Informed Trading and the Dynamics of Client-Dealer Connections in Corporate Bond Markets*

Robert Czech — Bank of England

Gábor Pintér — Bank of England

18th December 2020

Abstract

Using a unique non-anonymous UK dataset, we show that clients in corporate bond markets outperform when they trade with more dealers. The effect is stronger for informationally sensitive clients, assets, and during informationally intensive periods including COVID-19. Identifying clients who simultaneously trade in government and corporate bonds reveals that connections have a larger and more persistent effect in the corporate bond market. Using a Kyle (1989)-type model, we show that both the degree of inter-dealer competition and the magnitude of private information could explain the strength of the performance-connection relation; only the latter mechanism is supported by the data.

Keywords: Informed Trading, Corporate Bonds, Client-Dealer Connections, Inter-Dealer Competition, COVID-19

*We would like to thank Peter Kondor, Daniel Paravisini, Davide Tomio, Shengxing Zhang and participants at the 2020 European Economic Association Annual Congress and the Bank of England seminar for helpful comments. Special thanks to Dan Bernhardt for his detailed comments on our earlier draft. The views expressed in this paper are those of the authors, and not necessarily those of the Bank of England or its committees.
Emails: robert.czech@bankofengland.co.uk and gabor.pinter@bankofengland.co.uk.

1 Introduction

The smooth operation of corporate bond trading is vital for corporate finance, real investment and the macroeconomy. The size of corporate debt outstanding has increased dramatically, especially since the Great Recession. Corporate bonds are not only a main source of funding for real investment, but recently became instruments of unconventional monetary policy as well. Hence, understanding how this market operates is of critical importance.

One dominant view in the literature is that investors are unequally informed, and variation in bond prices is due to information-motivated trading. We contribute to this stream of the literature in four ways. First, we use a unique transaction-level dataset from the UK, which covers the *identities of both counterparties*, to show that clients have systematically higher trading performance when trading corporate bonds with more dealers compared to when trading with fewer dealers. This is consistent with informed traders using transactions with multiple dealers as a means of concealing private information.[1]

Second, we take the analysis further by exploiting the *asset-level* heterogeneity in corporate bond markets. We are able to compare trades of the same client, on the same day, across different bonds, and find that the trades executed with more dealers are more profitable than trades executed with fewer dealers. We find that the economic magnitude of our baseline result is sizeable: trading with an additional dealer increases performance by about 3bps over a five-day horizon. The positive relation between client connections and trading performance is statistically significant for up to a month without any sign of a reversal.

Third, we exploit variation in connections to quantify the relative importance of information *across markets*. Our unique dataset allows us to identify clients who simultaneously trade both in the government bond and corporate bond markets of the UK. We find that the effect of connections is stronger and more persistent for corporate bonds than for government bonds.

Fourth, motivated by the cross-market result, we build a Kyle (1989)-type model to show that both the degree of inter-dealer competition and the magnitude of private information could, in theory, explain the strength of the performance-connection relation. According to

[1] In stock markets, similar mechanisms have been studied in the context of order splitting and stealth trading (Barclay and Warner, 1993; Chakravarty, 2001; Alexander and Peterson, 2007; Garvey, Huang, and Wu, 2017) or venue choice (Zhu, 2014; Ye and Zhu, 2020). Our results also complement the findings reported by Kondor and Pinter (2019) in the context of government bond markets.

the first mechanism, the informed client's return from increased dealer connections is larger when inter-dealer competition is lower (e.g. in corporate bond markets compared to government bond markets). This is because lower competition increases dealers' strategic considerations, leading to more bid-shading in the inter-dealer market (Viswanathan and Wang, 2004), which, in turn, slows down information diffusion. This allows the informed client to make more profits through interacting with more dealers, compared to a scenario with higher inter-dealer competition. According to the second mechanism, more volatile bond fundamentals could also generate larger marginal gains from an increase in connections. More precisely, the magnitude of private information likely increases with the volatility of asset fundamentals (Odders-White and Ready, 2008), allowing informed traders to acquire a larger amount of private information and, in turn, to make higher profits through splitting informed orders across multiple dealers. Our empirical tests strongly support the second mechanism related to the magnitude of private information, while the inter-dealer competition channel is rejected by the data.

