Clients' Connections

Measuring the Role of Private Information in Decentralised Markets

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The views expressed are those of the authors and not necessarily those of the Bank of England, the MPC, the FPC or PRC.

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- The main challenge: neither private information nor the identitites of its owners are observable
- We propose a **new proxy for private information** in dealer markets: clients' connections
  - definition of connections: the number of dealers with whom a client trades in a time period.

Main Findings

- **Time-variation** in connections is a proxy for (private) information
  - Client makes more profit after trading with more dealers

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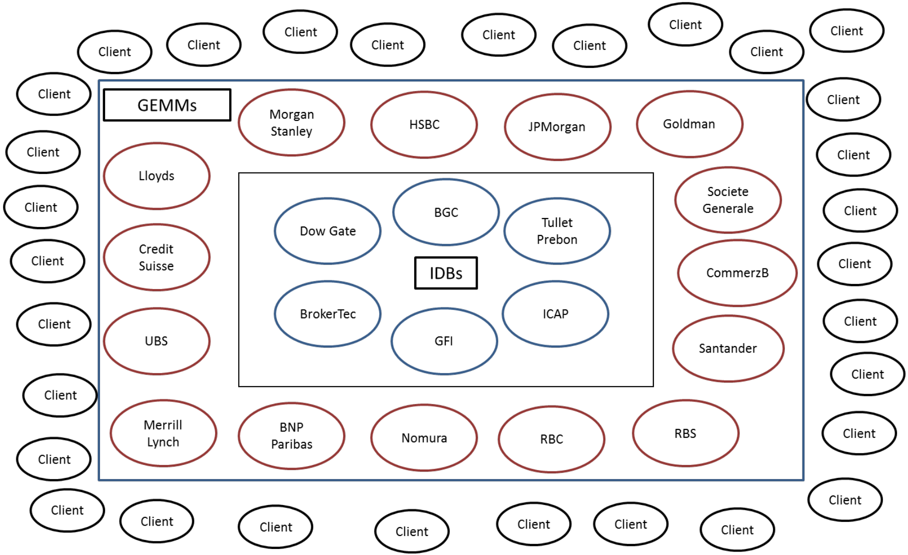
- Total connections in the market helps explain yield dynamics
- Application 1: dealers pass on information, from their informed clients, to their subsidiaries
- Application 2: informed clients better predict the order-flow intermediated by their dealers

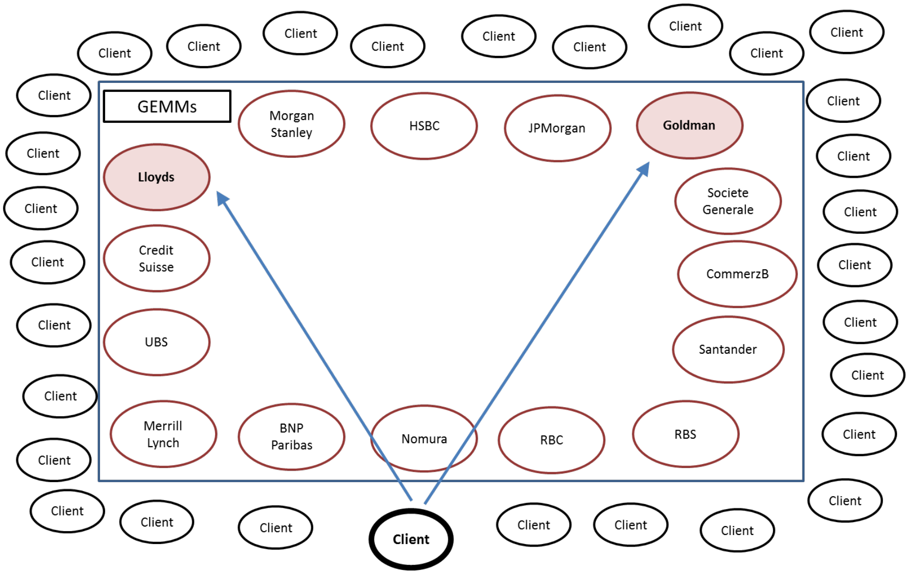
Outline

1. Market Structure and Data
2. Connections as Proxy for Private Information
3. Application 1: Dealers Learn from Informed Clients
4. Application 2: Nature of Private Information
5. Event Study - Brexit Referendum 23/06/2016

