Mechanism Selection and Trade Formation on Swap Execution Facilities: Evidence from Index CDS[*†]

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Abstract

The Dodd-Frank Act mandates that certain standard OTC derivatives be traded on swap execution facilities (SEF). This paper provides a granular analysis of SEF trading mechanisms, using message-level data for May 2016 from the two largest customer-to-dealer SEFs in index CDS markets. Both SEFs offer various execution mechanisms that differ in how widely customers' trading interests are exposed to dealers. A theoretical model shows that although exposing the order to more dealers increases competition, it also causes a more severe winner's curse. Consistent with this trade-off, the data show that customers contact fewer dealers if the trade size is larger or nonstandard. Dealers are more likely to respond to customers' inquiries if fewer dealers are involved in competition, if the notional size is larger, or if more dealers are making markets. Finally, dealers' quoted spreads and customers' transaction costs increase in notional quantity and the number of dealers involved. In addition to results related to the winner's curse, past trading relationships also affect customers' requests and dealers' responses. Our results contribute to the understanding of swaps markets by providing insights into the trade-offs faced by investors and dealers.

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. The Act's goal of increased transparency in these markets likely reflected their economic significance. As of June 2016, OTC derivatives markets worldwide for all asset classes had a notional outstanding amount of $544 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 over $7 trillion of CDS volume[4] and close to $103 trillion of IRS volume in 2016.

This paper provides a granular analysis of SEF trading mechanisms in U.S. index CDS markets after the Dodd-Frank implementation. Understanding SEF trading mechanisms and the associated behavior of market participants is important since 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

[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.

(Tradeweb) in May 2016. These two SEFs specialize in customer-to-dealer trades. According to *SEF Tracker*, in 2016, Bloomberg and Tradeweb were the top two SEFs in the index CDS market, capturing market shares of 74% and 13%, respectively. Therefore, data from these two SEFs offer a comprehensive view of activities in SEF-traded index CDS. Relative to publicly reported data, our data have at least two advantages. First, our data contain messages throughout the trade formation process, including customers' inquiries, dealers' responses, and resulting trades (or lack thereof). Second, our data contain identifiers for customers and dealers. These details enable us to observe the behavior of customers and dealers at a granular level.

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 are offered the following execution mechanisms:

- Central limit order book (CLOB). Customers may execute against existing orders or post new orders on a mostly transparent order book.

- Request for quote (RFQ). Customers select multiple dealers and request quotes from them, revealing the 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 ask multiple dealers to send indicative quotes throughout the day and respond to one of them by proposing to trade at the dealer's quote.

In a sense, from CLOB to RFQ to RFS, one's detailed order is progressively exposed to fewer market participants.[5]

We find that among these three major mechanisms, the RFS mechanism captures the most activity in our sample. On both SEFs, the CLOB has low activity. Moreover, conditional on using RFQ, customers on average only request quotes from about four dealers, even though they can request quotes from more dealers on both platforms. The salient empirical pattern that customers generally expose their orders to relatively few dealers (or to other customers in the case of the CLOB) strongly suggests that competition is not the only economic force that drives customers' choice of trading mechanisms.

[5] Customers receive quotes from multiple dealers under both RFQ and RFS. A key difference, however, is that the RFS quotes are indicative and RFQ quotes are generally firm.

To better understand the incentives at play, we propose and solve a model of SEF trading. In the model, the customer first contacts k dealers simultaneously in an RFQ process, and then dealers periodically smooth inventories among themselves on an interdealer SEF. Although everyone in our model has symmetric information about the asset's fundamental value, the interdealer trades create a winner's curse for the dealer who "wins" the customer's order in the RFQ, and this winner's curse is more severe if the customer contacts more dealers in the RFQ. To see the intuition, suppose that the customer is selling an index CDS. In equilibrium, the dealer who wins the RFQ infers that he has the lowest inventory among the k dealers contacted. Therefore, the winning dealer infers that the total inventory of all dealers is more likely to be long, which leads to a lower expected interdealer price than the unconditional expected price. This adverse inference discourages each participating dealer from bidding a high price for the customer's order, and it is more severe for a larger k. We show that dealers' response rates are decreasing in k precisely because of this winner's curse problem. On the other hand, a larger k does reduce each participating dealer's information rent. 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. The model makes additional predictions regarding the determinants of response rates in RFQs.

The trade-off between competition and winner's curse is the organizing theme in our empirical analysis. We begin by analyzing the customer's choice of trade mechanism, where the key decision is how widely the customer exposes his trading interest. We find that a larger trade size significantly reduces the customer's likelihood of choosing RFQ 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 5.3%. If an RFQ is used by the customer, the same increase in notional quantity reduces the number of contacted dealers by approximately half a dealer (i.e., 0.55), which is fairly substantial given that the average number of dealers queried is around four. In addition, customers tend to expose their orders to fewer dealers if the trade size is nonstandard or if it is early in the trading day.

Next, we examine dealers' strategic responses to RFQs. Again, on the two SEFs, dealers selected for RFQs observe how many other dealers are competing for the order (but not the responses of other dealers). Overall, dealers' response rates to RFQs are high, around 80% to 90% on contracts subject to the SEF mandatory trading requirement. As predicted by the model, we find that RFQ response rates decrease in the number of dealers selected

Table 1: Summary of empirical findings. Positive (+) and negative (−) signs refer to the signs of statistically significant coefficients on the whole sample. Empty entries denote statistical insignificance. "N/A" means a variable is not in the particular regression. Columns (2)–(6) are restricted to RFQs.

	(1) RFQ probability	(2) # Dealers queried in RFQ	(3) Dealers' response rate	(4) Transaction probability	(5) Dealers' quoted spread	(6) Customers' transaction costs
Notional quantity	−	−	+	+	+	+
Standard quantity	−	−		−		
# Streaming quotes			+			
Last 4 hours of trading	+	+				
# Dealers queried in RFQ	N/A	N/A	−		+	+
Past trading relationship	N/A	N/A	+	N/A		N/A

(suggesting a winner's curse effect), increase in notional quantity (suggesting larger gains from trade), and increase in the number of contemporaneous streaming quotes (suggesting it is easier to offload position in interdealer markets). Inquiries in RFQs 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 find that dealers' quoted spreads and customers' transaction costs in RFQs increase in notional quantities, which is consistent with larger gains from trade on those orders between customers and dealers. Put differently, customers' demand for immediacy could be higher for larger orders, so they are willing to pay more for liquidity. Spreads and costs also increase in the number of dealers selected, which is consistent with the winner's curse effect. That said, the economic magnitude of these estimates is rather small.

While the competition-versus-winner's curse trade-off is the main theme of our analysis, we also examine the effect of past trading relationships between customers and dealers. We find that in RFQs a customer tends to select dealers who account for a larger fraction of the customer's past trading volume in index CDS. Conversely, conditional on being selected in RFQs, a dealer responds more frequently to customers who account for a larger fraction of the dealer's past trading volume in index CDS. A dealer's quoted spread is not significantly affected by relationships, however. The evidence supports relationship as another determinant in the trade formation process on SEFs.

Table 1 summarizes the empirical findings discussed above. Overall, the empirical evidence is consistent with the trade-off between competition and winner's curse. Customers internalize this trade-off when selecting the trading mechanism, and dealers respond to it throughout the trade formation process. The evidence also suggests that the past trading relationship matters for the customer's selection of dealers in trade requests and for dealers' response rates.

Relation to the literature. Our paper contributes to the small but growing literature that analyzes swaps markets after the implementation of Dodd-Frank. Combining publicly-reported interest rate swaps data from swap data repositories (SDRs) with a private data set acquired from a clearinghouse, Benos, Payne, and Vasios (2016) analyze the impact of the introduction of SEFs on the U.S. interest rate swaps market. The authors interpret their findings as indicative of improved liquidity and reduced execution costs for end-users. The authors attribute the biggest improvements in liquidity to the introduction of SEFs. Collin-Dufresne, Junge, and Trolle (2016) use swap data reported on SDRs to analyze the difference in trading costs between dealer-to-customer (D2C) and interdealer (D2D) 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. Related to earlier rules in swaps market, 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 behaviors throughout the trade formation process, from the initial customer inquiry to dealers' responses to the final transaction confirmation, all with time stamps. That is, we have information about the identity of each customer, the identity of each dealer contacted by a customer, the time of those contacts, the response of each dealer, the method of execution (e.g., RFS vs RFQ), as well as data that are publicly available, which are typically the price and the notional value of each transaction. Equipped with this level of granularity, we can separately analyze, both theoretically and empirically, the demand for liquidity (customers' inquiries) and the supply of liquidity (dealers' responses), which would not be possible if only the price and notional size of completed transactions were observed. For example, we can investigate the responses of individual dealers to a request for quote. Moreover, identity information in the data allows us to study how past trading relationships affect the trade formation process. Overall, the granular nature of the data enables us to ask economic questions that are distinct from the papers mentioned above.

Our study also contributes to the understanding of new electronic trading mechanisms in previously over-the-counter (OTC) markets. Hendershott and Madhavan (2015) compare the transaction costs of voice trading versus electronic RFQs in U.S. corporate bond markets. They report that even for inactively traded bonds, the electronic RFQ mechanism is associated with lower trading costs. In the European corporate bond market, Fermanian, Guéant, and Pu (2015) fit a statistical model to the distribution of RFQ data obtained from an investment bank. Their results indicate that, among other things, response rates drop as more dealers are included in the RFQ. Collin-Dufresne, Junge, and Trolle (2016) examine mid-market matching and workup on GFI, an interdealer SEF.