Our detailed dataset allows us to control for alternative, non-information based explanations. For example, investors could be hit by liquidation shocks (Barbon, Maggio, Franzoni, and Landier, 2019), which are potentially correlated across clients and affect both connections with dealers as well as future performance. The inclusion of client-day fixed effects allows us to control for the effects of such time-varying, client-specific shocks. Another possible concern is that our results are driven by correlated trading needs of uninformed investors, resulting in a spurious correlation between bond returns and client connections. We show that our results are driven by sophisticated investors (i.e. hedge funds and asset managers) who are more likely to be exposed to informational signals about asset pay-offs than unsophisticated investors. The fact that we do not observe any relation between the performance and connection dynamics of unsophisticated clients is an important cross-check, as it helps to rule out the uninformed demand pressure hypothesis. Moreover, all our regressions control for the trading volume of clients, which also helps to rule out both of these alternative explanations.

The superior performance of sophisticated clients also alleviates concerns about a supply-based interpretation of our results. For instance, clients may increase their connections when their preferred dealer bank is running low on inventory or breaches certain risk limits. However, it is unlikely that such supply shocks would lead to higher client performance, and to a differential impact on sophisticated vs. non-sophisticated investors. Moreover, we also show that the superior trading performance of sophisticated investors does not revert in the subsequent month, which is consistent with standard models of informed trading.

We also show that our regression results are not driven by the alternative explanation of dealers having private information (Li and Song 2019, 2020; Glode and Opp 2020; Brancaccio, Li, and Schurhoff 2020), which they may pass on - either intentionally or unintentionally - to their clients. We include dealer-time fixed effects to control for the linear effect of any dealer-specific shocks on a given trading day. We also allow these fixed effects to vary depending on the strength of a client's relationship with a given dealer, thereby controlling for the possibility that dealers pass on information only to selected clients – i.e. those clients that have a stronger trading relationship with the dealer (Di Maggio, Franzoni, Kermani, and Sommavilla 2019). Our baseline results are unaffected by the inclusion of these controls.

To corroborate our information-based interpretation of the baseline results, we devise six additional empirical tests using different sources of variation in our unique dataset. First, we show that a long-short portfolio based on the order flow of highly connected clients positively forecasts corporate bond returns for up to thirty days. Importantly, we do not observe such a persistent return-predictive pattern for the order flow of less connected clients.

Second, we find that the total number of connections of sophisticated clients per bond and day is positively related to future absolute bond returns up to one month. We do not find a significant relation between bond returns and the total number of connections of non-sophisticated clients, which is consistent with our prior that predominantly sophisticated traders split their trades to hide private information.

Third, we show that the effect is also stronger for clients who hold credit default swap (CDS) contracts (either long or short) written on the issuer of the traded bond. Trading in CDS allows investors to gain an information edge on credit risk fundamentals (Norden and Weber, 2004; Forte and Pena, 2009). CDS investors then profit from this advantage by concealing their private information through an increase in connections. Importantly, the CDS test helps us rule out the possible concern that dealer banks are the leading informed traders in the corporate bond market who pass on valuable information to sophisticated clients. We show that even *within* the sophisticated investor category, there is a more pronounced relation between trading performance and client connections for the subset of better informed CDS investors.

Fourth, we also show that the performance-connection effect is concentrated in the high-yield segment of the corporate bond market. The economic magnitude is large: if a client increases the number of dealer connections by one when trading high-yield bonds, then the client's weighted trading performance increases by more than 8bps over a five-day horizon. Conversely, we do not find a significant effect for the safer investment-grade segment. This is consistent with Lu, Chen, and Liao (2010), who show that information asymmetry and uncertainty is more pronounced for speculative-grade issuers compared to investment-grade firms.

Fifth, we seek to identify informationally intensive days at the aggregate level to further explore the information-based explanation of the client connection effect. We show that our baseline effect is stronger during the arrival of large macroeconomic surprises. Moreover, we identify days with high bond price dispersion to further corroborate the results on informationally intensive trading days. The idea is that price dispersion increases with the information asymmetry between investors and dealers, hence creating lucrative opportunities for informed traders. Consistent with the information-based interpretation of our results, we show that an increase in connections is more profitable on days with high price dispersion.

Sixth, we identify informationally intensive periods at the bond level as well. We find that rating changes are such events: we establish that rating changes have significant price effects, and show evidence for pre-announcement price drifts starting about three days before the rating announcement. This suggests that at least some of the rating changes are predictable.[2] Importantly, we show that the performance-connection relation is stronger during trading days leading up to the rating change. Moreover, we also connect these results to our finding that client connections positively predict bond returns. We show that sophisticated investors start increasing their connections about three days prior to rating announcements (around the same time as prices start their pre-announcement drift). In contrast, unsophisticated investors do not start changing their connections till after the rating change has become public knowledge.

