Private Information and Client Connections in Government Bond Markets*

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Abstract

In government bond markets the number of dealers with whom clients trade changes through time. Our paper shows that this time-variation in clients' connections serves as a proxy for time-variation in private information. Using proprietary data covering close to all dealer-client transactions in the UK government bond market, we show that clients have systematically better performance when trading with more dealers, and this effect is stronger during macroeconomic announcements. Most of the effect comes from clients' increased ability to predict future yield changes (anticipation component) rather than these clients facing tighter bid-ask spreads (transaction component). To explore the nature of this private information, we find that clients with increased dealer connections can better predict the fraction of the aggregate order flow that is intermediated by dealers they regularly trade with. Positive trading performance is concentrated in those periods when clients have more dealer connections than usual.

JEL Classification: G12, G14, G24

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1 Introduction

The smooth operation of government bond trading is the backbone of developed financial markets. The rates of the yield curve serve as benchmarks in many financial transactions, they affect government financing costs and play an important role for the implementation of monetary policy. Hence, understanding how this market operates is of critical importance.

The classic view of government bond market activity is that variation in interest rates is mainly due to public information flow. According to this view, public news lead to instantaneous adjustments of the yield curve, and trading activity is the outcome of subsequent rebalancing. Since Fleming and Remolona (1997, 1999) there has been accumulating evidence that part of the price discovery in government bond markets occurs through trading activity. This suggests that clients and dealers have heterogeneous private information (or heterogeneous interpretation of public information) which is aggregated through trading, leading to changes in the yield curve.

In this paper, we contribute to this evidence by presenting three new empirical results. First, we identify a proxy for the variation in clients' private information in government bond markets. In particular, we show evidence that the time-variation in a client's connectedness, that is, the variation in the number of dealers with whom a client is trading within a given time-period, works well as such a proxy. Second, using this insight, we characterise the nature of private information the client is relying on. We find that informed clients forecast and trade against the composition of their own dealers' order flow. For example, these clients rebalance their trades towards short maturity assets a few days before their dealers receive orders predominantly for short maturity assets. Third, we find that these informed clients forecast the order flow of dealers that they have a regular relationship with, and not the order flow of newly connected dealers, suggesting that information flows from regular connections and not from new connections. These results are consistent with our proposed theoretical framework where connectedness serves as an instrument of concealing information (rather than playing an active role in the information acquisition process).

For our analysis, we exploit the structure of the UK gilt market and a detailed, transaction-level proprietary database. Conventional gilts are trading via primary dealers, usually referred to as gilt-edged market makers. Whenever clients (including foreign central banks, commercial banks, asset managers amongst others) trade these assets, they do so almost exclusively by trading with a dealer. Interestingly, there is a significant time-variation in the number of dealers with whom a given client trades across months and even across trading days. The basic premise of our paper is that this time-variation can help us learn about the nature of the relevant private information in this market. Using a simple model in the spirit of Glosten and Milgrom (1985), we explore the idea that trading with more dealers may be advantageous because it helps the client hide her private information. This, however, requires the client to reach out for quotes from more dealers, which is costly. Therefore, the client will do so only when the benefit of hiding information is sufficiently large, that is, when her information is sufficiently precise. In these periods, the client should overperform.

To illustrate the viability of this idea, we first analyse trading around the Brexit referendum. Based on public polls, the chances of a leave or a remain outcome were close to 50-50 leaning slightly towards remain immediately before the vote. The common perception was that a leave outcome would likely trigger a fall in interest rates, leading to an immediate downward shift in the yield curve on 24 June. Given the large uncertainty before the vote, market participants were motivated to either reduce their exposure radically, or to generate private information and bet on the outcome.[1] In line with our hypothesis, we show that a change in their number of dealer connections helps identify the client group with private information. In particular, the group of clients who were connected with more dealers on the day before the referendum persistently increased the duration of their positions for days before the referendum and, subsequently, outperformed other clients when the yield curve dropped on 24th of June.

Then we turn to systematic evidence. Most importantly, we should observe that when clients are connected to more dealers, their trades are more profitable. This effect should not be driven by smaller price impact, but by forecasting future price movements. That is, the price of gilts that clients buy in these periods should increase in subsequent days compared to the price of gilts that they sell. We also expect these differential effects to be more pronounced in more information sensitive periods, for example, around important macroeconomic announcements. We find empirical evidence for each of these predictions.

We go further and search for the source of private information captured by the time-variation in clients' connectedness. First, we show that trades which predict the maturity structure of market makers' total order flow are profitable. That is, it would be valuable for clients to be able to predict this maturity structure, because whichever maturity market makers sell, the price of the given bonds tend to go up. Then, we check whether clients can actually predict that. In particular, we look for co-movement between the maturity structure of connected client's trades and that of various segments of the market makers' order flow a few days later. We find that whenever the client is connected, the structure of her trades predict the part of the order flow which goes through the given client's primary dealers. However, she cannot predict the structure of the order flow which goes through other dealers. This suggests that a client becomes more connected when obtains information about

[1]Reportedly, major hedge funds ordered private opinion polls to generate an informational edge for this bet and earned handsomely on those bets:

> "Behind the scenes, a small group of people had a secret – and billions of dollars were at stake. Hedge funds aiming to win big from trades that day had hired YouGov and at least five other polling companies [...]. Their services, on the day and in the days leading up to the vote, varied, but pollsters sold hedge funds critical, advance information, including data that would have been illegal for them to give the public. Some hedge funds gained confidence, through private exit polls, that most Britons had voted to leave the EU, or that the vote was far closer than the public believed – knowledge pollsters provided while voting was still underway and hours ahead of official tallies." ("The Brexit Short: How Hedge Funds Used Private Polls to Make Millions", Bloomberg Businessweek, 25th June, 2018)

the maturity of her dealer's future order flow.

In addition, we show that the predictable part of the order flow is intermediated by those dealers that the client traded with not only on the day of increased connectedness (and of profitable trades) but during the preceding trading days as well. In contrast, the order flow of newly connected dealers is not predicted by informed clients, suggesting that connectedness merely helps transform private information into higher returns by concealing information (as in our model) instead of playing an active role in the information acquisition process. A limitation of our analysis is that we cannot observe whether the client is gathering information from the quotes she receives from her dealers, or dealers leak the information to its best clients.

Related Literature There is a growing empirical literature focusing on the role of dealer-client network in financial markets.[2] For example, Li and Schurhoff (2014) and Hollifield, Neklyudov, and Spatt (2017) study whether clients, trading with more central dealers, face higher or lower spreads. Gabrieli and Georg (2014) and Maggio, Kermani, and Song (2017) focus on the effect of the trading network on the transmission of shocks. Both highlight that the failure of a core dealer causes the connected dealers to change their pricing functions and to become less profitable. The recent work of Maggio, Franzoni, Kermani, and Sommavilla (2018), perhaps most related to our paper, analyses the broker-client network of a centralized stock-exchange, and argues that clients with more connected brokers are making more informed trades. A key difference between these papers and ours is that we focus on the *time-variation* in client connectedness rather than relying mainly on the cross-sectional variation in the centrality of dealers. Moreover, we separate the effect of client connectedness on the execution cost from the effect on the ability to predict price movements.

Our paper is also related to the large empirical literature on price discovery (Hasbrouck 1991; Evans and Lyons 2002) in financial markets. A partial list of papers focusing on government bond markets includes Fleming and Remolona (1997, 1999), Balduzzi, Elton, and Green (2001), Green (2004), Brandt and Kavajecz (2004), Andersen, Bollerslev, Diebold, and Vega (2007), Pasquariello and Vega (2007), Valseth (2013) amongst others. We add to this literature by showing that variation in client connectedness is related to the price discovery process in the UK gilt market. We are able to do so due to the important feature of our dataset that for each trade we can observe the identity of both parties. This allows us to map out the market's network structure and to explore its links with the process of price discovery.

The remainder of the paper is as follows: Section 2 introduces the environment, concepts and hypothesis illustrated by the example of financial betting around the Brexit referendum;

[2] There is a related, growing theoretical literature on financial trading in networks, such as Veldkamp, Lucca, and Boyarchenko (2017), Condorelli, Galeotti, and Renou (2017), Choi, Galeotti, and Goyal (2017), Malamud and Rostek (2017), Manea (2018) and Babus and Kondor (2018) amongst others.

Section 3 describes the data sources and provides summary statistics; Section 4 presents the empirical results on using client connectedness as a proxy for private information; Section 5 explores the nature of private information; Section 6 concludes.

2 Concepts, Hypotheses and Betting on Brexit

We start this section with a basic description of the micro-structure of the UK gilt market. Then, with the illustration of a simple model, we discuss our main hypotheses. Finally, we illustrate the viability of these hypotheses by taking a closer look at the gilt trading activity around the Brexit referendum.

2.1 Primary Dealers in the UK Gilt Market

The key actors in the UK gilt market are the primary dealers, also known as gilt-edged market markers (GEMMs). In our sample period between 2011 and 2017, their number fluctuates between 20 and 24. From now on, we refer to this group as dealers. The UK Debt Management Office (DMO) tenders new issues of government securities to dealers. Clients, as asset managers, commercial banks and foreign central banks buy and sell government securities mostly through bilateral transactions to this group.[3] Primary dealers are committed to make, on demand, continuous and effective two-way prices to their clients by regulation. They also must maintain a minimum market share (DMO, 2011).[4]

When a client trades in the UK gilt market, she can observe quotes of all dealers on electronic trading platforms. However, these observed quotes are merely indicative and only small trades can be executed at these prices. If the client wishes to trade a larger quantity, she directly contacts the dealers typically via the phone. Unlike other, centralised exchanges (e.g. the UK gilt futures market) that are increasingly automated, the gilt cash market, which our study focuses on, continues to retain its traditional OTC characteristics where reputation and trading relationships matter largely for dealers (to continue to attract order flow and thereby trading profitably) as well as for clients (to receive favourable price quotes.)

In our sample, we observe that clients tend to trade with a relatively small and persistent subset of all the dealers. In practice, this subset corresponds closely to the subset they requests quotes from. Based on interviews with traders, we understand that clients perceive that asking quotes from many dealers can be costly.[5] In particular, the main (perceived or

[3] In our sample, only about 1% of client trades are directly between clients.

[4] See Benos and Zikes (2018) for further details about the institutional arrangements of the UK gilt market.

[5] Moreover, even the dealer whose quote is accepted by the client pays some informational cost, as all the other dealers who have also been requested to provide quotes will know that the transaction took place. (In fact, the runner-up in the auction gets informed specifically that her quote was the second best.) Especially in the case of a large transaction, the dealers whose quotes were not accepted might use this price and

real) cost of asking for quotes, but not trading with some of the dealers is that it might damage the relationship between the client and the given dealers. For example, a dealer might feel that she gives out information on her inventory when providing tight quotes. This information might be used against the dealer. If this is not reciprocated with executed trades, the dealer might decide to give less informative, that is, less tight quotes to that particular client next time.

2.2 Client Connectivity and Private Information

The basic thought experiment behind our hypotheses is as follows. We conjecture that the main advantage of trading with more dealers is that it helps the trader to hide its private information.[6] However, this requires the client to reach out for quotes from those dealers, which might be costly. Then, the client will do so only when the advantage is large, that is, when its information is sufficiently precise.

There are multiple testable implications of this idea. We derive these hypotheses formally in Appendix B in a simple model of trading and network formation. We consider informed clients and uninformed liquidity traders interacting with market makers. The trading protocol is a modified version of Glosten and Milgrom (1985). The new element is that clients can decide whether to seek bid and ask quotes from one or more risk neutral, competitive market makers in each round. Sampling quotes from more market makers is costly. After observing the quotes, clients can decide whether to buy or sell a unit or abstain from trading in each round. The informativeness of clients' signals vary in the time-series and in the cross-section. We assume that announcements correspond to periods with more informative signals for many clients. The implications of the model are summarised in the following Corollary.

Corollary 1 *Under parametric assumptions, there is an equilibrium with the following features.*

1. *(Connectedness signals information) A more connected speculator is more informed, therefore, earns higher expected return on her trades, conditionally or unconditionally on trading size and trading intensity.*

2. *(Anticipation effect) A more connected speculator's buy trades predict higher future value, and sell trades predict lower future value.*

quantity information against the dealer (with the accepted quote) when she tries to manage the resulting change in her inventory in the inter-dealer market.

[6] Since Kyle (1985), the micro structure literature has extensively studied how private information can be concealed by, for example, splitting large orders in smaller amounts over time to avoid market impact (See Garleanu and Pedersen (2013) and Mascio, Lines, and Naik (2017) for recent contributions). To conceal information, market participants may use various mechanisms, as discussed in Duffie and Zhu (2017), such as workups (Fleming and Nguyen, 2017) and dark pools (Menkveld, Yueshen, and Zhu, 2017; Buti, Rindi, and Werner, 2017).

3. *(Announcements) The relation between connectedness and trading performance is stronger around announcements.*

The Corollary states that we should observe that when clients are connected to more dealers, they overperform. Also, this overperformance should not come from smaller price impact.[7] Instead, the price of government bonds, purchased by clients in these periods, should increase in subsequent days compared to the price of bonds they sell. Third, we expect these differential effects to be more pronounced in more information-sensitive periods, for example, around important macroeconomic announcements.

In Section 4, we test these hypotheses and find strong evidence for each of these predictions. In Section 5, we go further and search for the source of the private information captured by the time-variation in clients' connectedness. We provide detailed empirical evidence that the nature of private information proxied by connectedness pertains to information about the order flow that is intermediated by those dealers that the given client regularly trades with. Before turning to systematic evidence, we illustrate these ideas by zooming in on the trading activity around the Brexit referendum.

2.3 Betting on Brexit: An Event Study

As a motivating example, we take a closer look at the connectedness-performance relationship during the days around the Brexit referendum on leaving the European Union.

The referendum took place on Thursday 23 June 2016, and the results that 51.9% of the participants voted to leave became public on Friday morning (24 June 2016). Based on polls, the chances of a leave or a remain vote were close to 50-50 leaning slightly towards remain immediately before the vote. Either way market prices were expected to jump. In particular, the common perception was that a leave result would likely to trigger a rate cut soon, leading to an immediate downward shift in the yield curve on 24 June. Figure 1a shows that this is indeed what happened: the yield curve dropped immediately, while the Bank of England cut the interest rate by 0.25% in August.

Given the large uncertainty before the vote, market participants were motivated to either reduce their exposure radically, or to generate private information and bet on the outcome. Reportedly, major hedge funds ordered private opinion polls to generate an informational edge.[8] Our main hypothesis implies that we should be able to separate these two groups from each other based on the change of their connectivity before the vote. We should see that clients with private information increase the number of dealers they trade with to hide this information. Furthermore, they should be the group who, in average, increases

[7] In fact, in our model price impact, the difference between the execution price of a given client, and the average execution price of other clients, can go up or down with connectedness depending on the parameters.

[8] See quote and reference from Bloomberg Businessweek in introduction.

the duration of its portfolio to speculate on the Leave outcome and when the yield curve eventually jumps, they should overperform the others.

To verify this hypothesis, we group all those private clients who traded on the referendum day 23 June into two groups based on the following client-specific measure:

$$\alpha_i = connectivity_{i,Jun23} - \overline{connectivity_i} \tag{2.1}$$

where $connectivity_{i,Jun23}$ is the number of dealers that client i traded with on the day of the referendum; the term $\overline{connectivity_i}$ is the average daily connectivity of client i based on the whole sample (2011 Oct – 2017 Jun). The variable α_i captures whether the given client, on the referendum day, had unusually high or low connectivity compared to its own long-run average. We identify 125 private clients who traded on the day of the referendum,

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

Client Type	α Mean	Centrality Mean	Volume Mean	Net Duration Mean	Number of Clients
Low-α	-0.80	1.57	13,200,000	1,973,631	63
High-α	0.98	3.51	25,600,000	106,000,000	62

Client Type	5-day Performance Mean	5-day Performance Median	5-day Perf. Deviation Mean	5-day Perf. Deviation Median	Number of Clients
Low-α	-0.0040	-0.00013	-0.0040	-0.00017	63
High-α	0.0031	0.00025	0.0028	0.00065	62

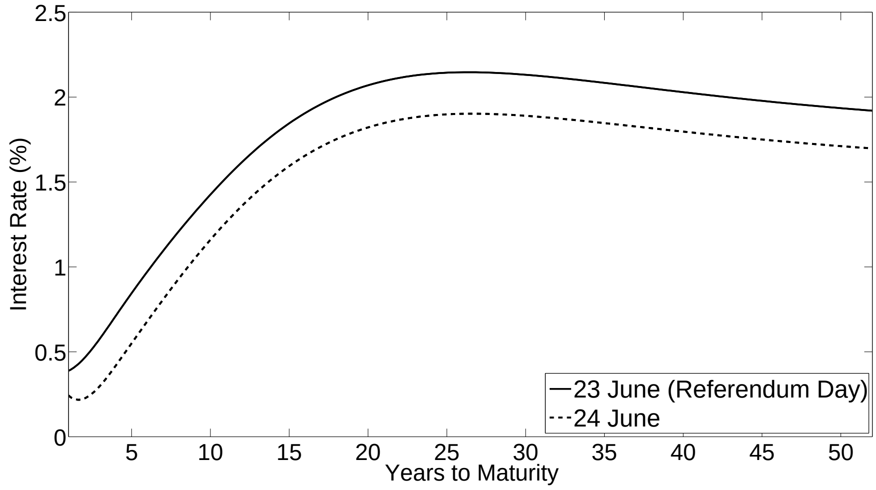
Notes: this table provides descriptive statistics of the 125 identified private clients that traded on 23 June 2016. These clients are placed in two groups depending on whether their α is below (top row) or above (bottom row) the median value of α. Performance is measured in log points. The measure α and connectedness are measured in terms of number of dealer connections. Volume and Net Duration are in £.