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 short the stock and drive down the stock price. In our model, the customer contacts multiple dealers simultaneously.

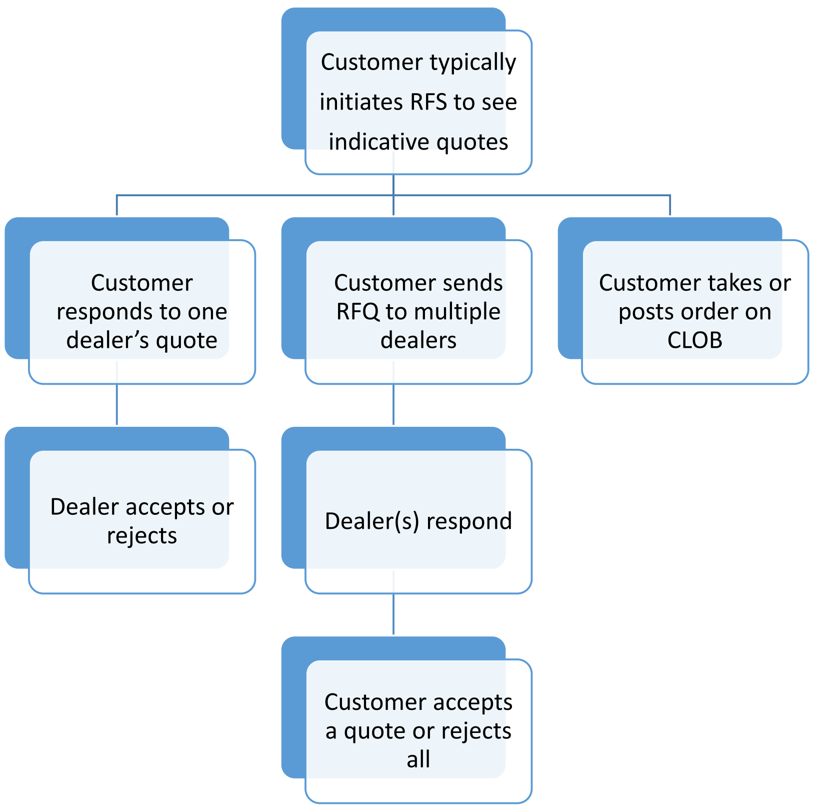
A number of papers have studied the effect of relationships on trading behavior in OTC markets. Using enhanced TRACE data in corporate bond markets, Di Maggio, Kermani, and Song (2017) find that dealers offer lower spread to counterparties with stronger prior trading relations, and this pattern is magnified during stressful periods as measured by higher VIX. Using data on transactions of insurance companies in corporate bond markets, Hendershott, Li, Livdan, and Schürhoff (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 (2017) find that customers in index CDS markets who trade with more dealers and have connections to more active dealers incur lower transaction costs. 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. Our evidence from SEFs is complementary to these studies: Customers' requests and dealers' responses rates depend positively on past relationship, but dealers' price quotes do not.

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.[6]

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 (e.g., RFQ and RFS). 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. Figure 1 provides a stylized representation of the trading process on these two SEFs.

Figure 1: Representation of the trading process for index CDS on Bloomberg and Tradeweb 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.[7] That indication of interest automatically

[6]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.

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

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.[8] At this point, the customer has a choice among interacting with the CLOB, responding to one of the RFS quotes, or initiating a request for quote (RFQ).

In using the CLOB, the customer can either take one of the firm orders on the CLOB (aggressive side), at the size and price of the existing order, or post their own firm order on the CLOB (passive side) and wait for another trader to take it.

The customer may also respond to the stream of indicative quotes provided by dealers by selecting one quote and informing that dealer about the side of the transaction (i.e., buy or sell) and the associated quantity. 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.

Finally, the customer can choose to send an RFQ. The RFQ process is essentially a kind of 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.[9]) 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 whether 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 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.

[8] On Bloomberg SEF, the CLOB is anonymous.

[9] According to Fermanian, Guéant, and Pu (2015), in European corporate bond markets, Bloomberg Fixed Income Trading sets a limit of up to six dealers in a single RFQ.

3 Data and Summary Statistics

We focus on index CDS, an important derivative class that is, for the most part, subject to the CFTC's SEF trading rules. Publicly available data sources[10] indicate that, over the time period covered by our sample (May 2016), the average daily notional of CDS swaps traded on Bloomberg and Tradeweb was about $16 billion, with 84% of that traded on Bloomberg. Out of the $16 billion traded, two thirds of trades were in CDX indices, while the rest were in iTraxx indices. From these data, we also observe that a little over 90% of the notional value of transactions on these two SEFs are based on MAT contracts, which is a statistic that is also reflected in our proprietary data set.

For our main analysis, we use message-level data from Bloomberg and Tradeweb in May 2016. These two venues specialize in customer-to-dealer trades and account for more than 85% of all SEF trading volumes in the index CDS market in 2016. 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, 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 trades for which SEF trading is required, namely MAT contracts and trades whose sizes are below the contract-specific minimum block sizes.[11] MAT contracts include the on-the-run and the first off-the-run series with a 5-year tenor in four indices: CDX NA IG, CDX NA HY, iTraxx Europe, and iTraxx Crossover.[12] By CFTC rules, non-MAT contracts and block-sized trades 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.
- We also focus on single-contract trades and exclude package trades such as rolls (selling an off-the-run index CDS and simultaneously buying the on-the-run index).
- For RFQs, we exclude sessions that involve fewer than three dealers. These sessions

[10] Our data source is Clarus Financial Technology, a company specializing in aggregating and analyzing publicly available swaps data.

[11] 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.

[12] 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.

are exempt from the MAT trading rules.

- Finally, among the three mechanisms, the order book has very low activity, so we exclude this mechanism from the analysis.

The resulting data sample includes 8399 RFQ and RFS sessions, of which 5567 sessions are on the four CDX indices and 2832 sessions are on the four iTraxx indices. This is the data sample we use for the rest of the paper.

Figure 2 plots the probability distribution of the number of dealers contacted in RFQs. The probability masses add up to one, although we separately label CDX and iTraxx 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 just below 30% of the RFQ sessions. In about 18% of the sessions the customer selects four dealers. Customers rarely select more than five dealers for their RFQs.

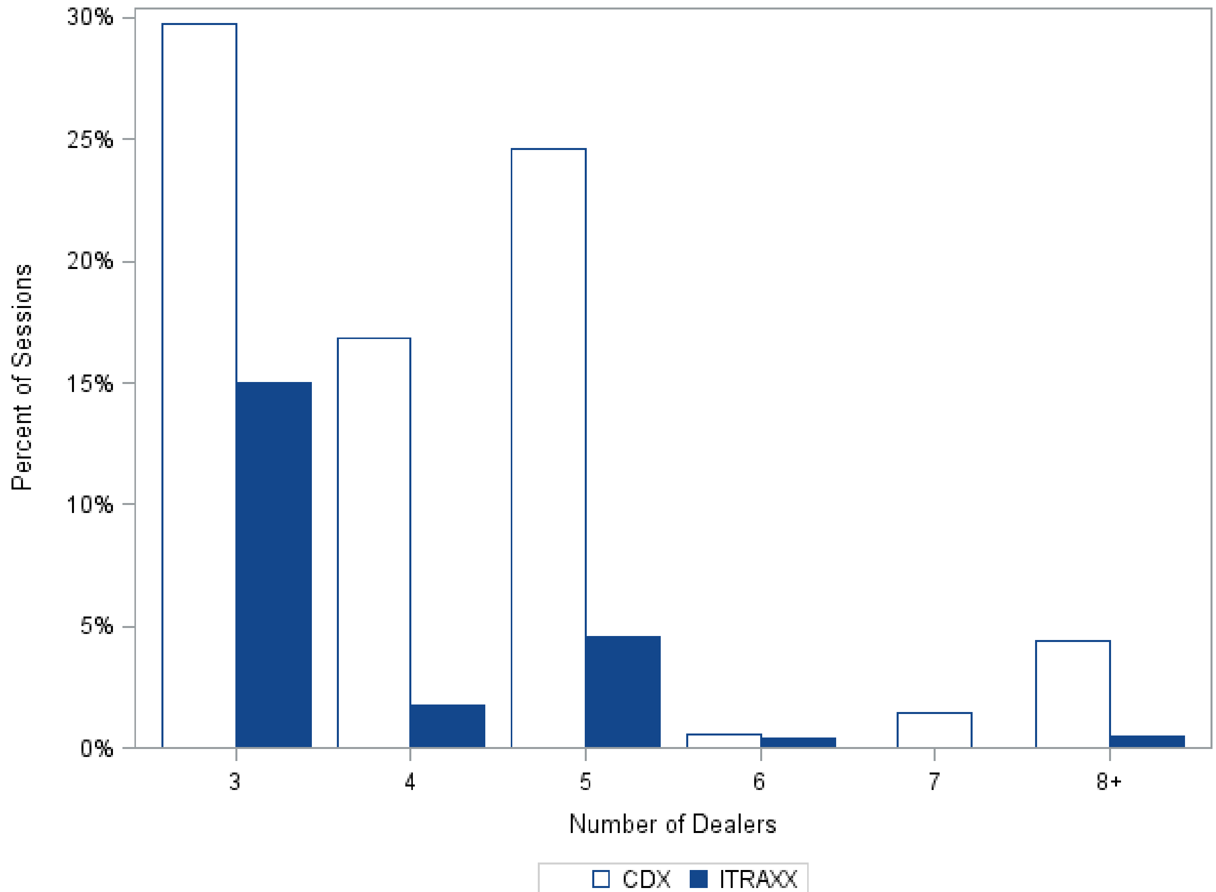
Figure 3 reports dealers' response statistics in RFQs. The x-axis shows the number of dealers contacted and the y-axis shows the average number of dealer responses. The numbers on top of the histograms are the dealer response rate. We again separately report CDX and iTraxx. The overall pattern is that response rates are high but decrease in the number of dealers requested. The response rate is above 90% if the customer requests quotes from 3–5 dealers and decrease slightly, to about 80%, if the customer requests quotes from 6–7 dealers. If the customer requests quotes from at least eight dealers, the number of responding dealers in RFQs plateaus at about seven on average.

