Agents’ Behavior on Multi-Dealer-to-Client Bond Trading Platforms

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Motivation

A structural model of client-dealer quoting behavior

Inference

Empirical results

Extensions
Trading of corporate bonds on the secondary market: Over The Counter, traditionally.

Recent evolutions: “electronification” of financial markets.

Lack of standardization and illiquidity of most corporate bonds ⇒ no match-based model (order books) similar to equity markets.
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Several types of bond-platforms have emerged.

Multi-dealer-to-client (MD2C) trading platforms: Bloomberg Fixed Income Trading (FIT), Tradeweb and MarketAxess.
Motivation: the Request For Quotes (RFQ) process

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3. The client selects dealers (up to 6 dealers on Bloomberg FIT), and sends one RFQ through the platform to them, with a volume (notional), and the side (“buy” or “sell” order).
4. Requested dealers can answer a price to the client for the transaction. Dealers know the identity of the client, the number of requested dealers but not the prices that are streamed by other dealers.

They only see a composite bid/offer price, based on some of the best streamed prices: the CBBT price (Bloomberg FIT).
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6. Each dealer knows whether a deal was done (with him/her, but also with another dealer, without knowing the identity of this dealer) or not.

7. If a transaction occurred, the best dealer usually knows the cover price (second best price), if there is one.
Motivation

The electronification of the request process between supply-siders and liquidity providers generates a lot of data.

But the full amount of information for any RFQ process is not available to dealers ⇒ a “partial information” problem.
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- supplied by one of the most important dealers in European corporate bonds (BNP Paribas);
- A fraction of the RFQs received by this dealer over one year (part of 2013 and 2014).
- Each RFQ characteristics (date, hour, id of the client, Isin of the bond, buy/sell side, notional, number of dealers requested, etc.), contextual information (BNPP answered prices, CBBT prices), and the outcomes of the RFQ (deal or not, cover price if a trade with BNPP).
Motivation: the goal

- A parsimonious **model for the RFQ process**, in which the (unobserved) prices answered by other dealers follow an unknown distribution, and where clients decide to trade or not to trade depending on a (unobserved) reservation value following another unknown distribution.
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- Dependence of the behavior of dealers on the number of dealers requested, the type of bonds, etc.
A RFQ $i$ corresponding to a “buy” order: the client sends a request to buy the bond. The dealer then answers a quote to sell the bond.
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2. This client sends a RFQ to \( n_i + 1 \) dealers – \( n_i \in \{0, \ldots, 5\} \) – to buy a number of bonds.

   Dealer \( k \)’s own evaluation of the bond price: he/she answers a binding price \( W_{k,i} \) (no collusion between dealers).

   \( W_{k,i} \) will be the transaction price if the dealer \( k \) is chosen by the client: the \( n_i + 1 \) dealers compete with each other.
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3. A deal occurs iff a dealer proposes a bond price that is lower than $V_i$: the deal price is $\min_{k=0,\ldots,n_i} W_{k,i}$. 
Assumption: \( V_i \sim F(\cdot|\Omega_i), \ W_{k,i} \sim G(\cdot|\Omega_i) \).

In the case of “sell” RFQs, same notations with a star: \( F^*, G^* \).

The distributions of dealers’ quotes are assumed to be the same across dealers and clients.

To complete the model specifications, we state our assumptions concerning the functional form of the functions \( F \) and \( G \).
It is convenient to work with “reduced quotes”:

\[
(V_i - CBBT_i)/\Delta_i \quad \text{for clients, and}
\]

\[
(W_{k,i} - CBBT_i)/\Delta_i \quad \text{for dealers, where}
\]

- $CBBT_i$ is the CBBT offer price in the case of a “buy” RFQ, and the CBBT bid price in the case of a “sell” RFQ.
- $\Delta_i$ is the streamed bid-to-mid \(i.e.,\) half the streamed bid-ask spread constitutes a proxy of liquidity.
The model: covariates

Include some bond/RFQ characteristics (volume, investment grade/high-yield, maturity, issuer, inventory, etc.).