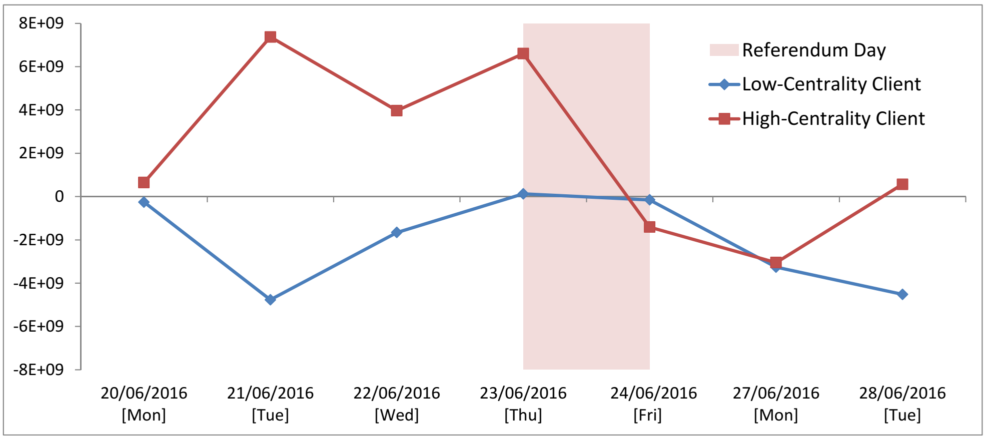
and Table 1 provides summary statistics of their performance and connectedness. High-α clients traded with approximately one (0.98) additional dealer compared to their respective average. In turn, low-α clients traded with approximately one (0.8) fewer dealer compared to their respective average.

We find that high-α clients performed much better on the referendum day compared to low-α clients. For example, the mean 5-day performance of the high-α clients was about 31bp which was more than 70bp higher than the mean performance of the low-α clients. This is primarily due to the fact that high-α clients substantially increased their long position on gilts before yields dropped sharply in the following days: the average high-α client's change in net duration was more than 50 times (106m) that of the low-α client (1.9m).

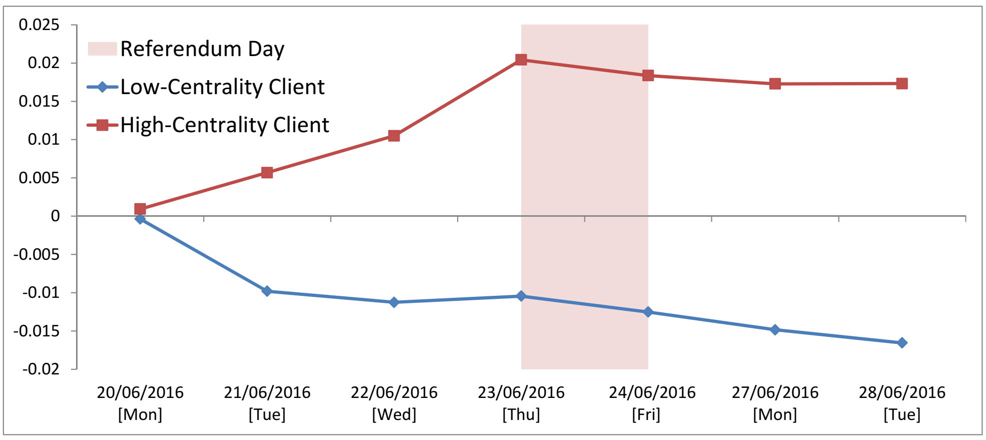
Figure 1: Betting on Brexit: Centrality and Performance

(a) UK Yield Curve Before/After Referendum





(b) Aggregate Daily Net Duration of High-α and Low-α Clients



(c) Cumulative Returns of Low-α and High-α Clients.

Notes: In Panel 1a, the daily yield curve estimate is based on end-of-day closing prices. In Panel 2b, the red squared line depicts the evolution of the duration-weighted net position of those 63 clients that have high within-connectedness (high α 2.1) on the day of the referendum. The blue circled line evolution of the duration-weighted net position of those 62 clients that have low within-connectedness (low α 2.1) on the day of the referendum. In Panel 2c, the red squared line depicts the cumulative average returns of those 63 clients that have high within-connectedness (high α 2.1) on the day of the referendum. The blue circled line depicts cumulative average returns of those 62 clients that have low within-connectedness (low α 2.1) on the day of the referendum. The average returns for both groups are weighted by the individual clients' daily trading volume. The returns are computed using the closing price on 29 June 2016 as the reference price.

We now explore whether the trading behaviour of high-α clients was different from that of the low-α clients, not only on the day of the referendum, but during the days leading up to the vote. Figure 2b shows that clients with above the average dealer connections on the day of the referendum (high-α clients) built up long positions not only on 23 June but also during 21-22 June. They seem to close a large fraction of these positions after the referendum. These trades benefited largely from the drop in yields (rise in prices) on 24 June and 27 June. In contrast, low-α clients were selling gilts during 21-22 June before prices started increasing on 24 June.

A similar picture emerges when we compute performance measures for the two groups of clients. For each transaction over the period 20 June – 28 June, we compute:

$$Performance_j = \left[\ln\left(P^{June29}\right) - \ln\left(P_j^{\star}\right)\right] \times \mathbf{1}_{B,S}, \tag{2.2}$$

where $P_j^{\star}$ is the transaction price, P^{June29} is the closing price of the corresponding gilt on 29 June, and $\mathbf{1}_{B,S}$ is an indicator function equal to 1 when the transaction is a buy trade, and -1 when it is a sell trade. All transactions-specific returns are then averaged within the day using the pound volume of the trades as weights. We then compute average returns for the low-α and high-α groups using the individual clients' daily trading volume as weights. Figure 2c then shows the cumulative returns for the two groups of clients. The result confirms that the clients that experienced unusually high level of connectivity on the day of the referendum were the ones to bet for a leave outcome, experiencing high trading performance during the week of the referendum.

Now we turn to systematic evidence.

3 Data and Summary Statistics

Data Source To analyse how the dynamics of client-dealer connections are related to clients' trading performance and information, one needs a detailed transaction-level dataset which contains information on the identity of both sides of a trade. The proprietary ZEN database maintained by the UK Financial Conduct Authority (FCA), fittingly provides this information together with information on the transaction date and time; the execution price and quantity; the International Securities Identification Number (ISIN); the account number, the buyer-seller flag. The ZEN database contains trade reports for all secondary-market transactions, where at least one of the counterparties is an FCA-regulated entity. We focus exclusively on conventional gilts. From now on we refer to primary dealers as dealers. Given that all dealers in our sample are FCA-regulated, we have at least one report for each dealer-client transaction, thereby giving us virtually full coverage of the client trade universe. Our sample covers the period between October 2011 and June 2017. We match our transaction-level data with information on bond duration and end-of-day closing prices obtained from Datastream.

Identifying Clients A key aspect of our empirical analysis is to exploit the time-variation in client-dealer connections, which requires the matching of each transaction with a client identifier. The names of clients are recorded as unstructured strings of text in the ZEN database. Moreover, a typical client tends to have multiple accounts with different client names across accounts and also within the same account. We use a textual algorithm that searches the unstructured strings of names and accounts, and assigns a unique client identifier to each transaction. When constructing client identifiers, we aim at the highest possible level of consolidation by treating parent companies, subsidiaries and different arms as one client. We end up with 474 identified clients and about 1.67 million trades transacted by them. The trading activity of these clients covers around 80% of all client activity (in terms of trading volume) in the UK gilt market.

Client-Dealer Connections Our baseline measure of client connectivity is the number of dealers a given client is connected to in a given time period. A client is connected to a dealer if it trades with the dealer at least once.[9] Since client connectivity is a key variable in our analysis, we provide some descriptive statistics to describe it.

Table 1 presents summary statistics based on our baseline regression sample that is aggregated to the client-month level. We find that the average client in a given month is connected to four dealers and carries out about 19 transactions with them. There is substantial sample variation: the average difference in connections between the 90th and 10th percentile is 11. To illustrate how much of the variation in client connectivity is a cross-sectional phenomenon, we compute the averages of our measures at the client-level, and plot the resulting distribution in a histogram (Top Row of Figure 5). We find that the distribution of the connectivity measure is positively skewed, with the mass of clients having low values and a few clients exhibiting large values.

Clients that are on average more connected can differ from less connected clients along other time-invariant characteristics such as size, business model etc. To control for this, we purge out client fixed effects from our connectivity measures and plot the resulting distribution in a histogram (Bottom Row of Figure 5). We find substantial within-client variation: the average difference in connections between the 90th and 10th percentile is 4.5, which is non-negligible compared to the corresponding value using across-client variation (7.5). Similarly, the standard deviation of first-order connections is around 3.3 in the cross-section and still as high as 1.9 when using only the within-client variation. This substantial

[9]To check for the robustness of our results, we also use eigenvector centrality (Bonacich and Lloyd, 2001) as an alternative measure of connectivity. This measure, used in recent papers (Maggio, Kermani, and Song, 2017), not only takes into account the number of dealers a given client trades with but also the number of other clients that are connected to those dealers that the given client trades with.

within-variation in connectedness is an important feature of the data, which our empirical analysis will primarily rely on.

4 Proxying Client's Private Information

4.1 Measuring Trading Performance

Baseline Measure To measure trading performance, we follow Maggio, Franzoni, Kermani, and Sommavilla (2018) and compute the T-day-horizon return on each trade of client i in month t, measured as the percentage difference between the transaction price and the closing price T days after the transaction date.[10] Formally, for each trade j, we construct the measure $Performance_{i,t}^{T}$ as follows:

$$Performance_j^T = \left[\ln\left(P^T\right) - \ln\left(P_j^\star\right)\right] \times \mathbf{1}_{B,S}, \tag{4.1}$$

where $P_j^\star$ is the transaction price, P^T is the T-day ahead closing price of the corresponding gilt, and $\mathbf{1}_{B,S}$ is an indicator function equal to 1 when the transaction is a buy trade, and -1 when it is a sell trade. All transactions-specific returns are then averaged within month t using the pound value of the trades as weights. As robustness, we also present the results using unweighted monthly average returns.

Table 1 summary statistics of the 3-day and 5-day (weighted and unweighted) performance measures. Panel C shows that average performance is significantly larger for clients with more dealer connections compared to clients with fewer connections. More importantly, as shown in Panel D, we also find that the average client performs significantly better in months with more dealer connections compared to months when the same client has fewer connections. For example, the average client has a 1.5bp higher 5-day performance in high-connectedness months compared to low-connectedness months.

Decomposing Trading Performance We now propose a decomposition method which extends our baseline performance measurement. The T-day performance of a client on a trade can be high because the given client faces lower price impact compared to other clients trading at the same time. We refer to this as the transaction component of performance. Alternatively, trading performance can be high because the given client can better anticipate future prices changes. We refer to this as the anticipation component of performance.

[10]The T-day horizon starts at the start of each day and ends after T days. We use overlapping time windows. For example, to compute one-day performance measures ($T = 1$), we compare all trades on day 1 to the closing price on day 2, and compare all trades on day 2 to the close price on day 3, and so on.

Building on 4.1, we compute the decomposition for each transaction j as follows:

$$\ln\left(P^{T}\right)-\ln\left(P_{j}^{\star}\right)\approx\underbrace{\left[\ln\left(P^{T}\right)-\ln\left(\overline{P}\right)\right]}_{Anticipation}+\underbrace{\left[\ln\left(\overline{P}\right)-\ln\left(P_{j}^{\star}\right)\right]}_{Transaction},\tag{4.2}$$

where $\overline{P}$ is the only new term which denotes the average transaction price (based on all available dealer-client trades in the corresponding gilt) measured around the time of transaction j. To estimate $\overline{P}$, we experiment with two time definitions. First, we use all relevant trades on the day of transaction j to compute the average transaction price $\overline{P}$. As a second, more accurate measure, we split each trading day into three parts, and compare the transaction price to the corresponding one of the three intra-day averages.[11] Given the trade-level decomposition, we then collapse our dataset at the client-month level using both volume-weighted and unweighted monthly average returns.

Note that most of the recent empirical work on financial networks (Afonso, Kovner, and Schoar, 2014; Hendershott, Li, Livdan, and Norman, 2017; Hollifield, Neklyudov, and Spatt, 2017; Maggio, Kermani, and Song, 2017) focused on the transaction component. Distinguishing between the transaction component and the anticipation component allows us to test whether higher connectedness increases performance because clients can achieve more favourable deals (at lower mark-ups) or because clients have private information about future price changes.

Predicting Changing Yield Curve vs Noise We also explore whether a client's T-day performance on a trade can be high because the client can better predict changes in the shape of the yield curve, or because the client can better predict changes in the distance of individual gilt yields (pricing error) from an otherwise unchanged yield curve. We compute the decomposition for each transaction j as follows:

$$\ln\left(P^{T}\right)-\ln\left(P_{j}^{\star}\right)\approx\underbrace{\left[\ln\left(M^{T}\right)-\ln\left(M^{0}\right)\right]}_{Curve-Shift}+\underbrace{\left\{\left[\ln\left(P^{T}\right)-\ln\left(M^{T}\right)\right]+\left[\ln\left(M^{0}\right)-\ln\left(P_{j}^{\star}\right)\right]\right\}}_{Pricing-Error}\tag{4.3}$$

where M^0 and M^T are the end of 0-day and 5-day prices implied by standard yield curve models (Nelson and Siegel, 1987; Svensson, 1994).

An Alternative Performance Measure Our performance measure compares the transaction price with the future market price of the security. Whether a client liquidates her position at that future price, or holds on to it, does not influence our measure. That is, our performance measure might not correspond to realised profits. This is in contrast to the bulk of previous empirical work on over-the-counter markets which measures performance as the

[11] The intra-day time windows are <11am, 11am-15pm and >15pm, which are set to have an approximately even number of transactions across the time windows.

return on dealers' round-trip transactions. The reason why we do not follow that approach is that our focus is not on the performance of dealers – who trade very frequently and tend to finish their day with small net positions – but on clients. In our sample, clients trade for heterogeneous reasons. In aggregate, they tend to persistently accumulate positions as they ultimately purchase most of the issued securities by the DMO. Individually, some trade frequently, some buy and hold. Some might aim for profit by turning over their portfolio quickly, others might aim instead to acquire their desired positions at a favourable price. Our performance measure is neutral to the objective of the client. If the client manages to buy at a low price or sell at a high price compared to the price in the subsequent period, we measure that as a high value transaction.