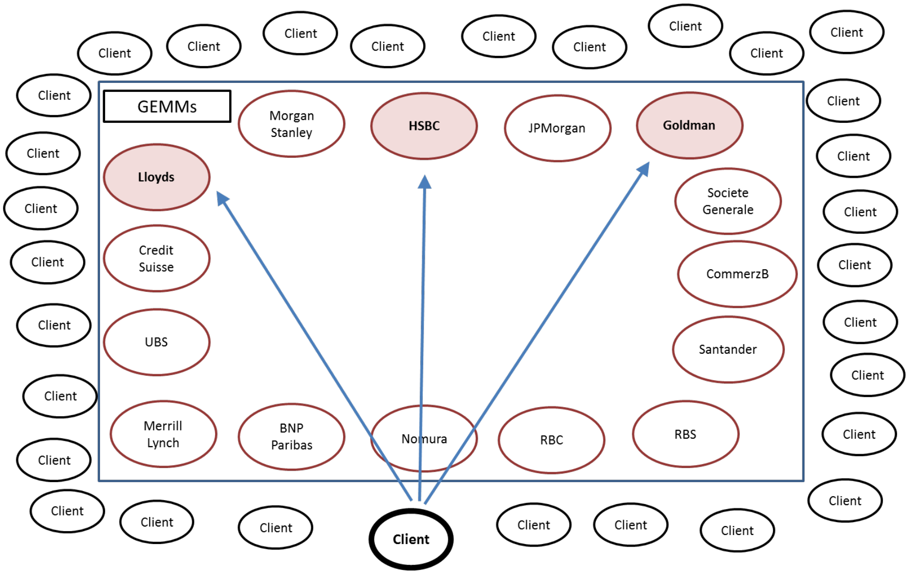
Structure of the UK Gilt Market



Illustrating Time-variation in Connections: t



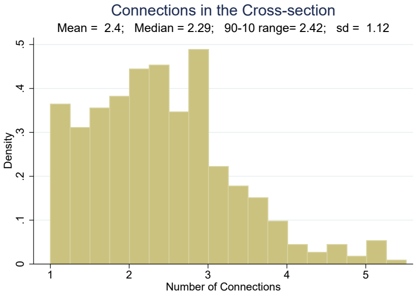
Illustrating Time-variation in Connections: t+1

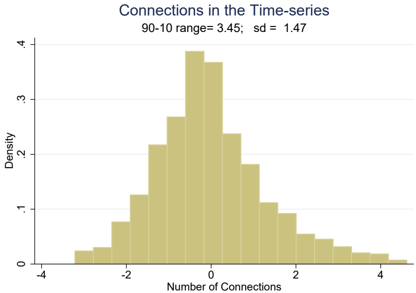


Data

- ZEN database: all the trades of gilts (and other fixed-income instruments) where one of the counter-parties is regulated by FCA
- 2011-2017
- for each transaction: price, quantity, direction, time-stamp, and the **identities of both counter-parties** (unlike in TRACE dataset)
- identify 480 clients during that period (covering 80% of universe of client trading volume) Summary Stats
- from Datastream: daily closing prices, basic gilt characteristics

Connections in the cross-section and in the time-series





Notes: these figures summarise the time-series and cross-sectional variation in our first-order centrality measure. The left panel plots the distribution of mean client Connections. To construct the right panel, we first run a panel regression to purge out client and day fixed effects ($Centrality_{i,t} = \alpha_i + \mu_t + \varepsilon_{i,t}$), and plot the distribution of the residuals ($\varepsilon_{i,t}$).

Cost and Benefits of Connections

Theoretical Model based on Glosten-Milgrom (1985)

- Benefit of connections: Trading with more dealers helps clients hide private information
- Cost of connections: reaching for quotes & establishing new dealer relationships is costly

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  If this is true, we should observe that:
  - more connected client's buy (sell) trade predicts higher (lower) future value
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  - the relation between connection and performance is stronger around informational events and informationally sensitive clients (e.g. hedge funds)
- Splitting trades in the *cross-section* instead of splitting over *time* (Kyle, 1985)

4 Testable Hypotheses

- **Hypothesis 1** [Profits] Time periods with more connections for a given client is associated with higher trading profit.
- **Hypothesis 2** [Client Type] These effects should be stronger for more sophisticated traders
- **Hypothesis 3** [Anticipation] More connections for a client *i* in a given period are associated with a stronger positive relation between her buy (sell) trades and subsequent price increases (decreases)
- **Hypothesis 4** [Aggregate Implications] Periods with higher aggregate connections are associated with larger absolute innovations in yields.