Table 2 shows the summary statistics of key variables that we use in the empirical analysis. We report the whole sample as well as CDX and iTraxx separately. We observe that customers, on average, select RFQ 36% of the time for all products (CDX and iTraxx combined), 42% of the time for CDX, and 24% for iTraxx. Conditional on selecting RFQ, a customer on average queries 4.1 dealers and gets back 3.6 responses. Both numbers are slightly higher in CDX than iTraxx. The notional quantity has a mean of $21 million and a standard deviation of about $22 million.[13] For each contract, a few notional quantities occur with very high probability in the data, and we label them as "standard" quantities.[14] On

[13]The average order size in our sample is smaller than that reported in Haynes and McPhail (2017) due to different methodologies in constructing the data sample. Haynes and McPhail (2017) 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 (2017), but not in our sample. Moreover, Haynes and McPhail (2017) remove all trades with notional size less than $5 million, whereas we do not impose a lower bound on the size of the order.

[14]For CDS IG, standard sizes include 10, 20, 25, 50, and 100 million USD notional. For CDS HY, standard sizes include 5, 10, 15 and 25 million USD. For iTraxx Europe, standard sizes include 10, 20, 25 and 50 million

Figure 2: Number of dealers contacted in RFQs

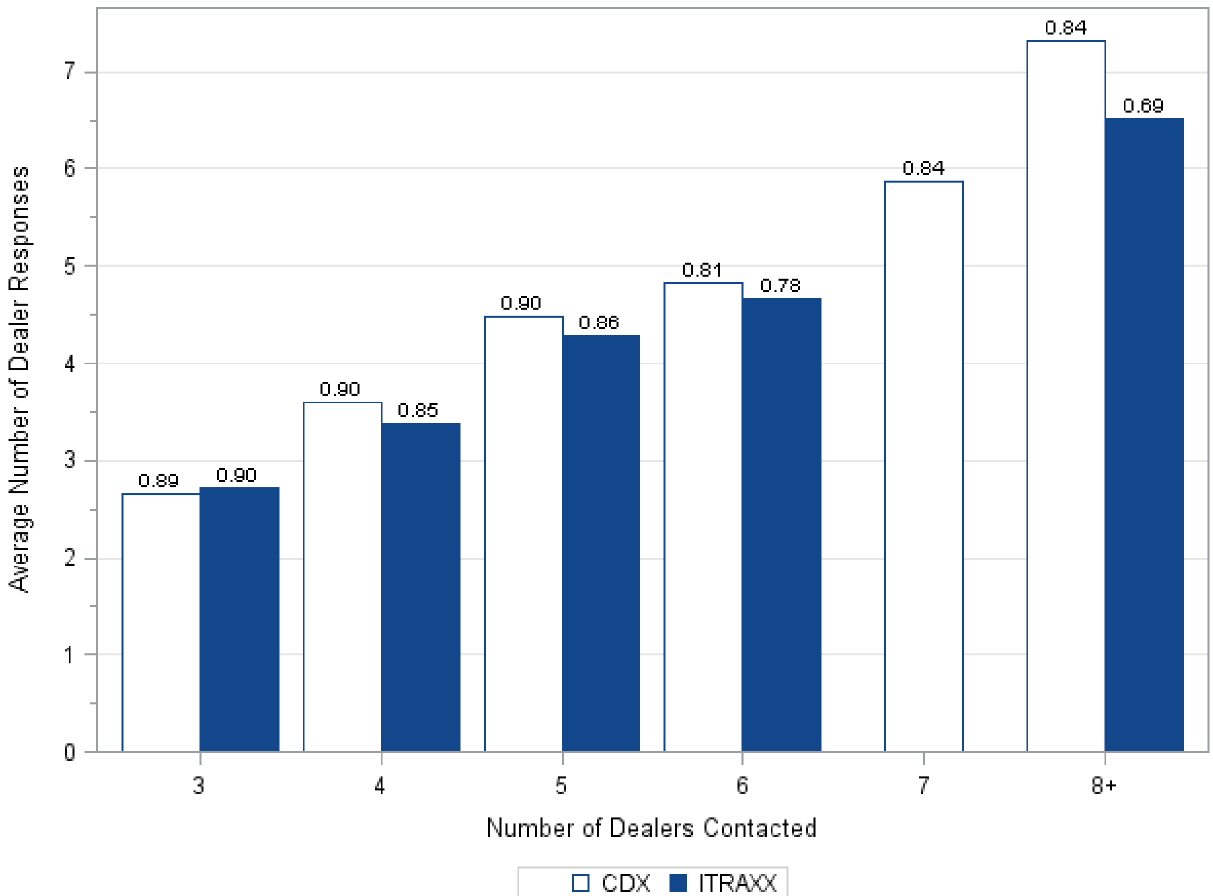


average, more than 60% of the trades are in those standard quantities. When a customer sends out an RFQ or RFS inquiry, about 17 to 19 streaming quotes are available on the index. Slightly less than 30% of the sessions occur in the last four hours of active trading for the day. Customer buys and sells are balanced. In about 8% of the sessions, the quote seeker (or customer) is in fact a dealer, in the sense that the quote seeker has provided quotes to customers in other sessions.

Finally, to construct variables that measure past trading relationships between customers and dealers, 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

EUR. For iTraxx Crossover, standard sizes include 3, 5, 10, 15, and 20 million EUR.

Figure 3: Number of dealers responding to RFQs and response rates



the identifier of each counterparty. We focus on all index CDS trades (including non-MAT contracts and block trades) from January to April 2016, four months before our main sample of May 2016. 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. To better understand the economic forces at play, in this section we provide a parsimonious

Table 2: Summary statistics for key empirical variables

	ALL	CDX	ITRAXX
Variable	Mean Std. dev.	Mean Std. dev.	Mean Std. dev.
Number of sessions	8399	5567	2832
RFQ dummy [0/1]	0.36 0.48	0.42 0.49	0.24 0.43
Number of dealers queried in RFQ	4.12 1.35	4.25 1.38	3.67 1.15
Number of dealers' responses in RFQ	3.64 1.36	3.77 1.40	3.19 1.09
Notional quantity ($ million)	21.12 22.03	20.71 23.04	21.93 19.86
Quantity is standardized [0/1]	0.64 0.48	0.63 0.48	0.66 0.47
Number of streaming quotes in RFS	17.56 7.19	16.94 6.39	18.79 8.41
Last 4 hours of trading [0/1]	0.27 0.45	0.26 0.44	0.30 0.46
Customer is buyer dummy [0/1]	0.50 0.50	0.50 0.48	0.49 0.50
Customer is dealer dummy [0/1]	0.08 0.27	0.08 0.04	0.08 0.27

model of SEF trading, solve the optimal strategies of customers and dealers, and derive a few comparative statics that can be tested in the data. The model in this section formalizes the competition-versus-winner's-curse trade-off that we described in the Introduction, and hence organizes subsequent empirical analysis around this central trade-off. That said, the details of this theoretical model are not required for understanding the empirical results in later sections, so readers may skip directly to Proposition 3, where the empirical predictions are summarized.

4.1 Model setup and preliminary solution for interdealer SEF

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 $k \in \{1, 2, 3, ..., n\}$ dealers and sends an RFQ to them. Only the k selected dealers observe y. As in the RFQ protocol in practice, the k selected dealers observe the customer's supply y. 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 i.i.d. with cumulative distribution function $F : (-\infty, \infty) \mapsto [0, 1]$ and mean 0. We denote the total inventory held by dealers before the D2C trade by $Z \equiv \sum_i z_i$. 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 $t \in \{0, \Delta, 2\Delta, ...\}$, 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

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

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.

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

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

4.2 Equilibrium in the RFQ market

In the previous subsection we have solved D2D trading and calculated each dealer's continuation value right after the D2C trading, as in equation (6). In this subsection we solve the dealers' and customers' strategies in the D2C market.

Without loss of generality, we will consider $y > 0$, that is, the customer is selling the asset and the dealers are buying it.

Step 1: Converting to an auction problem. Without loss of generality, suppose that the selected dealers in the RFQ are 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

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

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.

Step 2: Solving dealers' bidding strategies conditional on k, the number of dealers selected. Dealer i's value 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

$Z_{-i}^k \equiv \sum_{j \neq i, 1 \leq j \leq k} z_j$.