Still, as a robustness test, we construct a second performance measure which measures realised profit in a given month directly, building on the average-cost-approach of inventory valuation. In particular, for each client i, gilt a, month m, we compute:

$$R_{i,a,m} = \left[\ln \left(\frac{\sum_{j^S=1}^{J^S_{i,a,m}} P_{i,a,j^S} Q_{i,a,j^S}}{\sum_{j^S=1}^{J^S_{i,a,m}} Q_{i,a,j^S}} \right) - \ln \left(\frac{\sum_{j^B=1}^{J^B_{i,a,m}} P_{i,a,j^B} Q_{i,a,j^B}}{\sum_{j^B=1}^{J^B_{i,a,m}} Q_{i,a,j^B}} \right) \right] \times \min \left[\sum_{j^S=1}^{J^S_{i,a,m}} Q_{i,a,j^S}, \sum_{j^B=1}^{J^B_{i,a,m}} Q_{i,a,j^B} \right], \tag{4.4}$$

where $J^p_{i,a,m}$, with $p = S, B$, denote the total number of monthly, gilt-specific sale and buy transactions, respectively, while P_{i,a,j^p} and Q_{i,a,j^p} corresponds to the price and quantity of transaction j^p. We then compute the weighted average of $R_{i,a,m}$ across gilts (using the client's monthly trading volume in gilt a as weights) to obtain a realized profit measure at the client-month level.

4.2 Client Connectivity and Trading Performance

Given the trading performance measures (4.1 and 4.2) we now explore empirically whether a client's trading performance increases when the given client increases its connections with the primary dealer sector. In this Subsection, our results are based on data at monthly frequency. This is to reduce measurement noise and also to avoid oversampling those clients who trade actively, possibly on most trading days. Nevertheless, as will be shown in Subsection 4.4, our results are robust to using data at daily frequency.

Baseline Results Our baseline specification is the following monthly panel regression:

$$Performance^T_{i,t} = \beta \times ClientConnections_{i,t} + X_{i,t} + \alpha_i + \mu_t + \varepsilon_{i,t}, \tag{4.5}$$

where $Performance^T_{i,t}$ is the trading performance of client i in month t at horizon T; $ClientConnections_{i,t}$ is the number of primary dealers the given client is connected to in month t; $X_{i,t}$ includes controls such as the number of transactions and trading volume; α_i and μ_t are client and time fixed effects. Throughout the analysis, in computing standard errors we take the most conservative approach, and employ two-way clustering at the client and time level. This procedure allows for arbitrary correlation across time and across clients.

The main coefficient of interest in 4.5 is β which captures the relation between client connectivity and trading performance. Table 2 reports our baseline results with panel A and panel B showing the results for value-weighted and unweighted trading performance, respectively. Each column corresponds to a different trading horizon going from $T = 0$ to $T = 5$. We find a positive relationship between client connectivity and trading performance, which is statistically significant at almost every horizon for both types of performance measures. This complements the evidence of Maggio, Franzoni, Kermani, and Sommavilla (2018) on the role of broker centrality in affecting the trading performance of stock market participants in the US.[12] Moreover, we find little evidence that variation in a client's trading volume or number of transactions would affect the given client's trading performance.[13]

The results are also economically significant. For example, using the estimate (0.489bp) in Column 6 of Table 2, we find that if a client increases the number of its dealer connections by one, then its trading performance doubles relative to its mean (we are using the fact that the median and mean 5-day returns are 0.45bp and 0.43bp, respectively). Table 3 further illustrates the economic significance of the performance-connectedness relationship. Panel 3a compares months when clients have low connectedness to months when they have high connectedness. Single-sorting using the within-variation in connectedness, we find that the difference in median performances is about 0.5bp, consistent with our baseline regression results (Table 2). Moreover, clients trade much more when they are more connected: the median trading volume is about £15million (£53million) in months when the client has fewer (more) dealer connections than its sample average. The performance difference coupled with the difference in trading volume in high and low connectivity months implies that the majority of positive trading performance is concentrated in high connectivity months.

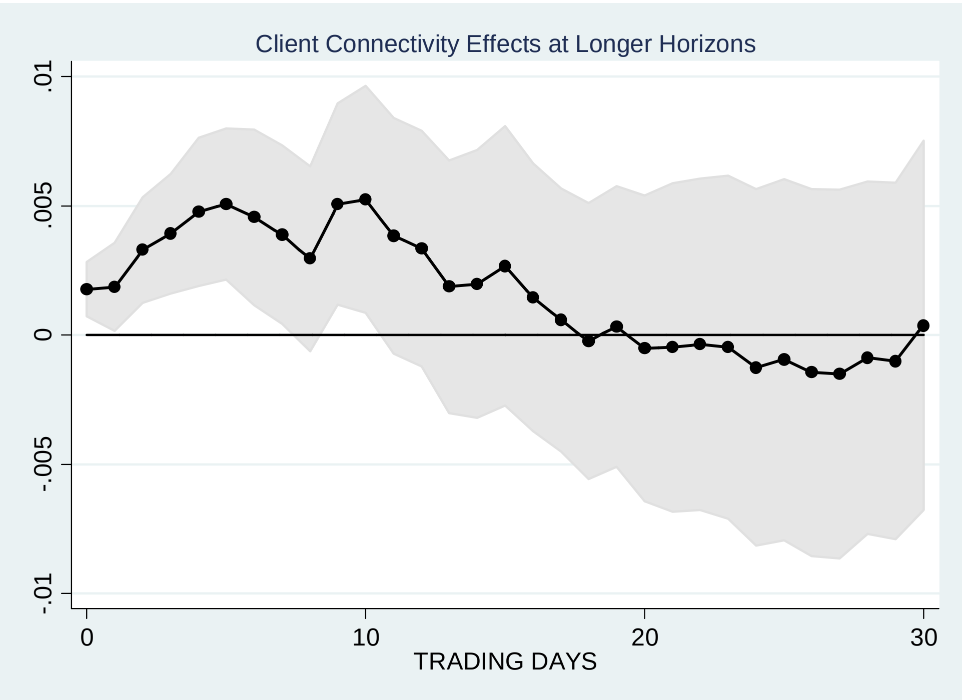
To reinforce that our results are not simply picking up the effect of trading volume (driving both connections and performance), in panel 3b, we extend this analysis and double-sort our sample using the within-variation both in connectedness and in trading volume. The performance difference in high and low connectivity months is approximately the same irrespective of whether the client's trading volume is high or low, and thereby the majority of positive trading performance continues to coincide with high connectivity months.

[12]In terms of research design, the difference between our analysis and theirs is that we essentially compare the trades of a connected client to the trades of the same client when she was more/less connected. Maggio, Franzoni, Kermani, and Sommavilla (2018) compares the trades of a client that are channeled through more connected brokers to the trades of the same client that are channeled through less connected brokers.

[13]Figure 20 in the Appendix shows the results from a pooled regression with client fixed effects excluded. While client connectedness continues to have a significantly positive relationship with trading performance, the coefficients on trading volume and transaction number also appear statistically significant in the cross-section. This may be explained by the fact that our clients include a range of investor types (e.g. insurance companies, hedge funds, pension funds). Also, the cross-sectional distribution of size and transaction number may be correlated with other characteristics, as studied extensively by the mutual fund literature (Elton, 1993; Chen, Jegadeesh, and Wermers, 2000; Kacperczyk, Sialm, and Zheng, 2005).

Moreover, we assess the persistence of the effect of client connectivity and gradually increase the trading horizon up to 30 days ($T = 30$) while re-estimating our baseline regression 4.5. In Figure 2, we present the 30 estimated βs, using the value weighted performance measure, together with the 90% confidence bands. We find that the effect peaks at the 5-day horizon, but we still find that client connectivity significantly affects performance at the 10-day horizon. The effect then gradually decays, with the point estimate reaching zero at the 17-day horizon. According to our model, the intuition is as follows. The client might

Figure 2: Baseline Performance Regressions over 0-30 day Horizons



Notes: this figure plots the estimated β coefficients from our baseline regression 4.5 up to 30-day horizon ($T = 30$), using the value weighted performance variable as the regressand, measured in basis points. We include as a control the natural logarithm of the pound trade volume of each client ("Volume") and the natural logarithm of the number of monthly transactions ("Transactions"). To reduce noise, we winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. The shaded area denotes the 90% confidence band, It is based on robust standard errors, using two-way clustering at the month and the client level.

trade because of liquidity reasons or on private information. Only in the latter case she is motivated to request for more quotes and, consequently, to trade with more dealers. This is so, because there is no need to hide the exact composition of its trades if its for liquidity reasons. This is why we find that trades in months when the client is more connected are more profitable. Time-variation in connectedness is a proxy for the level of private information behind the client's trade.

Note that our theory does not imply causality between connectedness and performance in any direction. Instead, both higher performance and higher connectedness are caused by more private information.

Decomposing Trading Performance into Transaction and Anticipation Components Given our baseline results, we now explore the channels through which client connectivity is related to trading performance. Specifically, we test whether more connected clients may perform better because they get better deals compared to other clients trading around the same time (transaction component) or because they can better anticipate future price changes over the coming trading days (anticipation component). To this end, we estimate two modified versions of our baseline specification (4.5) with the trading performance measure replaced with the anticipation and transaction components (4.2). Table 4 shows the decomposition results for the 5-day value-weighted performance measure.

Our results show that the dealer, when more connected, tends to perform significantly better in each component. When more connected, she tends to trade at a more favourable price and to the direction of future price movements. Quantitatively, we find that the anticipation component has much higher role in the overall higher performance of clients when they are more connected. In particular, less than 20% of our baseline effect is explained by the transaction component, with the anticipation component being responsible for the majority of our baseline effect.

Forecasting the Yield-Curve and Noise Figure 6 and 7 show the decomposition of Figure 3 into the component of yield curve forecasts and noise forecasts as specified by (4.3). Looking at the two figures together, there is some evidence that the yield curve component is stronger than the pricing-error component. Note, that if pricing-errors are not persistent beyond a day, than the transitional component in (4.2) is expected to be close to the pricing-error component in (4.3).

Centrality and Realized Profit As a robustness check we run our baseline specification with our within-month realized profit measure on the right hand side. As the first panel of Table 5 shows, while higher connectedness of a given client is associated with higher realized profit, this relationship is not significant in the full sample. However, if we focus on those client-month observations when the given client trades frequently (i.e. more than the median number of transactions), the relationship is significant. Our interpretation is that our within-month realized profit measure captures high value trades only for those clients and for those periods when the client trades a lot within a month.

So far, our empirical results provide support for the first three predictions of our theoretical framework, summarised in Proposition (1). We now turn to the fourth prediction of the model, namely, that the relationship between connectivity and trading performance is stronger when price volatility is higher.

4.3 Macroeconomic Announcements

Since Fleming and Remolona (1997, 1999); Brandt and Kavajecz (2004), there has been ample empirical evidence on the effect of scheduled macroeconomic announcements on government bond prices and volatility. Green (2004) finds that the informational role of trading increases following announcements, indicating that the release of public information raises the level of information asymmetry in the government bond market. His evidence suggests that some market participants have an advantage at processing the newly arrived information. Building on this literature, we now explore whether the effect of client connectivity on trading performance is different following the arrival of public information.

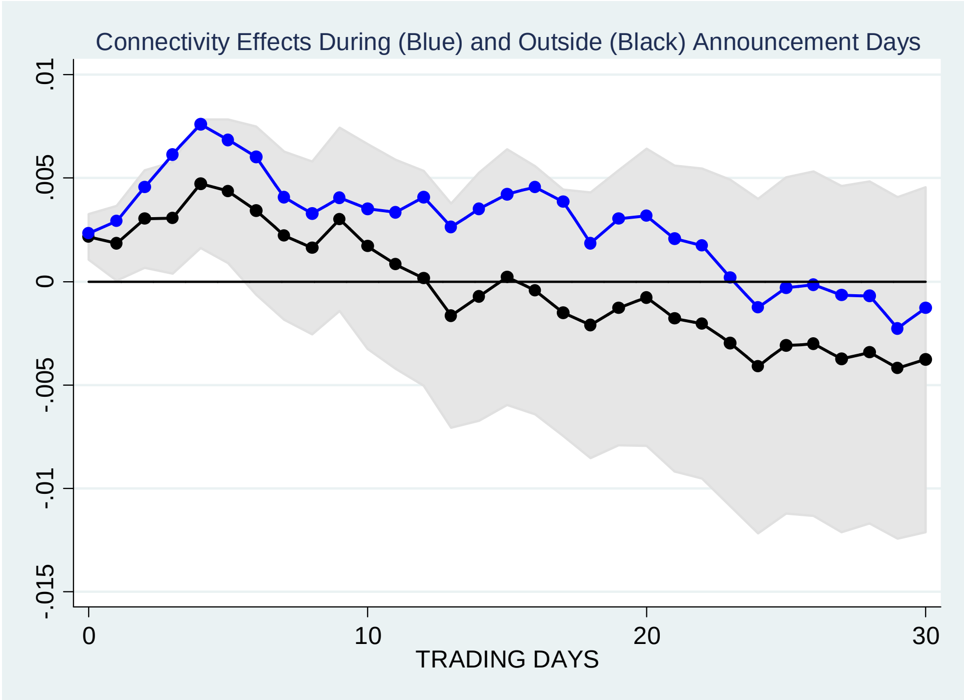
Our baseline analysis relies on UK monetary policy announcements and the release of the consumer price index. Policy announcements include the publication of the quarterly inflation report, the policy interest rate decision of the Monetary Policy Committee (MPC) and the release of the minutes (Table 17).[14] Out of the 1470 trading days in our sample, we end up with 196 trading days that coincide with news about the policy interest rate and inflation. In the spirit of our analysis above, we compute two sets of monthly performance measures for each of our client: one that is based on all announcement days, and another based on all other trading days without announcements. Accordingly, we extend our baseline regression 4.5. and estimate the following model:

$$
\begin{aligned}
Performance^{T}_{i,t,p} = \rho \times D^{Ann}_{i,p} \times ClientConnections_{i,t} \\
+ \beta \times ClientConnections_{i,t} + X_{i,t} + \alpha_i + \mu_t + \varepsilon_{i,t,p}
\end{aligned}
\tag{4.6}
$$

where $D^{Ann}_{i,p}$ is a dummy variable taking value 1 if the performance measure is based on trading days with macroeconomic announcements and 0 otherwise. The term ρ is the coefficient of interest which measures whether connectedness has differential effect on performance during announcements, compared to non-announcement days. Table 18 and 19 show that the effect of client connections on trading performance is substantially stronger on trading days of scheduled inflation or interest rate announcements. For example, the point estimate 0.00308 in Table 18 suggests that the effect of trading with an additional dealer on the 3-day performance is twice as strong on an announcement day than on a trading day without announcements, with the difference being highly statistically significant. To assess the persistence of the effect, we gradually increase the trading horizon up to 30 days ($T = 30$), and re-estimate our regression model 4.6. The black line in Figure 3 represents the 30 estimated βs associated with non-announcement days, using the value weighted performance measure, together with the 90% confidence bands. The blue line shows the effect of connectedness on announcement days. We find that, at all trading horizons, the relationship between connectedness and trading performance is stronger during macroeconomic announcements than

[14] See Gerko and Rey (2017) for further details on the institutional arrangements of the UK and US monetary policy decision making process.

Figure 3: Performance Regressions over 0-30 day Horizons: Trading Days With and Without Release of Macroeconomic News



Notes: the black line plots the estimated β coefficients from the regression 4.6 up to 30-day horizon ($T = 30$), using the value weighted performance variable (based on non-announcement days) as the regressand, measured in basis points. The blue line plots the sum of the estimated coefficients $\rho + \beta$, representing the effect on announcement days. We include as a control the natural logarithm of the pound trade volume of each client ("Volume") and the natural logarithm of the number of monthly transactions ("Transactions"). To reduce noise, we winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. The shaded area denotes the 90% confidence band associated with the estimated β coefficients, It is based on robust standard errors, using two-way clustering at the month and the client level.

on non-announcement days. This is consistent with the prediction of our model in Section 2.

As a further robustness check, we include additional announcement days in our analysis such as the release of UK real activity indicators (unemployment, average earnings, manufacturing production and GDP) as these indicators have been found to strongly affect the government bond markets in the US (Fleming and Remolona 1997, 1999). We also add the days of the release of US FOMC statements and minutes, as recent evidence showed strong effects of US monetary policy shocks affecting global financial markets (Miranda-Agrippino and Rey (2015); Gerko and Rey (2017)). This leaves us with 422 trading days that coincide with macroeconomic announcements. Tables 23–24 show that the results are similar to our baseline.

4.4 Results from Daily Data

Our results so far were based on data at monthly frequency. This was to reduce measurement noise and also to avoid oversampling those clients who trade actively, possibly on most trading days. However, one concern might be that monthly averaging introduces problems of time aggregation which makes it difficult to accurately measure the dynamics of client-dealer connections. To address this, we re-estimate most of our regressions on daily data. Interestingly, the time-series variation in client connections continues to be substantial when we go to daily frequency. Table 6 shows that the standard deviation of connectedness is about 1.5 when using only the within-variation, i.e. the average client frequently changes the number of dealers that she trades across trading days.