We conclude our empirical analysis with a case study of the COVID-19 crisis, presented

[2]This is consistent with previous evidence on the predictability of rating changes in the US corporate bond market (Holthausen and Leftwich, 1986; Goh and Ederington, 1993; May, 2010).

in Section 8. This analysis also provides an out-of-sample test of our baseline results, as the more recent sample period spanning the COVID-19 crisis requires the use of a different dataset. We show that the connection-performance relation continues to hold in this sample, and the role of connections is substantially stronger during COVID-19, with the majority of the effect concentrating in the pre-BoE and pre-Fed announcement periods.

Related Literature There is a growing empirical literature focusing on the role of dealer-client networks in financial markets. For example, Hollifield, Neklyudov, and Spatt (2017) and Li and Schürhoff (2019) study whether clients who trade with more central dealers face higher or lower spreads. Gabrieli and Georg (2014), Maggio, Kermani, and Song (2017) and Di Maggio, Franzoni, Kermani, and Sommavilla (2019) focus on the effects of trading networks on the transmission of shocks. Our paper complements these papers (which are mainly focused on *cross-sectional* characteristics, such as the core-periphery structure of OTC markets) by highlighting the *dynamic* and endogenous nature of trading relationships in OTC markets.

Our paper is also related to the empirical literature on informed trading in corporate bond markets (Ronen and Zhou, 2013; Kedia and Zhou, 2014; Han and Zhou, 2014; Wei and Zhou, 2016; Hendershott, Kozhan, and Raman, 2020). These papers typically use the TRACE database, in which the identity of clients is not observable. Our non-anonymous dataset and empirical design allow us to identify informed client types, as well as the time periods and assets with the highest magnitudes of private information.

Closest to our empirical analysis are two recent papers. First, Kondor and Pinter (2019) analyses the relation between client-dealer connections and performance in government bond markets. Compared to their approach, we exploit the asset-level heterogeneity as well as other specific features of corporate bond markets to develop our empirical tests; and we are also able to compare the effects of connections *across markets* by identifying a common set of clients operating simultaneously in corporate and government bond markets. Second, Hollifield, Neklyudov, and Spatt (2020) analyses trade-splitting of *dealers* in corporate bond markets, focusing on dealers' inventory management considerations. Compared to their focus, we study how *clients* vary their number of counterparties, and test whether this behaviour proxies informed trading.

Our theoretical model is a variant of Kyle (1989), and is related to three strands of literature. First, the framework is inspired by the previous literature on trading on multiple exchanges (Pagano, 1989; Chowdhry and Nanda, 1991; Dennert, 1993; Bernhardt and Hughson, 1997; Baruch, Karolyi, and Lemmon, 2007; Bernhardt and Taub, 2008). Despite featuring the idea of splitting orders across markets, previous studies typically focus on the possibility of liquidity traders increasing their presence in multiple markets. In contrast, our model focuses on how equilibrium outcomes are affected by the possibility of informed traders interacting with more or fewer dealers. Second, the model is related to papers on decentralised exchanges (e.g. Glode and Opp (2016), Malamud and Rostek (2017) and Babus and Kondor (2018) among others). Third, we build on Viswanathan and Wang (2004) in modelling the inter-dealer broker market in the spirit of Kyle (1989).

Our case study of the COVID-19 crisis in the UK complements the growing literature on the impact of the COVID-19 crisis on US bond markets (Falato, Goldstein, and Hortaçsu 2020; Ma, Xiao, and Zeng 2020; Kargar, Lester, Lindsay, Liu, Weill, and Zuniga 2020; Haddad, Moreira, and Muir 2020; O'Hara and Zhou 2020).

The remainder of the paper is organised as follows. Section 2 describes the data sources and provides summary statistics; Section 3 presents the baseline results; Section 4 provides further tests for our information-based interpretation; Section 5 shows that our results are robust to various dealer characteristics. Section 6 compares the effects of connections across corporate and government bond markets. Section 7 presents our theoretical model and the related empirical tests. Section 8 presents an analysis of the COVID-19 period. Section 9 concludes.

