The Scope of OTC Relationships

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Abstract

We document that customers concentrate their OTC trading partners across asset classes. We also find that traders employed by a large European investment bank internalizes customers' relationships with other departments within the bank. We show that customers obtain a type of liquidity insurance by concentrating their trading with a particular dealer. In goods times they pay wider spreads than new customers, while in bad times they receive tighter spreads. Finally, we shed light on the role of salespeople in investment banks. We show that customers who are matched with powerful salespeople obtain even tighter spreads in bad times and pay a relatively smaller liquidity insurance premium in good times.

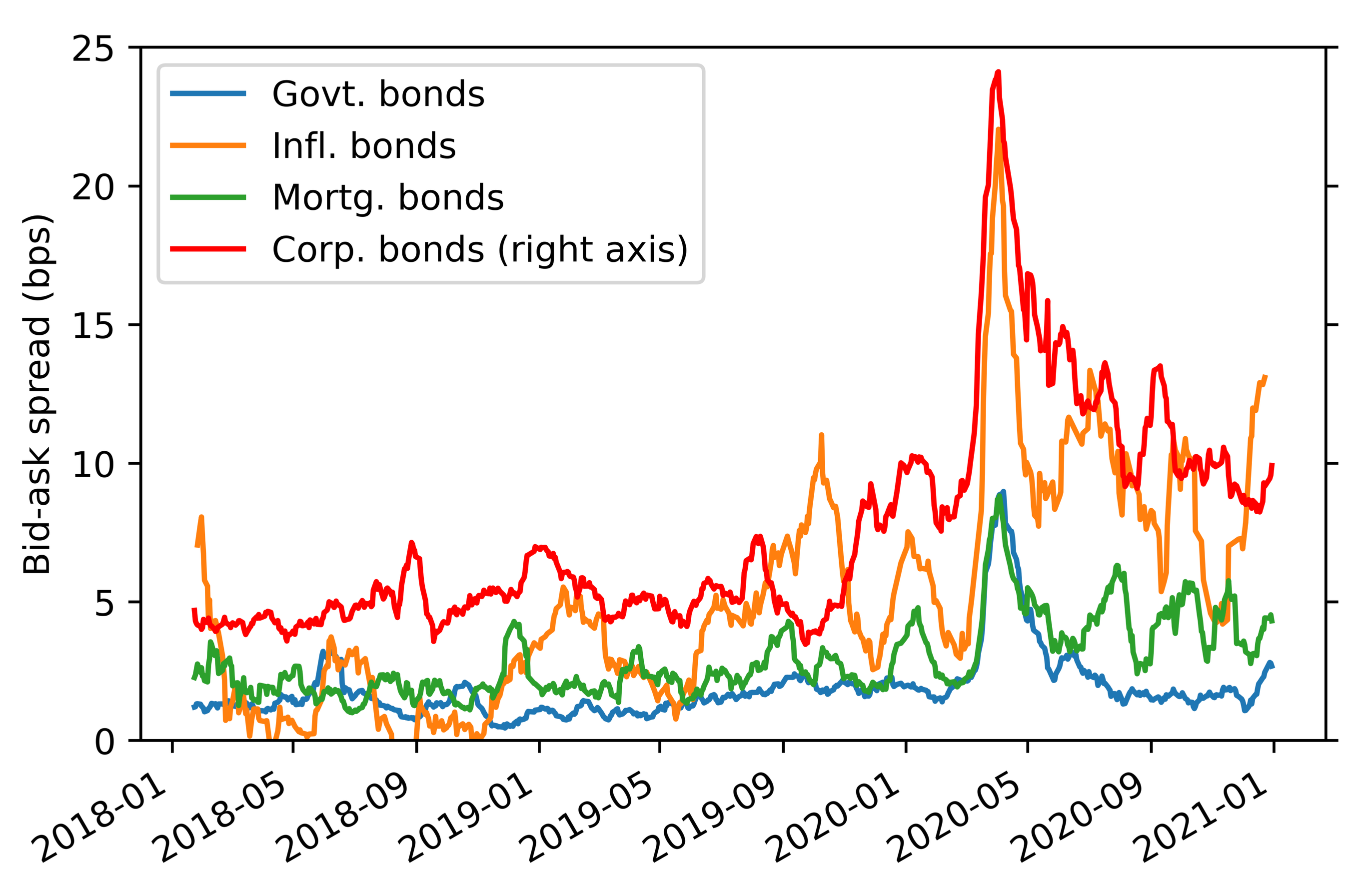
Motivation

- In the U.S. corporate bond market 65% of customers trade 80% or more of their yearly volume with just three counterparties, **What induces market participants in OTC markets to concentrate their trading with a select few dealers?**
- Most large OTC broker-dealers are active across multiple asset classes and currencies. **Are trading relationships dependant on activity in other asset classes?**
- Broker-dealers employ a significant amount of "salespeople", who intermediate between customers and traders. **Which role do the salespeople play in maintaining the trading relationship?**

Data

- 1,453 handcollected RTS28 reports from 2018-2021
  - Covers 14 different asset classes that are traded OTC (e.g. equity options, FX swaps, repo)
  - MiFID II requires investment companies to report their 5 most significant counterparties in each asset class
- Trade-level dataset from an anonymous European investment bank (among the top15 largest in Europe by total assets)
  - 1.391.829 requests-for-quote received by the fixed income department from 2018-2021
  - Covers different asset classes classes: corporate bonds, government bonds, inflation-linked bonds, mortgage bonds and interest-rate derivatives
  - Each trades contains an anonymous customer, trader and salesperson ID

Figure 1: Quoted bid-ask spreads in European bond markets during the 2020 crisis



Cross-market concentration of trading relationships

We first analyse the RTS28 reports to investigate whether investors concentrate their trading partners across asset classes. To test this, we run the regression:

$$Relationship_{c,d,m,y} = \beta_0 + \beta_1 AvgRelationship_{c,d,-m,y} + \alpha_{d,m,y} + \varepsilon_{c,d,m,y}$$