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Measuring Performance

- for each transaction τ of client i of gilt j, we measure signed h-day return by

$$r^h_{i,j,\tau} = s_{i,j,\tau} \left(\ln p_{j,\tau+h} - \ln p_{i,j,\tau} \right) \tag{3.1}$$

where $s_{i,j,\tau} = +/-$ is the direction of the transaction

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- Example: 3-day performance on trade when buying it on Monday at £100, and price on Thursday is £120:

$$\log(120) - \log(100) \approx 20\%$$

- We then calculate unweighted and volume weighted daily average

Decomposing Performance

- we further decompose our performance measure 3.1 as:

$$r^h_{i,j,\tau} = \underbrace{s_{i,j,\tau}\left(\ln \bar{p}^{s_{i,j,\tau}}_{j,\tau} - \ln p_{i,j,\tau}\right)}_{\text{transaction cost component}} + \underbrace{s_{i,j,\tau}\left(\ln p_{j,\tau+h} - \bar{p}^{s_{i,j,\tau}}_{j,\tau}\right)}_{\text{anticipation component}}$$

where $\bar{p}^{s_{i,j,\tau}}_{j,\tau}$ is the average transaction (bid or ask) price of gilt j in a given interval around τ (i.e. a day/three hours)

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- Example: buying it on Monday at £100, when everyone else is buying it at £105 [price on Thursday is £120]:

$$\underbrace{\log(105) - \log(100) \approx 5\%}_{\text{transaction cost component}} \quad \underbrace{\log(120) - \log(105) \approx 15\%}_{\text{anticipation component}}$$

Baseline Regression Model

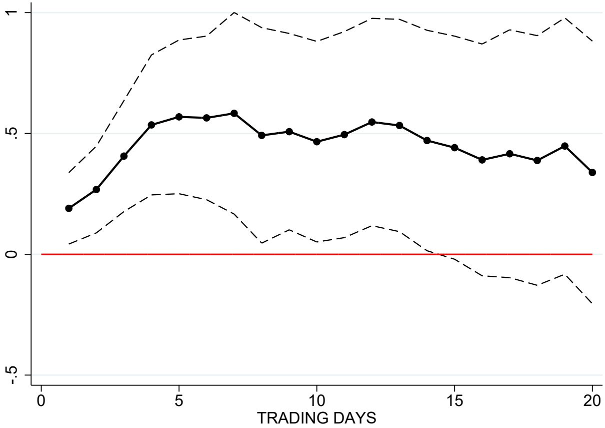
- We estimate at the client-day level:

$$Performance_{i,t}^{T} = \beta \times Connections_{i,t} + Controls_{i,t} + \alpha_{i,year} + \mu_t + \varepsilon_{i,t}$$

- for our various performance measures, over $T = 1, \ldots 20$
- *Controls* include (i) daily number of transactions and (ii) trading volume
- winsorize LHS at 1%-level, and double cluster all standard errors at the client and day level

H1: Performance Up to 20-day Horizon

Figure: Connections and Performance over 1-20 Day Horizons



H2: Sophisticated vs Unsophisticated Clients

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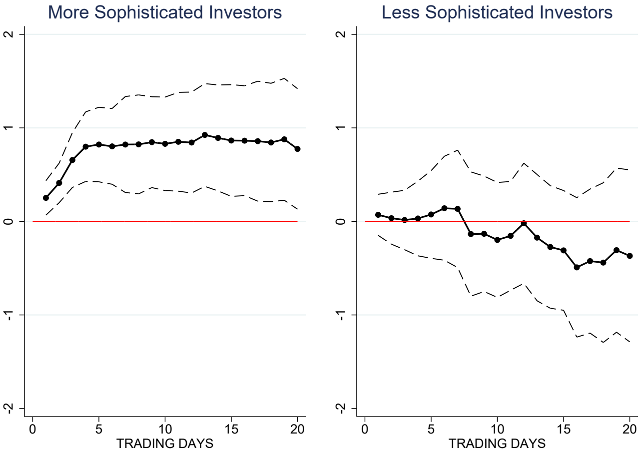