Covariates stacked into a vector \( Z := [Z_1, Z_2]' \).

\[
F(\xi|\Omega_i) = F_0\left(\frac{\xi - \text{CBBT}_i - Z'_{i,1}b_D}{\Delta_i} - Z'_{i,2}c_D\right),
\]

\[
F^*(\xi|\Omega_i) = F_0^*\left(\frac{\xi - \text{CBBT}_i - Z'_{i,1}b_D^*}{\Delta_i} - Z'_{i,2}c_D^*\right),
\]

\[
G(\xi|\Omega_i) = G_0\left(\frac{\xi - \text{CBBT}_i - Z'_{i,1}b_C}{\Delta_i} - Z'_{i,2}c_C\right),
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G^*(\xi|\Omega_i) = G_0^*\left(\frac{\xi - \text{CBBT}_i - Z'_{i,1}b_C^*}{\Delta_i} - Z'_{i,2}c_C^*\right),
\]

for some cumulative distribution functions \( F_0, F_0^*, G_0, \) and \( G_0^* \).
The exponential power distribution (Subotin, 1923):

$$f_{EP}(x; \mu, \sigma, \alpha) = \frac{1}{c\sigma} \exp \left( -|z|^\alpha / \alpha \right), \; x \in \mathbb{R},$$

$$\alpha > 1, \; \mu \in \mathbb{R}, \; \sigma > 0, \; z := (x - \mu)/\sigma, \; c := 2\alpha^{1/\alpha - 1}\Gamma(1/\alpha).$$
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Adding \(\lambda\) (asymmetry), the SEP distribution (Azzalini, 1985);

\[ f_{SEP}(x) = 2\Phi(w) f_{EP}(x; \mu, \sigma, \alpha), \ x \in \mathbb{R}, \quad (1) \]

\[ w := \text{sign}(z)|z|^{\alpha/2}\lambda(2/\alpha)^{1/2}, \ \Phi \text{ cdf of a } \mathcal{N}(0, 1). \]
The model: parametric specification

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The SEP reduces to the exponential power when \( \lambda = 0 \), to the skew normal when \( \alpha = 2 \), and to the normal when \( (\lambda, \alpha) = (0, 2) \).

We consider \( \alpha \leq 2 \), so that our distributions are fat-tailed. See Azzalini (1986), DiCiccio and Monti (2004).
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If $Z \sim SEP(0, 1, \alpha, \lambda)$, its moments are

$$E[Z^{2m}] = \alpha^{2m/\alpha} \Gamma((2m + 1)/\alpha)/\Gamma(1/\alpha), \ m \in \mathbb{N},$$

$$E[Z^{2m+1}] = \frac{2\alpha^{(2m+1)/\alpha} \lambda}{\sqrt{\pi} \Gamma(1/\alpha)(1 + \lambda^2)^{s+1/2}} \sum_{n=0}^{\infty} \frac{\Gamma(s + n + 1/2)}{(2n + 1)!!} \left( \frac{2\lambda^2}{1 + \lambda^2} \right)^n,$$

where $s = 2(m + 1)/\alpha$ and $(2n + 1)!! := 1 \cdot 3 \cdot \cdots (2n - 1) \cdot (2n + 1)$. 
The model: parametric specification

Assumption: the distribution functions $F_0$ and $F_0^*$ are of the skew exponential power type, $n = 0, \ldots, 5$.

Concerning clients: assume that $V_i$ is Gaussian conditionally to $\Omega_i$:

$$G_0(\cdot | \Omega_i) \sim \mathcal{N}(\nu, \tau^2), \quad G_0^*(\cdot | \Omega_i) = \mathcal{N}(\nu^*, (\tau^*)^2).$$

We expect $\nu > 0$ and $\nu^* < 0$. 
Estimation by Maximum likelihood is possible in theory, but tedious coding, numerical uncertainty (integrals) and slow convergence.
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**Alternative:** the Monte-Carlo Markov chain (MCMC) methodology, assuming a bayesian framework.

This means all parameters are random, but the reservation prices $V_i$ and the dealer prices $W_{i,k}$ too.

Since they are not observed in general, they have to be simulated, through Markov chains.
The underlying vector of model parameters $\zeta := (\tilde{\alpha}, \tilde{\beta})$, where $\tilde{\alpha}$ (resp. $\tilde{\beta}$) is the vector of parameters of $G$ (resp. dealers' quotes $F$).

