The Modern Bond Market

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Abstract

We identify a widespread practice that counteracts fragmentation in the corporate bond market. On modern trading platforms, traders can simultaneously request quotes for many bonds from dealers, then trade against any subset of the quotes. Such *List* requests comprise 80% of all requests on MarketAxess. Using 10 million requests in 2021-2022 with List-level identifiers, we document that traders substitute across bonds within the same List. Within a List, a request quoted a better-ranking spread (lower transaction cost) is substantially more likely to fill than a worse-ranking request quoted a nearly identical spread. Dealers and proprietary traders tend to substitute, especially between bonds with similar maturity and yield, whereas asset managers do not. Bond ratings do not matter for substitution conditional on maturity and yield.

Keywords: Corporate bonds, fragmentation, multi-dealer platforms, List trading, substitution

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I. Introduction

Most corporate bonds do not trade on a given day, as the market is fragmented across numerous outstanding bond issues. This fragmentation threatens to disperse liquidity across economically similar bonds. While other markets standardize assets to mitigate this threat, the corporate bond market does not, perhaps because issuing firms target particular debt structures (Rauh and Sufi, 2010; Colla, Ippolito and Li, 2013). Could a mechanism other than standardization overcome fragmentation in this market?

We document a widespread and simple mechanism that already does so. On modern trading platforms, a trader can simultaneously request quotes for often dozens of bonds from the same set of dealers. The dealers may provide quotes for all or some bonds, and the trader may accept any combination of those quotes, possibly from different dealers. Each trader can thus simultaneously request multiple bonds she considers substitutes and only select the ones quoted the smaller spreads, effectively aggregating liquidity that is otherwise fragmented across those bonds.[1] Such *List* requests comprise 80% of all requests on MarketAxess, the largest corporate bond trading platform.

We verify that traders submit Lists to substitute across bonds. Our setting is the 10 million corporate bond requests on MarketAxess in 2021 and 2022. We compare bond requests within the same List, stripping away all trader-and-time-specific confounders. We find three results. First, comparing similar bonds in the same List and quoted nearly identical spreads, traders are substantially more likely to trade the bond quoted the slightly smaller spread. Second, dealers and proprietary funds are far more likely to substitute within their Lists than asset managers. Third, traders treat different ratings as equally substitutable with each other conditional on maturity and yield—the specific ratings of bonds are not important to traders.

[1] Appendix C microfounds this claim in a model where traders are uncertain about the quotes they would receive and face the risk of losing access to past quotes.

Our key empirical challenge is that traders have downward-sloping demands. Even absent any substitution, a trader is more likely to trade the bonds quoted smaller spreads in her List. To remove the effects of a downward-sloping demand curve, we adopt the "class rank" design of Murphy and Weinhardt (2020). They isolate the impacts of a student's test-score rank in her class from that of the test score itself by controlling for a polynomial of the test score and class fixed effects. Mapped to our setting, a List corresponds to a class, its bond requests to students, and each bond's best quoted spread to a student's test scores. We compare the trade probabilities (fill rates) of bond requests at different within-List ranks, controlling for a polynomial of the bonds' best quoted spreads and List fixed effects. If traders substitute, then a higher ranked request would fill more often than a lower ranked request in the same List, conditional on the two requests having nearly identical best quoted spreads. We find that higher ranked requests are sharply more likely to fill than lower ranked requests in the same List.

Section II describes our data. We observe every request choice and outcome seen by traders, including time stamps, requested and filled quantities, trade direction, all quotes offered and chosen, and benchmark prices available to the trader when submitting her request. Most importantly, each bond request belongs to a set of requests that a trader submitted together, called an order. We know to which order each bond request belongs, and whether the order is a List, a portfolio trade, or a single bond request.[2] Each of 616,052 Lists in our sample contains between two and 60 bond requests, and 12.7 on average.

Section III tests our substitution hypothesis within Lists. We look for systemic differences in fill rates among bond requests that were quoted nearly identical spreads in the same Lists. If traders substitute, then the bond requests with the slightly smaller spreads will be

[2]Portfolio trades (Li, O'Hara, Rapp and Zhou, 2023) are a restrictive form of Lists, in which dealers must either submit a quote for all requested bonds or not reply, and the requesting trader must accept the quotes from the same dealer for all requested bonds or not trade. Portfolio trades comprise 2.5% of all requests, and $XX\%$ of all orders in our sample.

substantially more likely to fill, as the traders execute whichever requests quoted the smaller spreads. If traders do not substitute, the requests quoted similar spreads in the same List would have similar fill rates. To implement this design, we regress the fill status of a bond request on its within-List rank by best quoted spread, controlling for the cubic of this spread as well as List and bond fixed effects. Higher ranked requests have the smaller spreads. We find that a higher ranked request is 3.4 percentage points more likely to fill than a lower ranked request quoted nearly the same spreads. This estimate rises to 14 percentage points for Lists entirely comprised of high-yield (HY) bond requests while it is 2.5 percentage points for investment-grade (IG) Lists.

The lower intensity of substitution within IG Lists may be explained by convenience. Lists let traders avoid repeatedly navigating a menu on the trading platform, without forcing them to fill all requests or none. This convenience seems to drive a large portion of Lists: 45.7 percent of all Lists entirely fill and this share rises to 61.7 percent for asset managers, whose investment mandates likely limit their ability to substitute.

Section IV investigates whether traders submit Lists of convenience. We use the likelihood that at least one request in a List is left unfilled to separate such convenience Lists from the Lists within which traders substitute. Our data keeps requesting traders anonymous, and instead partitions them into dealers, proprietary traders, and asset managers. The trader type and a set of intuitive observables available at the time of requests strongly predict whether any request in a List will be left unfilled. The asset managers' Lists are the least likely to be left unfilled, consistent with institutions under investment mandates being more likely to submit convenience Lists, while the dealers' Lists are the most likely. We rerun our substitution test on Lists that are the least and the most likely to be left at least partly unfilled. A request's ranking has a large impact on its fill rate if the List is highly likely to be left unfilled, whereas the ranking has no impact if the List is unlikely to be so.

Section V exploits the "substitute Lists," those most likely to have a request left unfilled, to pinpoint the bond attributes that traders view to be important. If, say, maturity is important to bond traders, they would substitute more intensely between bonds that share similar maturities. We find that traders substitute more intensely among bonds with similar maturities and yields. In contrast, traders do not substitute more intensely among bonds with closer ratings.

Order identifiers allow us to rule out all confounders specific to trader-time-and-List characteristics. More precisely, the List fixed effects absorb all variation due to trader identity, her dealer connections or choice of contacted dealers, the date and time of her requests, the joint distribution of bonds and requested quantities in the List, and any interactions among these characteristics. The List fixed effects are important in practice. Appendix B finds that adding List fixed effects into a regression predicting quoted spreads increases its adjusted R-squared by 32 percentage points, to 50.7%, up from 18.7% when only including a benchmark spread and bond and date fixed effects.

We rule out four remaining threats to our identification. First, certain bonds may both be more likely to trade and rank highly in Lists for reasons other than substitution. For example, investment mandates could require trading certain bonds, which may well increase their liquidity (and so their rank). We consistently include bond fixed effects to absorb this confounder and any other time-invariant bond-level characteristics. Second, requests for certain quantities could both receive narrower spreads and be more likely to trade conditional on those spreads. For example, particularly large requests could signal private information or a liquidity shock. Adding the quadratic of requested quantity as a control affects neither our coefficient of interest nor the fit of our regression, reassuring us that differences in quantities do not confound our results. Third, traders sometime repeat unfilled requests on and off the platform (Kargar, Lester, Plante and Weill, 2023). Appendix D broadens the dependent variable to whether a request is filled *or* repeated on or off the platform, and redoes our analyses. All our results are robust to this change. Fourth, we estimate linear probability models and assume linearity in the effects of within-List rank. Appendix D shows that logit regressions yields the same results, flexibly controls for decile ranks, and confirms that the estimated effects are approximately linear over the decile ranks.

We proceed as follows. Section II describes the data and compares the composition of Lists to the random assignment benchmark. Section III documents substitution across bonds within Lists. Section IV separates substitution Lists from convenience Lists. Section V identifies the bond attributes within which traders substitute. Section VI concludes with our contributions to the literature.

II. Data

Section II.A explains trading protocols for corporate bonds on MarketAxess. Section II.B describes the raw data, sample construction, and defines variables.

A. *Empirical Setting*

MarketAxess is the largest electronic platform for corporate bond trades in the US, where it hosts about 20% of all corporate bond trades. Its trading protocol has three steps. First, a trader invites any number of available dealers to offer quotes for her chosen bond, quantity, and trade direction.[3] The trader specifies several other request attributes, such as the time that dealers have to respond and whether to simultaneously submit the request to all participants anonymously (via the "Open Trading" option). Figure 1 depicts the screen that traders use to submit requests. Second, each invited participant may offer a quote. Each invited dealer sees the requesting trader's identity and the number of invited dealers, though not the other dealers' identities. In practice, most traders invite all available dealers.