High- vs Low-Information Days

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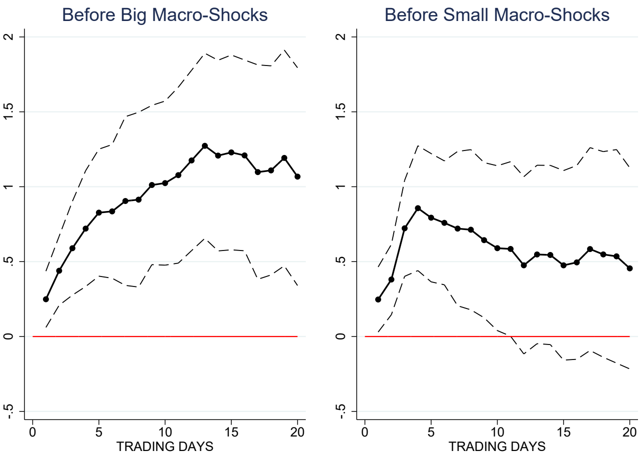

H3: Decomposing Performance [4-day ahead]

Table: Decomposing the effect into transaction & anticipation effects.

	(1) Baseline	(2) Transaction	(3) Anticipation
Client Connections	0.487***	0.099**	0.383**
	(3.08)	(2.53)	(2.37)
Volume	0.248	-0.090	0.318*
	(1.40)	(-1.51)	(1.81)
Tran.	-1.350***	-0.198	-1.098**
	(-3.14)	(-1.57)	(-2.56)
N	100414	100348	100348
R^2	0.057	0.100	0.055
Day FE	Yes	Yes	Yes
Client*Year FE	Yes	Yes	Yes

H4: Total Market Connections and the Yield Curve

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- We estimate daily time-series regressions:

$$|\Delta Yield_t| = \alpha + \beta \times TotalConnections_t + Controls_t + \varepsilon_t$$

where $Controls_t$ include:
(i) $Volume_t$ (Karpoff, 1987) and
(ii) $NumOfClients_t$ (Tauchen-Pitts, 1983)

H4: Total Market Connections and the Yield Curve

Table: Daily Changes in Yields and Aggregate Connections

	$\lvert \Delta Yield_t^{5Y} \rvert$			
	(1)	(2)	(3)	(4)
$\Delta \log(Connections_t)$	0.0277***		0.0233***	0.0234***
	(7.27)		(4.17)	(2.26)
$\Delta \log(Volume_t)$		0.0100***	0.0025	0.0025
		(6.11)	(1.07)	(1.06)
$\Delta \log(NumOfClients_t)$				-0.0001
				(-0.01)
N	1449	1449	1449	1449
R^2	0.040	0.030	0.041	0.041

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Dealers Learn from Informed Order Flow

Identification through Dealers' Affiliates

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- Identification strategy: for each dealer, distinguish between:
    - trading accounts of market-making function (mainly client trades, many transactions, primary auctions) from
    - trading accounts of client-like arms of dealers (mainly dealer trades, few transactions, e.g. asset-manager arms) $\longrightarrow$ **dealers' affiliates**

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  - trading accounts of client-like arms of dealers (mainly dealer trades, few transactions, e.g. asset-manager arms) $\longrightarrow$ **dealers' affiliates**
- Do dealers' affiliates perform better when their dealer trades with more high-connection clients?

Estimating the Information Flow from Clients to Dealers

- Estimate the performance regression for dealers' affiliates:

$$AffilPerformance^{T}_{i,t} = \beta \times InfShare_{i,t} + X_{i,t} + \alpha_i + \mu_t + \varepsilon_{i,t}, \quad (4.1)$$