**Algorithm 1 Specific Gibbs sampler**

1. Initialize (e.g. at random) $(\tilde{\alpha}^0, \tilde{\beta}^0, V^0, W^0)$
2. for iteration $t=1$ to $T$
   a. Simulate $\tilde{\alpha}^t$ from $\pi(\tilde{\alpha}^t | \tilde{\beta}^{t-1}, V^{t-1}, W^{t-1}, X, \Omega)$
   b. Simulate $\tilde{\beta}^t$ from $\pi(\tilde{\beta}^t | \tilde{\alpha}^t, V^{t-1}, W^{t-1}, X, \Omega)$
   c. Simulate $V^t$ from $\pi(V^t | \tilde{\alpha}^t, \tilde{\beta}^t, W^{t-1}, X, \Omega)$
   d. Simulate $W^t$ from $\pi(W^t | \tilde{\alpha}^t, \tilde{\beta}^t, V^t, X, \Omega)$
3. end for

The Markov chain $(\tilde{\alpha}^t, \tilde{\beta}^t, V^t, W^t)_{t=1}^T$ converges in law towards its stationary distribution given the data. We deduce the law of $(\tilde{\alpha}, \tilde{\beta})$ given $(X, \Omega)$ (the "posterior").
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Algorithm 2 Specific Gibbs sampler

Initialize (e.g. at random) $(\tilde{\alpha}^0, \tilde{\beta}^0, V^0, W^0)$

for iteration $t=1$ to $T$ do
    Simulate $\tilde{\alpha}^t$ from $\pi(\tilde{\alpha}^t | \tilde{\beta}^{t-1}, V^{t-1}, W^{t-1}, X, \Omega)$
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### Empirical results: model parameters

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<thead>
<tr>
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<tr>
<td><strong>“buy” RFQs</strong></td>
<td></td>
<td>mean</td>
<td>1.41</td>
<td>1.35</td>
<td>-0.61</td>
<td>2.90</td>
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<td><strong>“sell” RFQs</strong></td>
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<td>mean</td>
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**Table:** Estimation of the model parameters for the “buy” and “sell” RFQs, by MCMC. Statistics computed over the last 1500 iterations among 3000.
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All these random parameters have very tight distributions: means and medians are close to one another.
Empirical results: estimated distributions of reduced quotes

Figure: Distributions $F_0$ and $G_0$ estimated using the “buy” RFQs. Red line: SEP distribution for the dealers’ quotes. Green line: Gaussian distribution for the clients’ reservation prices.
Empirical results: estimated distributions of reduced quotes

Figure: Distributions $F_0^*$ and $G_0^*$ estimated using the “sell” RFQs. Red line: SEP distribution for the dealers’ quotes. Green line: Gaussian distribution for the clients’ reservation prices.
The distributions of the dealers’ quotes are clearly asymmetric (skewed).

In the case of a “buy” RFQ, almost no difference between answering a high price and a very high price.

However, a significant difference between answering a low price and a very low price: in both cases a trade may occur!
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These distributions are also heavy-tailed.

In practice, some dealers could not answer effectively: they do not answer fast enough; some other dealers are not interested in trading the requested bond, or dealing with this client...
Empirical results: estimated distributions of reduced quotes

Figure: Comparison of the distributions of dealers’ quotes and clients’ reservation prices for “buy” and “sell” RFQs. Red: SEP distributions for the dealers. Green: Gaussian distributions for the clients. Solid lines: “buy” RFQs. Dotted lines: “sell” RFQs, after symmetrization.
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<th>kurtosis</th>
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<td>6.188</td>
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<td>6.360</td>
<td>-1.395</td>
<td>9.851</td>
</tr>
</tbody>
</table>

**Table:** First four moments of the distributions of the dealers’ quotes (when the model parameters are fixed to their means).
Empirical results: the influence of competition

It is likely that the behavior of dealers and clients depends on the level of competition.

(i) how does the distribution of answered quotes depend on the number of dealers requested?

(ii) are the distributions of clients’ reservation prices similar for clients requesting a few dealers and clients requesting a lot of dealers?

(iii) do clients obtain better prices by requesting more dealers?
## Empirical results: the influence of competition

The table below shows the estimation of the model parameters for the “buy” RFQs and for different fixed numbers of dealers.