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.,

$$
\begin{aligned}
0 &= \left(A_1 - A_2 y E \left[Z_{-i}^k \mid \min_{j \neq i} z_j > z^* \right] - (A_2 + B) z^* y - \beta(z^*) y \right) P(\min_{j \neq i} z_j > z^*) \\
&= \big(A_1 - A_2 y (k-1) E\left[z_j \mid z_j > z^* \right] - (A_2 + B) z^* y - \underline{p} y \big) \left(1 - F(z^*)\right)^{k-1} \qquad (12)
\end{aligned}
$$

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 equation (12), the cutoff z^* is given by

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

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 equation (13).

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

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

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

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

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

The bidding strategy in equation (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 "information rent" because inventory is private information. A higher number of dealers k reduces this information rent. On the other hand, a higher k linearly increases the winner's curse problem, which is shown in the last term of equation (15). To see the intuition, suppose the customer is selling and dealers are buying. Dealer i's winning of the RFQ implies that all other invited dealers' inventories are more positive than dealer i's. 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 equation* (13)*. Moreover, conditional on responding to the RFQ, dealer i's responding price (per unit notional) is given by equation* (15)*.*

Step 3. The customer's choice of the number of dealers queried. Suppose the customer selects k dealers in the RFQ. Let z^m be the minimum of $z_1, z_2, ..., z_k$. The distribution of z^m is

$$G(z^m) = 1 - (1 - F(z^m))^k. \tag{16}$$

So the customer's revenue per unit of notional is

$$\pi_c = \underline{p} + E[(\beta(z^m) - \underline{p}) \cdot 1(z^m < z^*)] = \underline{p} + \int_{-\infty}^{z^*} (\beta(z^m) - \underline{p}) dG(z^m). \tag{17}$$

We can also write

$$\pi_c - \underline{p} = \int_{-\infty}^{z^*} (\beta(z^m) - \underline{p}) dG(z^m) = \int_{-\infty}^{z^*} (1 - (1 - F(z^m))^k)(-\beta'(z^m)) dz^m. \tag{18}$$

The customer solves the problem

$$\max_k \pi_c. \tag{19}$$

Ignoring the integer constraint on k^*, the first-order condition is $d\pi_c/dk = 0$, and the second-order condition is $d^2\pi_c/dk^2 < 0$. We do not have an explicit expression for the optimal k, but it can be calculated numerically.

4.3 Comparative statics and empirical predictions

In this subsection we compute the comparative statics of the model. Variables of interest include:

- Dealers' probability of responding to the RFQ;
- Dealers' response prices, conditional on responding to the RFQ;
- The customer's choice of k, the number of dealers to inquire in the RFQ.

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

$$\frac{\partial z^*}{\partial k} = -\frac{\partial \Gamma/\partial k}{\partial \Gamma/\partial z^*} < 0, \tag{20}$$

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

Note that the above calculation takes all primitive model parameters (except k) as given. By varying k but holding all else fixed, we recognize that the customer's actual choice of k may not be completely explained by the primitive model parameters such as y, n, λ, and $\underline{p}$. For example, a customer's compliance office may have specific requirements on k, which is idiosyncratic and unobservable to us. In this sense, we could view the observed k as the sum

$$k = k^* + \epsilon, \tag{21}$$

where k^* is the theoretical optimal number of dealers contacted given the primitive model parameters, and ϵ is the residual that is orthogonal to the primitive model parameters. Therefore, given the residual variation in observed k caused by ϵ, taking the partial derivative with respect to k is still a valid exercise.

By the same logic, we can calculate the partial derivatives of z^* with respect to each of y, n, λ, and $\underline{p}$, while holding fixed all else, including k. This is consistent with our subsequent multivariate panel regressions.

We have

$$\frac{\partial z^*}{\partial y} = -\frac{\partial \Gamma / \partial y}{\partial \Gamma / \partial z^*}. \tag{22}$$

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

$$\frac{\partial \Gamma}{\partial y} = \frac{\partial (A_1/y)}{\partial y} - \frac{\partial \underline{p}}{\partial y} = \underbrace{-\frac{\lambda}{rn}(1 + 0.5C(n-2))}_{<0,\text{ dealer's decreasing value}} - \underbrace{\frac{\partial \underline{p}}{\partial y}}_{<0,\text{ customer's decreasing reservation value}}. \tag{23}$$

Thus, $\frac{\partial z^*}{\partial y} > 0$ if and only if $\frac{\partial \Gamma}{\partial y} > 0$, which has the intuitively 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 equation (13) simplifies to:

$$\Gamma = v - \frac{\lambda}{r}\frac{3n-4}{2n(n-1)}y - \frac{\lambda}{r}\frac{n-2}{n(n-1)}(k-1)E[z_j \mid z_j > z^*] - \frac{\lambda}{r}\frac{2}{n}z^* - \underline{p}. \tag{24}$$

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 equation (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:

$$\frac{\partial \beta(z_i)}{\partial k} = -(A_2 + B)\left[\underbrace{\frac{(1-F(z^*))^{k-1}\frac{\partial z^*}{\partial k}}{(1-F(z_i))^{k-1}}}_{<0,\text{ as } \partial z^*/\partial k < 0} + \underbrace{\int_{u=z_i}^{z^*} \frac{\partial}{\partial k}\left(\frac{1-F(u)}{1-F(z_i)}\right)^{k-1} du}_{<0}\right] - \underbrace{A_2 E[z_j \mid z_j > z_i]}_{>0}. \tag{25}$$

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 information rent decreases as k increases. But the last term shows that dealer i's winner's curse problem becomes more severe as k increases.

Similarly,

$$\frac{\partial \beta(z_i)}{\partial y} = \underbrace{\frac{d(A/y)}{dy}}_{<0} - (A_2 + B)\frac{(1-F(z^*))^{k-1}}{(1-F(z_i))^{k-1}}\frac{\partial z^*}{\partial y}. \tag{26}$$

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 $\partial \Gamma / \partial y > 0$.

Finally, we again take $\Delta = 0$ and rewrite equation (15) as:

$$\beta(z_i) = v - \frac{\lambda}{r}\frac{3n-4}{2n(n-1)}y - \frac{\lambda}{r}\frac{2}{n}\left(z_i + \frac{\int_{u=z_i}^{z^*}(1-F(u))^{k-1}du}{(1-F(z_i))^{k-1}}\right) - \frac{\lambda}{r}\frac{n-2}{n(n-1)}(k-1)E[z_j \mid z_j > z_i]. \tag{27}$$

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

The customer's choice of k. In principle, by the implicit function theorem,

$$\frac{\partial k^*}{\partial y} = -\frac{\frac{\partial^2 \pi_c}{\partial k \partial y}}{\frac{\partial^2 \pi_c}{\partial k^2}}, \tag{28}$$

where k^* is the optimal number of dealers selected in the RFQ, ignoring the integer constraint. So $\frac{\partial k^*}{\partial y} > 0$ if and only if $\frac{\partial^2 \pi_c}{\partial k \partial y} > 0$. The comparative statics of k^* with respect to other parameters can be represented in a similar fashion. Unfortunately, we have not found a tractable way to sign these partial derivatives, so the theory so far does not make unambiguous predictions for k^*.

Summary of empirical predictions from the model. The following proposition summarizes the comparative statics that we obtain above.

Proposition 3. *Suppose that the interdealer market is open continuously ($\Delta = 0$). 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.*[15]

[15] If the customer is selling, as in the model, we expect $\underline{p} < v$, so a higher $\underline{p}$ leads to a lower response

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.

The model does not make unambiguous predictions on other market outcomes, such as the customer's choice of mechanisms.

Note that the comparative statics in Proposition 3 refer to partial derivatives. For example, when considering how the response rate $F(z^*)$ depends on notional size y, Proposition 3 only takes into account the direct effect of y on the response rate and not the indirect effect of y on z^* through its effect on k, the optimal number of dealers selected. In some cases, we cannot sign the total derivative, because the indirect effects may lead in opposite directions. Since the empirical response rates in Section 6 really examine the total effect, we may need additional information to generate predictions. For these instances, we generate predictions for total derivatives by combining Proposition 3 and the empirical patterns reported in Section 5.

4.4 Model extensions to relationships (costly solicitation of quotes or costly participation in RFQs)

Besides the winner's curse explanation, there are complementary explanations why a customer exposes his intended trade to few dealers. One possibility is the "relationship" between the customer and the dealers. For example, the customer may frequently use a small number of dealers for clearing trades, for the execution of non-standard derivatives that are not subject to central clearing, or for obtaining investment research. Both sides may benefit from the resulting economy of scale and scope.

Relationships are two-sided. On the one hand, a customer may feel reluctant to invite "non-relationship" dealers into the RFQ for fear of "upsetting" his relationship dealers and making other parts of business difficult. This aspect of relationship may be modeled, in a reduced-form way, by assuming that the customer incurs a cost for adding each dealer to the RFQ. This higher cost of soliciting bids corresponds to weaker bargaining power on the part of the customer. This model extension and some numerical comparative statics are provided in Appendix A.

On the other hand, given the costs of pricing trades and back-office services, a dealer

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.

may prioritize a relationship customer's requests over those of non-relationship customers. A simple way to capture this aspect is to assume that a dealer pays a cost to participate in a customer's RFQ. The more important is the customer to the dealer, the lower is the participation cost. This model extension and some numerical comparative statics are provided in Appendix B.