[3]Traders differ in the sets of dealers they can contact, and each dealer may be unavailable for certain bonds or time periods.

Third, the trader observes all quotes (if any), then rejects all quotes or trades against exactly one quote (nearly always the best-priced quote).

Traders can bundle requests for different bonds into an *order*. All requests in an order are sent to the same dealers and share most attributes, except the chosen bond and quantity. MarketAxess offers three types of orders. *List* order allows each invited dealer to offer quotes for any subset of its bond requests. A List requester can accept quotes from different dealers for different bond requests, though she can only accept one quote per request. Portfolio trade (PT) requires each responding dealer to offer a quote for every bond request in the order, and cannot be submitted via Open Trading. If at least one dealer responds to a PT, the requester must reject all quotes or accept the complete set of quotes from one dealer. Single request-for-quote (SRFQ) contains one bond request.

B. Sample Construction

Raw sample. We obtain all corporate bond requests submitted on MarketAxess in 2021 and 2022, corresponding to 9,756,101 requests across 2,316,772 orders. Each observation is a bond request. Table I provides examples of requests in Lists. Order identifiers link together the bond requests belonging to the same order. Another field specifies whether the order is a List or a PT.

The following fields are determined at the order level: the timestamp, the trader type, the number of dealers invited to bid on each request, the time that invited dealers have to offer quotes, and whether the order was also submitted via Open Trading. The bond grade determines the pricing protocol, with high-yield bonds quoted in dollars and investment-grade bonds in the percent spread over some benchmark yield. We do not observe trader identities, and instead see the type of requesting traders partitioned into "Asset Manager," "Broker-Dealer," and "Other." The Asset Managers include mutual funds, insurers, and other nonproprietary funds. The Broker-Dealers include all registered dealers. The Others include hedge funds and other proprietary funds.

The following fields are specific to each request: the bond CUSIP, requested quantity in face value, request direction (buy or sell), the number of invited dealers, every quote received and whether it was from a dealer or a nondealer, and the quantity traded and at which quote. We compress these fields in four ways. (i) We do not differentiate between dealer and nondealer quotes, since this is not relevant for our question. (ii) We do not explore the number of invited dealers, because most requests reach many dealers, 39 on average and 14 at the bottom tenth percentile. (iii) Our main variable of interest is a dummy variable "Filled" that equals one if and only if the traded quantity is nonzero and equal to the requested quantity. Only 0.5% of requests trade a quantity other than the requested quantity. (iv) We keep the best quotes and discard all other quotes, because traders almost always either accept the best quote or reject all quotes.

Supplementary data. Mergent-FISD provides bond ratings and remaining maturities. Moreover, we obtain the complete panel of "CP+" bid and ask prices and yields spanning our sample period from MarketAxess. The CP+ is a common benchmark that is updated in real time for the vast majority of corporate bonds, as often as every 15 seconds. MarketAxess feeds the dealers' recent indicative prices and yields, actual quotes, and trade prices, alongside other information, into a machine learning algorithm to generates the CP+ prices and yields. Most traders on MarketAxess subscribe to CP+, and these traders observe corresponding CP+ values before they finalize their bond requests.

Variable construction. To measure transaction costs of different bonds requested, we compute quoted spreads taking the contemporaneous CP+ midprice as the bond's fundamental value. We observe the quoted prices for every HY bond request that received a quote, and the trade price for every IG request that traded. For the IG requests that received a quote but did not trade, we only observe the difference between the quoted yield and the yield on the corresponding benchmark treasury bond. We convert the best quoted yields of these requests into prices using the methodology in Appendix A.

The best *quoted spread* is the difference between the best quoted price and the CP+ midprice normalized by the CP+ midprice, measured in basis points:

$$\text{Quoted spread} = (2 \cdot \text{buy} - 1) \cdot \frac{\text{Best quoted price} - \text{CP+ midprice}}{\text{CP+ midprice}},$$

where the dummy variable *buy* equals one if and only if the request is a buy request.

The *rank by quoted spread* is the percentile of each request's best quoted spread among all best quoted spreads in its List, in ascending order. For each List, we assign rank one, the top rank, to the request with the smallest best quoted spread and assign rank zero, the bottom rank, to the request with the widest best quoted spread. Other requests are assigned a rank between zero and one linearly and in ascending order by best quoted spread. Requests tied at the same spread in the List are randomly ordered among themselves. Requests without a quote are treated as if their best spreads were wider than the widest spread we observe in our sample. Table I illustrates how we rank requests and shows an example for a List.

Sample exclusions. We drop all single bond requests (1,941,656 requests) and all portfolio trade requests (243,546 requests).

Final sample. Our final sample consists of 7,814,445 requests across 616,052 Lists. Table II defines all key variables. Table III presents the summary statistics of the final sample at the request-level. Asset managers submit the majority of List requests, while dealers and proprietary traders submit about a fifth each. Nearly all requests have contemporaneous CP+ values reported by the platform and receive at least one quote, allowing us to compute quoted spreads. Traders decline to fill one-third of requests that receive a quote. Table IV presents the summary statistics of the final sample at the List-level. Most Lists consist of requests in the same bond grade and trade direction. About half of the Lists fail to entirely fill, even ignoring requests that did not receive quotes.

III. Do Traders Substitute Within Lists?

We test whether traders substitute across bonds within Lists. Section III.A details our empirical design. Section III.B presents the results.

A. Econometric Framework

Traders who substitute within their Lists would trade the highest ranked bond requests in theirs Lists by best quoted spread, and leave others unfilled. A simple approach would compare the fill rates of the highly ranked requests to lower ranked requests. We would conclude that traders substitute across bonds within Lists if the highly ranked requests have the higher fill rates.

The simple approach falsely attributes three other sources of positive correlation between fill rate and within-List rank to substitution. First, under downward-sloping demand, requests quoted smaller spreads are more likely to fill, and those requests would mechanically be more highly ranked in their Lists. Second, certain bonds may systemically fill more often and receive smaller spreads. For example, investment mandates might force many traders to buy a highly liquid bond included in many indices, leading the requests for this bond to have high fill rates and be highly ranked. Third, traders can vary in their tendency to fill requests. Consider an "inattentive" trader who fills every request in her List and an "opportunistic" one who only fills if the quoted spread is exceptionally small. The highly ranked requests are likely to fill in either trader's Lists, whereas the lower ranked requests would only fill in the inattentive trader's List. Because the inattentive trader can sometimes be opportunistic and vice versa, this confounder cannot fully be avoided even with trader fixed effects.

We instead compare the fill rates of requests for similar bonds that were quoted nearly identical spreads within the same List. Our implementation regresses the fill status of each request on its within-List rank by best quoted spread, controlling for a cubic of the best quoted spread and List and bond fixed effects. The cubic terms flexibly control for downward sloping demands, and thus we are effectively comparing requests that were quoted nearly identical spreads. The List effects ensure within-List comparisons, removing all time-and-trader-specific differences in fill rates. The bond effects partial out time-invariant bond attributes, keeping comparisons between similar bonds. We conclude that traders substitute if the higher ranked bond requests are substantially more likely to fill than the lower ranked requests in the same List.

We estimate following regression:

$$F_{b,\ell,t} = a_0 R_{b,\ell,t} + \text{cubic}(S_{b,\ell,t}) + \alpha_{\ell,t} + \gamma_b + \text{quadratic}(Q_{b,\ell,t}) + \varepsilon_{b,\ell,t}. \tag{1}$$

The dummy variable $F_{b,\ell,t}$ equals one if and only if the bond request b in List ℓ submitted on date t is filled in full quantity. The variable of interest is $R_{b,\ell,t}$, the rank by *Quoted spread* of bond request b in List ℓ. The coefficient a_0 would be strictly positive if traders substitute across bonds within Lists. All specifications control for the cubic of the *Quoted spread* $S_{b,\ell,t}$, and List and bond fixed effects, $\alpha_{\ell,t}$ and γ_b. Some specifications add the quadratic of requested quantity $Q_{b,\ell,t}$ as a control. While we use requests that did not receive a quote to determine ranks, they are excluded when estimating (1), because they lack a well-defined quoted spread.

Related design. Equation (1) is equivalent to the specification of Murphy and Weinhardt (2020) (their eqn. (1)). Murphy and Weinhardt (2020) identify the impact of each student's within-class rank by test score on her future achievement. Their empirical challenges mirror ours: future achievement is increasing in the test score itself, and differences in class composition and quality might generate positive correlation between class rank and future achievement in the absence of any rank effects. Mapping classes to Lists, students to bond requests, and test scores to *Quoted spread*s establishes the equivalence between their regression specification and ours.

B. Results

Table V presents the coefficient estimates from (1). Conditional on the *Quoted spread* and bond fixed effects, the highest ranked bond request is 3.4 percentage points more likely to fill than the lowest ranked request in the same List. Adding the quadratic of requested quantity hardly affects this estimate. The effect is far larger, 14 pp, for Lists comprised of HY bond requests, about the same for mixed-grade Lists, and smaller for IG Lists. We conclude that traders substitute within Lists, and especially intensely so within HY Lists. That traders do not strongly substitute within IG Lists hints at a driver of List trading aside from substitution.