<table>
<thead>
<tr>
<th></th>
<th>dealers</th>
<th>clients</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\alpha$</td>
<td>$\lambda$</td>
</tr>
<tr>
<td>$n_i = 1$</td>
<td>mean</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.33</td>
<td>0.22</td>
</tr>
<tr>
<td></td>
<td>1.24</td>
<td>0.18</td>
</tr>
<tr>
<td></td>
<td>1.32</td>
<td>0.21</td>
</tr>
<tr>
<td></td>
<td>1.40</td>
<td>0.24</td>
</tr>
<tr>
<td></td>
<td>0.12</td>
<td>0.06</td>
</tr>
<tr>
<td>$n_i = 2$</td>
<td>mean</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.42</td>
<td>0.68</td>
</tr>
<tr>
<td></td>
<td>1.36</td>
<td>0.64</td>
</tr>
<tr>
<td></td>
<td>1.42</td>
<td>0.68</td>
</tr>
<tr>
<td></td>
<td>1.48</td>
<td>0.72</td>
</tr>
<tr>
<td></td>
<td>0.09</td>
<td>0.07</td>
</tr>
<tr>
<td>$n_i = 3$</td>
<td>mean</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.51</td>
<td>1.23</td>
</tr>
<tr>
<td></td>
<td>1.45</td>
<td>1.15</td>
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<tr>
<td></td>
<td>1.50</td>
<td>1.22</td>
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<tr>
<td></td>
<td>1.56</td>
<td>1.29</td>
</tr>
<tr>
<td></td>
<td>0.08</td>
<td>0.11</td>
</tr>
<tr>
<td>$n_i = 4$</td>
<td>mean</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.31</td>
<td>1.18</td>
</tr>
<tr>
<td></td>
<td>1.28</td>
<td>1.14</td>
</tr>
<tr>
<td></td>
<td>1.31</td>
<td>1.17</td>
</tr>
<tr>
<td></td>
<td>1.34</td>
<td>1.21</td>
</tr>
<tr>
<td></td>
<td>0.05</td>
<td>0.06</td>
</tr>
<tr>
<td>$n_i = 5$</td>
<td>mean</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.46</td>
<td>1.85</td>
</tr>
<tr>
<td></td>
<td>1.43</td>
<td>1.76</td>
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<tr>
<td></td>
<td>1.46</td>
<td>1.83</td>
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<tr>
<td></td>
<td>1.49</td>
<td>1.92</td>
</tr>
<tr>
<td></td>
<td>0.05</td>
<td>0.11</td>
</tr>
</tbody>
</table>

Table: Estimation of the model parameters for the “buy” RFQs and for different fixed numbers of dealers.
Empirical results: the influence of competition