5 Customer Choice of Mechanism and Inquiries

Now, we turn to empirical evidence, beginning with the customer's choice of execution mechanism. While the model of Section 4 does not make unambiguous predictions on the customer's choice of mechanisms, the model is nonetheless useful as guidance for possible economic channels at play. Between RFS and RFQ, RFS involves the customer receiving fewer firm quotes but, on the other hand, also reduces the severity of the winner's curse because only one dealer observes the intended trade of the customer. In contrast, the RFQ mechanism results in a higher number of firm quotes, but it also incurs a more severe winner's curse. The same can be said if the customer contacts more dealers in an RFQ. Specifically, in this section we analyze two decisions made by the customer:

- Under what conditions does the customer select RFQ versus RFS?
- Conditional on selecting an RFQ, what determines the number of dealers the customer contacts?

5.1 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:

$$P(y_{itm} = 1) = \frac{\exp(\beta' X_{itm})}{1 + \exp(\beta' X_{itm})}, \tag{29}$$

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 0 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. It 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 trade. This could be a proxy for how many dealers are actively trading in this contract, or n in the model.
- 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 (quote seeker) 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.

The last five dummy variables are controls that do not necessarily correspond to any variable in the model.

Table 3 reports the results of regression (29). Column (1) pools all contracts, while column (2) and (3) examine CDX and iTraxx 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 -0.00241 means that a \$22 million increase in notional quantity, which is approximately one standard deviation of notional quantities in the sample (see Table 2), reduces the probability of initiating an RFQ by 5.3% ($= 0.00241 \times 22$). A comparison between columns (2) and (3) suggests that this effect on quantity is comparable between CDX and iTraxx, although the effect on CDX is a little larger.

The regression also shows that standard notional sizes are more likely to be executed

Table 3: Logistic regression of RFQ dummy. All estimates are marginal effects.

	(1) ALL	(2) CDX	(3) ITRAXX
Quantity in millions	-0.00241***	-0.00260***	-0.00179**
	(-4.07)	(-3.97)	(-2.41)
Quantity is standardized (0/1)	-0.243***	-0.243***	-0.211***
	(-18.21)	(-17.02)	(-11.63)
# Streaming quotes	0.00148	0.00216	0.000349
	(1.44)	(1.62)	(0.34)
Last 4 hours of trading (0/1)	0.0600***	0.0555**	0.0480***
	(3.14)	(2.35)	(3.02)
Customer is buyer (0/1)	0.0341**	0.0422**	0.00818
	(2.23)	(2.09)	(0.29)
Customer is dealer (0/1)	-0.107**	-0.207***	0.0704*
	(-2.43)	(-3.48)	(1.72)
Observations	8399	5567	2832
Pseudo R^2	0.2400	0.1821	0.3444

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

by RFS than RFQ. By column (1), if a customer inquiry has a standard notional size, the probability of using RFQ declines by 24.3%, which is large statistically and economically. Columns (2) and (3) show that this effect is similar between CDX and iTraxx. 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.

RFQs are used more frequently 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. Again, CDX and iTraxx show similar patterns on this dimension.

Finally, there is no conclusive evidence regarding whether dealers use RFQs more or less frequently than nondealers when acting as quote seekers, since the signs for CDX and iTraxx are opposite.

5.2 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 subsection—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:

$$P(Y = y_{itm} \mid Y \geq 3, X_{itm}) = \frac{\exp(-\lambda)\lambda^{y_{itm}}}{y_{itm}!} \cdot \frac{1}{P(Y \geq 3 \mid X_{itm})}, \tag{30}$$

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 subsection. 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 4 reports marginal effects from fitting the truncated Poisson model (30). Column (1) shows the pooled regression with all indices, whereas columns (2) and (3) provide the results for CDX and iTraxx separately.

As is the case with the choice between RFQ and RFS in the previous subsection, 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 −0.0249. A \$22 million increase in the notional size reduces the number of dealers requested by about 0.55, which is economically significant since the average number of dealers queried in RFQs is just over 4. Columns (2) and (3) show that the effects are quite similar between CDX and iTraxx, although the coefficients for CDX are slightly more negative.

Analogously to the RFQ/RFS results, here customers choose fewer dealers if the notional size is standard. The customer on average chooses 0.26 fewer dealers in the RFQ if the trade size is standard. The effect is stronger for CDX but insignificant for iTraxx. Again, this is consistent with the interpretation that standard sizes imply lower gains from trade. It is also consistent with the interpretation that it is easier to conduct post-trade transaction cost analysis on standard sizes.

During the last four hours of active trading, a customer using RFQ selects about 0.3 more dealers. The coefficient is significant for CDX but not for iTraxx.

Interestingly, while dealers use RFQ less frequently when they are customers (see Table 3), conditional on using RFQ, dealers tend to solicit more quotes. On average, about 1.3 additional dealers are queried if the customer is a dealer. This magnitude is large economically since the average number of dealers queried in RFQs is just over 4.

Summarizing, Table 3 and Table 4 reveal that customers tend to expose their orders to fewer dealers if the trade size is larger, if the trade size is nonstandard, or if it is early in the trading day. Although the model of Section 4 does not make clear predictions on the signs of these coefficients, it does provide a possible interpretation: customers strategically choose their execution mechanism and (at least partly) internalize the dealers' winner's curse problem.

5.3 Which dealers to select in an RFQ?

We conclude this section by conducting a simple test of whether past trading relationships affect a customer's likelihood of selecting a dealer in an RFQ. We denote by $N_{c,d}$ the total number of RFQ sessions in which customer c contacts dealer d in our sample. We denote by $DealerShare_{c,d}$ the fraction of customer c's trading volume in index CDS that is attributable to dealer d from January to April 2016. This statistic is calculated from trade repository data using all index CDS trades. We then run the following regression:

$$\frac{N_{c,d}}{\sum_{d'} N_{c,d'}} = \delta_d + \beta \cdot DealerShare_{c,d} + \epsilon_{c,d}. \tag{31}$$

Table 4: Number of dealers requested in RFQs, fitted to Poisson distribution.

	(1) ALL	(2) CDX	(3) ITRAXX
Quantity in millions	-0.0249***	-0.0256***	-0.0195**
	(-8.38)	(-8.18)	(-2.57)
Quantity is standardized (0/1)	-0.255**	-0.360**	0.309
	(-2.27)	(-2.55)	(1.11)
# Streaming quotes	-0.00122	0.00451	-0.0125**
	(-0.21)	(0.69)	(-1.99)
Last 4 hours of trading (0/1)	0.323***	0.346***	0.116
	(3.80)	(3.30)	(0.70)
Customer is buyer (0/1)	0.0785	0.125	-0.165
	(0.72)	(0.97)	(-0.71)
Customer is dealer (0/1)	1.344***	1.367***	0.742**
	(7.46)	(8.66)	(2.55)
Observations	3028	2352	676
Pseudo R^2	0.2171	0.1257	0.1419

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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, β captures the effect of past trading relationships above and beyond the general "attractiveness" of each dealer. In our estimation, the coefficient β has a point estimate of 0.22 and t-statistics of 18.9, indicating that past trading relationship is a strong determinant of which dealers are selected by customers in RFQs.

6 Dealer Responses Rates and Transaction Probabilities

Having analyzed the customers' choices, we now turn to dealers' responses. In particular, we are interested in:

- whether dealers respond to RFQs; and
- the probability that a trade ultimately occurs through RFQ.

Recall that dealers do observe how many dealers the customer selects in an RFQ.

Proposition 3 of Section 4 makes the following predictions on the response probability of dealers in terms of partial derivatives (under stated conditions):

$$\frac{\partial z^*}{\partial y} > 0, \quad \frac{\partial z^*}{\partial |v - \underline{p}|} > 0, \quad \frac{\partial z^*}{\partial n} > 0, \quad \frac{\partial z^*}{\partial \lambda} < 0, \quad \frac{\partial z^*}{\partial k} < 0. \tag{32}$$

On the other hand, Table 4 of Section 5.2 shows that, in the data,

$$\frac{\partial k}{\partial y} < 0, \quad \frac{\partial k}{\partial |v - \underline{p}|} > 0, \quad \frac{\partial k}{\partial n} \leq 0, \quad \frac{\partial k}{\partial \lambda} > 0, \tag{33}$$

where the third item is labeled as a weak inequality because the coefficient on the number of streaming quotes is negative but not statistically significant.

