect mainly comes from HY. In addition, market makers select about 2.2 additional dealers when acting as quote seekers, and the effect for HY is about twice as large as IG.

Summarizing, Tables 5 and 6 reveal that customers tend to expose their orders to fewer dealers if the trade size is larger (for both regressions), if the trade size is standard (only for the RFQ versus RFS regression), or if it is early in the trading day (only for the number of dealers selected in RFQs).

6.3. Which dealers to select in an RFQ?

We conclude this section by conducting a simple test of how customer-dealer relationships affect a customer's likelihood of selecting a dealer in an RFQ. The left-hand variable is denoted $N_{c,d}$, the total number of RFQ sessions in which customer c contacts dealer d throughout our sample, for all pairs (c, d). On the right-hand side, we use two proxies for relationship, as described in the data section. The first proxy is a dummy variable, $CM_{c,d}$, which is equal to one if customer c's clearing member is affiliated with dealer d. The second proxy, denoted by $DealerShare_{c,d}$, is the fraction of customer c's trading volume in all index CDS that is attributable to dealer d from January to April 2016, calculated from transactions reported to swap data repositories. Both proxies capture how important a dealer is for a customer, either for clearing or revealed by past transactions.

We then run the following regression:

$$\frac{N_{c,d}}{\sum_{d'} N_{c,d'}} = \delta_d + \beta_1 \cdot CM_{c,d} + \beta_2 \cdot DealerShare_{c,d} + \epsilon_{c,d}. \tag{26}$$

where δ_d is the dealer fixed effect, which controls for differences between dealers that may cause customers generally to prefer certain dealers over others. Therefore, the two coefficients β_1 and β_2 capture the effect of relationship above and beyond the general "attractiveness" of each dealer.

Table 7 shows the result of this regression, where we suppressed the estimates of the dealer fixed effects. As expected, both proxies of relationship are highly significant and positive. Customers are more likely to seek quotes from dealers affiliated with their clearing members, as well as from dealers who account for a larger fraction of their past trading volume. For example, fixing a dealer, if the dealer is affiliated with the customer's clearing member, then this dealer has a 1.9% higher "RFQ share." This magnitude is not trivial compared to the unconditional mean of "RFQ share" of 5%, since there are 20 dealers. Likewise, fixing a dealer, if the dealer accounts for say 5% of customer A's past trading volume but 15% of customer B's past trading volume, then customer B is more likely to send RFQs to the dealer than customer A is, by about 2.2% ($= 0.217 \times 10\%$).

Table 7
Customers' choice of dealers in RFQs.
Statistical significance: * for $p < 0.05$, ** for $p < 0.01$, and *** for $p < 0.001$, where p is the p-value. The data sample is described in Table 3, restricted to RFQs. $CM_{c,d}$ is equal to one if customer c's clearing member is affiliated with dealer d, and zero otherwise. $DealerShare_{c,d}$ is the fraction of customer c's trading volume in all index CDS that is attributable to dealer d from January to April 2016.

	Estimate	t-stat
$CM_{c,d}$	0.019***	4.12
$DealerShare_{c,d}$	0.217***	18.49
Observations	4003	
R^2	0.341	

7. Dealers' response rates in RFQs

Having analyzed the customers' choices, we now turn to dealers' response rates in RFQs. As outlined in the discussion of empirical strategy in Section 5, we can now derive the model's implications for dealers' response rates by combining the theory-implied partial derivatives $\frac{\partial z^*}{\partial \bullet}$ in Proposition 3 and the empirical sign of $\frac{\partial k}{\partial \bullet}$ in Section 6. In particular, Table 6 of Section 6.2 shows that, in the data,

$$\frac{\partial k}{\partial y} < 0, \quad \frac{\partial k}{\partial |v - \underline{p}|} \le 0, \quad \frac{\partial k}{\partial n} \le 0, \quad \frac{\partial k}{\partial \lambda} > 0, \tag{27}$$

where the second term is labeled " ≤ 0" because the estimate on standardized dummy is significant only for IG (recall standardized size means lower gains from trade), and the third item is labeled as " ≤ 0" because the coefficient on the number of streaming quotes is negative but not statistically significant.

By combining the inequalities in (19) and (27), we can sign the total derivatives:

$$\frac{dz^*}{dy} = \underbrace{\frac{\partial z^*}{\partial k}}_{<0,\text{ in theory}} \underbrace{\frac{\partial k}{\partial y}}_{<0,\text{ in data}} + \underbrace{\frac{\partial z^*}{\partial y}}_{>0,\text{ in theory}} > 0, \tag{28}$$

$$\frac{dz^*}{d|v - \underline{p}|} = \underbrace{\frac{\partial z^*}{\partial k}}_{<0,\text{ in theory}} \underbrace{\frac{\partial k}{\partial |v - \underline{p}|}}_{\le 0,\text{ in data}} + \underbrace{\frac{\partial z^*}{\partial |v - \underline{p}|}}_{>0,\text{ in theory}} > 0, \tag{29}$$

$$\frac{dz^*}{dn} = \underbrace{\frac{\partial z^*}{\partial k}}_{<0,\text{ in theory}} \underbrace{\frac{\partial k}{\partial n}}_{\le 0,\text{ in data}} + \underbrace{\frac{\partial z^*}{\partial n}}_{>0,\text{ in theory}} > 0, \tag{30}$$

$$\frac{dz^*}{d\lambda} = \underbrace{\frac{\partial z^*}{\partial k}}_{<0,\text{ in theory}} \underbrace{\frac{\partial k}{\partial \lambda}}_{>0,\text{ in data}} + \underbrace{\frac{\partial z^*}{\partial \lambda}}_{<0,\text{ in theory}} < 0, \tag{31}$$

Table 8
Logistic regression on whether a dealer responds to an RFQ or not.
Reported estimates are marginal effects. t-statistics are in parentheses (* for $p < 0.05$, ** for $p < 0.01$, and *** for $p < 0.001$, where p is the p-value). The data sample is described in Table 3, restricted to RFQs. The right-hand variables are defined right after Eqs. (24) and (32).

	(1) ALL	(2) IG	(3) HY
Quantity in millions USD	0.000676**	0.000596**	0.00102
	(2.82)	(2.78)	(1.55)
Quantity is standardized (0/1)	-0.00762	0.000580	-0.00550
	(-0.82)	(0.05)	(-0.38)
# Streaming quotes	0.00230***	0.00338*	0.00172**
	(3.71)	(2.55)	(2.76)
Last 4 hours of trading (0/1)	-0.00987	-0.00962	-0.000120
	(-1.32)	(-1.04)	(-0.01)
Customer is buyer (0/1)	0.00866	0.00155	0.00876
	(1.52)	(0.19)	(1.02)
Dealer is customer's clearing member	0.0322***	0.0295**	0.0355**
	(3.76)	(2.93)	(2.88)
Customer share of dealer's 4-month volume	0.363	0.567	0.147
	(1.42)	(1.23)	(0.68)
Customer is asset manager (0/1)	0.0318*	0.0462**	0.0167
	(2.01)	(2.79)	(0.53)
Customer is hedge fund (0/1)	0.0334	0.0258	0.0394
	(1.91)	(1.43)	(1.22)
Customer is bank/broker (0/1)	-0.0103	-0.0238	0.0270
	(-0.36)	(-0.97)	(0.61)
Customer is dealer (0/1)	0.0123	-0.000543	0.0213
	(0.53)	(-0.02)	(0.65)
# Dealers queried, residual	-0.00856***	-0.0199***	0.0000916
	(-5.12)	(-6.43)	(0.03)
Observations	12431	5713	6715
Pseudo (R^2)	0.0533	0.0961	0.0471

where "in theory" refers to Eq. (19) and "in data" refers to Eq. (27). These total derivatives take into account the indirect effect through endogenous changes in k and allow us to empirically test the theory in light of this additional information. In addition, as discussed in Section 4, to the extent that the observed k contains an idiosyncratic component that is not explained by other primitive model parameters, $\partial z^*/\partial k < 0$ can also be directly tested in the data.