<table>
<thead>
<tr>
<th></th>
<th>dealers</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\alpha^*$</td>
<td>$\lambda^*$</td>
<td>$\mu^*$</td>
<td>$\sigma^*$</td>
<td>$\nu^*$</td>
<td>$\tau^*$</td>
</tr>
<tr>
<td>$n_i = 1$</td>
<td>mean</td>
<td>1.28</td>
<td>0.10</td>
<td>0.07</td>
<td>0.89</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>$q_{25%}$</td>
<td>1.20</td>
<td>0.04</td>
<td>0.02</td>
<td>0.87</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>$q_{50%}$</td>
<td>1.27</td>
<td>0.10</td>
<td>0.06</td>
<td>0.89</td>
<td>0.29</td>
</tr>
<tr>
<td></td>
<td>$q_{75%}$</td>
<td>1.36</td>
<td>0.15</td>
<td>0.11</td>
<td>0.91</td>
<td>0.32</td>
</tr>
<tr>
<td></td>
<td>std dev.</td>
<td>0.12</td>
<td>0.08</td>
<td>0.08</td>
<td>0.03</td>
<td>0.06</td>
</tr>
<tr>
<td>$n_i = 2$</td>
<td>mean</td>
<td>1.16</td>
<td>-0.41</td>
<td>0.26</td>
<td>1.40</td>
<td>-1.42</td>
</tr>
<tr>
<td></td>
<td>$q_{25%}$</td>
<td>1.12</td>
<td>-0.43</td>
<td>0.23</td>
<td>1.38</td>
<td>-1.54</td>
</tr>
<tr>
<td></td>
<td>$q_{50%}$</td>
<td>1.16</td>
<td>-0.41</td>
<td>0.26</td>
<td>1.40</td>
<td>-1.39</td>
</tr>
<tr>
<td></td>
<td>$q_{75%}$</td>
<td>1.21</td>
<td>-0.38</td>
<td>0.28</td>
<td>1.42</td>
<td>-1.29</td>
</tr>
<tr>
<td></td>
<td>std dev.</td>
<td>0.07</td>
<td>0.04</td>
<td>0.04</td>
<td>0.03</td>
<td>0.21</td>
</tr>
<tr>
<td>$n_i = 3$</td>
<td>mean</td>
<td>1.10</td>
<td>-0.59</td>
<td>0.29</td>
<td>1.77</td>
<td>-1.58</td>
</tr>
<tr>
<td></td>
<td>$q_{25%}$</td>
<td>1.05</td>
<td>-0.61</td>
<td>0.26</td>
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<td>-1.67</td>
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<td></td>
<td>$q_{50%}$</td>
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<td>0.28</td>
<td>1.77</td>
<td>-1.57</td>
</tr>
<tr>
<td></td>
<td>$q_{75%}$</td>
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<td>0.31</td>
<td>1.80</td>
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</tr>
<tr>
<td></td>
<td>std dev.</td>
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<td>0.05</td>
<td>0.04</td>
<td>0.04</td>
<td>0.17</td>
</tr>
<tr>
<td>$n_i = 4$</td>
<td>mean</td>
<td>1.05</td>
<td>-0.71</td>
<td>0.37</td>
<td>2.21</td>
<td>-1.94</td>
</tr>
<tr>
<td></td>
<td>$q_{25%}$</td>
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<td>0.35</td>
<td>2.19</td>
<td>-2.00</td>
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<td></td>
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<td>0.37</td>
<td>2.21</td>
<td>-1.92</td>
</tr>
<tr>
<td></td>
<td>$q_{75%}$</td>
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<td>0.39</td>
<td>2.24</td>
<td>-1.86</td>
</tr>
<tr>
<td></td>
<td>std dev.</td>
<td>0.03</td>
<td>0.03</td>
<td>0.02</td>
<td>0.03</td>
<td>0.13</td>
</tr>
<tr>
<td>$n_i = 5$</td>
<td>mean</td>
<td>1.23</td>
<td>-1.20</td>
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<td>2.84</td>
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<td>0.69</td>
<td>2.82</td>
<td>-2.07</td>
</tr>
<tr>
<td></td>
<td>$q_{50%}$</td>
<td>1.24</td>
<td>-1.20</td>
<td>0.70</td>
<td>2.84</td>
<td>-2.00</td>
</tr>
<tr>
<td></td>
<td>$q_{75%}$</td>
<td>1.25</td>
<td>-1.17</td>
<td>0.71</td>
<td>2.87</td>
<td>-1.94</td>
</tr>
<tr>
<td></td>
<td>std dev.</td>
<td>0.03</td>
<td>0.04</td>
<td>0.02</td>
<td>0.03</td>
<td>0.09</td>
</tr>
</tbody>
</table>

Table: Estimation of the model parameters for the “sell” RFQs and for different fixed numbers of dealers.
Empirical results: the influence of competition

<table>
<thead>
<tr>
<th>“buy”</th>
<th>mean</th>
<th>variance</th>
<th>skewness</th>
<th>kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>$n_i = 1$</td>
<td>0.046</td>
<td>1.381</td>
<td>0.004</td>
<td>4.395</td>
</tr>
<tr>
<td>$n_i = 2$</td>
<td>0.650</td>
<td>2.560</td>
<td>0.401</td>
<td>4.188</td>
</tr>
<tr>
<td>$n_i = 3$</td>
<td>1.169</td>
<td>4.027</td>
<td>0.395</td>
<td>2.127</td>
</tr>
<tr>
<td>$n_i = 4$</td>
<td>1.571</td>
<td>6.133</td>
<td>0.683</td>
<td>3.323</td>
</tr>
<tr>
<td>$n_i = 5$</td>
<td>2.082</td>
<td>8.193</td>
<td>0.497</td>
<td>1.962</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>“sell”</th>
<th>mean</th>
<th>variance</th>
<th>skewness</th>
<th>kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>$n_i = 1$</td>
<td>0.169</td>
<td>1.154</td>
<td>0.109</td>
<td>9.341</td>
</tr>
<tr>
<td>$n_i = 2$</td>
<td>-0.402</td>
<td>2.758</td>
<td>-0.656</td>
<td>9.714</td>
</tr>
<tr>
<td>$n_i = 3$</td>
<td>-0.856</td>
<td>4.240</td>
<td>-1.146</td>
<td>10.436</td>
</tr>
<tr>
<td>$n_i = 4$</td>
<td>-1.285</td>
<td>6.491</td>
<td>-1.490</td>
<td>10.672</td>
</tr>
<tr>
<td>$n_i = 5$</td>
<td>-1.628</td>
<td>7.117</td>
<td>-0.878</td>
<td>4.114</td>
</tr>
</tbody>
</table>