IV. Do Traders Submit Lists for Convenience?

Substitution does not explain the substantial proportion of Lists whose every request fills. We consider the convenience of submitting multiple bond requests at once as an alternative motive for certain Lists.

A. Context and the Empirical Framework

Context. Figure 1 depicts an order screen on MarketAxess. Among the selections a trader must make for an order are the set of dealers who will receive the order, the length of time they have to respond, and details of the pricing protocol. Each order opens a separate window. For the traders who lack automation or do not trade corporate bonds full-time, it would save significant time and bother to periodically submit a single List, rather than a sequence of single bond requests.

Econometric framework. A trader would not intend to substitute between bonds that were requested together purely for convenience. Such "convenience Lists" would exhibit high fill rates and little substitution. Less flexible traders whose investment mandates require the trading of particular bonds and those lacking automation or employees dedicated to bond trading would be more likely to submit convenience Lists.

We devise a two-step test for the presence of convenience Lists. First, a submitter of a convenience List would fill every request as long as the their quotes are not too costly, whereas a List made of substitute bond requests would leave some filled unless all its requests received exceptionally good quotes. Using this intuition, we identify a convenience List by a low predicted probability that a request in the List remains unfilled. Second, we re-estimate the regression (1) on the convenience Lists and on the "substitute Lists," which are highly likely to have a request left unfilled. Confirmation of two hypotheses would lead us to conclude that Lists are submitted for convenience as well as substitution. *(i)* Less flexible traders would disproportionately submit convenience Lists. *(ii)* Having a higher within-List rank by best quoted spread would strongly increase the fill rate of requests in the substitute Lists, and would not increase fill rates in the convenience Lists.

We interpret asset managers as the less flexible traders, and dealers and proprietary traders as the more flexible ones. The dealers and the proprietary traders are less likely to be restricted by investment mandates than asset managers. The dealers and the proprietary traders are also more likely to be automated and have dedicated bond traders, because the ability to act quickly and superior analysis are especially important for them.

We take a kitchen-sink approach to estimate the probability that a List entirely fills. More precisely, we regress whether any request in a List is unfilled on a broad cross-section of variables known to the requesting trader at the time of her submission. The resulting regression for List ℓ of length k is the following:

$$\begin{aligned}\mathbb{1}_{\ell,k}\{\text{List } \ell \text{ is partly unfilled}\} = HY_\ell + Mixed_\ell + AssetManager_\ell + Dealer_\ell \\ + \sum_{c \in \mathcal{C}} \Big(\beta_c m_\ell(c) + \delta_c s_\ell(c)\Big) + \mathbf{X}_{\ell,k}\beta + \phi_k + \varepsilon_{\ell,k}.\end{aligned} \tag{2}$$

The dependent variable is a dummy that equals one if and only if at least one request in List ℓ is unfilled. Dummies HY_ℓ and $Mixed_\ell$ indicate whether the List is purely HY or mixed grade. Dummies $AssetManager_\ell$ and $Dealer_\ell$ indicate whether the List's requester was an asset manager or a broker-dealer. The baseline are purely IG Lists by proprietary traders. The control variables $m_\ell(c)$ and $s_\ell(c)$ are the mean and the standard deviation of a request-level characteristic c computed across all requests in List ℓ. The set $\mathcal{C}$ of request characteristics includes bond maturity, bond rating, and requested quantity. Other controls $\mathbf{X}_{\ell,k}$ are the shares of requests in ℓ that are buy requests, for privately placed bonds, and missing a contemporaneous CP+ price. The List-length fixed effects ϕ_k flexibly control for any effects of List lengths $k \in \{1, \ldots, 60\}$.

B. Results

Table VI presents the estimates from (2). The Lists of asset managers are by far the least likely to leave a request unfilled, being 31 percentage points less likely to do so than the proprietary traders' Lists, and the dealers' Lists are the most likely, being 9 pp more likely to do so than the proprietary traders' Lists. The magnitudes of these effects persist as we add a battery of controls. Moreover, the trader-type dummies yield the largest increase in the fit of the estimated regression, consistent with the flexibility of the requesting trader driving substitution in Lists. On the other hand, while the grade composition of Lists have large coefficients when estimated alone, they become small when the full set of explanatory variables are included.

Table VII confirms that traders do not substitute within convenience Lists and intensely do so within the substitute Lists. We define the convenience Lists as the Lists whose predicted probability of leaving a request unfilled, estimated by (1), is in the bottom quartile of all Lists. The substitute Lists are those whose predicted probabilities are in the top quartile. Separately estimating our main regression (1) on the convenience and the substitute Lists, the highest ranked requests by best quoted spread are 1.8 percentage points more likely to fill than the lowest ranked requests within the same convenience List. In contrast, within substitute Lists, the highest ranked requests are 20 pp more likely to fill than the lowest ranked requests. We conclude that traders sometimes submit Lists for convenience and that the concentration of convenience Lists explains the weak substitution within the IG Lists.

V. What Bond Attributes Matter to Traders?

We exploit substitute Lists to identify the bond attributes that are important to traders. We find that remaining maturity and yield spread are important to traders, whereas bond ratings are not important conditional on maturity and yield spread.

Empirical framework. If an attribute is important to a trader, she would treat the bonds that share this attribute as closer substitutes than the bonds that do not. She would then especially be likely to fill a bond request whose quoted spread is smaller than the other bonds in the List with the same important attribute than those without. Applying this intuition to our design, given an attribute, we split each List into two *subLists* corresponding to the requests whose attribute is larger or smaller than the median within the List. We rank requests by their best quoted spreads within the subLists, then add these within-subList ranks to our main specification (1). For the attributes important to traders, the corresponding within-subList rank would substantially increase fill rates of requests above and beyond the overall within-List rank. We bring this modified design to the subsample of substitute Lists, because convenience Lists would not be informative about how traders substitute across bonds.

More precisely, consider the two subLists of List ℓ for some attribute $\mathcal{A} \in \{$bond rating, remaining maturity, yield spread$\}$. For maturity, one subList includes the requests in ℓ whose remaining bond maturity is less than the median across those requests, and the other subList includes the other requests in ℓ. Requests exactly at the median are randomly assigned. Analogous steps generate the subLists for the other attributes.

We estimate the following specification on the subsample of substitute Lists:

$$F_{b,\ell,t} = a_1 R^{\mathcal{A}}_{b,\ell,t} + a_0 R_{b,\ell,t} + \text{cubic}(S_{b,\ell,t}) + \alpha_{\ell,t} + \gamma_b + \text{quadratic}(Q_{b,\ell,t}) + \varepsilon_{b,\ell,t}. \tag{3}$$

The new independent variable, $R^{\mathcal{A}}_{b,\ell,t}$, is the within-subList rank by best quoted spread of bond request b in List ℓ on date t in attribute $\mathcal{A}$. We compute this rank the same way as the overall within-List rank $R_{b,\ell,t}$, except we treat the subList for attribute $\mathcal{A}$ to which request b belongs as an entire List. All other terms in (3) are identical to (1). We conclude that an attribute is important to traders if the coefficient a_1 is substantially positive.

We perform two falsification tests of this specification. First, we randomly split Lists and estimate the impacts of ranks within the resulting random subLists. We falsify our design if these random subLists have significant impacts. Second, we estimate (3) on the subsample of convenience Lists. We falsify our design if the convenience Lists exhibit substantially positive coefficients on the List or the subList rankings.

Results. Table VIII presents the estimates from (3). For the substitute Lists, the within-subList ranks in maturity and yield spread are statistically and economically significant and positive, both when the subList ranks are included separately or altogether. The subList rank in rating is economically small when included separately and insignficiant when included altogether. For the convenience Lists, every List and subList rank coefficient is insignificant.

The random subList rank is insignificant everywhere. We conclude that remaining maturity and yield spread are important to traders, whereas bond ratings are not.

VI. Contributions

Over-the-counter trading is typically modeled as search for a single asset (e.g., Duffie, Garleanu and Pedersen, 2005). Vayanos and Weill (2008) introduce two assets with identical cashflows into the search framework and show that one asset endogenously becomes more liquid. Sambalaibat (2022) adds nondirected search in CDS and bond markets and show that the presence of the CDS market increases liquidity in the bond market. Milbradt (2017) allows for a continuum of heterogeneous bonds and show that firms can prefer issuing fragmented bonds. Oehmke and Zawadowski (2015) and Oehmke and Zawadowski (2017) model substitution between bonds and their CDS and show that bond fragmentation drives trading in the more liquid CDS market. None of these models incorporate substitutability between multiple assets as we do.

Recent theories analyze multi-dealer platforms, such as MarketAxess. Baldauf and Mollner (2023) consider the potential for information leakage from contacting many dealers. Wang (2023) shows that it is optimal for traders request quotes only a few dealers at a time. We instead examine whether a trader would request multiple bonds at once, while keeping dealer competition constant.