Where $Relationship_{c,d,m,y}$ is the % of volume or number of orders between client c and dealer d in market m in year y and $AvgRelationship_{c,d,-m,y}$ is the average relationship in all other markets than m.

Table 1 reports the regression results. We see that there is a strong correlation between the relationship intensity between a given dealer and customer across asset classes. The regression results imply that a customer who is already trading a lot of interest rate derivatives with a specific dealer will, on average, also use this dealer to trade e.g. corporate bonds.

Table 1: Cross-market regression results

	(1) % Volume	(2) % Volume	(3) % Orders	(4) % Orders
Avg % Volume	0.404***	0.324***		
	(5.93)	(4.58)		
Avg % Orders			0.519***	0.437***
			(7.52)	(6.51)
Cons	0.155***	0.155***	0.133***	0.135***
	(25.48)	(18.35)	(22.49)	(17.47)
r^2	0.045	0.331	0.073	0.399
Dealer x Market x Year FEs	✗	✓	✗	✓
N	1,453	1,000	1,453	1,000

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Relationship pricing

We now use the request-for-quote dataset to test the impact of a customer's relationship on his trades' bid-ask spreads, by running the following regression:

$$BidaskSpread_{c,i,t} = \beta_0 + \beta_1 Relationship_{t,c,l} + \beta_2 Relationship_{t,c,l} \cdot VIX_t + \beta_5 X_{i,t,c} + \alpha_i + \delta_{m,t} + \varepsilon_{c,i,t}$$

Where the left-hand side is the effective bid-ask spread for customer c trading instrument i on day t. $Relationship_{t,c,l}$ is standardized by its std. dev. and measures the past amount of trading volume done by customer c. X includes trade-level controls such as the number of competing bidders and trade size.

Table 2 reports the regression results. In the first specification, $\hat{\beta}_1 = 3.38$ and $\hat{\beta}_2 = -0.164$, implying that when $VIX = 0$ a customer with a 1 std. dev. stronger relationship pays a 3.4 bps higher spread. However during market crises, when the VIX is high, say $VIX = 50$, the same customer would pay 4.8 bps lower spread.

In specification 3 and 4, we decompose the relationship intensity into a $within$ and $outside$ component. The $within$ component measures the relationship within an asset classes, e.g. corporate bonds or interest rate derivatives, whereas the $outside$ component measures the relationship with all other departments. We see that the coefficients on both relationship measures are similar to specifications 1 and 2. This shows that a trader pricing a mortgage bond internalizes customers' past history not just with the mortgage department, but also with the dealer's other departments.