Table: First four moments of the distributions $F_0(\cdot; n)$ and $F_0^*(\cdot; n)$ of the dealers’ quotes (when the model parameters are fixed to their means).
Empirical results: the influence of competition

Figure: SEP distributions \((F_0(\cdot; n))_n\) for the dealers’ quotes on some subsamples of “buy” RFQs (fixed values of \(n_i\)). Blue dashed line: \(n = 1\). Blue solid line: \(n = 2\). Black dash-dotted line: \(n = 3\). Black dotted line: \(n = 4\). Black solid line: \(n = 5\). Red line: all “buy” RFQs.
Empirical results: the influence of competition

Figure: SEP distributions \( (F_0^*(:, n))_n \) for the dealers’ quotes on the subsamples of “sell” RFQs (fixed values of \( n_i \)). Blue dashed line: \( n = 1 \). Blue solid line: \( n = 2 \). Black dash-dotted line: \( n = 3 \). Black dotted line: \( n = 4 \). Black solid line: \( n = 5 \). Red line: all “sell” RFQs.
Empirical results: the influence of competition

In the case of “buy” (resp. “sell”) RFQs, the more dealers in competition, the higher (resp. lower) their answered quotes, i.e. the more conservative their answered quotes.

Possible explanations:

“Discouragement”? With many dealers, little chance to be chosen, and therefore no reason to spend time choosing a “aggressive” price.

A client requesting only a few dealers may be a client who has a close relationship with one or all of the dealers requested.

Selection bias: when a client requests $n + 1$ dealers, he may simply pick the dealers who have streamed the best prices.

Dealers who do not answer: the larger the number of requested dealers, the higher the probability that a dealer does not have time to answer.
Empirical results: the influence of competition

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Possible explanations:

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- A client requesting only a few dealers may be a client who has a close relationship with one or all of the dealers requested.
- **Selection bias:** when a client requests $n + 1$ dealers, he may simply pick the dealers who have streamed the best prices.
- Dealers who do not answer: the larger the number of requested dealers, the higher the probability that a dealer does not have time to answer.
Empirical results: the influence of competition

Figure: Gaussian distributions $\left(G_0(\cdot; n)\right)_n$ for the clients’ reservation values on the subsamples of “buy” RFQs. Blue dashed line: $n = 1$. Blue solid line: $n = 2$. Black dash-dotted line: $n = 3$. Black dotted line: $n = 4$. Black solid line: $n = 5$. Green line: all “buy” RFQs.
Empirical results: the influence of competition

Figure: Gaussian distributions \((G_0^*(\cdot; n))_n\) for the clients’ reservation values on the subsamples of “sell” RFQs. Blue dashed line: \(n = 1\). Blue solid line: \(n = 2\). Black dash-dotted line: \(n = 3\). Black dotted line: \(n = 4\). Black solid line: \(n = 5\). Green line: all “sell” RFQs.
Empirical results: the influence of competition

Monotonicity of implied (reduced) reservation prices with respect to the number of dealers.

Possible explanations:
- clients who are very confident in their views about a bond they want to buy or sell may tend to contact more dealers to be sure to quickly obtain an acceptable price;
- some (very demanding) clients may send RFQs to the 2 or 3 dealers who have streamed the most interesting prices, because they do not expect others to propose interesting prices;
- some informal agreements between clients and dealers may be reached outside of the MD2C platform.
Empirical results: the influence of competition

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Possible explanations:

- clients who are very confident in their views about a bond they want to buy or sell may tend to contact more dealers to be sure to quickly obtain an acceptable price;
Empirical results: the influence of competition

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Possible explanations:

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Empirical results: the influence of competition

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- some informal agreements between clients and dealers may be reached outside of the MD2C platform.
Empirical results: best prices