We belong to the empirical literature on multi-dealer platforms. Hendershott and Madhavan (2015) examine factors that determine whether a trader use a platform or bilaterally trade with a dealer. O'Hara and Alex Zhou (2021) find that the introduction of multi-dealer platforms reduced transaction costs. Allen and Wittwer (2023) identify relationship discounts as the driver of limited platform adoption in sovereign bond markets. Kargar et al. (2023) document that traders often repeat unfilled requests both on and off platforms. Hendershott, Livdan and Schürhoff (2021) find that the option to anonymously request quotes from nondealer participants improves transaction costs. No prior work studies Lists, despite their dominance on the largest corporate bond platform and their ability to aggregate liquidity across substitute bonds.

A complementary literature examines portfolio trading, which involves simultaneously trading a set of bonds with the same dealer. Meli and Todorova (2022) develop an algorithm to identify portfolio trades in TRACE. Li et al. (2023) apply this algorithm and find that portfolio trading increases bond market liquidity. Wittwer and Allen (2024) document frequent bundling of buy and sell trades in fixed income markets. The bonds in a bundle or a portfolio trade must be complements. We instead document that the dominant form of trading on the largest corporate bond platform is used to substitute across bonds.

Chaudhary, Fu and Li (2022) measure the price impacts of demand shocks on sets of similar bonds. List trading is a potential channel through which demand shocks propagate across similar bonds.

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Table I: Example of Observations in the Same List

The Table shows the composition of a specific List RFQ order of length 10. Each line is a separate request for a bond with a different CUSIP identifier within the same order. *"Quoted spread"* measures the difference between the best offered price and the CP+ midprice as a percentage of the midprice. *"Rank by quoted spread"* takes the value of 1 for the bond with the lowest *"Quoted spread"* in the list and 0 for the one with the highest, linearly decreasing inbetween. Table II defines all other variables.

Order ID	CUSIP	Buy	Requested quantity ($ '000)	Responses	Quoted spread (bps)	Filled	Rank by quoted spread
90982045	89055FAC7	1	250	3	22.86	1	1.00
90982045	25257DAA6	1	250	5	37.43	1	0.89
90982045	05453GAC9	1	250	7	45.34	1	0.78
90982045	043436AX2	1	250	6	83.66	1	0.67
90982045	52736RBJ0	1	250	5	89.24	0	0.56
90982045	75606DAQ4	1	500	2	94.21	0	0.44
90982045	00081TAK4	1	500	5	113.36	1	0.33
90982045	44267DAF4	1	500	4	159.68	1	0.22
90982045	390607AF6	1	250	1	271.98	0	0.11
90982045	45174AAA0	1	500	0	-	0	0.00

Table II: Variable definitions

Name	Variable definition
List attributes:	
Length	number of different bonds requested in a List
Asset Manager	requester type is flagged as asset manager
Broker-Dealer	requester type is flagged as broker-dealer
Other	indicator if requester type is flagged neither as asset manager, nor as broker-dealer by the platform
Request attributes:	
Requested quantity	par value of bonds requested in thousands of USD
Buy direction	indicator of 1 if buy, 0 if sell
Remaining maturity	the remaining time to maturity of the bond in years
Investment Grade (IG)	bond requested using High Grade protocol
High Yield (HY)	bond requested using High Yield protocol
S&P rating	S&P rating of the bond at the time of the request in notches ($AAA = 1$ to $D = 22$)
Has CP+ price	indicator whether a CP+ algorithmic price is available
Outcomes:	
Responses	number of dealer responses to the given request
No response	indicator of getting no responses for a given request
Quoted spread	the difference between the best offered price and the CP+ midprice as a percentage of the midprice
Rank by quoted spread	within a list we rank *Best quoted spread* from lowest (rank 1) to highest (rank 0), if the CP+ price does not exist for the bond or there are no responses, it is assumed to have the highest transaction cost
Filled	indicator whether the request was filled in full quantity
Rejected all quotes	indicator whether all offers were rejected conditional on getting at least one response
Entirely Filled	indicator whether all requests in the List are filled
Partially Unfilled	indicator if at least one request in the List is left unfilled

Table III: Summary Statistics at the Request-level

Mean and 10th, 25th, 50th, 75th and 90th percentile of the most important request-level variables using all 7,814,445 requests submitted in Lists.

	Mean	p10	p25	p50	p75	p90
Submitter types:						
Asset Manager	0.567	0	0	1	1	1
Broker-Dealer	0.216	0	0	0	0	1
Other	0.217	0	0	0	0	1
Request attributes:						
Buy	0.473	0	0	0	1	1
Requested quantity	0.456	0.006	0.025	0.165	0.587	1
CP+ available	0.970	1	1	1	1	1
Bond attributes:						
S&P rating	9.18	5	7	9	11	14
Remaining maturity	8.87	2.41	3.88	6.2	9.17	23.3
Outcomes:						
Filled	0.631	0	0	1	1	1
No response	0.064	0	0	0	0	0
Outcomes $\mid \geq 1$ **responses:**						
Quoted spread (bps)	32.1	-4.23	2.07	10.6	35.1	92.2
Responses	8.39	2	4	8	12	15
Filled	0.674	0	0	1	1	1
Rejected all quotes	0.326	0	0	0	1	1

Table IV: Summary Statistics at the List-level

Mean and 10th, 25th, 50th, 75th and 90th percentile of the most important list-level variables using all 616,052 Lists.

	Mean	p10	p25	p50	p75	p90
List attributes:						
Length	12.7	2	3	6	15	38
All buys	0.470	0	0	0	1	1
All sells	0.514	0	0	1	1	1
Mixed direction	.0161	0	0	0	0	0
All IG	.722	0	0	1	1	1
All HY	.23	0	0	0	0	1
Mixed grade	.0475	0	0	0	0	0
Submitter type:						
Asset Manager	.643	0	0	1	1	1
Broker-Dealer	.124	0	0	0	0	1
Other	.234	0	0	0	0	1
Outcomes:						
Entirely filled	.457	0	0	0	1	1

Table V: Fill Rates Conditional on the Rank by Best Quoted Spread

Results of regression specification (1). An observation is a bond request in a List. We exclude requests that did not receive a quote. The dependent variable is a dummy "Filled" indicating whether a bond request fills. The main independent variable of interest is *"Rank by quoted spread"* takes the value of 1 for the bond with the lowest *"Best quoted spread"* in the list and 0 for the one with the highest, linearly decreasing inbetween. Columns (1)-(3) include all lists with increasing number of controls. Column (4) includes Lists purely composed of HY bond requests, Column (5) includes Lists that include both HY and IG bond requests, Column (6) includes Lists purely composed of IG bond requests. Table II defines all variables. Square brackets indicate t-statistics clustered by List and by Bond.

	All Lists			HY	Mixed	IG
	(1) Filled	(2) Filled	(3) Filled	(4) Filled	(5) Filled	(6) Filled
Rank by quoted spread	0.033	0.034	0.034	0.14	0.039	0.025
	[29.9]	[31.4]	[31.4]	[53.6]	[9.75]	[24.5]
Adjusted R^2	0.709	0.714	0.714	0.615	0.630	0.739
Within R^2	0.097	0.086	0.086	0.128	0.090	0.059
List FE	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE	No	Yes	Yes	Yes	Yes	Yes
Spread Controls	Yes	Yes	Yes	Yes	Yes	Yes
Quantity Controls	No	No	Yes	Yes	Yes	Yes
Number of Lists	592,041	591,920	591,920	137,651	28,035	426,142
Number of Bonds	17,235	16,484	16,484	4,296	13,465	12,763
Number of Obs.	7,137,208	7,136,345	7,136,345	1,807,005	421,849	4,906,056

Table VI: Predicting Substitute Lists

Results of regression specification (2). An observation is a List. The dependent variable is a dummy *"Partially Unfilled"* that takes the value of 1 if at least one request in the List is left unfilled. Columns (1) to (7) include an increasing number of controls. *"Quantity controls"* refers to the mean and standard deviation of the log of the *"Quantity requested"* within the List. *"Direction controls"* covers the share of buy requests within the list, while *"Maturity controls"* refers to the mean and standard deviation of maturity within the List. *"Other controls"* includes the mean and standard deviation of ratings within the List, the share of bonds without a CP+ price and the share of Rule 144A bonds in the List. Table II defines all variables. Square brackets indicate t-statistics clustered by List and by Bond.