To test these predictions, we run a logistic regression of the binary choice of responding or not responding:

$$P(y_{d,itm} = 1) = \frac{e^{\beta'[X_{itm}, k^{res}_{itm}, CM_{c,d}, CustomerShare_{d,itm}, \delta_d]}}{1 + e^{\beta'[X_{itm}, k^{res}_{itm}, CM_{c,d}, CustomerShare_{d,itm}, \delta_d]}}, \quad (32)$$

where $y_{d,itm} = 1$ if dealer d responds to the RFQ session itm, and zero otherwise. The vector of right-hand-side variables consists of the following:

- X_{itm}, as defined in Section 6.1.
- k^{res}_{itm}, defined as the residual from running an ordinary least square (OLS) regression of the number of dealers requested in the RFQ, k_{itm}, on X_{itm}. We take the residual to ensure that k^{res}_{itm} is orthogonal to the other explanatory variables.
- $CM_{c,d}$, which is a dummy variable equal to one if dealer d is affiliated with customer c's clearing member, and zero otherwise.
- $CustomerShare_{d,itm}$, defined as the fraction of dealer d's total trading volume in index CDS that is attributable to this particular customer from January to April 2016. Like $DealerShare_{c,d}$ in regression (26), $CustomerShare_{d,itm}$ is calculated from trade repository data using all index CDS trades.
- δ_d, the dealer fixed effect. In this regression, δ_d controls for the average response probability of each dealer.

Table 8 reports the results, pooled across all indices in Column 1 and separately for IG and HY in Columns 2 and 3.

As predicted by (28), we find that a larger trade is more likely to generate dealer response for RFQs. For example, by Column 1, a \$21 million increase in the notional size—one standard deviation of notional sizes conditional on RFQ—increases an average dealer's response probability by about 1.4% ($= 0.000676 \times 21$). This effect is driven entirely by IG, whereas the coefficient in the HY regression is statistically insignificant.

As predicted by (30), a higher number of streaming quotes (interpreted as a larger n in the model) is more likely to generate dealer response in RFQs. The estimate of 0.0023 in the pooled regression implies that it takes about four additional dealers streaming quotes to increase the response probability by 1%. This effect is about twice as large in IG than in HY. The intuition from the model is that as more dealers are actively trading a contract, the price impact cost of offloading positions in the interdealer SEF is smaller. Thus, dealers are more likely to respond to customers' requests when n is larger.

Although the coefficient on the standardized dummy is negative as predicted in Eq. (29) (recall standardized trades mean smaller gain from trade $|v - \underline{p}|$ in our interpretation),

Table 9
Dealers' response rate in RFQs, OLS.
t-statistics are in parentheses (* for $p < 0.05$, ** for $p < 0.01$, and *** for $p < 0.001$, where p is the p-value). The data sample is described in Table 3, restricted to RFQs. The right-hand variables are defined right after Eqs. (24) and (32).

	(1) ALL	(2) IG	(3) HY
Quantity in millions USD	0.000504*	0.000578**	0.000600
	(2.48)	(2.95)	(0.93)
Quantity is standardized (0/1)	-0.0116	-0.00557	-0.0116
	(-1.10)	(-0.44)	(-0.70)
# Streaming quotes	0.00204*	0.00332*	0.00143
	(2.79)	(2.09)	(1.80)
Last 4 hours of trading (0/1)	-0.00666	-0.0169	0.00845
	(-0.77)	(-1.33)	(0.69)
Customer is buyer (0/1)	0.0114	0.00302	0.0144
	(1.92)	(0.29)	(1.53)
Customer is asset manager (0/1)	0.0263	0.0472*	0.0138
	(1.23)	(2.29)	(0.27)
Customer is HF/PTF/PE (0/1)	0.0357	0.0354	0.0437
	(1.52)	(1.59)	(0.89)
Customer is bank/broker (0/1)	-0.0249	-0.0560	0.0354
	(-0.57)	(-1.31)	(0.57)
Customer is dealer (0/1)	0.0225	0.0142	0.0374
	(0.75)	(0.44)	(0.74)
# Dealers queried, residual	-0.00842**	-0.0291***	0.00131
	(-3.37)	(-8.54)	(0.34)
Observations	3028	1425	1603
Adjusted (R^2)	0.022	0.081	0.010

the estimate is not statistically significant. The same can be said about the dummy variable for the last four hours of active trading, which we use as a proxy for inventory cost λ.

The number of dealers selected (as a regression residual) has a negative coefficient, as predicted by Proposition 3. Selecting more dealers than expected in the RFQ reduces a dealer's response probability by about 0.9%. The intuition is that the winner's curse problem is more severe if the customer selects more dealers. Again, since the optimal k^* is endogenous, we have assumed that residual variation in k that is not captured by the right-hand-side variables X_{itm} is a result of customer-specific and idiosyncratic considerations that are orthogonal to the winner's curse problem faced by dealers. One extreme example of such considerations would be an institutional investor's compliance office requiring the trading desk to request as many quotes as possible. In this case, we would expect the observed k to be higher than the optimal k^* and the investor to receive a lower response rate.

Separately from winner's curse, the customer-dealer clearing relationship is strongly associated with a higher response rate, by about 3.2%. Past trading relationship, however, is not statistically significant.

Across customer types, asset managers receive a higher response rate, relative to the omitted "Other" category, by about 3.2%. The same is true for the hedge fund/proprietary trading firm/private equity category, albeit with weaker statistical significance.

Table 9 reports the results of a closely related regression at the session level:

$$y_{itm} = \beta'[X_{itm}, k_{itm}^{res}] + \epsilon_{itm}, \tag{33}$$

where $y_{itm} \in [0, 1]$ is the dealers' response rate in the RFQ session itm. This regression is at the session level, so it does not include the relationship measures (*CM* or *CustomerShare*) or dealer fixed effects. As expected, the results are very similar to those in Table 8. Response rates are higher if orders are larger, if more dealers are making markets, or if the customer selects fewer dealers in the RFQ.

We conclude this section by examining under what conditions an RFQ session results, or does not result, in a transaction.

We run the following logistic regression:

$$P(y_{itm} = 1) = \frac{e^{\beta'[X_{itm}, k_{itm}^{res}]}}{1 + e^{\beta'[X_{itm}, k_{itm}^{res}]}}, \tag{34}$$

where y_{itm} takes the value of one if the RFQ session itm results in a trade, and zero otherwise.