Figure: Distribution of the best (reduced) quote \((\min_k W_{k,i} - CBBT_i)/\Delta_i\) proposed to clients, calculated on each subsample of “buy” RFQs. Blue dashed line: \(n = 1\). Blue solid line: \(n = 2\). Black dash-dotted line: \(n = 3\). Black dotted line: \(n = 4\). Black solid line: \(n = 5\).
Figure: Distribution of the best (reduced) quote $(\max_k W_{k,i} - CBBi)/\Delta_i$ proposed to clients, calculated on each subsample of “sell” RFQs. Blue dashed line: $n = 1$. Blue solid line: $n = 2$. Black dash-dotted line: $n = 3$. Black dotted line: $n = 4$. Black solid line: $n = 5$. 
Empirical results: best offered prices

The average of the best price proposed to the clients tends to behaves monotonically with the number of dealers requested, as expected through the visual inspection of the previous figures.

<table>
<thead>
<tr>
<th>total number of dealers</th>
<th>“buy” RFQs</th>
<th>“sell” RFQs</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>-0.611</td>
<td>0.757</td>
</tr>
<tr>
<td>3</td>
<td>-0.641</td>
<td>0.917</td>
</tr>
<tr>
<td>4</td>
<td>-0.735</td>
<td>1.065</td>
</tr>
<tr>
<td>5</td>
<td>-0.940</td>
<td>1.257</td>
</tr>
<tr>
<td>6</td>
<td>-0.951</td>
<td>1.197</td>
</tr>
</tbody>
</table>

**Table:** Average of the best (reduced) quotes proposed to clients, for different levels of competition.
Empirical results: hit ratios

Hit ratios = the probability to trade, given that the RFQ led to a trade with one of the dealers.
Empirical results: hit ratios

Hit ratios = the probability to trade, given that the RFQ led to a trade with one of the dealers. For “buy” RFQs, if $n_i + 1$ dealers are requested, the hit ratio is the function of the (reduced) quote answered by the dealer

$$
\delta \mapsto (1 - F_0(\delta; n_i))^{n_i}.
$$

For “sell” RFQs, it is $\delta \mapsto F_0^*(\delta; n_i)^{n_i}$. 

Hit ratios are monotonic functions of the dealer prices. Hit ratios are decreasing functions of the number of requested dealers: the more dealers, the lower the probability to be the one who offers the best price.
Hit ratios = the probability to trade, given that the RFQ led to a trade with one of the dealers. For “buy” RFQs, if $n_i + 1$ dealers are requested, the hit ratio is the function of the (reduced) quote answered by the dealer

$$\delta \mapsto (1 - F_0(\delta; n_i))^{n_i}.$$ 

For “sell” RFQs, it is $\delta \mapsto F_0^*(\delta; n_i)^{n_i}$. 

Hit ratios are monotonic functions of the dealer prices. 

Hit ratios are decreasing functions of the number of requested dealers: the more dealers, the lower the probability to be the one who offers the best price.
Figure: Hit ratios for a “buy” RFQ, as a function of the answered reduced quote, for fixed numbers of competing dealers. Blue dashed line: \( n = 1 \). Blue solid line: \( n = 2 \). Black dash-dotted line: \( n = 3 \). Black dotted line: \( n = 4 \). Black solid line: \( n = 5 \).
Figure: Hit ratios for a “sell” RFQ, as a function of the answered reduced quote, for fixed numbers of competing dealers. Blue dashed line: $n = 1$. Blue solid line: $n = 2$. Black dash-dotted line: $n = 3$. Black dotted line: $n = 4$. Black solid line: $n = 5$. 
Empirical results: probability to trade

Probability to trade, given the price proposed and the number of dealers requested.

For “buy” RFQs, if $n_i + 1$ dealers are requested, this probability is the function of the dealer’s (reduced) quote

$$\delta \mapsto (1 - F_0(\delta; n_i))^{n_i} (1 - G_0(\delta; n_i)).$$

For “sell” RFQs, it is $\delta \mapsto F_0^*(\delta; n_i)^{n_i} G_0^*(\delta; n_i)$. 
Empirical results: probability to trade

Figure: Model probability of closing a “buy” deal, as a function of the answered (reduced) quote, for fixed numbers of competing dealers. Blue dashed line: $n = 1$. Blue solid line: $n = 2$. Black dash-dotted line: $n = 3$. Black dotted line: $n = 4$. Black solid line: $n = 5$. 
Empirical results: probability to trade

Figure: Model probability of closing a “sell” RFQ deal, as a function of the answered (reduced) quote, for fixed numbers of competing dealers. Blue dashed line: \( n = 1 \). Blue solid line: \( n = 2 \). Black dash-dotted line: \( n = 3 \). Black dotted line: \( n = 4 \). Black solid line: \( n = 5 \).
Unlike what happens with hit ratios, the probability to trade is an increasing function of the number of requested dealers.
Unlike what happens with hit ratios, the probability to trade is an **increasing function** of the number of requested dealers.