	(1) Partially Unfilled	(2) Partially Unfilled	(3) Partially Unfilled	(4) Partially Unfilled	(5) Partially Unfilled	(6) Partially Unfilled	(7) Partially Unfilled
High Yield List	0.23	0.17	0.15	0.14	0.14	0.17	0.027
	[49.3]	[60.4]	[56.6]	[54.8]	[55.3]	[68.5]	[7.21]
Mixed grade List	0.18	0.10	0.12	0.096	0.097	0.098	0.037
	[38.5]	[24.7]	[29.2]	[22.5]	[23.2]	[24.3]	[10.2]
Asset Manager		-0.37	-0.38	-0.38	-0.38	-0.35	-0.31
		[-68.4]	[-72.5]	[-74.0]	[-70.5]	[-75.3]	[-73.4]
Broker-Dealer		0.17	0.10	0.067	0.072	0.076	0.096
		[43.3]	[27.4]	[20.3]	[20.7]	[23.7]	[31.2]
Adjusted R^2	0.041	0.219	0.252	0.271	0.284	0.298	0.321
List Length FE	No	No	No	Yes	Yes	Yes	Yes
Quantity Controls	No	No	Yes	Yes	Yes	Yes	Yes
Direction Controls	No	No	No	No	Yes	Yes	Yes
Maturity Controls	No	No	No	No	No	Yes	Yes
Other Controls	No	No	No	No	No	No	Yes
Number of Obs.	616,052	616,052	616,048	616,048	616,048	602,299	600,383

Table VII: Fill Rates in Substitute and Convenience Lists

Results of regression specification (1) split by the predicted probability that the List entirely fills as estimated from (2). Column (1) includes the quarter of the Lists with the highest predicted probability of being *"Partially Unfilled"* based on the estimation results in Table VI, we call these substitute Lists. Column (2) includes the quarter of the Lists with the lowest predicted probability of being *"Partially Unfilled"* based on the estimation results in Table VI, we call these convenience Lists. An observation is a bond request in a List. We restrict the sample to the requests that received at least one response. The dependent variable is a dummy '*'Filled"* indicating whether a bond request fills. The independent variable of interest is *"Rank by quoted spread"* and takes the value of 1 for the bond with the lowest *"Quoted spread"* in the List and 0 for the one with the highest, linearly decreasing inbetween. Table II defines all variables. Square brackets indicate t-statistics clustered by List and by Bond.

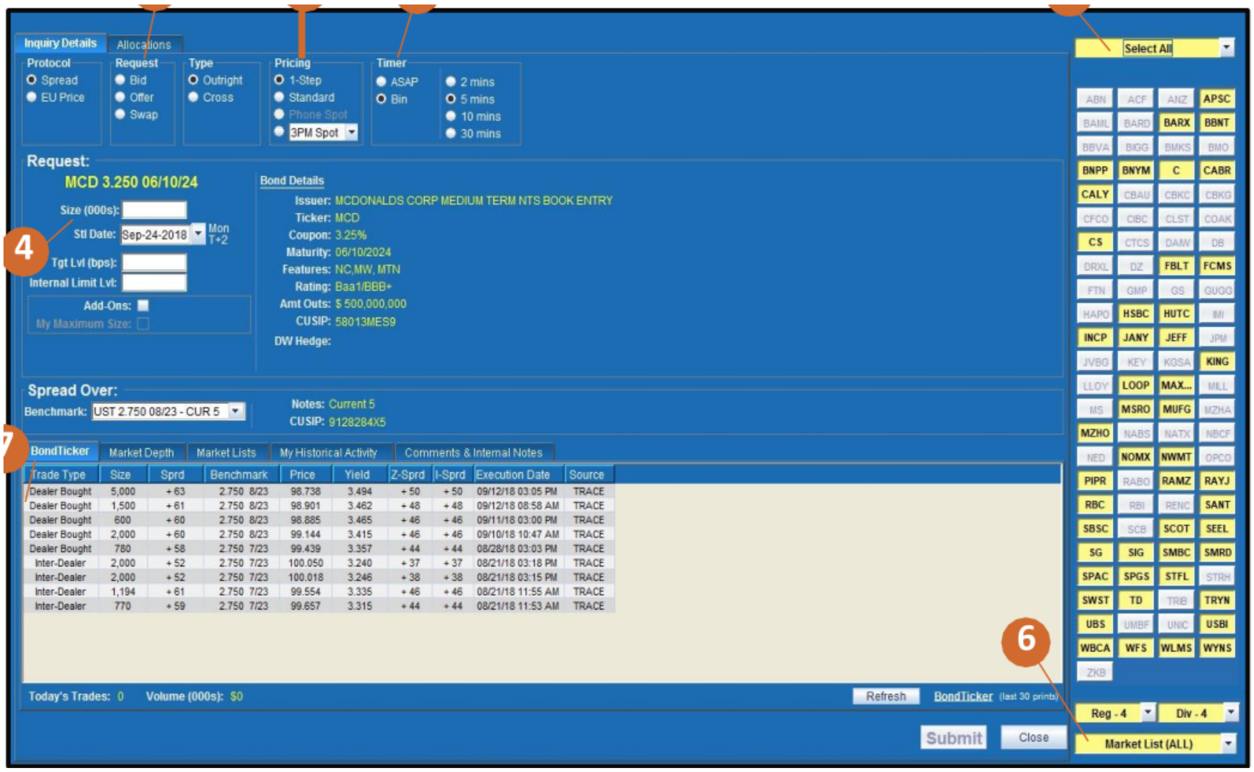
	Substitute Lists	Convenience Lists
	(1)	(2)
	Filled	Filled
Rank by quoted spread	0.20	0.018
	[74.1]	[17.3]
Adjusted R^2	0.563	0.491
Within R^2	0.116	0.030
List FE	Yes	Yes
Bond FE	Yes	Yes
Spread Controls	Yes	Yes
Quantity Controls	Yes	Yes
Number of Lists	146,998	149,654
Number of Bonds	15,320	12,358
Number of Obs.	2,252,402	2,213,842

Table VIII: Fill Rates by sublists formed by different bond attributes

Results of regression specification (1) with ranks within sublists. An observation is a bond request in a List. We restrict the sample to the requests that received at least one response. The dependent variable is a dummy *"Filled"* indicating whether a bond request fills. In each List we form sublists along several dimensions, where we split the list into two sublists at the median value of the given attribute. *"Sublist rank: attribute"* is the rank by *"Quoted spread"* within the sublist formed along the given attribute. Table II defines all variables. Square brackets indicate t-statistics clustered by List and by Bond.

	Substitute Lists					Conv. Lists
	(1)	(2)	(3)	(4)	(5)	(6)
	Filled	Filled	Filled	Filled	Filled	Filled
Rank by quoted spread	0.21	0.24	0.21	0.25	0.18	0.0087
	[51.7]	[61.8]	[54.5]	[68.7]	[30.6]	[3.68]
Sublist rank: maturity	0.032				0.028	0.0086
	[15.9]				[11.3]	[7.67]
Sublist rank: rating		0.0075			-0.00051	-0.0019
		[3.99]			[-0.21]	[-1.70]
Sublist rank: yield			0.028		0.019	0.00099
			[14.3]		[7.79]	[0.82]
Sublist rank: random				0.00088	-0.0050	0.0021
				[0.46]	[-1.83]	[1.73]
Adjusted R^2	0.564	0.557	0.562	0.561	0.560	0.489
Within R^2	0.119	0.119	0.119	0.118	0.120	0.029
List FE	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes
Spread Controls	Yes	Yes	Yes	Yes	Yes	Yes
Quantity Controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of Lists	84,663	82,754	82,333	112,166	52,605	73,976
Number of Bonds	14,733	14,756	14,748	15,075	14,285	11,036
Number of Obs.	1,576,606	1,645,747	1,605,999	2,173,818	948,315	1,196,451

Figure 1: MarketAxess Client Order Screen



A. Imputing Quoted Prices

We convert the quotes of IG requests that do not trade into prices using CP+ prices and yields. For every request, we observe the CP+ bid price, ask price, bid yield, ask yield, and the premium or discount (yield spread) of the CP+ bid and ask yields relative to the benchmark treasury yield. The quotes for IG requests are in terms of the yield spread.

A three-step method converts those quotes into prices. First, we recover the benchmark yield using the formula

$$\begin{aligned}\text{Benchmark yield} = {} & \frac{\text{`CP+ bid yield'} - \text{`CP+ bid yield spread'}}{2} \\ & + \frac{\text{`CP+ ask yield'} - \text{`CP+ ask yield spread'}}{2}.\end{aligned}$$

Second, we add the recovered benchmark yield to the best quoted yield spread to arrive at the *best quoted yield*. Third, a model-free linear transformation provides the best quoted price:

$$\begin{aligned}\text{Best quoted price} = {} & \text{`CP+ ask price'} \\ & - \frac{\text{`CP+ ask price'} - \text{`CP+ bid price'}}{\text{`CP+ bid yield'} - \text{`CP+ ask yield'}} \\ & \times (\text{best quoted yield} - \text{`CP+ ask yield'}),\end{aligned}$$

which we set to missing if the resulting best quoted price deviates by more than 50% from the CP+ midprice.

We verify this method using the IG requests that traded, for which we observe the trade price. In the subsample of such requests, we regress the trade price on the best quoted price computed under our method. The estimated regression has an R-squared equal 99.99 percent, the estimated intercept equal −.006 percent of the bond's face value, and the estimated coefficient equal 1.00005. We conclude that any noise in our method is unlikely to significantly influence our results.

B. Bond Price Uncertainty

We conservatively estimate the degree of traders' uncertainty over the spreads quoted for each bond request in their Lists at the time of submission. To do so, from the total variation in quoted spreads, we strip away all variation attributable to high-dimensional fixed effects and controls, some of which the trader could not have exactly known at submission.