Table 10 reports the results. The only variables that are significant are notional quantity and the standardized size dummy. In Column 1, a \$21 million increase in the order size increases the transaction probability by about 1.7% (= 0.00082×21), but standard-sized orders reduce the transaction probability by about 3.9%. To the extent that larger or nonstandard-sized orders tend to imply larger gains from trade, a higher transaction probability on those orders seems rather intuitive.

8. Dealers' pricing behavior in RFQs

The previous section investigates dealers' response rates in RFQs. Another important dimension of the equilibrium outcome is dealers' pricing behavior, which we study in this section. Let us emphasize that the model does not

Table 10
Logistic regression on whether a trade happens in RFQs.
Reported estimates are marginal effects. *t*-statistics are in parentheses (* for $p < 0.05$, ** for $p < 0.01$, and *** for $p < 0.001$, where p is the p-value). The data sample is described in Table 3, restricted to RFQs. The right-hand variables are defined right after Eqs. (24) and (32).

	(1) ALL	(2) IG	(3) HY
Quantity in millions USD	0.000820**	0.000894***	-0.000716
	(3.07)	(3.44)	(-1.40)
Quantity is standardized (0/1)	-0.0388***	-0.00740	-0.0602***
	(-3.88)	(-0.44)	(-6.33)
# Streaming quotes	0.00120	0.000829	0.000940
	(1.05)	(0.42)	(0.94)
Last 4 hours of trading (0/1)	0.00528	0.0117	-0.00146
	(0.44)	(0.57)	(-0.13)
Customer is buyer (0/1)	0.00314	-0.00263	0.00744
	(0.27)	(-0.18)	(0.46)
Customer is asset manager (0/1)	-0.0714	-0.0848	-0.0544
	(-1.61)	(-1.29)	(-1.18)
Customer is HF/PTF/PE (0/1)	-0.0484	-0.0725	-0.0308
	(-1.04)	(-0.96)	(-0.65)
Customer is bank/broker (0/1)	-0.0909	-0.124	-0.0675
	(-1.78)	(-1.57)	(-1.45)
Customer is dealer (0/1)	0.000212	-0.0192	0.00796
	(0.00)	(-0.21)	(0.13)
# Dealers queried, residual	0.00162	-0.0119	0.00784
	(0.37)	(-1.94)	(1.79)
Observations	3008	1405	1553
Pseudo (R^2)	0.0547	0.0826	0.0841

make unambiguous theoretical predictions about the comparative statics of quoted prices with respect to primitive model parameters. Nevertheless, the results are useful in revealing which factors affect pricing in the data and in what ways. Moreover, our model is capable of matching the magnitude of empirically observed transaction costs for certain parameter values, as shown in Appendix B.

We begin by measuring customer's trading costs. To do so, we need to define the benchmark price for comparison. For a given RFQ session *itm*, the benchmark price we use is the most recent trade (RFQ or RFS) for the same contract and on the *opposite* side, denoted p^-_{itm}. If session *itm* results in a trade, we denote the transaction price by p_{itm} and calculate the customer's round-trip transaction cost as

$$c_{itm} = \begin{cases} p_{itm} - p^-_{itm}, & \text{if the customer buys protection} \\ p^-_{itm} - p_{itm}, & \text{if the customer sells protection} \end{cases}. \quad (35)$$

The cost is in basis points.[18] Intuitively, the customer's round-trip transaction cost measures dealers' profit for intermediating buyers and sellers who arrive relatively close to each other. Note that we do not need to infer the direction of the trade for the customer (buy or sell) since it is observed in our data.

Table 11 reports the quantity-weighted mean, standard deviation, and certain percentiles of the distribution of transaction costs in RFQs, all in bps. Overall, transaction costs appear small; the transaction costs of on-the-run CDX.NA.IG and iTraxx Europe have a mean of around 0.2 bps and a standard deviation of 1.4 bps. For on-the-run CDX.NA.HY and iTraxx Crossover, the average costs are larger, at about 0.5 and 1.1 bps, but again not significant compared to their standard deviations of about 2.6 and 3.5 bps. The first off-the-run contracts have comparable average transaction costs but a much higher standard deviation due to the relatively small number of trades in these contracts.

We also find that RFS transactions have very similar transaction cost measures—the mean is generally within 1 bp and the standard deviation is 1–3 bps. Those statistics on RFS are not reported but available upon request.

We should caution that our estimates of transaction costs are likely noisy. By construction, the round-trip transaction cost defined in Eq. (35) contains the change in the fair value of CDS indices between the two consecutive customer trades. The price changes could be positive or negative, and these two outcomes are equally likely if CDS prices are martingales. Perhaps for this reason, even for the on-the-run indices, between 10% and 25% of the trades have a negative calculated trading cost. It could take a long sample period to wash out this noise, and our sample of one month may not be long enough. On the other hand, at least 75% of the trades have a positive measured cost, suggesting that noise is not the only reason why the average transaction cost is low in our sample.

The magnitude of our transaction cost estimates is close to that reported by Collin-Dufresne et al. (2018). From October 2013 to October 2015, they find that the effective half-spreads for D2C trades in CDX.NA.IG and CDX.NA.HY are 0.14 bps and 0.68 bps, respectively, which correspond

[18] In our data set, three of the four CDS indices are quoted in spread (i.e., essentially a premium), and one (CDX.NA.HY) is quoted in (bond equivalent) price. We convert the latter to spread, in basis points.

Table 11
Summary statics of quantity-weighted spread in RFQ trades, unit in bps.
The spread on a particular customer buy RFQ trade is measured as the RFQ transaction price minus the price of the last customer sell trade (RFQ or RFS). The spread on a particular customer sell RFQ trade is measured as the price of the last customer buy trade (RFQ or RFS) minus the current RFQ transaction price. The data sample is described in Table 3.

Contract	N	Mean	Std dev	10th Pct	25th Pct	50th Pct	75th Pct	90th Pct
CDX.NA.IG ON	948	0.17	1.35	-0.10	0.05	0.16	0.29	0.47
CDX.NA.HY ON	1030	0.47	2.57	-0.44	0.00	0.40	0.89	1.44
iTraxx Europe ON	270	0.21	1.45	-0.06	0.04	0.18	0.35	0.50
iTraxx Crossover ON	332	1.08	3.49	-0.25	0.32	0.99	1.63	2.63
CDX.NA.IG OFF	63	0.14	6.41	-2.25	0.11	0.44	0.77	1.20
CDX.NA.HY OFF	110	0.32	11.75	-3.29	-0.50	0.78	2.20	3.74
iTraxx Europe OFF	19	-0.04	14.81	-5.75	0.14	0.51	0.92	1.84
iTraxx Crossover OFF	15	2.40	17.57	-3.78	-1.15	1.10	5.60	12.13

Table 12
Individual dealers' quoted spread in RFQs in bps, measured relative to the last transaction price on the same contract and the opposite side.
t-statistics are in parentheses (* for $p < 0.05$, ** for $p < 0.01$, and *** for $p < 0.001$, where p is the p-value). The data sample is described in Table 3, restricted to RFQs. The right-hand variables are defined right after Eqs. (24) and (32).