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- where the informativeness of the dealer of the given affiliate is:

$$InfShare_{i,t} = \frac{Vol^{H}_{i,t}}{Vol^{L}_{i,t} + Vol^{H}_{i,t}}$$

Performance Regression of Dealers' Affiliates

Table: Dealers' Informed Clientele and the Performance of Dealers' Affiliates

	0-day	1-day	2-day
	(1)	(2)	(3)
InfShare	0.325	1.717**	2.080**
	(0.71)	(2.35)	(2.23)
DealerVolume	-0.020	-0.358*	-0.332
	(-0.17)	(-2.00)	(-1.24)
DealerConnections	0.003	0.022	-0.021
	(0.13)	(0.43)	(-0.24)
N	20898	20898	20898
R^2	0.079	0.082	0.078
Day FE	Yes	Yes	Yes
Affil.#Year FE	Yes	Yes	Yes

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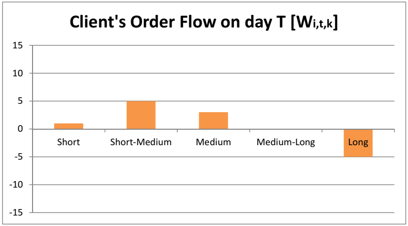
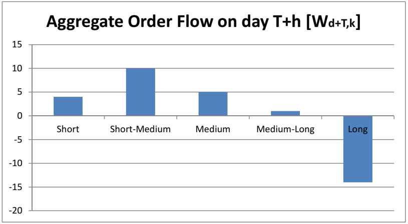
Measuring Order Flow Information

- Order flow drives prices in government bond markets (Fleming 1999, Brandt et al 2004, Green 2004)
- How to measure relevant information about future order flow?

A High Flow-Covariance Day: an Illustration





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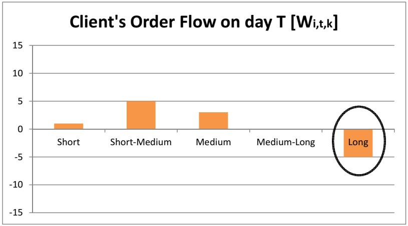
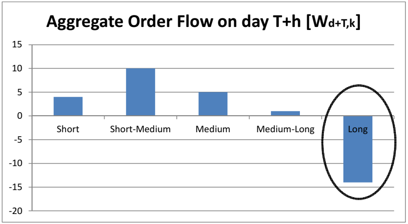
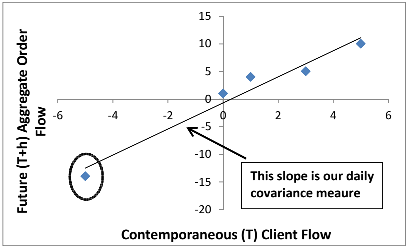
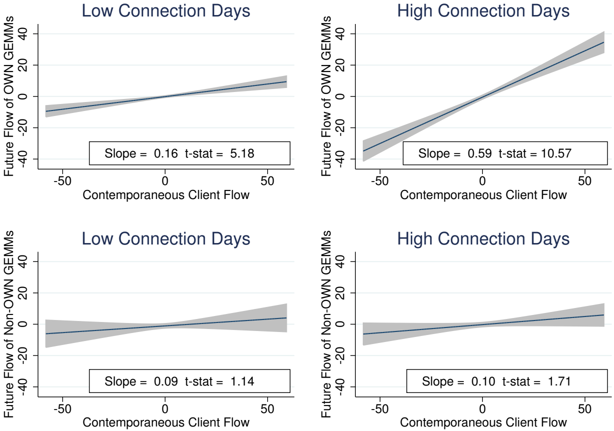






Decomposing Flows: Total via *i*'s Dealers vs other Dealers

Figure: Predicting Aggregate Order Flow: the Roles of Connections with Own Dealers



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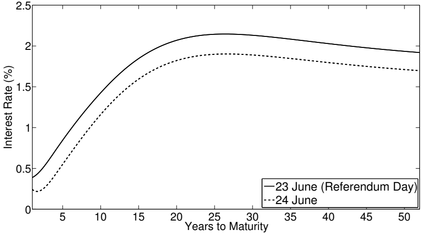
Brexit Referendum on 23 June 2016

- High information content of the event
- Brexit Referendum on Thursday (23 June 2016) $\rightarrow$ results became known on Friday morning (24 June 2016).
- The referendum results lead to an immediate drop in yields:
  - mainly parallel downward shift in the yield curve, rather than to changes in the slope.