A. Econometric Framework

We suppose the following. The best quoted spread $Q_{b,\ell(i,t),i,t}$ for bond b in List $\ell(i,t)$ sent by trader i at time t is

$$Q_{b,\ell(i,t),i,t} = f(\theta_{i,t}, L_{\ell(i,t)}) + B_b + \eta_{b,t} + \epsilon_{b,\ell,i,t}. \tag{4}$$

Trader- and List-specific component $f_t(\theta_{i,t}, L_{\ell(i,t)})$ is the combined impact of trader i's time-varying type $\theta_{i,t}$ (e.g., how informed she is about the future returns of b) and characteristics of List $\ell(i,t)$ (e.g., sets of invited dealers and bonds in the List). Time-invariant bond-specific component B_b captures the cross-sectional variation in bonds' quoted spreads that is constant across traders. It arises from, for example, differences in bond attributes. Time-varying bond-specific component $\eta_{b,t}$ represents changes in adverse selection risk or level of liquidity in the bond, perhaps due to dealer preference shocks particular to that bond. Both bond components B_b and $\eta_{b,t}$ as well as unexpected shocks to the quoted spread $\epsilon_{b,\ell,i,t}$ have zero mean over bonds b. All time-varying components have zero mean.

Under the conservative assumption that traders know $f(\theta_{i,t}, L_\ell)$ and B_b but not $\eta_{b,t}$ and $\epsilon_{b,\ell,i,t}$, the combination of List and bond fixed effects allow us to isolate the uncertainty faced by traders as they submit Lists. Stripping away all List-specific variation from the quoted spread Q yields

$$Q^{\ell\,\mathrm{FE}} := Q_{b,\ell(i,t),i,t} - \mathbb{E}_b[Q_{b,\ell(i,t),i,t}] = B_b + \eta_{b,t} + \epsilon_{b,\ell(i,t),i,t}.$$

Further removing bond-specific variation yields

$$Q^{\ell\,\mathrm{FE},b\,\mathrm{FE}} := Q^{\ell\,\mathrm{FE}} - \mathbb{E}_t[Q_{b,\ell(i,t),i,t}] = \eta_{b,t} + \epsilon_{b,\ell(i,t),i,t}.$$

Taken together, the share of total variation in best quoted spreads that a trader knows as she submits her List is given by

$$\frac{Var(Q^{\ell\,\mathrm{FE},b\,\mathrm{FE}})}{Var(Q_{b,\ell(i,t),i,t})}.$$

The empirical counterpart to this share is the adjusted R-squared from a linear regression of best quoted spread $Q_{b,\ell,t}$ on List and bond fixed effects, α_ℓ and γ_b,

$$Q_{b,\ell,t} = \alpha_{\ell,t} + \gamma_b + \mathbf{X}\beta + \varepsilon_{b,\ell,t}, \tag{5}$$

in which the controls $\mathbf{X}$ include up to two variables to yet more conservatively estimate traders' quote uncertainty.

Requested quantity is a key potential determinant of quotes that Equation (4) subsumes into unexpected shocks $\epsilon_{b,\ell(i,t),i,t}$. We assume that the requested quantity linearly and additively separably affects the best quoted spread. Under this assumption, controlling for requested quantity in (5) yields an adjusted R-squared that corresponds to the share of quote variation known to the submitting trader.

We further control for the bond's future realized return. The expected returns of a bond would be an important contributor to the time-varying bond component $\eta_{b,t}$ of quoted spreads. The future realized returns removes any variation in quotes due to changes in expected returns, which only a perfectly informed trader would be able to predict.

The *future realized return* of a bond request on day d is the simple return from the CP+ midprice on day d to the CP+ midprice seven calendar days later, accounting for accumulated coupon payments,

$$\text{Realized return}_d = \frac{\text{CP+ midprice}_{d+7} - \text{CP+ midprice}_d + \text{Acc. coupon}_{d,d+7}}{\text{CP+ midprice}_d}.$$

We take the CP+ midprice at 17:00 on the day to avoid any mechanical effects of the trade itself on the CP+ prices. The accumulated coupon calculation extracts coupon information from Mergent-FISD and follows the methodology of the WRDS Bond Returns database adapted to daily frequency. We omit future realized returns if the bond has floating-rate coupons or an irregular coupon schedule, thus our sample is smaller whenever including this variable.

Taken together, our design assigns to trader's uncertainty only the variation in quoted spreads that the regressors in specification (5) do not absorb. Doing so assumes that the traders perfectly know the effects of their own time-varying type interacted with all List-specific attributes, fixed bond characteristics, the requested quantity, as well as changes in future returns on their quoted spreads. We view the resulting adjusted R-squared as a conservative upper bound on the share of quoted-spread variation that traders can predict.

B. Results

Table IX presents the estimates from regression (5). The adjusted R-squared is below 50% across all specifications and both HY and IG bonds.[4] We therefore conservatively conclude

[4]Sample sizes vary as some Lists have exactly one request with a response, and because we cannot compute returns if the bond lacks CP+ prices or has nonstandard coupon rates or schedules.

that more than half of the total variation in best quoted spreads cannot be predicted by traders at the time of their List submissions. These traders thus face a high degree of quote uncertainty.

Three details of our estimates broadly support our econometric framework and economic intuition. First, having List fixed effects explains more than double the share of quoted-spread variation than having date fixed effects, consistent with time-varying trader type and List attributes playing a large role in quote setting. Second, the HY bond quotes are substantially less predictable than the investment-grade quotes in every specification, as we would expect given that the HY bonds are less liquid and higher risk. Third, adding future realized return hardly increases the explained share, consistent with the List and bond effects and the requested quantity capturing most of the plausibly explainable variation in quoted spreads.

Table IX: Explained Share of Best Quoted Spreads in Lists

Results of regression specification (5). An observation is a bond request in a List. The dependent variable is the best quoted spread. Table II defines all variables. Square brackets indicate t-statistics clustered by List and by Bond.

	All Lists				HY Lists	IG Lists
	(1) Quoted spread	(2) Quoted spread	(3) Quoted spread	(4) Quoted spread	(5) Quoted spread	(6) Quoted spread
CP+ implied spread	2.69	2.57	1.11	1.05	1.11	2.02
	[122.2]	[116.2]	[76.1]	[67.8]	[72.3]	[38.0]
Signed future returns				0.11		
				[91.0]		
Adjusted R^2	0.171	0.187	0.507	0.520	0.408	0.551
Within R^2	0.171	0.152	0.017	0.047	0.020	0.007
Quantity Controls	Yes	Yes	Yes	Yes	Yes	Yes
List FE	No	No	Yes	Yes	Yes	Yes
Bond FE	No	No	Yes	Yes	Yes	Yes
Date FE	No	Yes	No	No	No	No
Number of Lists	612,167	612,167	591,920	463,551	137,651	426,142
Number of Bonds	17,283	17,283	16,484	11,290	4,296	12,763
Number of Obs.	7,157,334	7,157,334	7,136,345	5,208,632	1,807,005	4,906,056

C. Model of Search Across Substitute Bonds

A. Trading Game

We write a very stylized model to help fix ideas. A risk-neutral trader seeks to buy one unit of a bond from a competitive dealer. We model a buying decision, sell is analogous. There are two perfectly substitutable bonds, and both bonds are worth a unit in terms of financial value. The reservation cost to the trader is assumed to be very high for one unit of bond and zero for the second unit, thus the trader wants to buy exactly one bond.

First, the trader either requests a quote for one bond from the dealer or submits a List that includes both bonds. The trader incurs a "reputation" cost $\eta > 0$ for each quote she rejects. This cost can represent the present value of worse quotes in unmodeled future periods as the dealer demands compensation to bother submitting quotes that are unlikely to fill.

Second, for each bond i, whether it is requested individually or as part of a List, the dealer submits a competitive ask quote equal to her reservation price, $1 + c_i$. The half spread c_i is independently drawn from an exponential distribution, $f(c_i) \overset{iid}{\sim} \frac{1}{\bar{c}} \exp^{-c_i/\bar{c}}$ for $c_i \geq 0$. Thus, the mean and the standard deviation of the half-spread are equal to each other, $\mathbb{E}[c_i] = \sqrt{Var(c_i)} = \bar{c}$. We refer to "spreads" to denote half spreads from now on.[5]

Third, if the trader requested one bond, she may reject the quote and request a quote for the second bond. The trader cannot trade the first bond if she rejects the first quote,[6] and thus the trader accepts the second quote whenever she requests it. If the trader submitted a List, she trades the lower quoted bond. The model leads to the below proposition:

Proposition 1. *The trader submits a list if the expected transaction cost $\bar{c}$ is high enough relative to the cost of rejecting a request, and submits up to two single-bond requests consec-*

[5]Both the exponential distribution and that the mean and standard deviation are closely related is consistent with what we see in the data.

[6]This assumption captures the trader's need for immediacy in a simple way. A trader who sequentially searches across multiple substitute bonds would sometimes need to trade the last requested bond.

utively otherwise.