	(1) ALL	(2) IG	(3) HY
Quantity in millions USD	0.00112*	0.000809	0.00702
	(2.38)	(1.54)	(1.26)
Quantity is standardized (0/1)	0.0549	0.0384	0.0459
	(1.41)	(1.62)	(0.48)
# Streaming quotes	-0.00376	-0.00462**	-0.00270
	(-1.04)	(-3.55)	(-0.51)
Last 4 hours of trading (0/1)	0.0224	-0.0382	0.0890
	(0.42)	(-1.60)	(0.96)
Customer is buyer (0/1)	0.0111	-0.0312	0.0631
	(0.13)	(-0.81)	(0.50)
Dealer is customer's clearing member	-0.0496	-0.0326*	-0.0470
	(-1.72)	(-2.15)	(-0.96)
Customer share of dealer's 4-month volume	-1.737	-0.880	-2.225
	(-1.72)	(-1.53)	(-1.29)
Customer is asset manager (0/1)	0.113	0.0268	0.236
	(0.67)	(0.26)	(0.51)
Customer is HF/PTF/PE (0/1)	0.0303	0.0703	0.0211
	(0.16)	(0.73)	(0.04)
Customer is bank/broker (0/1)	-0.0405	-0.0344	-0.0161
	(-0.20)	(-0.28)	(-0.03)
Customer is dealer (0/1)	0.428*	0.0273	0.713
	(2.45)	(0.31)	(1.57)
# Dealers queried, residual	0.0329	0.0337	0.0439
	(1.58)	(1.95)	(1.26)
Observations	11128	5138	5990
Adjusted (R^2)	0.164	0.047	0.094

to 0.28 bps and 1.36 bps round-trip costs. Because they use a much longer data sample, their estimates of transaction costs have more statistical power than ours. In addition, Collin-Dufresne et al. (2018) find that the transaction costs in D2D SEFs are even lower than those in D2C SEFs, suggesting that there may still be scope in further reductions in customer transaction costs.

The average transaction cost may not fully capture the pricing behavior of dealers because it is already conditional on the customer taking the best quote. To get a more granular view, we construct two additional measures of dealers' pricing behavior.

The first additional measure is individual dealer's quoted spread in bps. Denote dealer d's response price in RFQ session itm by $p_{d,itm}$. Then dealer d's quoted spread is

$$c_{d,itm}=\begin{cases} p_{d,itm}-p^{-}_{itm}, & \text{if the customer buys protection} \\ p^{-}_{itm}-p_{d,itm}, & \text{if the customer sells protection} \end{cases}. \tag{36}$$

The second additional measure of dealers' pricing behavior is the competitiveness of quotes in bps, defined as the absolute difference between the best dealer quote and the second-best dealer quote in the RFQ session itm. We label it $Competitive_{itm}$. The smaller is $Competitive_{itm}$, the more competitive are dealers' quotes.

Table 12, Table 13, and Table 14, respectively report results of the following three regressions:

Table 13
Competitiveness of bids in RFQs in bps, measured by the absolute difference between the best quote and the second-best quote (smaller values mean more competitive).
t-statistics are in parentheses (* for $p < 0.05$, ** for $p < 0.01$, and *** for $p < 0.001$, where p is the p-value). The data sample is described in Table 3, restricted to RFQs. The right-hand variables are defined right after Eqs. (24) and (32).

	(1) ALL	(2) IG	(3) HY
Quantity in millions USD	-0.0000504	-0.0000756	-0.000376
	(-0.50)	(-0.89)	(-0.63)
Quantity is standardized (0/1)	0.0160	0.00932	0.0216
	(1.99)	(1.52)	(1.42)
# Streaming quotes	-0.000967*	-0.00115*	-0.000885
	(-2.31)	(-2.39)	(-1.61)
Last 4 hours of trading (0/1)	0.00198	0.00174	-0.00255
	(0.26)	(0.28)	(-0.18)
Customer is buyer (0/1)	0.000985	-0.00978	0.0146
	(0.19)	(-1.63)	(1.73)
Customer is asset manager (0/1)	-0.00447	-0.0162	0.00955
	(-0.36)	(-0.79)	(0.52)
Customer is HF/PTF/PE (0/1)	-0.00737	-0.00316	-0.0106
	(-0.50)	(-0.17)	(-0.60)
Customer is bank/broker (0/1)	-0.0111	-0.0314	0.0172
	(-0.90)	(-1.29)	(0.49)
Customer is dealer (0/1)	-0.0525*	-0.0346	-0.0678*
	(-2.32)	(-1.38)	(-2.15)
# Dealers queried, residual	-0.00865**	-0.00834**	-0.00898*
	(-3.79)	(-3.11)	(-2.72)
Observations	2918	1385	1533
Adjusted (R^2)	0.334	0.041	0.395

Table 14
Transaction cost of customers in RFQs in bps, measured relative to the last transaction price on the same contract and the opposite side.
t-statistics are in parentheses (* for $p < 0.05$, ** for $p < 0.01$, and *** for $p < 0.001$, where p is the p-value). The data sample is described in Table 3, restricted to RFQs. The right-hand variables are defined right after Eqs. (24) and (32).

	(1) ALL	(2) IG	(3) HY
Quantity in millions USD	0.00103	0.000957	0.00552
	(1.84)	(1.62)	(1.09)
Quantity is standardized (0/1)	0.0333	0.0189	0.0323
	(0.90)	(0.69)	(0.38)
# Streaming quotes	0.000224	-0.00182	0.00206
	(0.07)	(-1.30)	(0.40)
Last 4 hours of trading (0/1)	-0.0159	-0.0555*	0.0190
	(-0.35)	(-2.19)	(0.25)
Customer is buyer (0/1)	-0.00989	-0.0325	0.0337
	(-0.11)	(-0.76)	(0.28)
Customer is asset manager (0/1)	0.0503	-0.0264	0.144
	(0.29)	(-0.32)	(0.31)
Customer is HF/PTF/PE (0/1)	-0.0467	0.0205	-0.101
	(-0.26)	(0.32)	(-0.20)
Customer is bank/broker (0/1)	-0.0538	-0.0518	-0.0412
	(-0.28)	(-0.51)	(-0.08)
Customer is dealer (0/1)	0.359	-0.0350	0.586
	(1.92)	(-0.58)	(1.23)
# Dealers queried, residual	0.00887	0.0223	0.00696
	(0.54)	(1.43)	(0.26)
Observations	2787	1300	1487
Adjusted (R^2)	0.069	0.026	0.042

$$c_{d,itm}=\beta'[X_{itm}, k^{res}_{itm}, CM_{c,d}, CustomerShare_{d,itm}, \delta_d] + \epsilon_{d,itm}, \quad (37)$$

$$Competitive_{itm} = \beta'[X_{itm}, k^{res}_{itm}] + \epsilon_{itm}, \quad (38)$$

$$c_{itm} = \beta'[X_{itm}, k^{res}_{itm}] + \epsilon_{itm}. \quad (39)$$

Reading across all three tables, we observe the following:

- Larger trades have higher quoted spreads (statistically significant) and higher transaction costs (statistically insignificant), but the magnitude of the estimate is very small, around 0.001 in both Tables 12 and 14. Notional quantity is not a significant determinant of the competitiveness of quotes.
- A higher number of streaming quotes (as a proxy of the number of dealers actively marking markets) and the number of dealers selected in RFQs both increase competition, as expected. There is some evidence that, for IG, a higher number of streaming quotes also reduce dealers' quoted spread. That said, the magnitude of all these estimates is very small.
- When dealers act as quote seekers, they tend to receive wider spreads from the other dealers, but the quotes from these other dealers are also more competitive. In the end, dealers incur slightly higher transaction costs of up to 0.6 bps on HY, but the estimate is not statistically significant.[19]
- None of the other variables seem to be significant determinants of pricing behavior.