Referendum on 23 June 2016: High-Connection Clients

Group clients (who traded on June 23) into two groups based on:

$$\alpha_i = connections_{i,Jun23} - \overline{connections}_i \tag{6.1}$$

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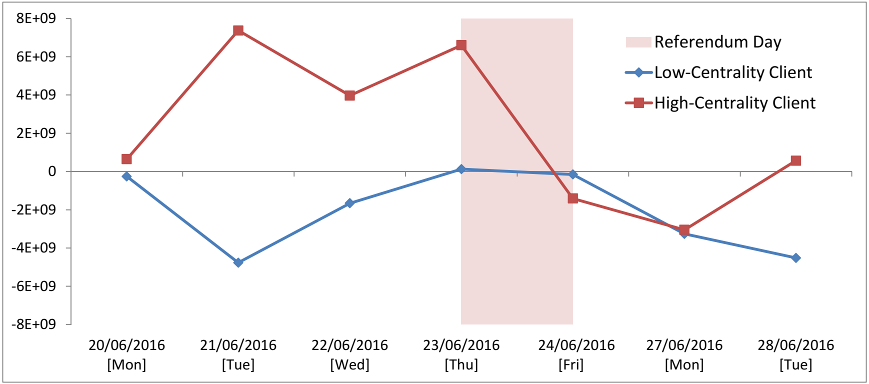
Table 1: Summary Statistics of the 125 Clients Trading on 23 June 2016

Client Type	5-day Perf. Mean	Number of Clients	α Mean	Volume Mean	Signed Duration Mean
Low-α	-0.004	63	-0.80	13.2m	1.9m
High-α	0.003	62	0.98	25.6m	106m

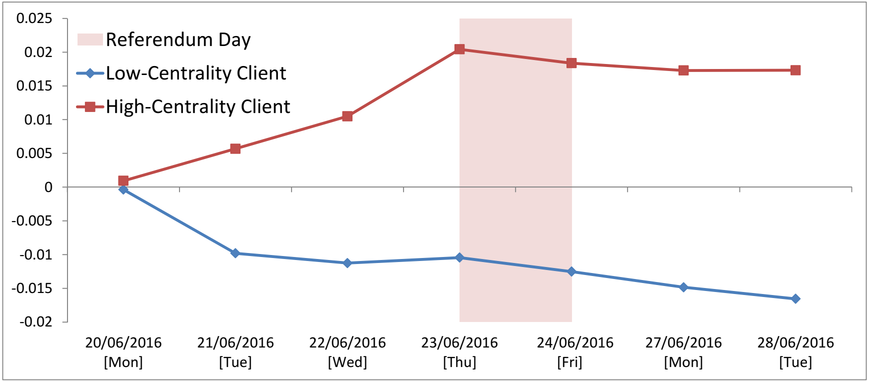
High-α and Low-α Clients Around the Vote: Positions

Figure: Aggregate Daily Net Duration of High-α and Low-α Clients



High-α and Low-α Clients Around the Vote: Performance

Figure: Cumulative Returns of Low-α and High-α Clients



Relation to Literature

- Literature on price discovery in government bond markets (Fleming 1999, Brandt et al 2004, Green 2004)
- Recent Literature of OTC markets: various theories of why network structure matters:
    - connected clients should earn higher returns:
        - more opportunities to intermediate (Atkeson et al, 2016)
        - better terms of trade as higher bargaining power (Hollifield et al, 2016)
        - more chance to learn: from more quotes (Babus and Kondor, 2017) or information leakages (di Maggio et al, 2017)
- Contribution of our paper twofold:
    1. Focus on the **time-variation** in client connections [rather than on the cross-sectional variation]
    2. Focus on **government bond markets** [a liquid market where private information should have limited role?!]

Extensions and Robustness Checks

- Alternative performance measure Realised Profits
- Aggregate Connections and Measures of Asymmetric Information Subrahmanyam
- Forecasting the Yield-Curve and Noise Forecasting Yield Curve Noise
- Client Heterogeneity High β-clients
- Further Decompositions of the Order Flow Market Order Flow
- Measuring connections with eigenvector-centrality Eigenvector-centrality
- Dealer Exits as Shocks to Connections GEMM Exits
- Results for corporate bonds are similar and stronger (Czech-Pinter, 2020)

Conclusion

- Main take-away: we propose a new proxy of private information in decentralised markets:

Client Connections!

References