Results for our performance regressions, presented in Table 7, are similar to our monthly regression results – though seem less persistent with the connectivity effect peaking at the four-day horizon. In Figure 8, we plot the estimated connectedness coefficients for longer horizons (8a) along with the interaction effects of monetary policy announcements (8b), corroborating the increased strength of the performance-connectedness relationship during the arrival of public information.

5 The Nature of Private Information

Our finding that a client tends to perform better when trading with more dealers suggests that time-variation in connectedness is a proxy for the level of client's private information. In this section, we use this proxy to explore the nature of private information in this market. This is an intriguing topic as the market for government bonds is often viewed as a market with little role for private information.

Our starting point is the ample empirical evidence in the literature (Evans and Lyons 2002; Brandt and Kavajecz 2004; Menkveld, Sarkar, and van der Wel 2012) that aggregate order flow dynamics explain prices in various dealer driven markets including government bond and currency markets. This literature observed that agents who have information about the future order flow in these markets can use this information profitably.

Motivated by this, we proceed in five steps. First, as presented in Subsection 5.1, we define measures of the co-movement of the composition of client's orders and the future aggregate order flow of a given group of clients. The idea is that whenever this measure is positive, the client, intentionally or by chance, is effectively front-running that group of clients. Second, as presented in Subsection 5.2, we test whether any of these measures identify profitable trades. We find that whenever the duration composition of a client's trade is similar to that of all the other clients in subsequent days, her performance is higher. Third, as presented in Subsection 5.3, we connect our baseline results to order flow information. In particular, we show that whenever a client is more connected, the composition of her trades tend to be more similar to the group of clients in subsequent days who are served by the same dealer. We also show that a client who is a regular counterparty of the given dealer can predict the composition of the order flow better. This suggests that dealers have an important role in disseminating order flow information towards their own, regular clients. Fourth, as presented in Subsection 5.4, we also show that all our findings are stronger for the group of clients who drove our baseline performance result. Finally, as presented in Subsection 5.5, we use our data at daily frequency which allows us to measure more accurately the timing of the formation of client-dealer connections, and thereby to assess whether connectedness might be part of the information acquisition process.

5.1 Measuring Co-movement between Client Trades and Future Order Flow

There are multiple ways to measure whether a client trades in the same direction other clients in the subsequent days. For each suggested measure, we start with the net trading position of client i, on day d, in asset a, $W_{i,d,a}$. We also compute the aggregated cumulative net trading position of group g between days $d+1$ and $d+T$ in asset a, denoted by $W^g_{d+T,a}$. The identity of group g will play an important role in section 5.3 where we identify the group of which order flow connected clients can forecast. For now, we set g for the group of all the clients in the market.

Then, our first daily covariance measure, $YC(1)^{T,g}_{i,d}$, is computed as follows:

$$YC(1)^{T,g}_{i,d} = \frac{1}{A}\sum_{a=1}^{A}\left(W_{i,d,a} - \frac{1}{A}\sum_{a=1}^{A}W_{i,d,a}\right)\left(W^g_{d+T,a} - \frac{1}{A}\sum_{a=1}^{A}W^g_{d+T,a}\right). \tag{5.1}$$

where A is the total number of assets traded on the given day. This measure is high, if on a given day the given trader happens to buy (sell) more of the assets which, n the subsequent T days, group g also buys (sells) more of.

For our other covariance measures, we partition all transactions in K segments of equal size based on the modified duration of the traded gilts in that transaction. Then, we aggregate $W_{i,d,a}$ and $W^g_{d+T,a}$ across each segment, k, and denote them as $W_{i,d,k}$ and $W^g_{d+T,k}$ respectively. With the help of these objects we define two further measures as follows:

$$YC(2)^{T,g}_{i,d} = \frac{1}{K}\sum_{k=1}^{K}\left(W_{i,d,k} - \frac{1}{K}\sum_{k=1}^{K}W_{i,d,k}\right)\left(W^g_{d+T,k} - \frac{1}{K}\sum_{k=1}^{K}W^g_{d+T,k}\right). \tag{5.2}$$

$$YC(3)^{T,g}_{i,d} = \frac{1}{A}\sum_{a=1}^{A}\left(W_{i,d,a} - W_{i,d,k}\right)\left(W^g_{d+T,a} - W^g_{d+T,k}\right) \tag{5.3}$$

Measure $YC(3)^{T,g}_{i,d}$ is high, if the given client tends to concentrate its orders on the same securities within a given segment as group g in the subsequent T days. In contrast, $YC(2)^{T,g}_{i,d}$ is high, if the given client tends to concentrate its orders in the same segment as group g in the subsequent T days, regardless whether the actual securities in the given segment are the same. As

$$W_{i,d,a} - \frac{1}{A}\sum_{a=1}^{A}W_{i,d,a} = [W_{i,d,a} - W_{i,d,k}] + [W_{i,d,k} - \frac{1}{k}\sum_{k=1}^{k}W_{i,d,k}] \tag{5.4}$$

and

$$W^g_{d+T,a} - \frac{1}{A}\sum_{a=1}^{A} W^g_{d+T,a} \quad = \quad [W^g_{d+T,a} - W^g_{d+T,k}] + [W^g_{d+T,k} - \frac{1}{k}\sum_{k=1}^{k} W^g_{d+T,k}] \tag{5.5}$$

$YC(2)^{T,g}_{i,d}$ and $YC(3)^{T,g}_{i,d}$ are components of $YC(1)^{T,g}_{i,d}$.

This decomposition is interesting because we expect the prices of gilts with similar durations to react similarly to the aggregate order flow. Hence, it might be similarly profitable for a client to guess right the segments where future demand pressure will be concentrated, as opposed to guessing right the particular security. In that case, $YC(2)^{T,g}_{i,d}$ might be high, even if $YC(2)^{T,g}_{i,d}$ is low. In the next part, we test which of these measures corresponds to high profitability trades.

5.2 Which Type of Private Information is Profitable?

In this section, we test whether any of our covariance measures $YC(1), YC(2), YC(3)$ identify profitable trading days. We proceed as follows. Using the given measure $YC(\cdot)$, in each month we partition the trading days in two sets, $p \in \{Low, High\}$. A day is in the high (low) set, if $YC(\cdot)$ for the given day is larger (smaller) than its median in the full sample. Then, we estimate the following regression:

$$Performance^T_{i,t,p} = \gamma \times Q_{i,p} + \delta_{i,t} + \varepsilon_{i,t,p}, \tag{5.6}$$

where $Performance^T_{i,t,p}$ is the version of our baseline performance measure (4.1) which is aggregated only over set p of trading days in months t for client i. $Q_{i,p}$ is a dummy taking value 1 if the performance measure of client i is based on high-covariance trading days and 0 if it is based on low-covariance days. The term $\delta_{i,t}$ is a client-month fixed effect. Tables 8 and 9 show the results for each covariance measure $YC(1), YC(2), YC(3)$ when the covariance measure uses the cumulative aggregate client order flow at the 3-day horizon (columns 1-3) or 5-day horizon (columns 4-6). For both cases, we compute the turnover-weighted (Table 8) and unweighted (Table 9) performance measures at the 1-, 3- and 5-day horizons. The results show that covariance measure $YC(2)$ shown in panel (b) is our best choice to identify trades which are profitable because the composition of a client's portfolio is similar to that of the market in the subsequent days. This suggests that a client has strong incentives to guess whether future orders will be concentrated in the short or the long segment of the yield curve or in between. The effect is economically significant as trading performance can be 2-4bp higher on high covariance days. At the same time, as panel (c) illustrates, forecasting the exact security within the segment where the order flow would be concentrated does not seem to be profitable.

5.3 Connected Clients Predict the Order Flow

Let us return to our baseline result that the time-variation in a client's number of connections is a proxy for her level of private information. In this section, we collect evidence that this private information is on the duration composition of the future order flow of certain group of other clients, as measured by our covariance measure $YC(2)^{T,g}_{i,d}$. In this case, we expect that the covariance measure of a given client in a given month tends to be higher when this client is more connected. Hence, we compute monthly averages of $YC(2)^{T,g}_{i,d}$, denoted as $YC^{T,g}_{i,t}$ to estimate the following panel regression:

$$YC^{T,g}_{i,t} = \phi \times ClientConnections_{i,t} + X_{i,t} + \alpha_i + \mu_t + \varepsilon_{i,t}, \tag{5.7}$$

where the terms on the right-hand-side are identical to our baseline specification 4.5.

Panel A of Table 10 shows the results with respect to the total order flow ($g = Total$). While we see a positive relationship between the time-variation in connectedness and the duration decomposition of client's current trades at that of the aggregate order flow, this relationship is not strong.

Instead, in Panel B and C, we decompose aggregate order flow as follows. We isolate the part of the aggregate order flow that is intermediated through the dealers which a given client is connected to ($g = Own$) from the part that goes through all the other dealers that the given client is not connected to ($g = Non - Own$).

We further decompose the Own measure based on whether the given client has a more regular relationship with a dealer ($g = Regular$), distinguishing it from other client-dealer connections that are relatively new ($g = New$). We regard a client-dealer connection regular if the client traded with the given dealer in the current as well as in the previous month; whereas we regard a connection new if a client traded with the dealer in the current month but not in the previous month.

Note that, by the additivity of covariance, our measure is additive in the following sense:

$$YC^{T,Total}_{i,t} = YC^{T,Own}_{i,t} + YC^{T,Non-Own}_{i,t} = YC^{T,Regular}_{i,t} + YC^{T,New}_{i,t} + YC^{T,Non-Own}_{i,t}. \tag{5.8}$$

This property helps the interpretation of our results.

Perhaps the most intriguing finding of this part is in Panel B of Table 10. It decomposes the aggregate private client flow into the part that is intermediated by those dealers that the given client is connected to (Columns 1-3) in contrast with the order flow that is channelled through dealers that the client is not connected to (Columns 4-6). We find that it is the covariance with Own dealer order flow that correlates with the client's connectivity, and the effects for $Non - Own$ dealer order flow are economically and statistically insignificant. Our interpretation is that primary dealers, intentionally or unintentionally, disseminate information about the future orders towards (some of) their clients. We have little evidence on the exact mechanism. In principle, dealers' private information on their clients expected orders in the subsequent days might be revealed accidentally by the dealers' quotes. Or it might be that there is an intentional information flow from dealers to their best clients helping dealers to keep these clients. Indeed, Panel C shows that higher client connectivity predicts more the order flow intermediated by *Regular* dealers and predict less the order flow that goes through newly connected dealers. This is also consistent with Maggio, Kermani, and Song (2017) that finds evidence on the role of the trading relationship strength in affecting trading performance in the US stock market.

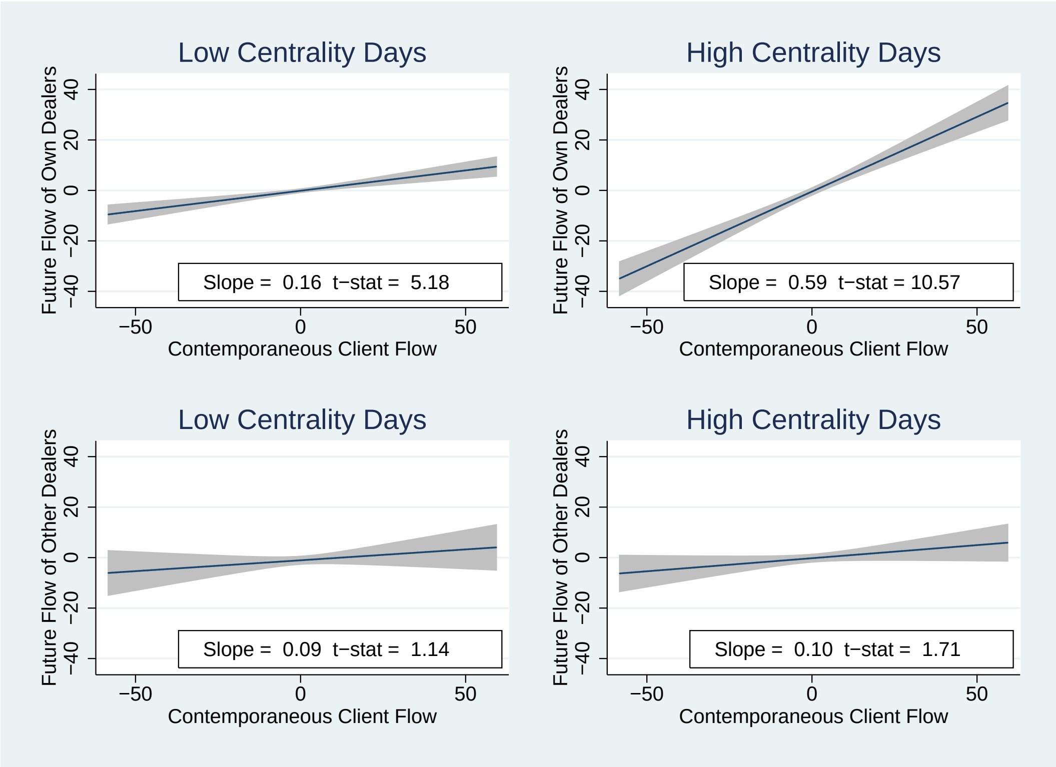
We provide further evidence on the importance of dealers in forecasting future flows, by using our dataset at a more disaggregated level. First, for each client i, we compute the daily net trading position in each duration bucket k (5.2). Second, we compute the future net trading position (cumulated over the subsequent T days) aggregated across all clients that trade with those dealers who are connected with client i in the given month. We refer to this as the future flow of Own dealers. We also compute the aggregate future client flow that is intermediated by those dealers who are not connected with client i in the given month. We refer to this as the future flow of Non-own dealers. Consistent with the evidence in Table 10, we expect to find that the relationship between client order flow and future flow of Own dealers should be higher in those months when the client has higher level of connectivity. In turn, we do not expect the relationship between client order flow and future flow Non-own dealers to be different in high and low connectivity months. Figure 4 shows the estimated regressions slopes from four separate linear regressions. The top (bottom) row shows the relationship between client flow and future flow of Own (Non-own) dealers. The right (left) column shows the relationship between the flows when the client is more (less) connected compared to its own average. We find that client flows co-move more strongly with Own dealer flows than with Non-own dealer flows, reflected by the statistically insignificant slope coefficients in the bottom row of Figure 4. Importantly, we find the strongest co-movement between client flows and future Own dealer flows when clients are more connected. This is shown by the regression coefficient in the top right panel (0.59) being almost four times larger than the slope in the top left panel (0.16).

Overall, the results of this and the previous subsections suggest that the nature of private information, proxied by client connectivity, is related to the order flow intermediated by the given client's dealers.

5.4 Variation in Clients' Performance Sensitivity

It is important to keep in mind that our baseline result in Table 2 masks significant heterogeneity across clients. For some of our clients there is a very strong co-movement between connectedness and performance while for others there is no co movement at all. Our interpretation is that not all clients are in the market to profit from short-term bets based

Figure 4: Contemporaneous Client Order Flow and Future Aggregate Order Flow: the Roles of Centrality and client-dealer connections



Notes: Each panel shows the estimated regression slope (with associated 90% confidence interval) that corresponds to the relationship between contemporaneous order flow of an individual client i and the aggregate cumulative future order flow of all clients. The units of observation are daily and duration-specific net trading positions of a given client i that are regressed against daily and duration-specific aggregate cumulative future net trading positions of all clients that are intermediated by all the dealers that client i is connected to (top row) and by all other dealers that client i is not connected to (bottom row). The left (right) column looks at the flow relationships in those months when client i is in the bottom (top) quartile of client connectedness (using within variation). The axes are measured in £1,000,000s.

on private information. In this section, we explore variation in the sensitivity of client's trading performance to connectedness to provide additional evidence to our narrative. In particular, we enforce the insights that (1) time-variation in connectedness is a proxy for private information on the duration composition of future order flows, (2) this information is disseminated by dealers to their own clients only, (3) regular clients tend to be more the recipients of this information.