The overall takeaway from this section is that index CDS transaction costs are fairly low. There is some evidence of dealers' strategic pricing behavior in the individual quotes data, albeit with small economic magnitude.

9. Concluding remarks

The Dodd-Frank Act introduced a formal regulatory framework for the OTC derivatives markets. An important aspect of Dodd-Frank for the trading of OTC derivatives is the MAT mandate, which requires that trades in certain liquid and standardized swaps be executed on swap execution facilities (SEFs). In this paper, we analyze message-level data of orders and transactions for index CDS that are subject to these rules. Our data are obtained from Bloomberg SEF and Tradeweb SEF for May 2016. These two SEFs represent about 85% of all SEF trading activities in index CDS in our sample period.

Bloomberg and Tradeweb offer various mechanisms for trading. After receiving indicative streaming quotes from dealers, customers may use the limit order book, run an auction with multiple dealers by RFQ, or contact one of the dealers streaming indicative quotes (RFS). In our sample, the order book has little activity. Between RFQ and RFS, RFS accounts for over 60% of customers' trading activity. Conditional on using RFQs, customers on average only request quotes from about four dealers. Data also show that wider exposure of orders reduces dealers' response rates in RFQs.

We propose a theoretical model of SEF trading that aims to organize these facts about customer and dealer behavior. What prevents customers from seeking quotes from as many dealers as possible? We propose two channels that reduce the benefits of increasing the number of competitors. The first is winner's curse that arises from the winning dealer's need to offload part of the acquired position in interdealer SEFs. The winning dealer becomes increasingly pessimistic about the expected interdealer price as the number of losing dealers in the customer's RFQ rises. The second channel is customer-dealer relationships, which we model as an explicit cost of adding non-relationship dealers in the RFQ. The relationship channel generates an interior optimal number of dealers requested, whereas all other comparative statics are derived from the winner's curse channel. Overall, the model provides empirically testable predictions regarding customers' and dealers' strategic behaviors, especially the response rate of dealers to RFQs.

Consistent with the model, further empirical tests show that order size, market conditions, the number of competitors, and customer-dealer relationships are all important determinants of strategies and outcomes in this market. Customers expose the order to fewer dealers if the order is larger or if it is early in the trading day. Dealers' response rates increase in order size, number of streaming quotes, and the clearing relationship with the customer, but response rates decrease in the number of dealers who compete in the RFQ. Dealers' quoted prices have mild variations with order size and the level of competition, but the magnitude of the estimates is not large. Heterogeneous customer types demonstrate different behavior, especially asset managers.

Judged from our evidence, SEF-traded index CDS market seems to be working well after Dodd-Frank—dealers' response rates are high, the vast majority of customer orders result in trades, and customers' transaction costs are low. That said, it remains relevant to ask whether SEF markets can be further improved.

Collin-Dufresne et al. (2018) find that interdealer trades of index CDS receive narrower spreads than D2C trades do. Interdealer SEFs typically use a combination of order book and "size discovery" mechanisms such as workups and matching sessions (see Collin-Dufresne et al., 2018; and Duffie and Zhu, 2017) which lead to lower transaction costs. A possible market design is to offer similar mechanisms on D2C SEFs as well. That said, the effective use of order book and size discovery mechanisms like

[19] Using more than two years of transaction data in three CDS indices on Bloomberg SEF, Haynes and McPhail (2019) find qualitatively similar results, that is, dealer-to-dealer trades have higher price impacts than dealer-to-customer trades. One interpretation is that dealers who trade on dealer-to-customer SEFs have found it difficult to execute trades on interdealer SEFs such as GFI. Collin-Dufresne et al. (2018) find that over 70% of CDX IG and CDX HY trades on GFI are executed by "workups" or "matching sessions." As shown by Duffie and Zhu (2017), these mechanisms generally facilitate larger trades but do not clear the market, that is, some orders are left unexecuted. Therefore, dealers who self-select to trade on D2C SEFs like Bloomberg could be attempting to execute these leftover orders, which tend to move prices and hence receive higher transaction costs.

those found on D2D SEFs likely requires that customers have the technological and operational capacity to dynamically manage trading strategies. For example, customers need to dynamically place and split orders and to decide how much of the order should be executed by size discovery. For active customers such as large asset managers, it could make sense to undertake the investment required to implement these strategies. However, for customers who trade infrequently, the current D2C mechanisms may be sufficient.[20] A careful counterfactual analysis on how different customers would react to the availability of other trading mechanisms is beyond the scope of this paper because it requires information on customer-specific costs of acquiring trading technology.

Another possible market design is to add a “divisible RFQ” protocol in which the customer can split the order among multiple dealers who participate in the RFQ, instead of giving the entire order to a single dealer. In a divisible RFQ, dealers would submit demand schedules (i.e., price-quantity pairs), and a customer can split his order among responding dealers according to the quoted prices. Because the winner’s curse in our model stems from the winning dealer’s need to offload part of his position in the interdealer SEF, the customer could reduce the winner’s curse problem by using a divisible RFQ. This design is more likely to be helpful for large orders, although a practical challenge is how dealers can efficiently enter price-quantity pairs in their quotes (RFQ responses).

Overall, by providing insight into the decision-making process of market participants, our study contributes to the understanding of SEF trading after Dodd-Frank. In particular, we find that a complex nexus of competition, winner’s curse, and relationship drives a customers’ choice of trading mechanisms and dealers’ liquidity provision in the course of executing a trade. Our results could be used not only to improve on existing market designs for OTC derivatives such as CDS and interest rate swaps, but also to inform the design of other fixed-income markets that are undergoing similar transitions toward multilateral electronic trading, such as Treasury securities, corporate bonds, and foreign exchange.

Appendix A. Proof of Proposition 3

Dealers’ probability of responding to the RFQ.

By Proposition 2, a dealer’s response probability to the RFQ is $F(z^*)$. Using the implicit function theorem, we can show that

$$\frac{\partial z^*}{\partial k} = -\frac{\partial\Gamma/\partial k}{\partial\Gamma/\partial z^*} < 0, \tag{40}$$

using the fact that A_2, B, C, and $E[z_j|z_j > z^*]$ are all positive (recall that $E[z_j] = 0$ by assumption). This comparative static implies that the response probability of each contacted dealer is lower if more dealers are selected in the RFQ.