For a given price answered by the dealer, two effects are present:

(i) the probability to propose the best price decreases with the number of competing dealers, and
Unlike what happens with hit ratios, the probability to trade is an increasing function of the number of requested dealers.

For a given price answered by the dealer, two effects are present:

(i) the probability to propose the best price decreases with the number of competing dealers, and

(ii) the probability to propose a price that reaches the client’s reservation value increases with the number of competing dealers, because clients requesting only a few dealers tend to be more demanding. The latter effect dominates.
Empirical results: covariates

- bond seniority: “Senior” corporate bonds versus all the other types of bonds (the reference category);
- “Centered Price”: the difference between the bond CBBT and the median of corporate bond prices in the database.
- “Investment Grade” and “High-Yield”. The reference category = bonds issued by financial institutions;
- “LogNotional”: the logarithm of the notional of the RFQ.

All the variables belong to the sub-vector $Z_2$, except the variable “Centered Price”, which is part of $Z_1$. 
## Empirical results: covariates

<table>
<thead>
<tr>
<th></th>
<th>&quot;Buy&quot; dealers</th>
<th>&quot;Buy&quot; clients</th>
<th>&quot;Sell&quot; dealers</th>
<th>&quot;Sell&quot; clients</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>q25%</td>
<td>q50%</td>
<td>q75%</td>
</tr>
<tr>
<td>Senior</td>
<td>0.060</td>
<td>0.012</td>
<td>-0.017</td>
<td>-0.072</td>
</tr>
<tr>
<td>Centered Price</td>
<td>-0.005</td>
<td>-0.005</td>
<td>0.006</td>
<td>0.004</td>
</tr>
<tr>
<td>Bond type</td>
<td>Investment Grade</td>
<td>0.009</td>
<td>0.007</td>
<td>0.113</td>
</tr>
<tr>
<td></td>
<td>High-Yield</td>
<td>-0.064</td>
<td>-0.051</td>
<td>0.010</td>
</tr>
<tr>
<td>LogNotional</td>
<td>0.035</td>
<td>0.030</td>
<td>0.101</td>
<td>0.036</td>
</tr>
</tbody>
</table>

|            | mean          | q25%          | q50%          | q75%          |
| std dev.   | 0.028         | 0.039         | 0.038         | 0.074         |
|            | 0.000         | 0.010         | 0.008         | 0.010         |
| std dev.   | 0.050         | 0.093         | 0.074         | 0.093         |
|            | 0.000         | 0.005         | 0.010         | 0.005         |
|            | 0.000         | 0.005         | 0.006         | 0.006         |
| std dev.   | 0.050         | 0.093         | 0.074         | 0.093         |
|            | 0.000         | 0.005         | 0.010         | 0.005         |
| std dev.   | 0.000         | 0.005         | 0.010         | 0.005         |

**Table**: Estimation of the effect of the covariates, by MCMC. Statistics computed over the last 5000 iterations among 10000.
Conclusions and extensions

We have

1. introduced a structural model to explain the "implicit" quoting processes of clients and dealers in multi-dealer to platforms
2. estimated the model by MCMC for buy/sell RFQs
3. studied the impact of the number of requested dealers and some covariates
Applications of our work are numerous.

- A dealer can expect to **better analyze/manage hit ratios**, and better estimate the probability to trade at a given price.
Conclusions and extensions

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- The behavior of dealers answering a RFQ indeed depends on the degree of competition.
- A good model to estimate the reservation value of clients is important to choose the answers to the clients.
The tails of the client quote distributions seem to be too fat.

Possible extensions of the current model (under progress):

1. Every dealer has a probability $p$ to answer any RFQ;
2. $F$ is a mixture of distributions.