We proceed in two steps. First, we re-estimate our baseline regression (4.1) for each client separately, and then sort the clients based on the their estimated β coefficients. We define a dummy variable, $D_i^{H\beta}$, which takes value 1 if the client's estimated β is above the median ('high-β clients') and takes value 0 otherwise ('low-β clients'). Second, we extend the empirical model 5.7, by adding the interaction term $D_i^{H\beta} \times ClientConnections_{i,t}$ to it, and estimate the following panel-regression:

$$\begin{aligned} YC_{i,t}^{T,g} = \rho \times D_i^{H\beta} \times ClientConnections_{i,t} \\ + \beta \times ClientConnections_{i,t} + X_{i,t} + \alpha_i + \mu_t + \varepsilon_{i,t,p} \end{aligned} \tag{5.9}$$

where ρ is the coefficient of interest which measures whether the effect of connectedness on the covariance measure is higher amongst those clients whose trading performance is more sensitive to connectedness ($D_i^{H\beta}$). Tables 11–13 confirms that the effect between connectedness and the ability to predict the order flow is significantly stronger amongst high-β clients compared to low-β clients. This is true for the aggregate order flow just as well, as for our decompositions. This group can forecast better the order flow of their own clients and the effect is stronger for clients who are regular than for those who are new comers to the particular dealer.

5.5 Daily Variation in Connections

We now turn to our daily data which allows us to measure more accurately the timing of the formation of client-dealer connection. First, we test at daily frequency whether information about the duration composition of future market order flow increases performance. To show this, we estimate the following regression:

$$Performance_{i,t}^{T} = \gamma \times Q_{i,t}^{G} + X_{i,t} + \alpha_i + \mu_t + \varepsilon_{i,t}, \tag{5.10}$$

where $Q_{i,p}^{G}$ (with $G = Total$) is a dummy taking value 1 if the performance measure of client i is based on high-covariance trading days and 0 if it is based on low-covariance days (Formula 5.2), with respect to the total market order flow. Table 14 shows that when the duration composition of the client's order flow has high covariance with that of the market one day (Table 15a) or three days (Table 15b) after the client traded, then the client's short-run performance increases by 2-3bp.

We argued that clients are less likely to predict the total market order flow than the order flow intermediated by the client's own dealers. We use our daily data to test whether such partial but more accessible information about the order flow still significantly profitable, by changing out dummy variable to $G = Own$. Table 15 shows that the estimated coefficients for $Q_{i,p}^{G}$ are roughly halved compared to Table 14, suggesting that predicting the order flow intermediated by the client's own dealers is, on average, about half as valuable for making profits than predicting the order flow of the whole market.

We now connect our results about client performance (Table 7) and about order flow predictions (14–15), and estimate whether clients can better predict their own dealer's order flow on trading days with unusually high connectedness. Unlike in our monthly specification, note that we define the client's own dealers with reference to the given trading day: own dealers are the ones that the client traded with on the day of the trade as well as during the past 10 trading days. The more accurate measurement of the timing of client-dealer connections allows us to better separate the time-variation in connectedness from the formation of client-dealer relationships, thereby assessing whether client connectedness is part of the information acquisition process or it is merely an instrument of concealing information.

To assess this, we turn to our covariance-connectedness regressions (5.7). Specifically, we estimate whether client connectedness predicts the covariance of the client's order flow with the whole market. As shown by Panel a of Table 16, we find only weak evidence for this, consistent with our monthly results. Moreover, as presented in Panel b of Table 16, we estimate whether higher connections predict higher covariance with the order flow of those dealers that the client traded with on the given trading day *as well as* during the preceding 10 trading days (columns 1-3). This is contrasted with the results when the covariance between the client's order flow and its dealer's is based on those dealers that the client only traded with on the given trading day, but not during the preceding 10 trading days (columns 4-6). The fact that more connected clients cannot predict the order flow of newly connected dealers (only that of the regular dealers) suggests that connectedness is not instrumental in the information acquisition process, but it merely helps transform information into better performance.

6 Summary and Conclusion

To conclude, our paper presents three main empirical findings. First, it shows that clients trading in the UK government bond market generate significantly higher abnormal returns in time periods when they have more dealer connections compared to months when they have fewer connections. To the extent that systematically higher trading performance is driven by private information, our results imply that client connectedness can be used as a proxy for private information. Second, we show that the nature of private information, that clients with more connections have, pertains to the aggregate order flow intermediated by the primary dealers that the clients trade with. Third, the predictable part of the order flow is intermediated by the client's regular dealers, suggesting that the acquisition of information precedes the increase in connectedness.

These results have several implications. First, our results highlight the relevance of financial network formation to the price discovery process in government bond markets. While the literature has extensively studied the role of private information and aggregate order flow in determining yield curve dynamics, we find that a better understanding of the network structure can sharpen our understanding of the price discovery process in these markets. Second, while a number of recent papers have studied the core-periphery structure of OTC markets (primarily focusing on the cross-sectional characteristics of dealer-client relationships), our results emphasize the dynamic and endogenous nature of networks. Third, slow trade execution is often regarded as optimal because it minimizes price impact, thereby helping to hide private information (Kyle, 1985). We find that trade execution with multiple primary dealers could serve a similar purpose, suggesting that splitting trades over time and across dealers may be substitutable. Investigating these issues both theoretically and empirically would provide interesting avenues for future research.

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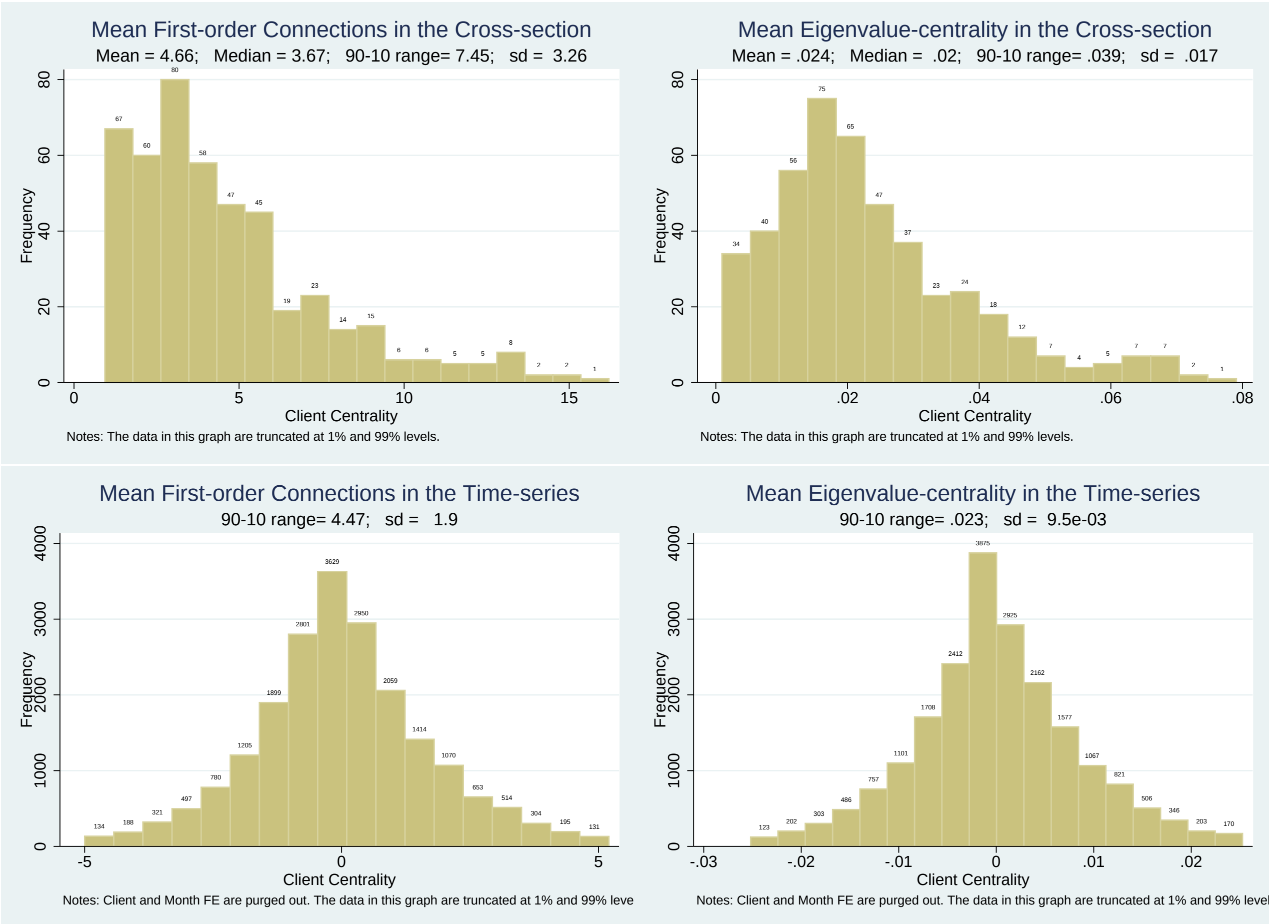
7 Figures and Tables

7.1 Summary Statistics

Figure 5: Time-series and Cross-sectional Variation in Centrality



Notes: these figures summarize the time-series and cross-sectional variation in our first-order (left column) and eigenvalue-centrality (right column) measures. The top row plots the distribution of mean client connectedness. To construct the bottom row, we first run a panel regression to purge out client and month fixed effects ($Connections_{i,t} = \alpha_i + \mu_t + \varepsilon_{i,t}$), and plot the distribution of the residuals ($\varepsilon_{i,t}$).

Table 1: Summary Statistics – Month-Client Level

(a) All Clients

	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	Median	p10	p90	sd	N
First Order Connection	5.434	4	1	12	4.086	21,170
Eigenvalue-centrality	0.0275	0.0230	0.00483	0.0588	0.0206	21,170
Transaction Number	86.70	19	4	184	274.8	21,170
$log(Volume)$	17.29	17.50	13.40	20.82	2.821	21,170
Average Monthly Duration	8.621	8.288	3.379	14.03	4.232	21,170

(b) Well Connected vs Less Connected Clients [Across-Client Variation]

	Below Median Centrality			Above Median Centrality		
	Mean	Median	sd	Mean	Median	sd
First Order Connection	2.478	2	1.251	8.951	8	3.454
Eigenvalue-centrality	0.0124	0.0121	0.00762	0.0455	0.0413	0.0163
Transaction Number	26.03	9	71.25	158.9	50	386.9
$log(Volume)$	16.12	16.30	2.610	18.67	18.93	2.412
Average Monthly Duration	8.203	7.621	4.570	9.118	9.011	3.730

(c) Well Connected vs Less Connected Clients [Across-Client Variation]

	Below Median Centrality			Above Median Centrality			Diff.
	Mean	Median	sd	Mean	Median	sd	t-stat
5-day Weighted Performance	-0.0591	0	44.75	1.084	0.794	32.10	-4.40***
5-day Unweighted Performance	-0.396	-0.0253	40.69	1.206	0.888	28.74	-3.05***
3-day Weighted Performance	-0.591	-0.235	34.59	0.696	0.476	24.85	-3.25***
3-day Unweighted Performance	-1.020	-0.502	31.61	0.661	0.418	22.14	-2.09**

(d) Well Connected vs Less Connected Months [Within-Client Variation]

	Below Median Centrality			Above Median Centrality			Diff.
	Mean	Median	sd	Mean	Median	sd	t-stat
5-day Weighted Performance	-0.0909	0.297	41.49	1.445	0.682	35.63	-2.77***
5-day Unweighted Performance	-0.224	0.363	37.65	1.326	0.624	32.06	-2.98***
3-day Weighted Performance	-0.473	-3.69e-07	32.15	0.828	0.424	27.44	-3.02***
3-day Unweighted Performance	-0.648	-0.0521	29.15	0.449	0.221	24.92	-2.72***

Notes: This table reports summary statistics for our baseline sample, covering 2011m10-2017m6, that is collapsed at the month-client level. Panel A reports summary statistics for all clients. Panel B differentiates between more connected and less connected clients by placing clients, in each month, into two groups based on whether their first-order centrality measure is below or above the median in the given month. Panel C and D report summary statistics on unweighted and volume-weighted performance measures at the 3-day and 5-day horizons, measured in basis points. Panel D places each client observation into two groups based on the within-variation of connectedness, i.e. depending on whether the client's first-order centrality measure is below or above the client's own median centrality measure based on the whole sample. The last column in Panel C and D reports the t-statistics associated with the test of whether performance is different for low and high connectivity clients (Panel C) and for low and high connectivity months (Panel D). Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

7.2 Baseline Results

7.2.1 Monthly Data

Table 2: Client Connectivity and Trading Performance: Baseline Results

	(1) 0-day	(2) 1-day	(3) 2-day	(4) 3-day	(5) 4-day	(6) 5-day
Client Centrality	0.001769***	0.001864*	0.003291***	0.003923***	0.004770***	0.005074***
	(2.762)	(1.808)	(2.652)	(2.778)	(2.740)	(2.856)
Volume	-0.000460	-0.000448	0.000419	0.000335	-0.001289	-0.001807
	(-0.388)	(-0.236)	(0.174)	(0.116)	(-0.426)	(-0.506)
Tran.	-0.001155	0.003164	0.000512	-0.002308	-0.004928	-0.004036
	(-0.687)	(1.122)	(0.123)	(-0.522)	(-0.956)	(-0.640)
N	20908	20908	20908	20908	20908	20908
R^2	0.056	0.037	0.039	0.036	0.034	0.035
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	Yes	Yes	Yes	Yes	Yes

(a) Turnover-weighted Trading Performance

	(1) 0-day	(2) 1-day	(3) 2-day	(4) 3-day	(5) 4-day	(6) 5-day
Client Centrality	0.00108*	0.00185*	0.00320***	0.00334**	0.00456***	0.00514***
	(1.880)	(1.965)	(2.749)	(2.248)	(2.750)	(2.975)
Volume	-0.00125	-0.00111	0.00145	0.00284	0.00187	0.00067
	(-1.241)	(-0.641)	(0.636)	(1.063)	(0.701)	(0.208)
Tran.	0.00126	0.00118	-0.00370	-0.00593	-0.00741	-0.00551
	(0.693)	(0.376)	(-0.935)	(-1.336)	(-1.541)	(-1.017)
N	20908	20908	20908	20908	20908	20908
R^2	0.092	0.051	0.047	0.044	0.039	0.039
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	Yes	Yes	Yes	Yes	Yes

(b) Unweighted Trading Performance

Notes: this table regresses the value-weighted (panel A) and unweighted (panel B) trading performance at different time horizons on our connectivity measures (4.5). The transaction-level data is collapsed at the client-month level. The performance measures are in %-points. We include as a control the natural logarithm of the pound trade volume of each client ("Volume") and the natural logarithm of the number of monthly transactions ("Tran."). To reduce noise, we winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and the client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 3: Illustrating the Economic Significance of the Connectedness

(a) Single-sorting by Connectedness

	Average Monthly Volume (in £000s)		Average Monthly 5-day Performance		Decomposition of Gross Performance	
	Mean	Median	Mean	Median	Mean	Median
Low Connectedness Months	308,000	15,000	-0.274	0.167	**-15%**	**6%**
High Connectedness Months	507,000	53,100	1.279	0.721	**115%**	**94%**
					100%	100%

(b) Double-sorting by Connectedness and Volume

		Average Monthly Volume (in £000s)		Average Monthly 5-day Performance		Decomposition of Gross Performance	
		Mean	Median	Mean	Median	Mean	Median
Low Volume Months	Low Connectedness Months	156,000	5,230	-0.097	0.00234	**-1%**	**1%**
Low Volume Months	High Connectedness Months	285,000	23,300	1.414	0.00821	**40%**	**20%**
High Volume Months	Low Connectedness Months	466,000	38,100	-0.456	0.00124	**-21%**	**5%**
High Volume Months	High Connectedness Months	742,000	111,000	1.137	0.00645	**83%**	**74%**
						100%	100%

Note: This table illustrates the economic significance of the performance-connectedness relationship. Panel *a* splits the sample (at the client-month level) into two groups using single-sorting, based on the within-variation of connectedness, i.e. the first (second) group contains the observations for those months when the given client had fewer (more) monthly connections compared to its sample average. Panel *b* splits the sample (at the client-month level) into four groups using double-sorting, based on the within-variation of both connectedness and trading volume. The numbers in bold decompose gross performance (defined as the product of volume and performance) into the contribution of each group. The 5-day performance measures are in basis points.