By combining the inequalities in (32) and (33), we can sign some of the total derivatives:

$$\frac{dz^*}{dy} = \underbrace{\frac{\partial z^*}{\partial k}}_{<0,\text{ in theory}} \underbrace{\frac{\partial k}{\partial y}}_{<0,\text{ in data}} + \underbrace{\frac{\partial z^*}{\partial y}}_{>0,\text{ in theory}} > 0, \tag{34}$$

$$\frac{dz^*}{d|v - \underline{p}|} = \underbrace{\frac{\partial z^*}{\partial k}}_{<0,\text{ in theory}} \underbrace{\frac{\partial k}{\partial |v - \underline{p}|}}_{>0,\text{ in data}} + \underbrace{\frac{\partial z^*}{\partial |v - \underline{p}|}}_{>0,\text{ in theory}} \Rightarrow \text{Ambiguous sign}, \tag{35}$$

$$\frac{dz^*}{dn} = \underbrace{\frac{\partial z^*}{\partial k}}_{<0,\text{ in theory}} \underbrace{\frac{\partial k}{\partial n}}_{\leq 0,\text{ in data}} + \underbrace{\frac{\partial z^*}{\partial n}}_{>0,\text{ in theory}} > 0, \tag{36}$$

$$\frac{dz^*}{d\lambda} = \underbrace{\frac{\partial z^*}{\partial k}}_{<0,\text{ in theory}} \underbrace{\frac{\partial k}{\partial \lambda}}_{>0,\text{ in data}} + \underbrace{\frac{\partial z^*}{\partial \lambda}}_{<0,\text{ in theory}} < 0, \tag{37}$$

where "in theory" refers to (32) and "in data" refers to (33). These total derivatives take into account the indirect effect through endogenous changes in k and allow us to empirically test the theory in the light of this additional information. 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:

$$P(y_{d,itm} = 1) = \frac{\exp\left(\beta'[X_{itm}, k_{itm}^{res}, CustomerShare_{d,itm}, \delta_d]\right)}{1 + \exp\left(\beta'[X_{itm}, k_{itm}^{res}, CustomerShare_{d,itm}, \delta_d]\right)}, \tag{38}$$

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:

- X_{itm}, as defined in Section 5.1.
- k_{itm}^{res}, defined as the residual from running an OLS regression of the number of dealers requested in the RFQ, k_{itm}, on X_{itm}. We take the residual to ensure that k_{itm}^{res} is orthogonal to the other explanatory variables.
- $CustomerShare_{d,itm}$, 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 (31), $CustomerShare_{d,itm}$ is calculated from trade repository data using all index CDS trades. For example, if the customer sending the RFQ accounts for 10% of dealer d's trading volume from January to April 2016, then $CustomerShare_{d,itm} = 0.1$. We expect the coefficient on $CustomerShare_{d,itm}$ to be positive, that is, a dealer is more likely to respond to a customer that has traded with him frequently in the past.
- δ_d, the dealer fixed effect. In this regression, δ_d controls for the average response probability of each dealer.

Table 5 reports the results, pooled across all indices in column (1) and separately for CDX and iTraxx in columns (2) and (3).

As predicted by (34), we find that a larger trade is more likely to generate dealer response for RFQs. For example, by column (1), a \$22 million increase in the notional size increases an average dealer's response probability by about 1.5% ($= 0.000665 \times 22$). This effect is driven entirely by CDX, whereas the coefficient in iTraxx regression is statistically insignificant.

As predicted by (36), a higher number of streaming quotes (interpreted as a larger n in the model) is more likely to generate dealer response in RFQs. Averaged between CDX

Table 5: Logistic regression on whether a dealer responds to an RFQ or not. Reported estimates are marginal effects.

	(1) ALL	(2) CDX	(3) ITRAXX
Quantity in millions	0.000665***	0.000739***	-0.000586
	(2.68)	(2.81)	(-1.51)
Quantity is standardized (0/1)	-0.0102	0.00505	-0.0645***
	(-1.20)	(0.63)	(-4.65)
# Streaming quotes	0.00238***	0.00313***	0.000449
	(3.71)	(3.97)	(0.44)
Last 4 hours of trading (0/1)	-0.00972	-0.00439	-0.0273*
	(-1.24)	(-0.51)	(-1.78)
Customer is buyer (0/1)	0.00857	0.00991	0.00516
	(1.58)	(1.45)	(0.32)
Customer is dealer (0/1)	-0.0159	-0.0159	-0.0183
	(-1.15)	(-0.87)	(-0.85)
Customer share of dealer notional	0.457*	0.482	0.153
	(1.67)	(1.39)	(0.46)
# Dealers queried, Res	-0.00831***	-0.00327**	-0.0202***
	(-4.17)	(-2.14)	(-4.29)
Observations	12431	9957	2474
Pseudo R^2	0.0493	0.0693	0.0987

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

and iTraxx, it takes about four additional dealers streaming quotes to increase the response probability by 1%. This effect is also entirely driven by CDX. 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.

If the customer contacts one more dealer than expected in the RFQ, dealers' response rates drop by about 0.8%. This is predicted by Proposition 3, with the intuition 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 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.

The coefficient on standard size is statistically insignificant and changes sign between CDX and iTraxx, which maps to the ambiguous theoretical prediction in (35). The coefficient on the last four hours of trading dummy is statistically significant only in the iTraxx subsample, which lends some support to prediction (37).

Finally, and separately from winner's curse, a dealer is more likely to respond to the RFQ if the customer accounts for a larger fraction of the dealer's past trading volume. This is consistent with the effect of past trading relationships, although the statistical significance of the coefficient is borderline.

Table 6 reports the results of a closely related regression at the session level:

$$y_{itm} = \beta'[X_{itm}, k_{itm}^{res}] + \epsilon_{itm}, \tag{39}$$

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 measure ($CustomerShare$) or dealer fixed effects. As expected, the results are very similar to those in Table 5. Response rates are higher if orders are larger, if more dealers are making markets, or if the customer selects fewer dealers in the RFQ.

Next, we examine under what conditions an RFQ session results, or does not result, in a transaction. In the model, an RFQ results in a transaction if at least one of the k contacted dealers respond, which happens with probability

$$T = 1 - (1 - F(z^*))^k. \tag{40}$$

A calculation analogous to (34)–(37) shows that $dT/d|v - \underline{p}| > 0$, but dT/dy, dT/dn, $dT/d\lambda$ and dT/dk all have ambiguous signs.

We run the following logistic regression:

$$P(y_{itm} = 1) = \frac{\exp\left(\beta'[X_{itm}, k_{itm}^{res}]\right)}{1 + \exp\left(\beta'[X_{itm}, k_{itm}^{res}]\right)}, \tag{41}$$

Table 6: Dealers' response rate in RFQs, OLS

	(1) ALL	(2) CDX	(3) ITRAXX
Quantity in millions	0.000533**	0.000687***	-0.000621
	(2.63)	(2.87)	(-1.58)
Quantity is standardized (0/1)	-0.0120	0.00277	-0.0783***
	(-1.29)	(0.31)	(-4.46)
# Streaming quotes	0.00207**	0.00281***	0.000500
	(2.77)	(3.02)	(0.38)
Last 4 hours of trading (0/1)	-0.00782	-0.00133	-0.0298
	(-0.87)	(-0.14)	(-1.50)
Customer is buyer (0/1)	0.0106*	0.0134	0.00289
	(1.89)	(1.56)	(0.18)
Customer is dealer (0/1)	-0.00639	0.0193	-0.0189
	(-0.36)	(1.10)	(-0.65)
# Dealers queried, Res	-0.00832***	-0.00142	-0.0292***
	(-3.52)	(-0.61)	(-3.66)
Observations	3028	2352	676
Adjusted R^2	0.018	0.028	0.049

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

Table 7 reports the results. For larger orders, our empirical results indicate that larger orders are more likely to result in a trade even though our theory is ambiguous about the sign of the relation. For orders with standard sizes, our theoretical predictions and empirical results align—these orders are less likely to result in a trade. In column (1), a $22 million increase in the order size increases the transaction probability by about 2%, but standard-sized orders reduce the transaction probability by about 3.4%. 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. None of the other covariates

Table 7: Logistic regression on whether trade happens in RFQs. Reported estimates are marginal effects.

	(1) ALL	(2) CDX	(3) ITRAXX
Quantity in millions	0.000943***	0.00104***	0.000110
	(3.20)	(2.61)	(0.26)
Quantity is standardized (0/1)	-0.0335***	-0.0277**	-0.0494***
	(-3.48)	(-2.50)	(-3.43)
# Streaming quotes	0.00124	0.000883	0.00285**
	(1.03)	(0.66)	(2.18)
Last 4 hours of trading (0/1)	0.00285	0.00767	-0.00229
	(0.22)	(0.52)	(-0.22)
Customer is buyer (0/1)	0.000582	-0.00150	0.0143
	(0.05)	(-0.11)	(1.09)
Customer is dealer (0/1)	0.0454	0.0541	0.0305
	(1.47)	(1.00)	(1.12)
# Dealers queried, Res	0.000139	-0.0000971	-0.00243
	(0.03)	(-0.02)	(-0.44)
Observations	3008	2352	656
Pseudo R^2	0.0467	0.0386	0.0554

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

are significant, with the exception of a positive coefficient on the number of streaming quotes for iTraxx. This is unsurprising given the ambiguous predictions.

7 Dealers' Quoted Spreads and Customers' Transaction Costs in RFQs

The previous section investigates dealers' response rates in RFQs and the probability that inquiries result in trades. Another dimension of the equilibrium outcome is dealers' quoted spreads and customers' transaction costs, which we study in this section.