Similarly, we have

$$\frac{\partial z^*}{\partial y} = -\frac{\partial\Gamma/\partial y}{\partial\Gamma/\partial z^*}. \tag{41}$$

We know $\partial\Gamma/\partial z^* < 0$. And

$$\frac{\partial\Gamma}{\partial y} = \frac{\partial(A_1/y)}{\partial y} - \frac{\partial \underline{p}}{\partial y} = \underbrace{-\frac{\lambda}{rn}(1+0.5C(n-2))}_{<0,\text{ dealer's decreasing value}} - \underbrace{\frac{\partial \underline{p}}{\partial y}}_{<0,\text{ customer's decreasing reservation value}}. \tag{42}$$

Thus, $\frac{\partial z^*}{\partial y} > 0$ if and only if $\frac{\partial\Gamma}{\partial y} > 0$, which has the intuitive interpretation that the customer’s reservation value decreases faster in quality than a dealer’s value does.

Finally, we compute the comparative statics of z^* with respect to primitive model parameters, n, λ, and $\underline{p}$. We will focus on the case of $\Delta = 0$, i.e., the market is open continuously, which is realistic. In this case, $C = 1/(n-1)$ and Eq. (13) simplifies to:

$$\Gamma = v - \frac{\lambda}{r}\frac{3n-4}{2n(n-1)}y - \frac{\lambda}{r}\frac{n-2}{n(n-1)}(k-1)E[z_j \mid z_j > z^*] - \frac{\lambda}{r}\frac{2}{n}z^* - \underline{p}. \tag{43}$$

Clearly, Γ is increasing in n but decreasing in λ and $\underline{p}$; and hence z^* is likewise increasing in n but decreasing in λ and $\underline{p}$.

Dealers’ response prices, conditional on responding to the RFQ. Conditional on responding to the RFQ, a dealer’s response price is given by Eq. (15). Note that z^* is endogenous and needs to be taken into account in computing the comparative statics of $\beta(z_i)$.

We directly calculate:

$$\frac{\partial\beta(z_i)}{\partial k} = -(A_2+B)\times\left[\underbrace{\frac{(1-F(z^*))^{k-1}\frac{\partial z^*}{\partial k}}{(1-F(z_i))^{k-1}}}_{<0,\text{ as }\partial z^*/\partial k<0} + \underbrace{\int_{u=z_i}^{z^*}\frac{\partial}{\partial k}\left(\frac{1-F(u)}{1-F(z_i)}\right)^{k-1}du}_{<0}\right] - \underbrace{A_2E[z_j \mid z_j > z_i]}_{>0}. \tag{44}$$

As before, the above expression illustrates the trade-off between competition and winner’s curse. The two terms in the square brackets show that dealer i’s market power decreases as k increases. But the last term shows that dealer i’s winner’s curse problem becomes more severe as k increases. The net effect is ambiguous.

Similarly,

$$\frac{\partial\beta(z_i)}{\partial y} = \underbrace{\frac{d(A/y)}{dy}}_{<0} - (A_2+B)\frac{(1-F(z^*))^{k-1}}{(1-F(z_i))^{k-1}}\frac{\partial z^*}{\partial y}. \tag{45}$$

[20] If a customer simply wishes to use a single market order to complete a transaction, Viswanathan and Wang (2004) show theoretically that, as long as the customer’s order is not driven by private information about fundamentals, a sequential market as in current practice—a customer runs an indivisible auction with dealers and the winning dealer subsequently redistributes it to other dealers—tends to be more efficient than an order book mechanism. If the customer order is too informative about the fundamental value of traded asset, Viswanathan and Wang (2004) show that the sequential market could break down and the order book mechanism is more robust.

Table 15
Model calibration, separately for IG and HY.

	IG	HY	Source
Set parameters			
Fundamental value (v)	0.01	0.05	Market practice
Discount rate (r)	1	1	Normalization
Number of dealers in the market (n)	16	18	Table 3
Trade size (y)	29	9	Table 3
Calibrated parameters			
λ	0.018 bps	0.098 bps	
δ, where $\underline{p} = v - \delta y$	0.031 bps	0.457 bps	
c	0.001 bps	0.018 bps	
Empirical moments			
# dealers requested	4.02	4.18	Table 3
Response rate	0.9	0.88	Table 3
Average transaction cost (half-spread)	0.09 bps	0.24 bps	Table 11
Fitted moments			
# dealers requested	4.02	4.21	
Response rate	0.9	0.88	
Average transaction cost (half-spread)	0.09 bps	0.24 bps	

Clearly, since A/y is decreasing in y, a sufficient condition for $\frac{\partial \beta(z_i)}{\partial y} < 0$ is that $\frac{\partial z^*}{\partial y} > 0$, which is implied by $\partial \Gamma/\partial y > 0$.

The comparative statics of $\beta(z_i)$ with respect to other parameters are not obvious. Again, take $\Delta = 0$ and rewrite Eq. (15) as:

$$\beta(z_i) = v - \frac{\lambda}{r}\frac{3n-4}{2n(n-1)}y - \frac{\lambda}{r}\frac{2}{n}\left(z_i + \frac{\int_{u=z_i}^{z^*}(1-F(u))^{k-1}du}{(1-F(z_i))^{k-1}}\right) - \frac{\lambda}{r}\frac{n-2}{n(n-1)}(k-1)E[z_j \mid z_j > z_i]. \quad (46)$$

Because z^* is increasing in n, the sign of $\partial\beta(z_i)/\partial n$ is not obvious. The same indeterminacy applies to λ.

Appendix B. Numerical comparative statics for the model of Section 4

In this appendix we illustrate the numerical solution for the model of Section 4. The objective of this appendix is to illustrate that the model is able to match the qualitative nature key summary statistics and comparative statics, but it is not meant to be a structural calibration. The latter likely requires a much richer dynamic model, in which multiple customers arrive sequentially.

Table 15 below calibrates the model to a few empirical moments, separately for IG and HY. The level of fundamental value v is inconsequential for equilibrium outcomes as all prices are relative to v. The interest rate r and the delay cost λ are not separately identified from the model because they appear in pairs, λ/r, so we normalize $r = 1$. The number of dealers n and average order size are set to the mean value as in Table 3. Three parameters need to be calibrated, (λ, δ, c), where λ is the inventory cost parameter, the customer's reservation price is $\underline{p} = v - \delta y$, and adding one more dealer to the RFQ incurs a cost of cy for the customer. Finally, dealers' inventory sizes $\{z_i\}$ are assumed to have a normal distribution with mean zero and standard deviation of \$100 million notional.

We target to match three empirical moments: the number of dealers requested, the average response rate, and the average transaction cost (half-spread). Because the number of dealers requested is not an integer at the mean, in the calibration we allow k to be any real number (instead of an integer). With three free parameters, we can match the three empirical moments well. Note that c need not be very large to generate an interior optimal number of dealers selected, k^*.

Figs. 5 and 6 illustrate the numerical comparative statics of the model for IG and HY indices, respectively. The baseline parameters in each figure are taken from Table 15, shown as dot-dashed lines. At those baseline parameters, we perturb, one at a time, trade size y, dealer inventory cost λ, and the number of dealers n. The variables of interest are the optimal number of dealers selected and the response rate. In these calculations the optimal number of dealers selected, k^*, is chosen to be the optimal one (with the constraint that it is an integer). The dot-dashed lines indicate the change in k^* as a primitive parameter changes.

The two left subplots of each figure show that a larger order size y reduces the optimal number of dealers requested (consistent with Table 6) but increases their response rate (consistent with Tables 8 and 9). The middle two subplots of each figure show that a higher inventory cost (proxy for last four hours of the trading day) increases the optimal number of dealers requested (consistent with Table 6) and reduces their response rate (Tables 8 and 9 show negative coefficients but they are not statistically significant).