Table 4: Client Connectivity and the 5-day Performance: Transaction vs Anticipation Effect

	(1) Baseline	(2) Transaction [Id]	(3) Anticip. [Id]	(4) Transaction [D]	(5) Anticip. [D]
Client	0.00507***	0.00050	0.00438**	0.00118**	0.00372**
Centrality	(2.856)	(1.363)	(2.564)	(2.248)	(2.161)
Volume	-0.00181	-0.00098	-0.00116	-0.00193*	-0.00037
	(-0.506)	(-1.458)	(-0.321)	(-1.821)	(-0.100)
Tran.	-0.00404	0.00079	-0.00419	-0.00054	-0.00280
	(-0.640)	(0.771)	(-0.659)	(-0.328)	(-0.447)
N	20908	20908	20908	20908	20908
R^2	0.035	0.073	0.034	0.066	0.034
Time FE	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	Yes	Yes	Yes	Yes

(a) Turnover-weighted Trading Performance

	(1) Baseline	(2) Transaction [Id]	(3) Anticip. [Id]	(4) Transaction [D]	(5) Anticip. [D]
Client	0.00514***	0.00075**	0.00425**	0.00118***	0.00371**
Centrality	(2.975)	(2.375)	(2.544)	(2.724)	(2.282)
Volume	0.00067	-0.00056	0.00122	-0.00122	0.00174
	(0.208)	(-1.110)	(0.378)	(-1.561)	(0.543)
Tran.	-0.00551	0.00040	-0.00576	-0.00025	-0.00516
	(-1.017)	(0.397)	(-1.083)	(-0.176)	(-0.983)
N	20908	20908	20908	20908	20908
R^2	0.039	0.143	0.035	0.116	0.034
Time FE	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	Yes	Yes	Yes	Yes

(b) Unweighted Trading Performance

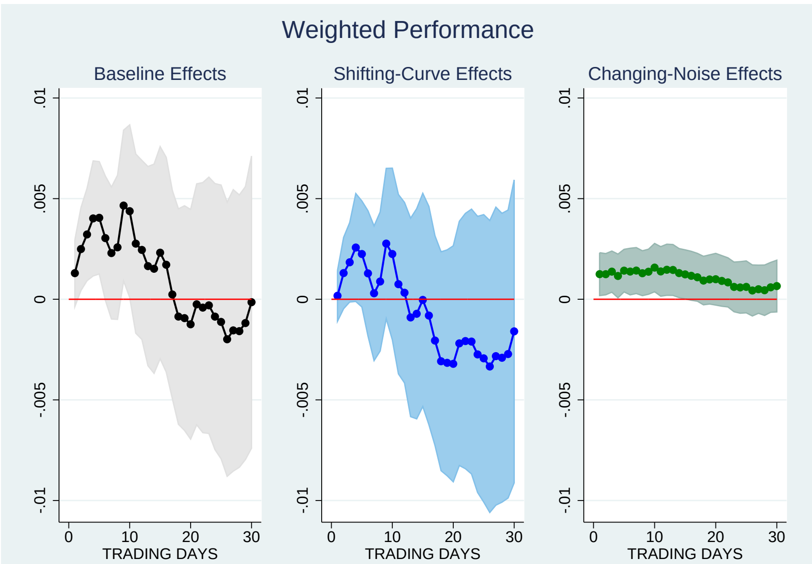
Notes: this table regresses the value-weighted (panel A) and unweighted (panel B) trading performance at the 5-day horizon horizons on our connectivity measures (4.5). The decomposition is based on 4.2. The transaction-level data is collapsed at the client-month level. We include as a control the natural logarithm of the pound trade volume of each client and the natural logarithm of the number of monthly transactions. To reduce noise, we winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and the client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 5: Client Connectivity and Realised Performance

	(1) Full Sample	(2) High Transaction Months
Client	0.00372	0.00577**
Centrality	(1.357)	(2.027)
Volume	-0.00318	-0.00771
	(-0.626)	(-1.024)
Tran.	-0.00169	-0.00345
	(-0.175)	(-0.303)
N	15242	9721
R^2	0.059	0.073
Time FE	Yes	Yes
Client FE	Yes	Yes

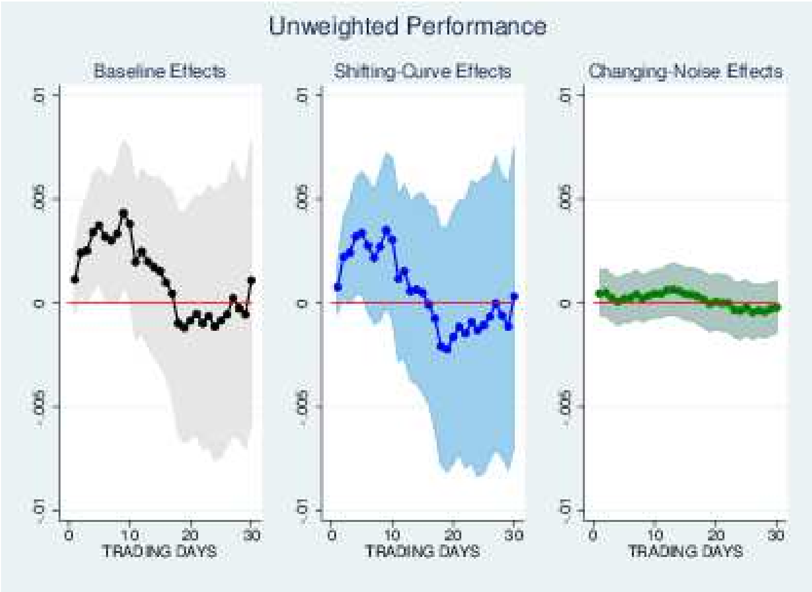
Notes: this table regresses the realised trading performance (5) on our connectivity measures. The transaction-level data is collapsed at the client-month level. We include as a control the natural logarithm of the pound trade volume of each client and the natural logarithm of the number of monthly transactions. To reduce noise, we winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and the client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Figure 6: Decomposing the Baseline Performance into Yield Curve Shifting and Changing Noise Effects



Notes: this figure plots the estimated β coefficients from variants of our baseline regression 4.5, where we use three measures of performance according to 4.3: (i) the baseline performance measure, (ii) the yield-curve shift component, and (iii) the noise component. We estimate the regression up to 30-day horizon ($T = 30$), using the value weighted performance variable as the regressand, measured in basis points. We include as a control the natural logarithm of the pound trade volume of each client ("Volume") and the natural logarithm of the number of monthly transactions ("Transactions"). To reduce noise, we winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. The shaded area denotes the 90% confidence band, It is based on robust standard errors, using two-way clustering at the month and the client level.

Figure 7: Decomposing the Baseline Performance into Yield Curve Shifting and Changing Noise Effects



Notes: this figure plots the estimated β coefficients from variants of our baseline regression 4.5, where we use three measures of performance according to 4.3: (i) the baseline performance measure, (ii) the yield-curve shift component, and (iii) the noise component. We estimate the regression up to 30-day horizon ($T = 30$), using the value weighted performance variable as the regressand, measured in basis points. We include as a control the natural logarithm of the pound trade volume of each client ("Volume") and the natural logarithm of the number of monthly transactions ("Transactions"). To reduce noise, we winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. The shaded area denotes the 90% confidence band, It is based on robust standard errors, using two-way clustering at the month and the client level.

7.2.2 Daily Data

Table 6: Client Connectedness at Daily Frequency

	Mean	Median	St.dev	Within St.dev	N
Connectedness	3.19	3	2.33	1.46	103,199

Note: the table presents summary statistics on client connectedness, defined as the number of dealers a client trades with on a given trading day. "Within St.dev" is the standard deviation of the estimated residual $\varepsilon_{i,t}$ from the regression $Connections_{i,t} = \alpha_i + \mu_t + \varepsilon_{i,t}$. The sample is based on trading days on which a client has more than two transactions.

Table 7: Client Connectivity and Trading Performance Using Daily Data

	(1) 1-day	(2) 2-day	(3) 3-day	(4) 4-day	(5) 5-day
Client	0.00053	0.00087	0.00280**	0.00431***	0.00281*
Centrality	(0.653)	(1.007)	(2.543)	(3.226)	(1.923)
Volume	0.00117	0.00146	0.00176	0.00146	0.00231
	(1.025)	(1.131)	(1.188)	(0.888)	(1.222)
Tran.	-0.00061	-0.00246	-0.00860***	-0.00811**	-0.00928**
	(-0.270)	(-0.898)	(-2.619)	(-2.101)	(-2.293)
N	103565	103565	103565	103565	103565
R^2	0.035	0.035	0.034	0.033	0.033
Time FE	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	Yes	Yes	Yes	Yes

(a) Turnover-weighted Trading Performance

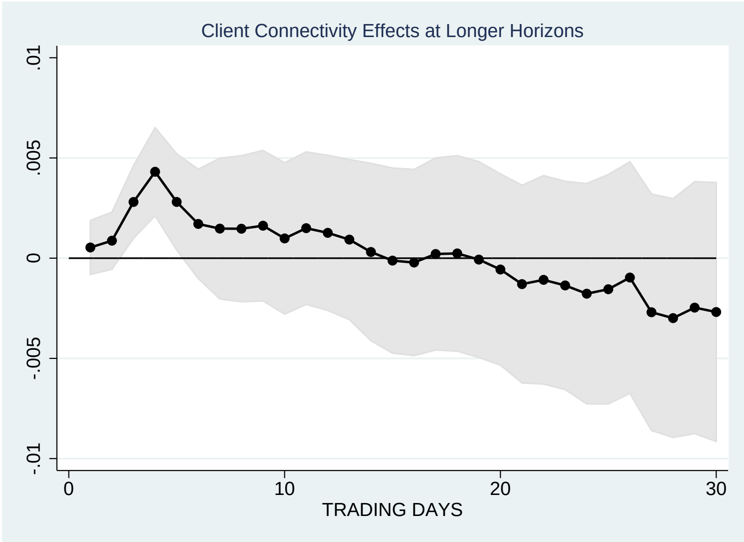
	(1) 1-day	(2) 2-day	(3) 3-day	(4) 4-day	(5) 5-day
Client	0.00120	0.00148	0.00269**	0.00418***	0.00301*
Centrality	(1.466)	(1.566)	(2.126)	(2.633)	(1.905)
Volume	-0.00044	0.00038	0.00102	0.00144	0.00143
	(-0.441)	(0.318)	(0.728)	(0.886)	(0.780)
Tran.	0.00070	-0.00107	-0.00603	-0.00789*	-0.00765
	(0.317)	(-0.360)	(-1.564)	(-1.737)	(-1.578)
N	103565	103565	103565	103565	103565
R^2	0.039	0.037	0.036	0.036	0.036
Time FE	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	Yes	Yes	Yes	Yes

(b) Unweighted Trading Performance

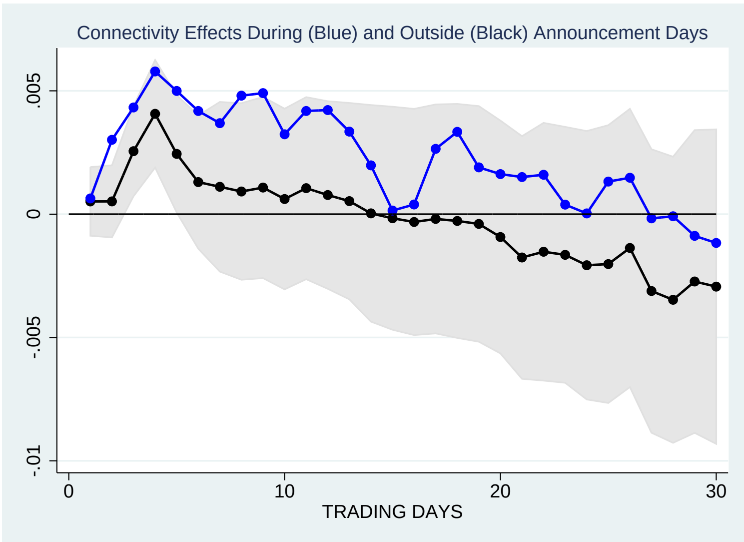
Notes: this table regresses the value-weighted (panel A) and unweighted (panel B) trading performance at different time horizons on our connectivity measures (4.5). The transaction-level data is collapsed at the client-month level. The performance measures are in %-points. We include as a control the natural logarithm of the pound trade volume of each client ("Volume") and the natural logarithm of the number of monthly transactions ("Tran."). To reduce noise, we winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and the client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Figure 8: Daily Performance Regressions over 0-30 day Horizons

(a) All Trading Days



(b) Announcement vs Non-announcement Days



Notes: Panel a plots the estimated β coefficients from our baseline regression 4.5 up to 30-day horizon ($T = 30$), using the value weighted performance variable as the regressand, measured in basis points. We include as a control the natural logarithm of the pound trade volume of each client ("Volume") and the natural logarithm of the number of daily transactions ("Transactions"). Panel b plots the results after including a dummy (interacted with connectedness) indicating the trading days that coincided with MPC announcements and release of inflation data. To reduce noise, we winsorise the sample at the 1%-level and use month-client observations that are based on at least three daily transactions. The shaded area denotes the 90% confidence band, It is based on robust standard errors, using two-way clustering at the day and the client level.

7.3 Connectivity and Covariance

7.3.1 Monthly Data

Table 8: Unweighted Trading Performance on High and Low Covariance Days

	3-day Covariance			5-day Covariance		
	1-day Perf	3-day Perf	5-day Perf	1-day Perf	3-day Perf	5-day Perf
γ	0.0230***	0.0134**	0.0023	0.0225***	0.0227***	0.0135*
	(4.218)	(2.246)	(0.360)	(3.161)	(3.511)	(1.750)
N	34868	34722	34626	34868	34722	34626
R^2	0.530	0.525	0.516	0.534	0.533	0.517

(a) **Total** Flow Covariance

	3-day Covariance			5-day Covariance		
	1-day Perf	3-day Perf	5-day Perf	1-day Perf	3-day Perf	5-day Perf
γ	0.0379***	0.0304***	0.0059	0.0368***	0.0389***	0.0198
	(4.921)	(3.650)	(0.671)	(3.154)	(3.172)	(1.446)
N	35012	34856	34648	35012	34856	34648
R^2	0.528	0.516	0.509	0.528	0.522	0.510

(b) **Across Segment** Flow Covariance

	3-day Covariance			5-day Covariance		
	1-day Perf	3-day Perf	5-day Perf	1-day Perf	3-day Perf	5-day Perf
γ	0.0009	-0.0029	-0.0010	0.0035	0.0029	0.0007
	(0.219)	(-0.579)	(-0.179)	(0.588)	(0.493)	(0.098)
N	34934	34736	34628	34934	34736	34628
R^2	0.521	0.527	0.516	0.530	0.533	0.521

(c) **Within Segment** Flow Covariance

Notes: this table regresses the unweighted trading performance at different time horizons on a dummy taking value 1 if the performance measure is based on high-covariance trades and 0 if it is based on low-covariance days (5.6). The three panels differ in terms of how the covariance is computed, corresponding to formulae 5.2, 5.1 and 5.3, respectively. The transaction-level data is collapsed at the client-month level. The performance measures are in percentage points. We winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and the client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 9: Weighted Trading Performance on High and Low Covariance Days

	3-day Covariance			5-day Covariance		
	1-day Perf	3-day Perf	5-day Perf	1-day Perf	3-day Perf	5-day Perf
γ	0.0250***	0.0107	-0.0017	0.0245***	0.0217***	0.0137
	(4.326)	(1.618)	(-0.231)	(3.144)	(2.851)	(1.554)
N	34868	34722	34626	34868	34722	34626
R^2	0.519	0.518	0.510	0.521	0.521	0.507

(a) **Total** Flow Covariance

	3-day Covariance			5-day Covariance		
	1-day Perf	3-day Perf	5-day Perf	1-day Perf	3-day Perf	5-day Perf
γ	0.0417***	0.0297***	0.0074	0.0415***	0.0412***	0.0244
	(5.117)	(3.192)	(0.765)	(3.539)	(3.235)	(1.622)
N	35012	34856	34648	35012	34856	34648
R^2	0.519	0.500	0.496	0.519	0.507	0.496

(b) **Across Segment** Flow Covariance

	3-day Covariance			5-day Covariance		
	1-day Perf	3-day Perf	5-day Perf	1-day Perf	3-day Perf	5-day Perf
γ	0.0022	-0.0048	-0.0034	0.0043	0.0030	0.0012
	(0.440)	(-0.924)	(-0.536)	(0.621)	(0.423)	(0.141)
N	34934	34736	34628	34934	34736	34628
R^2	0.517	0.518	0.511	0.519	0.526	0.514

(c) **Within Segment** Flow Covariance

Notes: this table regresses the value-weighted trading performance at different time horizons on a dummy taking value 1 if the performance measure is based on high-covariance trades and 0 if it is based on low-covariance days (5.6). The three panels differ in terms of how the covariance is computed, corresponding to formulae 5.2, 5.1 and 5.3, respectively. The transaction-level data is collapsed at the client-month level. The performance measures are in percentage points. We winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and the client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 10: Client Connectivity and Covariance with the Aggregate Order Flow