The main prediction in Section 4 that is related to dealers' quoted prices is $\partial\beta(z_i)/\partial y < 0$, under the condition that gains from trade between customers and dealers are increasing in trade size. (Note that a higher quoted spread means a lower $\beta(z_i)$ because dealers in our model are buyers.) However, because $\partial\beta(z_i)/\partial k$ is has an ambiguous sign, we also have ambiguous comparative statics:

$$\frac{d\beta(z_i)}{dy} = \underbrace{\frac{\partial\beta(z_i)}{\partial z^*}}_{<0} \underbrace{\frac{dz^*}{dy}}_{>0,\text{ in data}} + \underbrace{\frac{\partial\beta(z_i)}{\partial k}}_{\text{Ambiguous sign}} \underbrace{\frac{dk}{dy}}_{<0,\text{ in data}} + \underbrace{\frac{\partial\beta(z_i)}{\partial y}}_{<0} \Rightarrow \text{Ambiguous sign.} \tag{42}$$

Likewise, the theoretical comparative statics of $\beta(z_i)$ with respect to other primitive model parameters have ambiguous signs. Thus, the determinants of dealers' quoted spreads and customers' transaction costs are mainly an empirical question.

To measure dealers' spreads and customer's trading costs, we need to define the benchmark price for comparison. For RFQ session itm, the benchmark price we use is the most recent trade for the same contract and on the same side, denoted p^-_{itm}. Denote dealer d's response price in RFQ session itm by $p_{d,itm}$. The dealer's quoted spread is defined as

$$c_{d,itm} = \begin{cases} p_{d,itm} - p^-_{itm}, & \text{if the customer buys protection} \\ p^-_{itm} - p_{d,itm}, & \text{if the customer sells protection} \end{cases}. \tag{43}$$

The spread is in basis points.[16] Moreover, if session itm results in a trade, we denote the transaction price by p_{itm} and calculate the customer's transaction cost as

$$c_{itm} = \begin{cases} p_{itm} - p^-_{itm}, & \text{if the customer buys protection} \\ p^-_{itm} - p_{itm}, & \text{if the customer sells protection} \end{cases}. \tag{44}$$

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.

We separately run two regressions—one on individual dealers' spreads and one on the

[16] 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.

final transaction cost:

$$c_{d,itm} = \beta'[X_{itm}, k^{res}_{itm}, CustomerShare_{d,itm}, \delta_d] + \epsilon_{d,itm}, \tag{45}$$

$$c_{itm} = \beta'[X_{itm}, k^{res}_{itm}] + \epsilon_{itm}, \tag{46}$$

where, in terms of right-hand variables, regression (45) is analogous to (38), and regression (46) is analogous to (39).

Table 8 and Table 9 show results of regressions (45) and (46), respectively.

For larger trades, both individual dealers' spreads and customers' transaction costs are higher. The economic magnitude seems rather small, however. For example, a \$22 million increase in trade quantity only increases the transaction cost by about 0.04 bp ($= 0.00172 \times 22$).

Another pattern consistent between Table 8 and Table 9 is that individual dealers' spreads and customers' transaction costs are both higher if the customer solicits quotes from more dealers than anticipated. Although the estimates are all positive, the economic magnitude seems small. For example, selecting one more dealer than anticipated is associated with receiving higher quoted spreads from individual dealers (about 0.05 bp higher) and with a higher final transaction cost (about 0.03 bp higher). Recall that $\partial \beta_i(z_i)/\partial k$ has an ambiguous sign in the model of Section 4 because a higher k lowers information rents but also increases the winner's curse for dealers (see also (15)). That said, by (42), the fact that quoted spread increases in notional size y in the data suggests that even if $\partial \beta_i(z_i)/\partial k$ were negative, it could not be so negative as to make the sign of (42) positive.

Interestingly, when dealers act as quote seekers in RFQs, they tend to incur higher transaction costs than customers do (Table 9). Likewise, using more than two years of transaction data in three CDS indices on Bloomberg SEF, Haynes and McPhail (2017) 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, Junge, and Trolle (2016) 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.

Finally, and separately from winner's curse, Table 8 shows that past trading relationships do not have a statistically significant effect on dealers' quoted spreads to customers.

Table 8: Individual dealers' quoted spread in RFQ, measured relative to the last transaction price on the same contract and the same side.

	(1) ALL	(2) CDX	(3) ITRAXX
Quantity in millions	0.00238***	0.00115***	0.00996*
	(3.94)	(2.88)	(1.96)
Quantity is standardized (0/1)	-0.0111	0.0119	-0.0250
	(-0.42)	(1.59)	(-0.19)
# Streaming quotes	-0.00158	-0.000794	0.000654
	(-0.67)	(-1.36)	(0.07)
Last 4 hours of trading (0/1)	-0.0119	-0.00651	-0.0160
	(-0.36)	(-0.63)	(-0.09)
Customer is buyer (0/1)	-0.0284	-0.0135	-0.141
	(-0.38)	(-0.69)	(-0.43)
Customer is dealer (0/1)	0.223**	-0.00769	0.782**
	(2.12)	(-0.38)	(2.17)
Customer share of dealer notional	-0.856	-0.585	1.636
	(-1.18)	(-1.47)	(0.75)
# Dealers queried, Res	0.0469***	0.00115	0.217**
	(3.16)	(0.27)	(2.36)
Observations	11104	8941	2163
Adjusted R^2	0.091	0.119	0.061

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Transaction cost of customers in RFQs, measured relative to the last transaction price on the same contract and the same side.

	(1) ALL	(2) CDX	(3) ITRAXX
Quantity in millions	0.00172***	0.000811**	0.00467
	(3.25)	(2.32)	(1.64)
Quantity is standardized (0/1)	-0.0307	0.00956	-0.139
	(-1.50)	(1.16)	(-1.38)
# Streaming quotes	0.00105	0.000515	0.0000978
	(0.55)	(1.34)	(0.02)
Last 4 hours of trading (0/1)	-0.0319	0.000943	-0.158
	(-1.45)	(0.11)	(-1.60)
Customer is buyer (0/1)	-0.0147	-0.00644	-0.0536
	(-0.24)	(-0.38)	(-0.23)
Customer is dealer (0/1)	0.226***	-0.0299*	0.597***
	(3.11)	(-1.89)	(3.46)
# Dealers queried, Res	0.0328**	0.00506	0.122*
	(2.74)	(1.44)	(1.91)
Observations	2783	2149	634
Adjusted R^2	0.030	0.001	0.023

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

8 Conclusion

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 new rules. Our data were obtained from Bloomberg SEF and Tradeweb SEF and pertain to trading in 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, but the main ones analyzed in our paper are request for quote (RFQ) and request for streaming (RFS). Under both RFQ and RFS, customers receive quotes from multiple dealers. A key difference, however, is that the RFS quotes are indicative while RFQ quotes are generally firm. Moreover, a customer's detailed order information is only exposed to one dealer under RFS, even though the customer may be receiving quotes from many dealers. Our theoretical model of SEF trading emphasizes a fundamental trade-off when the customer exposes his order to more dealers: competition versus the winner's curse. In our model of the RFQ mechanism, contacting more dealers increases both competition and the winner's curse. This competition-versus-winner's-curse trade-off provides a basis for understanding customers' choices. At the same time, the model provides specific, empirically-testable predictions regarding some aspects of the behavior of customers and dealers, especially the response rate of dealers to RFQs.

Our empirical analysis starts with the customer's choice of trading mechanisms—in particular, how widely customers expose their trading interest to multiple dealers. We find that customers frequently use RFS, and if they use RFQ, they on average expose their orders to only four dealers. We also find that customers are significantly less likely to choose RFQ if their order has a larger notional size. For those orders where the customer does choose RFQ, larger trade size significantly reduces the number of dealers queried in the RFQ. Moreover, customers tend to expose their orders to fewer dealers if the trade size is nonstandard or if it is early in the trading day. These findings indicate that customers internalize the winner's curse faced by dealers.

Next, we examine dealers' strategic responses to RFQs. While dealers' response rates in RFQs are high on average (around 80% to 90% for MAT contracts), response rates tend to be lower if the customer includes more dealers in the RFQ, which is consistent with the concern over winner's curse. Response rates in RFQs are higher if the trade size is larger, suggesting larger gains from trade. Finally, dealers are also more likely to respond when more dealers are streaming quotes, suggesting the winner's curse is less concerning when it is easier to offload positions in the interdealer markets. Inquiries in RFQs 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 find that dealers' quoted spreads and customer's transaction costs in RFQs are generally larger if the notional quantity is larger, which is predicted by the model under the condition that there is greater surplus from larger trades. Moreover, consistent with the winner's curse, dealers' spreads and customer's transaction costs in RFQs are also higher if the customer selects more dealers than expected, although the economic magnitude of the estimate is rather small.

While the competition-versus-winner's curse trade-off is the main theme of our analysis, we also find evidence that past trading relationships matter in the trade formation process. For example, when sending RFQs, customers are more likely to select dealers that account for a larger share of the customer's past trading activity. Conversely, conditional on receiving an RFQ, a dealer is more likely to respond to customers that account for a larger share of the dealer's past trading activity.

Overall, our study contributes to the understanding of SEF trading by providing insight into the decision-making process of market participants. Specifically, this study highlights the trade-offs index CDS customers face when deciding among different execution mechanisms. Our results suggest that competition is not the only economic force that drives customers' choice of trading mechanisms and other decisions in the course of executing a trade. The evidence provides support for our theoretical model, in which choosing greater competition also causes a more severe winner's curse. By improving our understanding of the impact various institutional features and trade characteristics have on trader decisions, our results could be used to improve on existing market designs for SEFs or to help in the design of other markets that are undergoing similar transitions toward multilateral electronic trading.