The right two subplots of each figure show that the model-implied comparative statics with respect to n are generally non-monotone. The optimal k^* is equal to the number of dealers n if n is small, but an interior optimal k^* is obtained if n is sufficiently large. The average number of dealers in the data is sufficiently large that k^* obtains an interior solution. In that region, the model predicts that k^* is decreasing in n but response rate is increasing in n. In Table 6, the coefficient on n is negative but statistically insignificant. Tables 8 and 9 show that RFQ

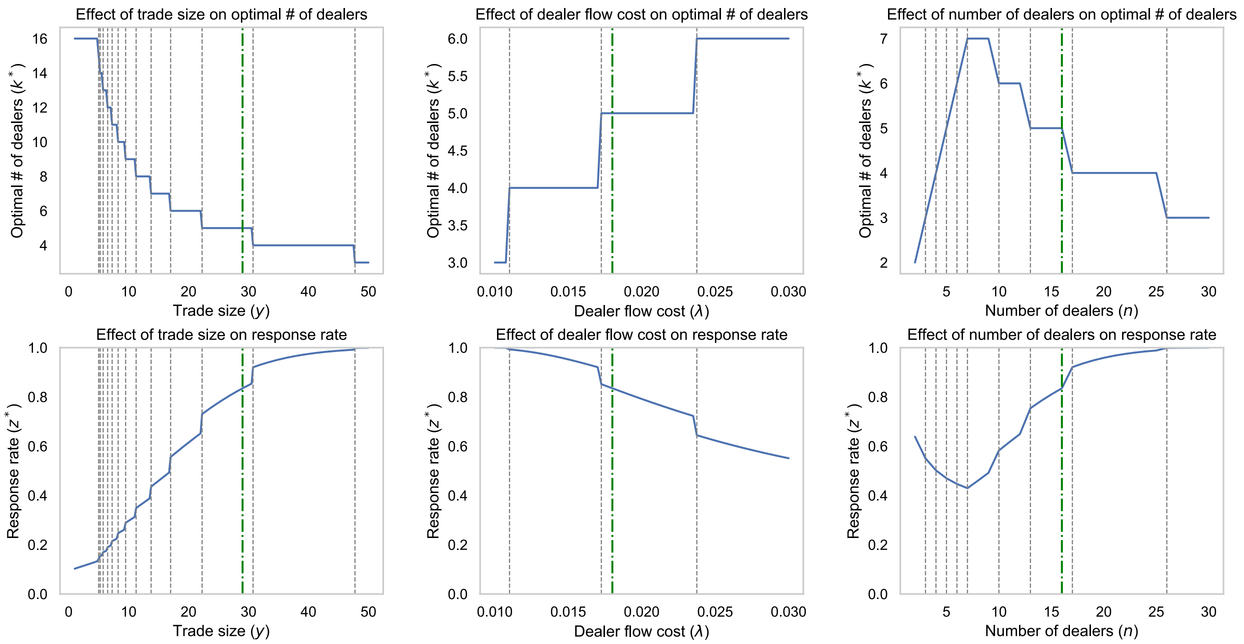

Fig. 5. Numerical comparative statics for IG indices. Parameters: dealer inventories are normally distributed with mean zero and standard deviation of \$100 million; $\nu = 0.01$ (100 bps), $\lambda = 0.018$ bps; customer reservation price is $\nu - 0.00031y$; and the cost of choosing an additional dealer per million of notional is 0.001 bp.

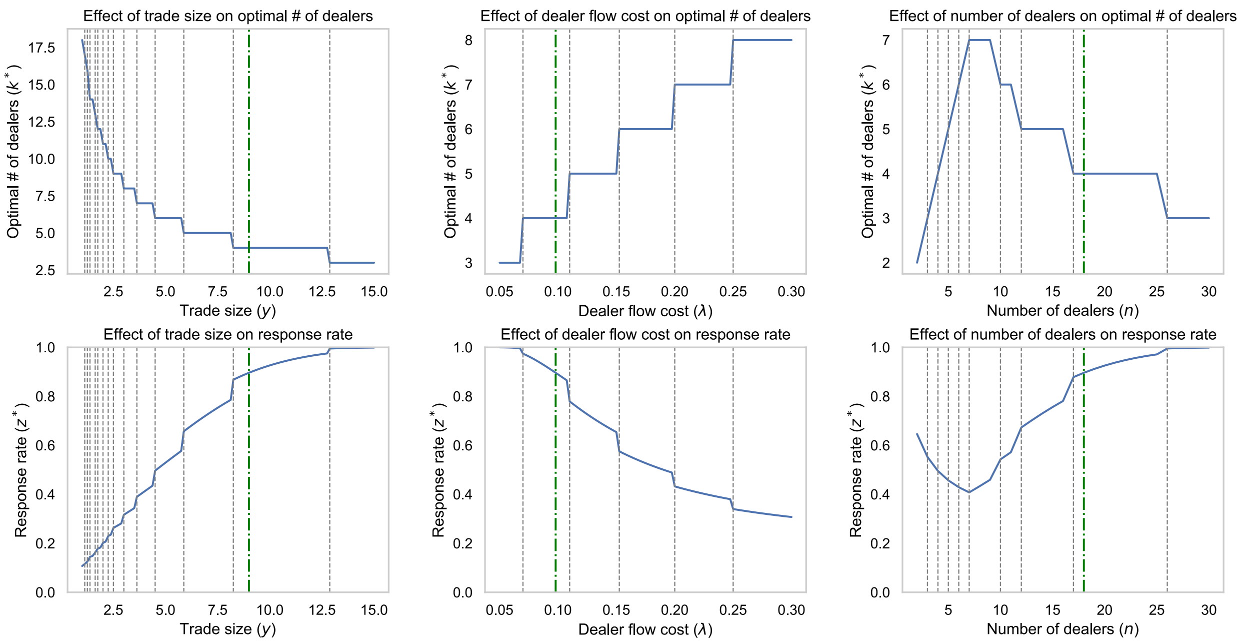

Fig. 6. Numerical comparative statics for HY indices. Parameters: dealer inventories are normally distributed with mean zero and standard deviation of \$100 million; $\nu = 0.05$ (500 bps), $\lambda = 0.098$ bps; customer reservation price is $\nu - 0.00457y$; and the cost of choosing an additional dealer per million of notional is 0.018 bp.

response rate is indeed higher if more dealers are making markets.

While our simple model can match key summary statistics and comparative statics of the data, it has limitations. One limitation is that all dealers treat the customer in the same manner and hence have symmetric quoting strategies. Therefore, the model misses the empirical pattern that a customer's clearing member responds to RFQs more often than other dealers on average. Building in this asymmetry requires a two-way relationship, that is, a clearing member derives some benefit from responding to RFQs sent by his customers. This point seems conceptually

Table 16
Direction of trades by dealers in D2C and D2D trades (only CDX).