	1-Day	3-Day	5-Day
Client	0.00623*	0.00206	-0.00068
Centrality	(1.684)	(0.483)	(-0.159)
Size	-0.00834	-0.00756	-0.00306
	(-1.042)	(-0.927)	(-0.360)
Intensity	0.01316	0.02825**	0.02261
	(0.993)	(2.030)	(1.586)
N	20289	20284	20279
R^2	0.033	0.031	0.028
Month/Client FE	Yes/Yes	Yes/Yes	Yes/Yes

(a) Total Client Order Flow

	Own GEMMs' Order Flow			Rest of GEMMs' Order Flow		
	1-Day	3-Day	5-Day	1-Day	3-Day	5-Day
Client	0.01007**	0.01030**	0.01086**	0.00265	0.00043	-0.00376
Centrality	(2.089)	(2.091)	(2.195)	(0.568)	(0.088)	(-0.839)
Volume	-0.00480	-0.00969	-0.00612	-0.00765	-0.00986	-0.00523
	(-0.490)	(-0.915)	(-0.617)	(-0.915)	(-1.257)	(-0.624)
Tran.	0.02565*	0.01916	0.00795	0.00613	0.02354*	0.01819
	(1.723)	(1.127)	(0.517)	(0.402)	(1.780)	(1.453)
N	19410	19407	19404	19410	19407	19404
R^2	0.037	0.034	0.034	0.030	0.034	0.030
Month/Client FE	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes

(b) Total Client Order Flow via Own GEMMS vs Non-own GEMMs

	Regular Client-GEMM Connections			New Client-GEMM Connections		
	1-Day	3-Day	5-Day	1-Day	3-Day	5-Day
Client	0.00781*	0.01253**	0.00848*	0.00693*	-0.00033	0.00709
Centrality	(1.707)	(2.596)	(1.808)	(1.732)	(-0.084)	(1.646)
Volume	0.00412	0.00204	0.00359	0.00163	-0.00934	-0.01390
	(0.518)	(0.250)	(0.409)	(0.157)	(-0.969)	(-1.426)
Tran.	0.01137	0.00075	-0.00540	0.00326	0.02653*	0.02233
	(0.808)	(0.055)	(-0.380)	(0.225)	(1.769)	(1.514)
N	18932	18929	18926	18932	18929	18926
R^2	0.037	0.033	0.033	0.028	0.028	0.030
Month/Client FE	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes

(c) Total Client Order Flow via Own GEMMS: Regular vs New Connections

Notes: this table regresses different versions of the covariance measure 5.2 on our connectivity measure and controls (5.7). The transaction-level data is collapsed at the client-month level. The performance measures are in basis points. In Panel (a) the outcome variable is the client's covariance with the aggregate client order flow in the market. In Panel (b) the outcome variable if the client's covariance with the aggregate order flow intermediated by the dealers that the client is connected to (columns 1-3), and by all other dealers (columns 4-6). In Panel (c), the outcome variable is the client's covariance with the aggregate order flow intermediated by the dealers that the client is regularly trades with (columns 1-3) and by all other dealers that the client trades with in the given month but not in the previous month. We include as a control the natural logarithm of the pound trade volume of each client ("Volume") and the natural logarithm of the number of monthly transactions ("Tran."). To reduce noise, we winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and the client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 11: Client Connectivity and Covariance with the Aggregate Order Flow: The Role of High Performance Sensitivity Clients

	Total Market Order Flow		
	1-Day	3-Day	5-Day
Centrality	-0.00548	-0.00359	-0.00483
	(-0.964)	(-0.560)	(-0.826)
Centrality$\times D_{\beta}^{H}$	0.01663***	0.00707	0.00300
	(4.036)	(1.539)	(0.573)
Volume	-0.00859	-0.00768	-0.00315
	(-1.075)	(-0.940)	(-0.368)
Tran.	0.01342	0.02838**	0.02271
	(1.021)	(2.047)	(1.595)
N	20289	20284	20279
R^2	0.034	0.031	0.028
Month FE	Yes	Yes	Yes
Client FE	Yes	Yes	Yes

Notes: this table regresses the covariance measure 5.2 (with the aggregate market order flow) on our connectivity measure interacted with a dummy indicating high-β clients as well as other controls (5.9). The transaction-level data is collapsed at the client-month level. The performance measures are in basis points. We include as a control the natural logarithm of the pound trade volume of each client ("Volume") and the natural logarithm of the number of monthly transactions ("Tran."). To reduce noise, we winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and the client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 12: Client Connectivity and Covariance with the Aggregate Order Flow: The Role of High Performance Sensitivity Clients

	Own GEMMs' Order Flow			Rest of GEMMs' Order Flow		
	1-Day	3-Day	5-Day	1-Day	3-Day	5-Day
Centrality	-0.00262	0.00041	0.00159	-0.00250	-0.00421	-0.00807
	(-0.367)	(0.064)	(0.249)	(-0.421)	(-0.631)	(-1.344)
Centrality$\times D_{\beta}^{H}$	0.02296***	0.02041***	0.01969***	0.00732	0.00441	-0.00033
	(4.682)	(3.523)	(3.217)	(1.357)	(0.944)	(-0.068)
Volume	-0.00502	-0.01280	-0.00846	-0.00864	-0.01442*	-0.00539
	(-0.509)	(-1.238)	(-0.865)	(-1.009)	(-1.806)	(-0.626)
Tran.	0.02296	0.02034	0.00889	0.00724	0.02959**	0.01931
	(1.528)	(1.196)	(0.576)	(0.475)	(2.276)	(1.539)
N	18932	18929	18926	18932	18929	18926
R^2	0.037	0.032	0.034	0.031	0.034	0.031
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: this table the covariance measure 5.2 (with the aggregate market order flow intermediated by the client's own dealers (columns 1-3) and by all the other dealers (columns 4-6)) on our connectivity measure interacted with a dummy indicating high-β clients as well as other controls (5.9). The transaction-level data is collapsed at the client-month level. The performance measures are in basis points. We include as a control the natural logarithm of the pound trade volume of each client ("Volume") and the natural logarithm of the number of monthly transactions ("Tran."). To reduce noise, we winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and the client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 13: Client Connectivity and Covariance with the Aggregate Order Flow: The Role of High Performance Sensitivity Clients

	Regular Client-GEMM Connections			New Client-GEMM Connections		
	1-Day	3-Day	5-Day	1-Day	3-Day	5-Day
Centrality	-0.00373	0.00406	-0.00049	0.00051	-0.00812	0.00269
	(-0.498)	(0.608)	(-0.071)	(0.104)	(-1.620)	(0.523)
Centrality $\times D^H_\beta$	0.01817***	0.02012***	0.01652***	0.01269**	0.00666	0.01104*
	(4.092)	(3.532)	(3.093)	(2.380)	(1.116)	(1.692)
Volume	0.00391	0.00188	0.00343	0.00151	-0.00948	-0.01398
	(0.491)	(0.232)	(0.390)	(0.146)	(-0.985)	(-1.433)
Tran.	0.01167	0.00097	-0.00517	0.00343	0.02673*	0.02244
	(0.832)	(0.071)	(-0.365)	(0.238)	(1.792)	(1.527)
N	18932	18929	18926	18932	18929	18926
R^2	0.038	0.033	0.033	0.028	0.028	0.030
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: this table the covariance measure 5.2 (with the aggregate market order flow intermediated by the client's regular connections (columns 1-3) and by new connections dealers (columns 4-6)) on our connectivity measure interacted with a dummy indicating high-β clients as well as other controls (5.9). The transaction-level data is collapsed at the client-month level. The performance measures are in basis points. We include as a control the natural logarithm of the pound trade volume of each client ("Volume") and the natural logarithm of the number of monthly transactions ("Tran."). To reduce noise, we winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and the client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

7.3.2 Daily Data

Table 14: Weighted Trading Performance on Trading Days with High Covariance with the **Total Market** Order Flow

	(1) 1-day	(2) 2-day	(3) 3-day	(4) 4-day	(5) 5-day
$Q_{i,t}^{Total} = 1$	0.01814***	0.02550***	0.02838***	0.02573***	0.02309***
	(4.754)	(5.239)	(4.733)	(3.715)	(2.998)
Volume	0.00181	0.00211	0.00254*	0.00234	0.00316*
	(1.499)	(1.580)	(1.706)	(1.405)	(1.683)
Tran.	-0.00081	-0.00243	-0.00633**	-0.00390	-0.00671*
	(-0.387)	(-0.916)	(-2.163)	(-1.137)	(-1.947)
N	105190	105190	105190	105190	105190
R^2	0.037	0.036	0.036	0.034	0.033
Time FE	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	Yes	Yes	Yes	Yes

(a) Covariance with 1-day Ahead

	(1) 1-day	(2) 2-day	(3) 3-day	(4) 4-day	(5) 5-day
$Q_{i,t}^{Total} = 1$	-0.00133	0.00984**	0.02138***	0.02291***	0.02676***
	(-0.372)	(2.087)	(3.641)	(3.344)	(3.554)
Volume	0.00185	0.00213	0.00251*	0.00230	0.00308
	(1.528)	(1.581)	(1.662)	(1.367)	(1.630)
Tran.	-0.00062	-0.00224	-0.00623**	-0.00382	-0.00661*
	(-0.293)	(-0.839)	(-2.099)	(-1.106)	(-1.905)
N	105041	105041	105041	105041	105041
R^2	0.035	0.035	0.035	0.033	0.033
Time FE	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	Yes	Yes	Yes	Yes

(b) Covariance with 3-day Ahead

Notes: this table regresses the value-weighted (panel A) and unweighted (panel B) trading performance at different time horizons on our connectivity measures (4.5). The transaction-level data is collapsed at the client-month level. The performance measures are in %-points. We include as a control the natural logarithm of the pound trade volume of each client ("Volume") and the natural logarithm of the number of monthly transactions ("Tran."). To reduce noise, we winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and the client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 15: Weighted Trading Performance on Trading Days with High Covariance with the Market Order Flow Intermediated by **Own Dealers**

	(1) 1-day	(2) 2-day	(3) 3-day	(4) 4-day	(5) 5-day
$Q^{Own}_{i,t} = 1$	0.00673***	0.00841**	0.00963**	0.01054**	0.01238***
	(2.753)	(2.447)	(2.351)	(2.338)	(2.630)
Volume	0.00134	0.00158	0.00221	0.00206	0.00284
	(1.126)	(1.168)	(1.426)	(1.186)	(1.442)
Tran.	-0.00006	-0.00160	-0.00565*	-0.00395	-0.00704*
	(-0.026)	(-0.579)	(-1.865)	(-1.098)	(-1.931)
N	103103	103103	103103	103103	103103
R^2	0.034	0.035	0.034	0.033	0.033
Time FE	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	Yes	Yes	Yes	Yes

(a) Covariance with 1-day Ahead

	(1) 1-day	(2) 2-day	(3) 3-day	(4) 4-day	(5) 5-day
$Q^{Own}_{i,t} = 1$	-0.00199	0.00194	0.00653*	0.01069**	0.01071**
	(-0.896)	(0.598)	(1.673)	(2.478)	(2.299)
Volume	0.00134	0.00157	0.00218	0.00204	0.00281
	(1.115)	(1.153)	(1.397)	(1.166)	(1.422)
Tran.	0.00009	-0.00147	-0.00558*	-0.00390	-0.00692*
	(0.042)	(-0.531)	(-1.819)	(-1.074)	(-1.882)
N	102958	102958	102958	102958	102958
R^2	0.034	0.034	0.034	0.033	0.033
Time FE	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	Yes	Yes	Yes	Yes

(b) Covariance with 3-day Ahead

Notes: this table regresses the value-weighted (panel A) and unweighted (panel B) trading performance at different time horizons on our connectivity measures (4.5). The transaction-level data is collapsed at the client-month level. The performance measures are in %-points. We include as a control the natural logarithm of the pound trade volume of each client ("Volume") and the natural logarithm of the number of monthly transactions ("Tran."). To reduce noise, we winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and the client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 16: Client Connectivity and Covariance with the Aggregate Order Flow

	1-Day	3-Day	5-Day
Client	0.00476**	0.00043	-0.00005
Centrality	(2.291)	(0.226)	(-0.018)
Size	0.00543***	0.00407**	0.00322*
	(2.825)	(2.269)	(1.688)
Intensity	0.01543***	0.01489***	0.01231*
	(2.634)	(2.595)	(1.904)
N	103094	102949	102816
R^2	0.024	0.025	0.023
Month/Client FE	Yes/Yes	Yes/Yes	Yes/Yes

(a) Total Client Order Flow

	Traded with Dealers on Trading Day as well as During Past 10 Days			Traded with Dealers only on Trading Day		
	1-Day	3-Day	5-Day	1-Day	3-Day	5-Day
Client	0.00667***	0.00499***	0.00264*	-0.00019	-0.00074	-0.00064
Centrality	(2.866)	(3.602)	(1.682)	(-0.245)	(-0.740)	(-0.620)
Size	0.00374**	0.00114	0.00265**	0.00004	-0.00006	-0.00066
	(2.526)	(0.975)	(2.135)	(0.050)	(-0.062)	(-0.763)
Intensity	0.00893*	0.00354	0.00162	0.00245	0.00239	-0.00067
	(1.796)	(0.889)	(0.375)	(1.523)	(1.222)	(-0.365)
N	103103	102958	102825	103103	102958	102825
R^2	0.023	0.021	0.022	0.021	0.022	0.022
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	Yes	Yes	Yes	Yes	Yes

(b) Total Client Order Flow via Own Dealers

Notes: this table regresses different versions of the covariance measure 5.2 on our connectivity measure and controls (5.7). The transaction-level data is collapsed at the client-month level. The performance measures are in basis points. We include as a control the natural logarithm of the pound trade volume of each client ("Volume") and the natural logarithm of the number of monthly transactions ("Tran."). To reduce noise, we winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and the client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

7.4 Macroeconomic Announcements

Table 17: Economic Announcements

Announcement	Source	Cumulated Number of Announcement Days
Panel A: Core Announcements		
UK Inflation Report	Bank of England	
UK MPC Minutes	Bank of England	127
UK MPC Decision	Bank of England	
UK Inflation Rate	ONS	196
Panel B: Additional Announcements		
UK Earnings/Unemployment	ONS	
UK Manufacturing	ONS	356
UK GDP	ONS	
US FOMC Minutes	Federal Reserve	422
US FOMC Statement	Federal Reserve	

Notes: The table lists the major macroeconomic announcements that our analysis focuses on. Panel A lists the announcements related to UK nominal variables that we use for our benchmark analysis. Panel B includes additional announcements related to UK real variables and US monetary policy decisions. The third column denotes the cumulated number of trading days in our sample that coincide with macroeconomic announcements. In total, our sample includes 1470 trading days.