Proof. The trader's expected cost from initially submitting a List is $E[\min\{c_1, c_2\}] + \eta = \bar{c}/2 + \eta$. This follows from the following: The distribution of c_{min} is described by $P(c_{min} > y) = \prod_{i=1}^{2} P(c_i > y) = e^{-2\frac{1}{\bar{c}}y}$ and thus $E[c_{min}] = \int_0^\infty P(Y > y)\, dy = \frac{\bar{c}}{2}$. Given that the trader initially requests a quote for one bond, she optimally rejects the quote if its spread c_i exceeds a cutoff $\hat{c}$, $c_i > \hat{c}$. If the trader rejects the initial quote, she incurs the cost η and certainly accepts the second quote, whose expected spread is $\bar{c}$. Thus, the cutoff $\hat{c} = \bar{c} + \eta$. The trader's expected cost of submitting a single bond request is then $\bar{c}\left(1 - e^{-1-\eta/\bar{c}}\right)$. The probability that the first bond is accepted is $P(c_i < \hat{c}) = 1 - e^{-\hat{c}/\bar{c}}$ and in this case the conditional expectation is $E(c_i|c_i < \hat{c}) = \bar{c} - \frac{\hat{c}e^{-\hat{c}/\bar{c}}}{1-e^{-\hat{c}/\bar{c}}}$. Thus the expected cost of the trader of acquiring one bond through consecutive requests is

$$(1 - e^{-\hat{c}/\bar{c}})\left(\bar{c} - \frac{\hat{c}e^{-\hat{c}/\bar{c}}}{1 - e^{-\hat{c}/\bar{c}}}\right) + e^{-\hat{c}/\bar{c}}\,(\bar{c} + \eta) \tag{6}$$

Plugging in $\hat{c} = \bar{c} + \eta$ yields the expected cost of the consecutive transaction in the text. Taken together, the trader initially submits a List if $1/2 + \eta/\bar{c} < 1 - e^{-1-\eta/\bar{c}}$, and a single bond request otherwise. That $1/2 - e^{-1-x} - x$ is strictly positive at $x = 0$ and strictly decreasing in x' without a lower bound leads to the above proposition. □

Proposition 1 implies that, if the cost of rejecting a request does not grow with $\bar{c}$, the trader submits a list for sufficiently high expected spread $\bar{c}$. Which, given the exponential distribution of c_i, also means lists will be submitted if there is high uncertainty about the spread. If the cost of rejecting a quote is a real cost (like time), submitting a list is socially optimal whenever the trader chooses to do so. If the cost of rejecting a quote is a transfer (e.g., to the dealer in later transactions), then submitting a list would always be socially optimal.

B. Econometric Implications

The main competing explanation of substitute Lists in which some offers are not accepted are simple Lists of convenience in which the trader asks for several unrelated bonds. The main difference between the two is that in a List of convenience the decision whether to accept a quote for a given bond only depends on its own spread, while in a substitute List it also depends on the spread of the other bond in the List. With List fixed effects it is impossible to measure such "peer effects" and thus we derive a simple econometric method to measure the presence of substitute Lists and the strength of substitution.

Assume that there are two types of traders submitting such Lists of length two. A $\nu \in [0, 1]$ fraction of traders submit two bonds in a substitute List just as above. Denote by f_i the probability that the quote for bond i at transaction cost c_i is accepted by the trader. The trader will accept the offer for bond i if $c_i < c_j$, resulting in $f_i = 1$ and $f_j = 0$ ($j \neq i$). Portion $1 - \nu$ of the Lists are submitted by traders as Lists of convenience and the trader has an independent downward sloping demand for both bonds. Thus, the probability of accepting the quote for bond i (and thus the request being filled) is $f_i = 1 - \lambda_i \cdot c_i$ where $\lambda_i \geq 0$. Define the dummy variable "Upper Half" which equals one for bond i in List ℓ if and only if $c_{i,\ell} < c_{-i,\ell}$. With this mix of traders, the expected probability of filling the request for bond i in List ℓ is

$$f_{i,\ell} = \nu \cdot \text{Upper Half}_{i,\ell} + (1 - \nu) \cdot (1 - \lambda_i \cdot c_i) = 1 + \nu \cdot \text{Upper Half}_{i,\ell} - (1 - \nu) \cdot \lambda_i \cdot c_i,$$

where we neglected the fact that $f_{i,\ell} \in [0, 1]$ for simplicity. This leads to the following Proposition.

Proposition 2. *In the following regression specification with List fixed effects,*

$$f_{i,\ell} = \alpha + \beta \cdot \textit{Upper Half}_{i,\ell} + \gamma \cdot c_{i,\ell} + \delta_l + \epsilon_{i,\ell}, \tag{7}$$

the coefficient on Upper Half$_{i,\ell}$ *is* $\beta = \nu \geq 0$ *and the coefficient on the quoted (half) spread is* $\gamma = -(1-\nu) \cdot \overline{\lambda} \leq 0$, *where* $\overline{\lambda}$ *is the average* λ_i.

We base the empirical specification in our empirical analysis on equation (7) defined in Proposition 2.

D. Robustness

We find that our results are robust. Appendix D.A looks for heterogeneity in our results. Appendix D.B incorporates repeated requests. Appendix D.C replicates our results under the logit specification. Appendix D.D flexibly estimates the effects of decile rank on fill rates, and shows that the effects are approximately linear in rank. Table XI defines all variables introduced in this section.

A. Heterogeneity

Table X reproduces the fully saturated specification in Table V across subsamples split by List length, its trader type, and trade direction. Lists are either long, which include 10 or more requests, or short. They consist entirely of buy requests, sell requests, or (for a tiny proportion) mixed. Requesting traders are asset managers, broker-dealers, or proprietary traders (Other).

The results in Table X consistently show substitution, with estimated coefficients broadly similar to those in Table V. The dealers and proprietary traders tend to substitute far more intensely than asset managers, which echoes our finding in Table VI that the asset managers are the most likely to submit Lists for convenience. There is more intense substitution within the buy Lists than within the sell Lists, perhaps because buyers are not restricted by their current holdings.

B. Repeated Requests

Kargar et al. (2023) document that traders frequently repeat requests that do not fill. We now broaden our dependent variable to encompass both filled and repeated requests. We find that the repeated requests do not drive our results.

Intuition. Traders can substitute within Lists in two ways. First, at the extensive margin, traders can abandon the requests they leave unfilled in favor of higher ranked requests. Second, at the intensive margin, they can merely delay filling the lower ranked requests. For example, traders may face temporary budget constraints, and yet target a portfolio of specific bonds. Such traders would fill the higher ranked requests today, up to their budget constraints, then repeat the other requests as the constraints slacken.

This section isolates the intensity of substitution at the extensive margin by removing any substitution due to repeated requests in our estimates. More precisely, we replace the dependent variable in our main regression (1) with a dummy that equals one if and only if a request is filled *or* repeated, whether on MarketAxess or elsewhere.

Supplementary data. TRACE provides all corporate bond transactions including those outside MarketAxess. We use Enhanced TRACE for all bonds where it is available and standard TRACE for the other bonds. The standard TRACE truncates trading quantities above $1 million for HY bond trades and $5 million for IG trades, while including all bond trades. Enhanced TRACE does not truncate, while excluding privately placed (Rule 144A) bond trades.[7]

We match trades (filled requests) on MarketAxess to TRACE. All matches must have the same bond CUSIP and quantity, and have TRACE time stamp at most two minutes prior to and up to 24 hours after the MarketAxess time stamp. For the bonds retrieved from standard TRACE, we let any quantity above the truncation cutoff to be a potential match. In case of multiple matches, we check whether TRACE and MarketAxess recorded: (i) time stamps within 10 minutes of each other; (ii) trade prices within a rounding error; and (iii) consistent trader type—as a dealer-to-customer trade on TRACE if the requester were an asset manager or proprietary trader, and as an interdealer trade if a dealer was the requester. We select the match which satisfies the largest number of these three criteria.

[7] Academic TRACE neither truncates nor excludes any bonds, but is not available for our entire sample period at the time of analysis.

This procedure yields a unique match for 99.2% of the trades in our sample and fails to find a match for the remainder.

Variable construction. We identify "not abandoned" requests following Kargar et al. (2023). A request on MarketAxess is an *initial request* if, in the previous week, there was no unfilled request for the same bond, quantity, and trade direction by the same trader type. The request is *repeated* if it is unfilled and, in the next week, there is either *(a)* a request on MarketAxess for the same bond, quantity, and trade direction by the same trader type or *(b)* a trade on TRACE for the same bond and quantity and consistent trader type. We form sequences of repeated requests by linking each repeated request to the first request or trade that meets conditions (a) or (b). The request is *not abandoned* if it either fills or is repeated, and *eventually filled* if it either fills or the sequence of its linked repeated requests eventually ends in a trade. There are 6,390,705 initial requests in Lists.