Panel A: All days				*Panel B: Large days*			
Contract	Sign	Count		Contract	Sign	Count	
HY.25	-1	11	9.6%	HY.25	-1	5	7.9%
HY.25	0	93		HY.25	0	51	
HY.25	1	11		HY.25	1	7	
HY.26	-1	97	35.3%	HY.26	-1	41	38.0%
HY.26	0	76		HY.26	0	33	
HY.26	1	102		HY.26	1	34	
IG.25	-1	6	7.2%	IG.25	-1	4	7.4%
IG.25	0	65		IG.25	0	43	
IG.25	1	12		IG.25	1	7	
IG.26	-1	90	34.4%	IG.26	-1	46	39.0%
IG.26	0	93		IG.26	0	37	
IG.26	1	79		IG.26	1	35	

straightforward but the resulting model would no longer have closed-form, intuitive strategies.

Appendix C. D2C trades versus D2D trades

Our primary data set consists of D2C trades. This appendix briefly describes the connection between dealers' D2C trades and their D2D trades. This connection helps motivate our model based on winner's curse.

We complement our message-level data in the two D2C SEFs with data on all of the transactions taking place during the same period, collected from the trade repositories. We label Bloomberg and Tradeweb as D2C SEFs and label all other SEFs as D2D SEFs. Note that the D2D data include only transactions but not orders. Collin-Dufresne et al. (2018) provide a detailed analysis of D2D trading of index CDS.

We are primarily interested in whether a dealer's D2C trades and D2D trades are in the same or opposite directions. If trades happen in opposite directions, then this pattern indicates that dealers may be offloading D2C trades in D2D SEFs. Table 16 below provides evidence on the relationship between a dealer's D2D and D2C net trades. We use the term net trade to refer to the change in a trader's position over the course of a day. For example, a trader who took the long side of a $30 million trade in an index, and the short side of a $40 million trade in that same index on the same day would have a net trade of - $10 million on that date. The statistics shown in Table 16 are the counts of the signs of the correlations between a dealer's D2C and D2D daily net trades. Specifically, if a dealer is a net CDS buyer (negative net trades) on D2C SEFs on a given day and a net CDS seller on D2D SEFs on the same day, or the other way around, then we denote the sign of the correlation of their net trades as -1. If a dealer's net trades in the two types of SEFs are in the same direction, then the correlation is 1. If a dealer has a zero net trade on a contract on either D2C SEFs or D2D SEFs, but not both, then the correlation is set to zero. If a dealer has a zero net trade on a contract on both D2C SEFs and D2D SEFs, then we drop the dealer-day observation. This procedure produces, for each CDS index, a single number (-1, 0, or 1) for each dealer-day pair. In the trade repository data collected by the CFTC, there are not many D2D trades on iTraxx indices, so we focus on CDX in this exercise.[21] Panel A shows the statistics for the full sample (labeled "All days"). Panel B focuses on days on which the absolute value of a dealer's D2C net trade for each particular CDS index is larger than the average of her absolute D2C trade in that CDS index in our sample (labeled "Large days").

In Panel A, for the two on-the-run indices (IG.26 and HY.26), 34–35% of the dealer-day observations have opposite trade directions between the D2C segment and the D2D segment, and about the same fraction of observations have the same trade directions in the two segments. Again, these numbers exclude dealer-day observations for which a dealer makes zero net trades in both D2C SEFs and D2D SEFs on a day. In Panel B, on days when dealers make larger-than-average D2C trades, about 38 and 39% of the dealer-day observations have opposite directions between the two market segments. This evidence suggests that offloading part of a D2C trade in the D2D segment or the other way around is a realistic feature and happens with significant frequency, especially on days when the D2C trades are large.

Appendix D. Front-running concerns

A salient feature of the data is that customers limit their order exposure to only a few dealers. We have proposed winner's curse as a possible channel that partially offsets the benefit of competition. While an explicit cost seems important in generating an interior optimal number of dealers requested, all comparative statics are derived using the winner's curse channel and they fit the data quite well.

In this appendix, we discuss an alternative explanation for why customers limit their order exposure: front-running. That is, customers worry that a dealer who receives an RFQ may rush to trade in the same direction as the customer in other venues before the customer's RFQ

[21] One possible reason is that European dealers trade with each other on European venues that are outside the jurisdiction of the CFTC.

Table 17
Intraday switch statistics between D2D and D2C SEFs.

Panel A: Switch from D2C to D2D			*Panel B: Switch from D2D to D2C*		
	60 Min or less			60 Min or less	
Count	Sign	Avg time between switches	Count	Sign	Avg time between switches
370	-1	0:17:30	391	-1	0:16:53
388	1	0:16:44	304	1	0:18:38
	15 Min or less			15 Min or less	
Count	Sign	Avg time between switches	Count	Sign	Avg time between switches
200	-1	0:05:48	224	-1	0:05:52
215	1	0:05:44	153	1	0:05:48
	5 Min or less			5 Min or less	
Count	Sign	Avg time between switches	Count	Sign	Avg time between switches
92	-1	0:02:03	111	-1	0:02:14
111	1	0:02:18	80	1	0:02:08
	2 Min or less			2 Min or less	
Count	Sign	Avg time between switches	Count	Sign	Avg time between switches
51	-1	0:00:56	57	-1	0:00:57
49	1	0:00:55	41	1	0:00:57
	1 Min or less			1 Min or less	
Count	Sign	Avg time between switches	Count	Sign	Avg time between switches
29	-1	0:00:31	29	-1	0:00:27
23	1	0:00:25	21	1	0:00:28

is filled. Because an auction typically remains open for a short period of time (within a minute), the front-running hypothesis predicts that there should be D2C trades and D2D trades close to each other in time. Note that once a trade happens and is reported, it becomes public information and hence there would be no front-running concerns.

To evaluate the front-running possibility, Table 17 below shows some simple statistics on the time delays between D2C trades and D2D trades. We look for situations in which a dealer accumulates a net position on a D2C SEF and then *switches* to trading on a D2D SEF, or the other way around. The accumulation is the total change in position resulting from a series of trades on one type of venue. For example, if a dealer buys $20 million on a D2C SEF, then buys $30 million on a D2C SEF, and then sells $40 million on a D2D SEF, then the first two trades are part of a single accumulation, and there is one switch. The “sign” is -1 in this case because the cumulative D2C trades and the cumulative D2D trades are in opposite directions. If the sequence of trades is buying $20 million on a D2C SEF, selling $40 million on a D2D SEF, and then buying $30 million on a D2C SEF, then there are two switches, and both signs are -1. If a dealer buys $20 million on a D2D SEF and then buys $30 million on a D2C SEF, then there is one switch with a sign of 1.

Table 17 reports the number of switches and the average time between these switches from the last trade of the first series to the first trade of the second series, conditional on a trade within a fixed time interval (e.g., 60 min). For example, the first row of Panel A shows the 370 instances in which a dealer switches from D2C SEFs to D2D SEFs within one hour, with opposite trading directions. Within this set, the average delay between the last D2C trade and the first D2D trade is 17.3 minutes. The premise of the front-running hypothesis is that if dealers' front-running happened frequently, there would be many short-delayed switches with the sign of -1. But Table 17 shows that there are very few short-delayed switches. For example, there are only 29 instances in which a dealer switches from D2D SEFs to D2C SEFs within a minute and their trades are in opposite directions; and likewise for switches from D2C SEFs to D2D SEFs. The evidence therefore suggests that front-running is not a salient feature of the data.

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