The role of salespeople

Figure 2 shows the connections between the 5 most powerful salespeople employed at the dealer, their customers and the traders. Each salesperson is responsible for a handful of customer and connects the customer to the traders within the different asset classes. The salespeople is responsible for handling the overall relationship between the customer and the bank. To test whether salesperson contribute in enforcing trading relationships, we construct a $Relationship$ variable measuring past trading activity between a trader and a salesperson.

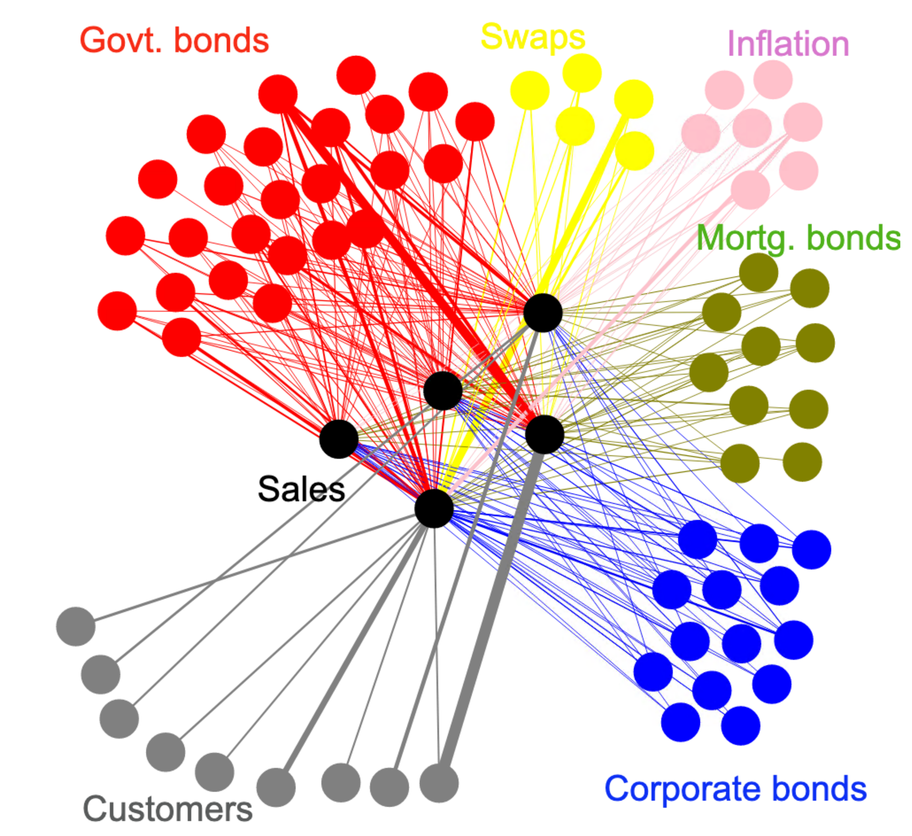


Figure 2: Network structure within the dealer

In untabulated regression analysis, we find that that customers who are matched with salespeople with strong relationships to traders, receive even lower spreads when VIX is high and pay less of a premium, when VIX is low.

Table 2: Relationship pricing regression results

	(1)	(2)	(3)	(4)
	LHS: Effective bid-ask spread in basis points			
$\text{Relationship}_{total}$	3.338***	0.728***		
	(9.58)	(3.97)		
$\text{Relationship}_{total} \cdot VIX$	-0.164***	-0.0419***		
	(-10.94)	(-4.68)		
$\text{Relationship}_{outside}$			1.419***	0.597**
			(5.09)	(2.79)
$\text{Relationship}_{outside} \cdot VIX$			-0.0684***	-0.0322**
			(-4.88)	(-2.84)
$\text{Relationship}_{within}$			3.075***	0.428*
			(8.52)	(2.13)
$\text{Relationship}_{within} \cdot VIX$			-0.151***	-0.0270**
			(-10.19)	(-2.84)
Unconditional mean	11.86	11.86	11.29	11.29
Controls	✓	✓	✓	✓
Day FEs	✓	✗	✓	✗
ISIN FEs	✓	✓	✓	✓
Asset class x Day FEs	✗	✓	✗	✓
r^2	0.429	0.507	0.431	0.509
N	581,864	581,864	569,172	569,172

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$