Table XII provides the summary statistics of initial requests. The majority of unfilled initial requests are abandoned, where 73.7% of initial requests are filled, 12.3% are repeated, and the remaining 14.1% are abandoned. Most of these repeated requests eventually fill. Only a small share of requests eventually fill off the platform. The statistics in Table XII are very close to those found in Kargar et al. (2023). At the List-level, at least one request is abandoned in 42.7% of Lists.

The initial requests that traders leave unfilled have far worse best quoted spreads conditional on receiving a quote. The average best quoted spread across all initial requests with a quote is 13.3 basis points, is sharply smaller for those that are filled at 5.26 bps, and far larger for those unfilled at 39.4 bps.

Results. Table XIII reproduces Table V under the dependent dummy variable that equals one if and only if the request is not abandoned. The highest ranked requests are substantially more likely to not be abandoned than the lowest ranked requests in the same Lists, especially for the HY Lists. We conclude that there is considerable substitution within Lists at the extensive margin.

C. Logit Specification

Table XIV reproduces Table V under the logit specification. Our results persist under this specification.

D. Linearity of Ranking Effects

A sequence of dummy variables indicates the decile rank of each request's best quoted spread among all best quoted spreads within its List. The *top-Kth decile request* indicates a bond request whose best quoted spread belongs to the smallest Kth decile among the best quoted spreads in its List. The top decile is $K = 1$ and the bottom decile is $K = 10$. Requests without a quote are treated as if their best quoted spread is larger than the largest one we observe in our sample.

Figure 2 plots the estimated coefficients for each decile from a regression identical to (1), except the rank $R_{b,\ell,t}$ is replaced by nine top Kth decile request indicators for $K \in \{2, \ldots, 10\}$. The top decile is the baseline. We find that the higher decile requests are more likely to fill than the lower decile requests in the same List. The estimated coefficients are linearly increasing across the deciles, consistent with linear rank effects.

Table X: Sample splits

Results of regression specification (1) with different sample splits of the full sample reported in Table V. An observation is a bond request in a List. We exclude requests that did not receive a quote. The dependent variable is a dummy *"Filled"* indicating whether a bond request fills. The main independent variable of interest is *"Rank by quoted spread"* takes the value of 1 for the bond with the lowest *"Best quoted spread"* in the list and 0 for the one with the highest, linearly decreasing inbetween. Column (1) includes only lists of length shorter than 10, while Column (2) includes all lists with length of at least 10. Column (3) includes only requests submitted by "Asset Managers", column (4) those submitted by "Broker-dealers" and Column (5) thos by "Other" traders. Column (6) only includes Lists that only include buy requests, while Column (7) those that only consist of sell requests. Table II defines all variables. Square brackets indicate t-statistics clustered by List and by Bond.

	Short Lists	Long Lists	Asset Manager	Broker-Dealer	Other	Buy	Sell
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Filled	Filled	Filled	Filled	Filled	Filled	Filled
Rank by quoted spread	0.026	0.038	0.018	0.21	0.098	0.045	0.021
	[26.0]	[24.7]	[18.1]	[63.6]	[37.7]	[29.8]	[18.5]
Adjusted R^2	0.654	0.727	0.531	0.424	0.601	0.693	0.738
Within R^2	0.079	0.088	0.085	0.115	0.122	0.089	0.081
List FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spread Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quantity Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Lists	362,959	228,860	387,154	72,863	131,668	284,473	309,921
Number of Bonds	15,744	15,840	15,814	14,116	14,594	15,504	15,858
Number of Obs.	1,478,523	5,656,909	4,306,489	1,300,009	1,527,954	3,362,713	3,765,759

Table XI: Additional Variable Definitions

Name	**Variable definition**
Initial request	indicator if there is no unfilled request in the previous 7 calendar days requesting the same bond in the same amount, direction and by the same trader type
Abandoned	indicator if an unfilled request is neither repeated on the platform nor filled in Trace within the 7 calendar days from the request
Repeated	indicator if after an unfilled request, a request for the same bond with the same quantity, direction and requester type is submitted on the platform or filled in Trace within 7 calendar days
Times repeated	for repeated trades the cumulative number of repeat requests on the platform less than 7 calendar days apart, including the request that is filled in Trace without a request on the platform
Eventually filled	a request is either filled on the platform right away or filled after repeated requests on the platform, or filled in Trace within the next 7 calendar days
None Abandoned	indicator if all of the unfilled requests in the List are either repeated on the platform or filled in Trace within 7 calendar days from the request; set to 1 if list is entirely filled

Table XII: Summary Statistics at the level of Initial Requests

	Mean	p10	p25	p50	p75	p90
Filled	0.737	0	0	1	1	1
Abandoned	0.141	0	0	0	0	1
Repeated	0.123	0	0	0	0	1
Times repeated | Repeated	2.17	1	1	1	2	4
Eventually filled	0.819	0	1	1	1	1
— on platform	0.772	0	1	1	1	1
— off platform	0.046	0	0	0	0	0
Quoted spread (bps)	13.3	-1.12	0.375	1.96	6.60	30.8
— | Filled	5.26	-1.48	0.089	1.34	3.72	13.2
— | Not filled	39.4	0.745	2.71	7.91	35.0	119

Table XIII: Using Not abandoned instead of Filled

This table exactly reproduces Table V by replacing the dependent variable with *"Not abandoned"* which indicates whether the bond request in the List was not abandoned (instead of *"Filled"* as in the baseline Table). The coefficients are the marginals. Results of regression specification (1). An observation is a bond request in a List. We exclude requests that did not receive a quote. The main independent variable of interest is *"Rank by quoted spread"* takes the value of 1 for the bond with the lowest *"Best quoted spread"* in the list and 0 for the one with the highest, linearly decreasing inbetween. Columns (1)-(3) include all lists with increasing number of controls. Column (4) includes Lists purely composed of HY bond requests, Column (5) includes Lists that include both HY and IG bond requests, Column (6) includes Lists purely composed of IG bond requests. Table II defines all variables. Square brackets indicate t-statistics clustered by List and by Bond.

	All Lists			HY	Mixed	IG
	(1) Not abandoned	(2) Not abandoned	(3) Not abandoned	(4) Not abandoned	(5) Not abandoned	(6) Not abandoned
Rank by quoted spread	0.025	0.026	0.026	0.058	0.030	0.015
	[34.3]	[35.7]	[35.7]	[33.2]	[10.1]	[19.9]
Adjusted R^2	0.468	0.474	0.474	0.357	0.450	0.530
Within R^2	0.012	0.012	0.012	0.011	0.017	0.013
List FE	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE	No	Yes	Yes	Yes	Yes	Yes
Spread Controls	Yes	Yes	Yes	Yes	Yes	Yes
Quantity Controls	No	No	Yes	Yes	Yes	Yes
Number of Lists	592,041	591,920	591,920	137,651	28,035	426,142
Number of Bonds	17,235	16,484	16,484	4,296	13,465	12,763
Number of Obs.	7,137,208	7,136,345	7,136,345	1,807,005	421,849	4,906,056

Table XIV: Logit regressions

This table is the same as Table V but with logistic specification instead of linear. All Lists in which all or no requests are *Filled* are automatically excluded from the logit specification because of the List fixed effects. The coefficients are the marginals. Bond fixed effects are excluded for technical reasons. Results of regression specification (1). An observation is a bond request in a List. We exclude requests that did not receive a quote. The dependent variable is a dummy *"Filled"* indicating whether a bond request fills. The main independent variable of interest is *"Rank by quoted spread"* takes the value of 1 for the bond with the lowest *"Best quoted spread"* in the list and 0 for the one with the highest, linearly decreasing inbetween. Columns (1)-(3) include all lists with increasing number of controls. Column (4) includes Lists purely composed of HY bond requests, Column (5) includes Lists that include both HY and IG bond requests, Column (6) includes Lists purely composed of IG bond requests. Table II defines all variables. Square brackets indicate t-statistics clustered by List and by Bond.

	All Lists		HY	Mixed	IG
	(1) Filled (logit)	(2) Filled (logit)	(3) Filled (logit)	(4) Filled (logit)	(5) Filled (logit)
Rank by quoted spread	0.27	0.27	0.25	0.36	0.23
	[160.8]	[151.4]	[71.0]	[57.9]	[91.8]
List FE	Yes	Yes	Yes	Yes	Yes
Bond FE	No	No	No	No	No
Spread Controls	Yes	Yes	Yes	Yes	Yes
Quantity Controls	No	Yes	Yes	Yes	Yes
Number of Obs.	3,499,459	3,499,459	1,280,637	220,291	1,998,531

Figure 2: The effect of deciles on fill rates

Results of regression specification (1) using Lists of *"Length"* of at least 10 but with decile dummies for rank within the List by *"Best quoted spread"* instead of the continuous variable *"Rank by quoted spread"* as independent variables. An observation is a bond request in a List. We exclude requests that did not receive a quote. The dependent variable is a dummy *"Filled"* indicating whether a bond request fills. The graph shows the coefficients on the 10 deciles, setting the first decile (the one with the lowest *"Quoted spread"*) as a zero. The shaded area is the 95% confidence interval.