2 Corporate Bond Data and Summary Statistics

Data Source To analyse the dynamics of client-dealer connections and how they relate to trading performance and information, one needs a detailed transaction-level dataset which contains information on the identity of both counterparties. Other datasets, such as the TRACE database for the US, do not contain this information. In contrast, the proprietary ZEN database maintained by the UK Financial Conduct Authority (FCA) provides information on traders' identities together with information on the transaction date and time; the execution price and quantity; the International Securities Identification Number (ISIN); the account number, and a buyer-seller flag. The ZEN database contains trade reports for all secondary-market transactions, in which at least one of the counterparties is a FCA-regulated entity. Importantly, the majority of client trades are with dealer banks, and all dealers in our sample are FCA-regulated. Therefore, we have at least one report for each dealer-client transaction, thereby giving us almost full coverage of the client trade universe. Our sample covers the period between September 2011 and December 2017. After filtering out all duplicates, erroneous entries and firm-internal trades, we are left with 2,533,529 observations.

We match our transaction-level data with information on bond ratings from Thomson Reuters Eikon, covering the three major rating agencies Moody's, Standard & Poor's (S&P) and Fitch. To enhance the comparability of bond ratings, we prefer ratings from Moody's as the default option due to the firm's vast market coverage. We use S&P ratings if ratings from Moody's are unavailable for a certain bond; and resort to Fitch ratings as a third option if necessary. Furthermore, we again use Thomson Reuters Eikon to collect data on bond characteristics such as the return, amount outstanding, coupon, issuance date, time-to-maturity, and issuer industry.

We also add information on clients' monthly holdings of single name credit default swaps (CDS) from the Depository Trust & Clearing Corporation's (DTCC) trade repository dataset, covering the period from November 2014 to October 2017. This regulatory dataset provides information on counterparties, notional amounts, mark-to-market values and initiation and maturity dates.[3] The DTCC trade repository data capture the vast majority of CDS positions and have previously been used in numerous academic studies. Within the DTCC's trade repository data, we observe positions meeting one of two conditions: (i) the underlying reference entity is a UK firm or (ii) at least one of the counterparties in the CDS is registered in the UK. The rich data hence allow us to measure a client's CDS gross and net notional amount written on the bond issuer in the month of the trade (if any).[4]

[3] See Czech (2019) for a detailed description of the CDS data.

[4] The CDS gross notional amount is defined as the total par amount of credit protection bought (or sold). The net notional amount is defined as the sum of net protection bought (sold) by counterparties that are net buyers (sellers) of protection for a particular reference entity, hence giving a better estimate of the net exposure.

Identifying Clients A key aspect of our empirical analysis is that we are able to see the identities of both counterparties for each transactions – a unique feature of the ZEN database. In the raw database, we identified over 2,000 unique customers that cover virtually the entire trading volume in the UK secondary market. Our baseline sample includes 'sophisticated' customers such as hedge funds and asset managers. We estimate the baseline effect separately for 'unsophisticated' clients (i.e. insurance companies, pension funds, government entities etc.) who are less likely trade on information. We end up with 577 and 733 unique sophisticated and unsophisticated clients, respectively. Each group represents about half of the total client sample both in terms of trading volume and number of transactions.

Client-Dealer Connections We consider two measures of client connections. First, we use the number of dealer banks a particular client is connected to on a given day, since the majority of trading volume initiated by clients is intermediated by these dealers. A client is connected to a dealer bank if it trades with this dealer at least once on a given day. When we collapse our data at the day-client-instrument level, daily connections of a client can vary across the bonds that she is trading.

Second, we relax this connection definition and propose a second measure which is the number of unique counterparties (dealer banks or other market participants) that the given client trades with on a particular day. This measure is motivated by the fact that certain larger clients started exhibiting dealer-type behaviour, similar to recent developments in the US corporate bond market (Choi and Huh, 2017; Bessembinder, Jacobsen, Maxwell, and Venkataraman, 2018). Since client connectivity is a key source of variation for our analysis, we provide some summary statistics to describe it.