Table 18: Turnover-weighted Performance: Trading Days With and Without Inflation & Monetary Policy News

	1-day	2-day	3-day	4-day	5-day
Centrality	0.00185*	0.00302**	0.00308*	0.00473**	0.00437**
	(1.680)	(2.106)	(1.874)	(2.508)	(2.074)
Centrality$\times ANN'$	0.00108	0.00153*	0.00308***	0.00289**	0.00249*
	(1.626)	(1.949)	(3.257)	(2.449)	(1.702)
Size	0.00130	0.00235	0.00379	0.00261	0.00165
	(0.712)	(1.009)	(1.356)	(0.905)	(0.483)
Intensity	0.00033	-0.00231	-0.00816*	-0.01075**	-0.00676
	(0.098)	(-0.509)	(-1.673)	(-2.047)	(-1.130)
N	34621	34621	34621	34621	34621
R^2	0.025	0.026	0.024	0.023	0.023
Client FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes

Notes: this table regresses the value-weighted (panel A) and unweighted (panel B) trading performance at different time horizons on our connectivity measures (4.5). The transaction-level data is collapsed at the client-month level. The performance measures are in basis points. We include as a control the natural logarithm of the pound trade volume of each client ("Volume") and the natural logarithm of the number of monthly transactions ("Tran."). To reduce noise, we winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and the client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 19: Turnover-weighted Performance: Trading Days With and Without Inflation & Monetary Policy News

	1-day	2-day	3-day	4-day	5-day
$\beta_{ANN'}$	0.00108	0.00146*	0.00233**	0.00230*	-0.00213
	(1.592)	(1.738)	(2.263)	(1.877)	(1.436)
N	27312	27312	27312	27312	27312
R^2	0.503	0.509	0.516	0.520	0.521

Notes: this table regresses the value-weighted (panel A) and unweighted (panel B) trading performance at different time horizons on our connectivity measures (4.5). The transaction-level data is collapsed at the client-month level. The performance measures are in basis points. We include as a control the natural logarithm of the pound trade volume of each client ("Volume") and the natural logarithm of the number of monthly transactions ("Tran."). To reduce noise, we winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and the client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Appendix

A Additional Tables and Figures

Table 20: Client Connectivity and Trading Performance: Excluding Client Fixed Effects

	(1) 0-day	(2) 1-day	(3) 2-day	(4) 3-day	(5) 4-day	(6) 5-day
Client Centrality	0.00207***	0.00157***	0.00234***	0.00212**	0.00218**	0.00209**
	(5.683)	(2.707)	(2.968)	(2.488)	(2.416)	(2.150)
Volume	0.00324***	0.00268**	0.00260**	0.00226*	0.00264**	0.00283*
	(4.741)	(2.536)	(2.072)	(1.731)	(1.999)	(1.896)
Transactions	-0.00619***	-0.00299	-0.00476*	-0.00378	-0.00588**	-0.00502
	(-5.573)	(-1.620)	(-1.957)	(-1.420)	(-2.026)	(-1.481)
N	20909	20909	20909	20909	20909	20909
R^2	0.013	0.006	0.006	0.006	0.007	0.007
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Client FE	No	No	No	No	No	No

(a) Turnover-weighted Trading Performance

	(1) 0-day	(2) 1-day	(3) 2-day	(4) 3-day	(5) 4-day	(6) 5-day
Client Centrality	0.00270***	0.00263***	0.00329***	0.00326***	0.00352***	0.00374***
	(6.268)	(4.511)	(4.621)	(3.902)	(4.105)	(4.037)
Volume	0.00427***	0.00425***	0.00454***	0.00396***	0.00414***	0.00391**
	(5.767)	(4.143)	(3.635)	(2.851)	(2.954)	(2.453)
Transactions	-0.00888***	-0.00787***	-0.01007***	-0.00944***	-0.01120***	-0.01087***
	(-5.767)	(-4.110)	(-4.464)	(-3.732)	(-4.037)	(-3.480)
N	20909	20909	20909	20909	20909	20909
R^2	0.024	0.010	0.010	0.008	0.009	0.008
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Client FE	No	No	No	No	No	No

(b) Unweighted Trading Performance

Notes: this table regresses the value-weighted (panel A) and unweighted (panel B) trading performance at different time horizons on our connectivity measures (4.5). The transaction-level data is collapsed at the client-month level. The performance measures are in basis points. We include as a control the natural logarithm of the pound trade volume of each client and the natural logarithm of the number of monthly transactions. To reduce noise, we winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and the client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 21: Client Connectivity and Trading Performance: Including Public Clients

	(1) 0-day	(2) 1-day	(3) 2-day	(4) 3-day	(5) 4-day	(6) 5-day
Client	0.001540***	0.001530	0.002873**	0.003267**	0.003943**	0.003924**
Centrality	(2.661)	(1.613)	(2.547)	(2.492)	(2.441)	(2.379)
Volume	-0.000678	-0.000695	-0.000136	-0.000086	-0.001696	-0.002134
	(-0.590)	(-0.384)	(-0.059)	(-0.031)	(-0.572)	(-0.617)
Transactions	-0.000658	0.004243	0.001879	-0.000739	-0.002751	-0.001692
	(-0.401)	(1.584)	(0.471)	(-0.175)	(-0.550)	(-0.277)
N	22912	22912	22912	22912	22912	22912
R^2	0.055	0.038	0.039	0.036	0.034	0.035
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	Yes	Yes	Yes	Yes	Yes

(a) Turnover-weighted Trading Performance

	(1) 0-day	(2) 1-day	(3) 2-day	(4) 3-day	(5) 4-day	(6) 5-day
Client	0.00089*	0.00157*	0.00286***	0.00288**	0.00386**	0.00411**
Centrality	(1.719)	(1.819)	(2.749)	(2.137)	(2.550)	(2.579)
Volume	-0.00149	-0.00126	0.00095	0.00253	0.00137	0.00013
	(-1.509)	(-0.752)	(0.427)	(0.980)	(0.525)	(0.042)
Transactions	0.00144	0.00188	-0.00227	-0.00434	-0.00513	-0.00293
	(0.827)	(0.628)	(-0.598)	(-1.031)	(-1.112)	(-0.562)
N	22912	22912	22912	22912	22912	22912
R^2	0.088	0.051	0.047	0.044	0.039	0.038
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	Yes	Yes	Yes	Yes	Yes

(b) Unweighted Trading Performance

Notes: this table regresses the value-weighted (panel A) and unweighted (panel B) trading performance at different time horizons on our connectivity measures (4.5). The transaction-level data is collapsed at the client-month level. The performance measures are in basis points. We include as a control the natural logarithm of the pound trade volume of each client and the natural logarithm of the number of monthly transactions. To reduce noise, we winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and the client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 22: Client Connectivity and Trading Performance: Using Eigenvalue-Centrality

	(1) 0-day	(2) 1-day	(3) 2-day	(4) 3-day	(5) 4-day	(6) 5-day
Client	0.342764***	0.352475*	0.699551***	0.831766***	0.969849***	1.021515***
Centrality	(2.740)	(1.732)	(2.765)	(2.864)	(2.797)	(2.785)
Volume	-0.000475	-0.000457	0.000343	0.000246	-0.001365	-0.001879
	(-0.401)	(-0.239)	(0.142)	(0.084)	(-0.448)	(-0.523)
Transactions	-0.001043	0.003335	0.000339	-0.002501	-0.004908	-0.003951
	(-0.630)	(1.187)	(0.082)	(-0.575)	(-0.965)	(-0.634)
N	20908	20908	20908	20908	20908	20908
R^2	0.056	0.037	0.039	0.036	0.034	0.036
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Client FE	No	No	No	No	No	No

(a) Turnover-weighted Trading Performance

	(1) 0-day	(2) 1-day	(3) 2-day	(4) 3-day	(5) 4-day	(6) 5-day
Client	0.23053**	0.38297**	0.66432***	0.66936**	0.85334**	0.99639***
Centrality	(1.996)	(2.044)	(2.787)	(2.186)	(2.541)	(2.853)
Volume	-0.00128	-0.00115	0.00138	0.00279	0.00186	0.00063
	(-1.265)	(-0.658)	(0.606)	(1.039)	(0.692)	(0.193)
Transactions	0.00120	0.00114	-0.00377	-0.00586	-0.00694	-0.00520
	(0.667)	(0.370)	(-0.962)	(-1.342)	(-1.453)	(-0.978)
N	20908	20908	20908	20908	20908	20908
R^2	0.092	0.051	0.048	0.044	0.039	0.039
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Client FE	No	No	No	No	No	No

(b) Unweighted Trading Performance

Notes: this table regresses the value-weighted (panel A) and unweighted (panel B) trading performance at different time horizons on our connectivity measures (4.5). The transaction-level data is collapsed at the client-month level. The performance measures are in basis points. We include as a control the natural logarithm of the pound trade volume of each client and the natural logarithm of the number of monthly transactions. To reduce noise, we winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and the client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

A.1 Announcements Including News About US FOMC and UK Real Variables

Table 23: Turnover-weighted Performance: Trading Days With and Without Inflation & Monetary Policy News; Including News About UK Real Variables and US Monetary Policy

	1-day	2-day	3-day	4-day	5-day
Centrality	0.00217**	0.00268**	0.00275*	0.00367**	0.00326
	(2.182)	(2.065)	(1.839)	(2.140)	(1.630)
Centrality×ANN'	0.00069	0.00137**	0.00256***	0.00180**	0.00192
	(1.182)	(2.166)	(3.151)	(2.061)	(1.635)
Size	0.00049	0.00269	0.00463*	0.00356	0.00225
	(0.299)	(1.225)	(1.763)	(1.260)	(0.724)
Intensity	0.00051	-0.00156	-0.00646	-0.00714	-0.00346
	(0.190)	(-0.416)	(-1.579)	(-1.649)	(-0.652)
N	37871	37871	37871	37871	37871
R^2	0.024	0.024	0.022	0.021	0.022
Client FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes

Notes: this table regresses the value-weighted (panel A) and unweighted (panel B) trading performance at different time horizons on our connectivity measures (4.5). The transaction-level data is collapsed at the client-month level. The performance measures are in basis points. We include as a control the natural logarithm of the pound trade volume of each client ("Volume") and the natural logarithm of the number of monthly transactions ("Tran."). To reduce noise, we winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and the client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 24: Turnover-weighted Performance: Trading Days With and Without Inflation & Monetary Policy News; Including News About UK Real Variables and US Monetary Policy

	1-day	2-day	3-day	4-day	5-day
$\beta_{ANN'}$	0.00065	0.00140**	0.00204**	0.00153*	0.00185*
	(1.120)	(2.335)	(2.523)	(1.832)	(1.668)
N	33812	33812	33812	33812	33812
R^2	0.506	0.512	0.520	0.527	0.525

Notes: this table regresses the value-weighted (panel A) and unweighted (panel B) trading performance at different time horizons on our connectivity measures (4.5). The transaction-level data is collapsed at the client-month level. The performance measures are in basis points. We include as a control the natural logarithm of the pound trade volume of each client ("Volume") and the natural logarithm of the number of monthly transactions ("Tran."). To reduce noise, we winsorise the sample at the 1%-level and use month-client observations that are based on at least 2 transactions in the month. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and the client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

B Theoretical Model

Consider rounds of trading of an asset with a value of $V_t = 0, 1$ with equal probability in each round. Let V_t be uncorrelated across periods. The trading protocol is a modified version of Glosten and Milgrom (1985). Traders can seek bid and ask quotes from one or more risk neutral, competitive market maker (MM) in each round. Sampling quotes from more market makers is costly. After observing the quotes, they can decide whether to buy or sell a unit in each round.

To convey the intuition we focus on the simplest possible case.

A client $i = 1, 2$, is assigned to two potential MMs. With respect to i, we index the MMs as $m^i = R, N$, for regular and new comer. For simplicity, we assume that the set of assigned MMs are disjunct across the two clients. Client i is present in the market at t with probability $(1 - \alpha)$. With probability α, a liquidity trader arrives instead to each of the MMs, m^i. The liquidity trader requests a quote and buys or sells with equal chance from his MM. The MMs do not know which of the two types arrive in a given period. Client i's signal, $s = H, L$ is informative:

$$\Pr(V = 1 | s = H) = \frac{1}{2} + \Delta_{ti}$$

where $\Delta_{ti} > 0$ might vary across clients and time. Δ_{ti} is observable for MMs. Before trading, the client decides whether to seek quotes from N as well, additional to the quote she observes from R. The additional quote costs c. In case she does so, she observes the quotes and picks an MM to trade with. In this case, the other MM does not trade. In periods when the client is present but does not seek quotes from N, a liquidity trader arrives instead and requests a quote and trades randomly.[15] After trading, positions are liquidated at the realised true value V_t.

The following Proposition characterizes the equilibrium in this stage game.

Proposition 2 *Let*

$$\bar{\Delta} = \frac{(\alpha + 1)}{(\alpha + 2)(1 - \alpha)} c$$

be within the support of Δ_{ti}.

1. *If $\Delta_{ti} < \bar{\Delta}$, the informed trader trade only with R and the equilibrium bid ask quotes*

[15] We make this assumption to ensure that regardless of the type of the trader and the decision of the informed, MMs are requested to provide exactly one quote. Hence, number of requests do not reveal information for the MM.

are

$$A^R\left(\Delta_{ti}<\bar{\Delta}\right)=\frac{1}{2}+\Delta_{ti}\left(1-\alpha\right)$$
$$B^R\left(\Delta_{ti}<\bar{\Delta}\right)=\frac{1}{2}-\Delta_{ti}\left(1-\alpha\right)$$
$$A^N\left(\Delta_{ti}<\bar{\Delta}\right)=B^N\left(\Delta_{ti}<\bar{\Delta}\right)=\frac{1}{2}.$$

2. *If $\Delta_{ti}>\bar{\Delta}$, the informed trader seeks quotes from both MM and trades with each with equal probability. The equilibrium bid ask quotes are*

$$A^R\left(\Delta_{ti}>\bar{\Delta}\right)=A^N\left(\Delta_{ti}>\bar{\Delta}\right)=\frac{1}{2}+\Delta_{ti}\frac{(1-\alpha)}{1+\alpha}$$
$$B^R\left(\Delta_{ti}>\bar{\Delta}\right)=B^N\left(\Delta_{ti}>\bar{\Delta}\right)=\frac{1}{2}-\Delta_{ti}\frac{(1-\alpha)}{1+\alpha}.$$

Proof. The quotes are derived by Bayes Rule. For example,

$$A_1^R\left(\Delta_{ti}<\bar{\Delta}\right)=E\left(V_t|\text{ a buy in }t,R,\Delta<\bar{\Delta}\right)=$$
$$=\frac{\left(\alpha\frac{1}{2}+(1-\alpha)\left(\frac{1}{2}+\Delta_{ti}\right)\right)\frac{1}{2}}{\left(\alpha\frac{1}{2}+(1-\alpha)\left(\frac{1}{2}+\Delta_{ti}\right)\right)\frac{1}{2}+\left(\alpha\frac{1}{2}+(1-\alpha)\left(1-\left(\frac{1}{2}+\Delta_{ti}\right)\right)\right)\frac{1}{2}}=\frac{1}{2}+\Delta_{ti}\left(1-\alpha\right).$$

When the trader observes quotes from both MMs, in equilibrium the two MMs has to submit the same quotes given the mixed strategy of acceptance from the trader. For this, the informed trader has to mix with probability half. Thus,

$$A_1^R\left(\Delta_{ti}>\bar{\Delta}\right)=E\left(V_t|\text{ a buy in }t,R,\Delta>\bar{\Delta}\right)=$$
$$=\frac{\left(\alpha\frac{1}{2}+(1-\alpha)\left(\frac{1}{2}+\Delta_{ti}\right)\frac{1}{2}\right)\frac{1}{2}}{\left(\alpha\frac{1}{2}+(1-\alpha)\left(\frac{1}{2}+\Delta_{ti}\Delta\right)\frac{1}{2}\right)\frac{1}{2}+\left(\alpha\frac{1}{2}+(1-\alpha)\left(1-\left(\frac{1}{2}+\Delta_{ti}\right)\right)\frac{1}{2}\right)\frac{1}{2}}=\frac{1}{2}+\Delta_{ti}\frac{(1-\alpha)}{1+\alpha}.$$

$\bar{\Delta}$ is derived by the indifference condition given c and the different quotes under the strategies of seeking and not seeking quotes from N. ■

To picture the implied time-series and cross-sectional evaluation of prices and trades, we assume that for each client i, this subgame is repeated in many time-periods. These games are independent from each other because all random variables are redrawn in each period and because the MMs are disjunct across the two clients. Suppose that Δ_{ti} is driven by a two-state Markov process, with states Δ_H,Δ_L and $\Delta_H>\bar{\Delta}>\Delta_L$ and suppose that

$$\frac{\Delta_H}{\Delta_L}<1+\alpha. \tag{B.1}$$

The correlation structure across time and clients in Δ_{ti} can be arbitrary.

To see the implications, note first that in intervals where the state is mostly Δ_H, clients connectedness is higher. This is so, because in state Δ_H they trade with both MMs with equal chance. Therefore, the connectedness of client i is a proxy for better information for client i. Also, in state Δ_H the client has higher expected profit for two separate reasons. First, with more precise information she anticipates the true value of V with higher precision. That is, she tends to buy when $V_t = 1$. Second, as long as condition (B.1) holds, her price impact is smaller as she can hide her information better.[16]

Suppose that announcements proxy for periods, when Δ_{it} is high for both clients. In this case, the average effect of connectedness on performance is higher, as both clients are in the high-centrality group, and only liquidity traders are in the low connectedness group.

These observations are summarized in Corollary 1.

[16] Condition (B.1) is necessary, because the bid-ask spread is influenced by two forces. When private information is more precise, adverse sellection is stronger, which increases bid-ask spreads in the Δ_H state. However, in that state, the client mixes between the two market makers, which reduces the bid-ask spread. Under (B.1) the latter dominates.