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Appendices

A Model Extension with Costly Solicitation of Quotes and Numerical Comparative Statics

In this appendix we consider a model extension in which the customer incurs a cost c of adding each dealer in the RFQ. As discussed in Section 4.4, this cost is a reduced-form way to capture the customer's concern of upsetting his relationship dealer. Since a larger trade usually implies a higher profit for the dealer handling this trade, we use a linear cost $c = c_0 y$, where c_0 is a constant and y is the notional quantity.

Therefore, the customer solves

$$\max_k \left\{ \max_{1 \le j \le k} \beta(z_j) - c_0 y k \right\}, \tag{47}$$

where $\beta(z_j)$ is equal to the equilibrium bid if $z_j \le z^*$ and $\underline{p}$ if $z_j > z^*$. The bidding strategy $\beta(\cdot)$ is the same as that in Section 4. Proposition 3 also remains valid in this extension.

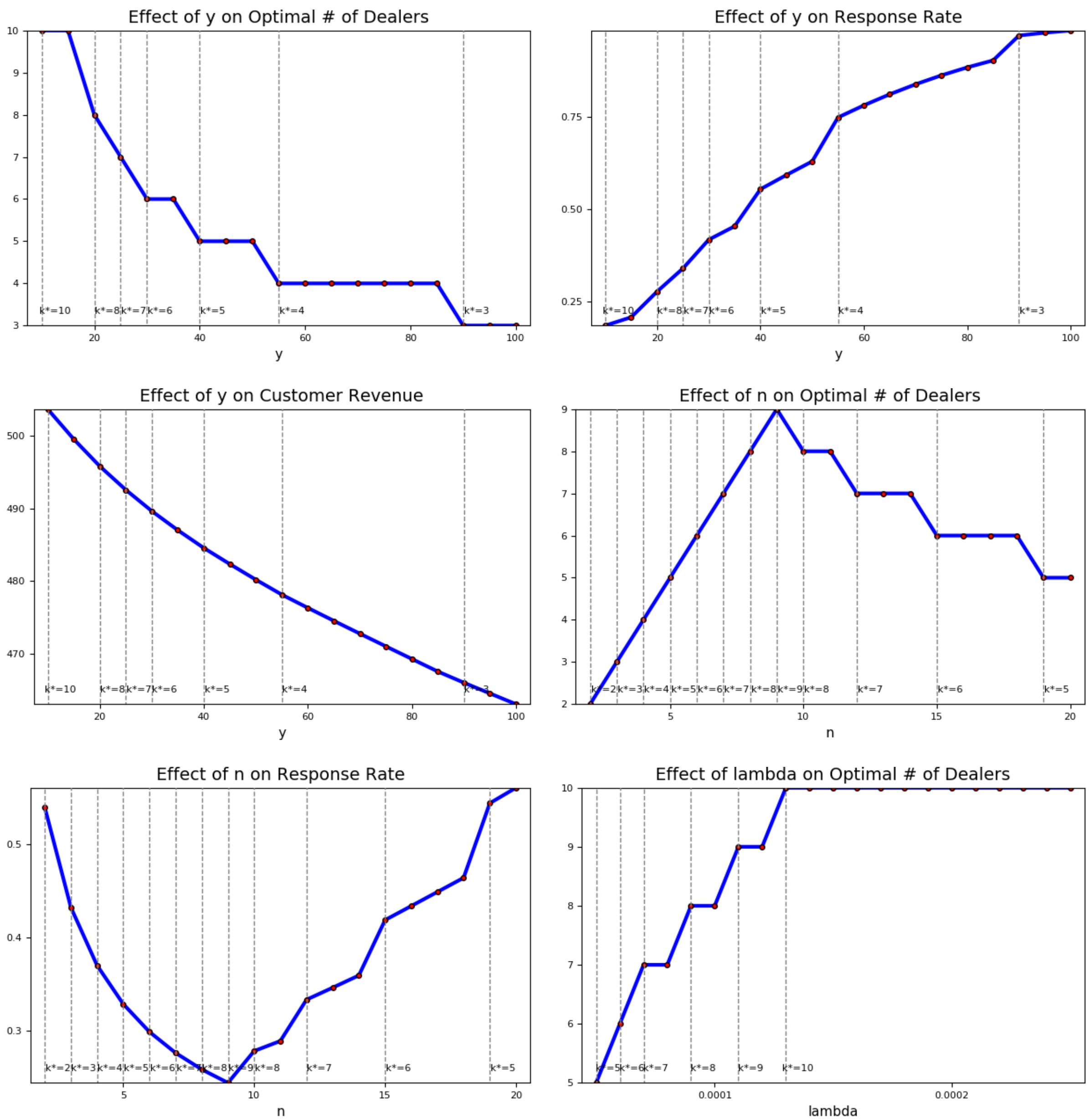
To illustrate that the model is able to generate predictions consistent with the data, Figure 4 shows a number of numerical comparative statics using the following baseline parametrization: $v = 0.05$ (500 bps), $r = 1$, $\lambda = 0.0001$, $n = 10$, $\underline{p} = v - 0.0001y$, $c = 5 \times 10^{-6} \times y$, and $F(z)$ is normal distribution with mean zero and standard deviation 100. If the x-axis is not k, the comparative statics are calculated for the optimal k^*, which are also labeled on the graphs.

These numerical comparative statics match the empirical results. As in Table 4, the customer selects more dealers if the notional size y is smaller (top left plot) or if the inventory cost λ is higher (bottom right plot). 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. This explains the hump-shape pattern in the middle right plot. Conditional on being selected into an RFQ, response rate is higher if the notional size is larger (top right plot) or if, assuming an interior solution of k^*, more dealers are making markets (bottom left plot). These are consistent with Table 5 and Table 6. Finally, consistent with Table 9, a higher notional size y reduces the customer's revenue, which maps to a higher transaction cost (middle left plot).

Moreover, in the numerical calculations the total derivatives that take into account the indirect effect through k happen to have the same sign as the partial derivatives. For example, in the top right plot of Figure 4, any segment of the solid line between two vertical dotted lines indicates that response rate increases in y when k is held fixed due to the integer constraint, which corresponds to a partial derivative in Proposition 3 and (32). Across the various segments of the solid line, response rate also increases in y, which corresponds to the total derivative in (34).

We have omitted other numerical comparative statics to conserve space, but they are available upon request.

Figure 4: Comparative statics in the model extension with costly solicitation of quotes



B Model Extension with Costly Participation and Numerical Comparative Statics

In this appendix we consider a model with costly participation of dealers in RFQs. In a setting with independent private values, Menezes and Monteiro (2000) have shown that restricting the number of bidders can improve the seller's revenue if participation is costly. The model of this section solves dealers' participation decisions and bidding strategies if their values become interdependent because of interdealer SEF trading.

The only difference of the model here, relative to that in Section 4, is that a dealer must incur a cost of c to bid in the RFQ. This cost could represent the opportunity cost of attention of the dealer bank's trader or the cost of evaluating the risk-return tradeoff before responding. In particular, we will consider the linear cost $c = c_0 y$, where $c_0 > 0$ is a constant and $y > 0$ is the notional amount the customer wishes to sell.

The equation characterizing the cutoff point z^* is given by

$$0 = (A_1 - A_2 y(k-1)E[z_j \mid z_j > z^*] - (A_2 + B)z^* y - \underline{p}y)(1 - F(z^*))^{k-1} - c_0 y, \tag{48}$$

$$0 = \frac{A_1}{y} - A_2(k-1)E[z_j \mid z_j > z^*] - (A_2 + B)z^* - \underline{p} - \frac{c_0}{(1 - F(z^*))^{k-1}} \equiv \hat{\Gamma}. \tag{49}$$

The only new term is the last term, $-\frac{c_0}{(1-F(z^*))^{k-1}}$. It can be shown that $\partial\hat{\Gamma}/\partial z^* < 0$ and $\partial\hat{\Gamma}/\partial k < 0$, as before. Therefore, the comparative statics about z^* in Section 4 stay the same.

For any $z_i < z^*$, dealer i's price quote is

$$\beta(z_i) = \frac{A_1}{y} - (A_2 + B)\left(z_i + \frac{\int_{u=z_i}^{z^*}(1 - F(u))^{k-1}du}{(1 - F(z_i))^{k-1}}\right) - A_2(k-1)E[z_j \mid z_j > z_i] - \frac{c_0}{(1 - F(z_i))^{k-1}}. \tag{50}$$

Since the extra term $-\frac{c_0}{(1-F(z_i))^{k-1}}$ does not involve y, the comparative statics about bids in Section 4 stay the same as well.

Figure 5 below shows numerical comparative statics using the following baseline parametrization: $v = 0.05$ (500 bps), $r = 1$, $\lambda = 0.0001$, $n = 10$, $\underline{p} = v - 0.0001y$, $c = 5 \times 10^{-6} \times y$, and $F(z) = 1 - \left(\frac{-x + \frac{\alpha}{\alpha+1}q}{q}\right)^{\alpha}$ for $z \in [-\frac{q}{\alpha+1}, \frac{\alpha q}{\alpha+1}]$, where $\alpha = 40$ and $q = 50$. If the x-axis is not k, the comparative statics are calculated for the optimal k^*, which are also labeled on the graphs.

We see that numerical comparative statics in Figure 5 have qualitatively similar shapes as those in Figure 4, with similar intuition.

Figure 5: Comparative statics in the model extension with costly participation