Table 1 presents summary statistics based on our baseline regression sample that is aggregated to the client-day level. Using the mean values, we find that the average client is connected to about two counterparties on a given day and carries out around seven transactions with them. There is substantial sample variation: the average difference in first order connections between the 90th and 10th percentile is 5. To illustrate how much of the variation in client connectivity is a cross-sectional phenomenon, we compute the average number of connections for each client across all her trading days, and plot the resulting distribution in a histogram (left column of Figure 11). 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 verify this, we use a regression model with client and day fixed effects to better isolate our connectivity measures. We plot the resulting distribution in a histogram (right column of Figure 11). We find substantial within-client variation: the average difference in first order connections between the 90th and 10th percentile is 3.2-3.6, which is much larger compared to the corresponding value using across-client variation (1-1.2). Similarly, the standard deviation of first-order connections is around 0.8-1.2 in the cross-section and around 1.5-1.7 when using only the within-client variation time-series.

To quantify the degree of dealer concentration in the corporate bond market, we report dealer market shares and the Herfindahl-Hirschman Index (HHI) across all bonds in our sample. Panel B of Table 1 shows that on average five dealer banks are actively trading a particular bond in a given month. The most active dealer bank in a given bond has an average market share of 62%, but with remarkable cross-sectional variation: the average difference between the 90th and 10th percentile is 67.1%. The top three dealer banks in terms of market share intermediate 91% of the total monthly trading volume of an average bond in our sample. This substantial market concentration is also reflected in the average HHI of 0.52, which is considered a highly concentrated market structure.[5]

3 Baseline Results

3.1 Measuring Trading Performance

Baseline Measure To measure trading performance, we follow Di Maggio, Franzoni, Kermani, and Sommavilla (2019) by computing the T-day-horizon return on each trade of client i on day t, measured as the percentage difference between the transaction price and the trade-

[5]The Herfindahl-Hirschman index is calculated for each bond by summing up the squared market shares of each active G15 dealer bank in a given month. Usually, a market is considered to be highly concentrated when the HHI is above 0.25.

weighted average price T days after the transaction date.[6] Formally, for each trade j, we construct the measure $Performance_j^T$ as follows:

$$Performance_j^T = \left[\ln\left(P^T\right) - \ln\left(P_j^\star\right)\right] \times \mathbf{1}_{B,S}, \tag{3.1}$$

where $P_j^\star$ is the transaction price, P^T is the T-day ahead trade-weighted average price of the corresponding bond, and $\mathbf{1}_{B,S}$ is an indicator function equal to 1 when the transaction is a buy trade, and equal to -1 when it is a sell trade.[7] All transactions-specific returns are then averaged within day t using the pound volume of the trades as weights (Bessembinder, Kahle, Maxwell, and Xu, 2009). As robustness, we also present the results using unweighted daily average returns.

Panel C of Table 1 shows that average performance is significantly larger for clients with more dealer connections compared to clients with fewer connections. More importantly, this panel also shows that the average client performs significantly better on days with more dealer connections compared to days when the same client has fewer connections. For example, the average client has a 2.5bps higher 5-day performance on high-connection days compared to low-connection days.

3.2 Client Connections and Trading Performance

Given the trading performance measures (3.1) we now explore empirically whether a client's trading performance increases when the given client increases its connections, either with all investors or only with dealer banks.

Client-Time Level Results Our baseline specification is the following daily panel regression:

$$Performance_{i,t}^T = \beta \times ClientConnections_{i,t} + Vol_{i,t} + \alpha_i + \mu_t + \varepsilon_{i,t}, \tag{3.2}$$

[6]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 trade-weighted average price on day 2, and compare all trades on day 2 to the trade-weighted average price on day 3, and so on.

[7]The forward-looking nature of our measure 3.1 aims to capture informational effects. This is distinct from the analysis of execution costs that are the focus of empirical studies motivated by search-theoretic models (Feldhutter, 2012; OHara, Wang, and Xing, 2018).

where $Performance^T_{i,t}$ is the trading performance of client i on day t at horizon T; $ClientConnections_{i,t}$ is the number of counterparties (either against all investors or only against dealer banks) client i is connected to on day t; $Vol_{i,t}$ denotes trading volume of client i on day t; α_i and μ_t are client and day fixed effects. Throughout the analysis, we take the most conservative approach in computing standard errors, and employ two-way clustering at the client and day level. This procedure allows for arbitrary correlation across days and across clients.

The main coefficient of interest in 3.2 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 volume-weighted and unweighted trading performance, respectively. Each column corresponds to a different trading horizon $T = 5, 10, 15$. We find a positive relation between client connectivity and trading performance, which is statistically significant at almost every horizon for both types of performance measures.

Recall, our regression results are based on a sample that only includes sophisticated clients, i.e. hedge funds and asset managers. These clients more likely trade on information, so the connection effects that our estimation is picking up are likely be related to information. An important first check of this is to re-run the estimation using only the unsophisticated clients that our analysis has excluded so far. Table 3 shows the results: we do not find significant estimates for client connections in any of the specifications. This result is important as it helps to rule out alternative explanations related to uninformed demand pressures that may be correlated across clients, driving both client's performance and connections. If such a mechanism would drive our baseline estimates, then we should not be observing such differential effects of connections on performance across sophisticated and unsophisticated clients.

Client-Time-Bond Level Results In addition to our baseline results, we now explore whether clients perform better when trading a bond with more dealers compared to trading a different bond with fewer dealers on the same day. Specifically, we use client-day fixed effects to control for time-varying, unobserved client-level heterogeneity. This client-time-bond level specification addresses the possible concern that the client-time level model 3.2 may be picking up time-varying client liquidity shocks (potentially correlated across traders), which generate the performance-connection relation.

Moreover, compared to government bond markets in which information likely pertains to aggregate order flow or public news (Brandt and Kavajecz, 2004; Pasquariello and Vega, 2007), private information in corporate bond markets is more likely to be bond-specific (Hendershott, Kozhan, and Raman, 2020). This may result in underestimating the informational effects of connections when using our client-time level 3.2. Accordingly, we now estimate the following client-time-bond regression:

$$Performance^{T}_{i,j,t} = \beta \times ClientConnections_{i,j,t} + Vol_{i,j,t} + \alpha_{i,t} + \mu_{j,year} + \varepsilon_{i,j,t}, \tag{3.3}$$

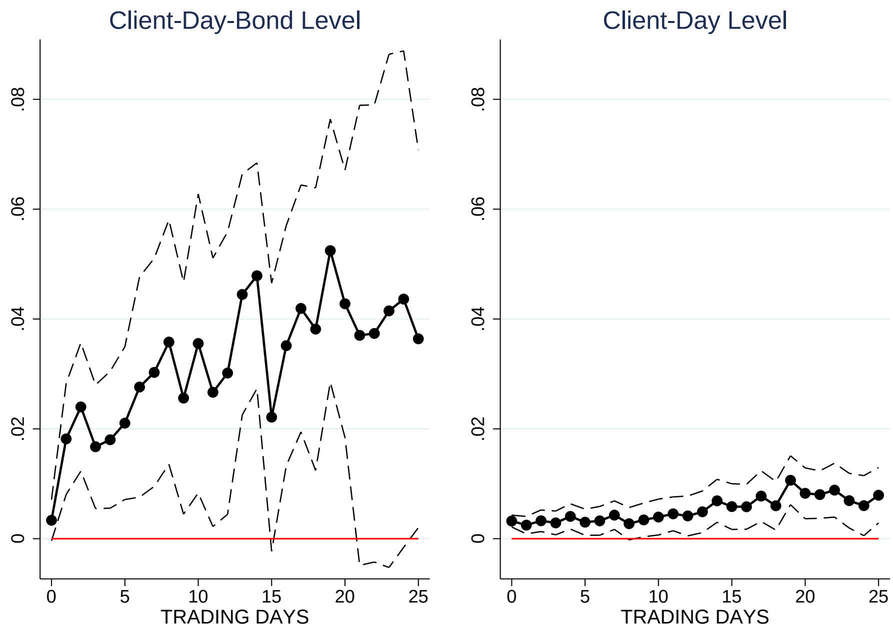
where $Performance^{T}_{i,j,t}$ is the trading performance of client i on day t at horizon T; $ClientConnections_{i,j,t}$ is the number of counterparties (either against all investors or only against dealer banks) the given client is connected to on day t for bond j; $Vol_{i,j,t}$ controls for the trading volume of client i on day t for bond j; $\alpha_{i,t}$ and $\mu_{j,year}$ are client-day and bond-year fixed effects.

The main coefficient of interest β now captures the relation between bond-specific client connectivity and trading performance. Table 4 reports our bond-specific baseline results. Each column corresponds to a different trading horizon, ranging from $T = 5$ to $T = 15$. We find a positive relation between bond-specific client connectivity and trading performance, which is statistically significant at almost every horizon for both types of performance measures.

The economic magnitude of our results is large. For example, Panel A of Table 4 shows that if a client increases the number of its connections by one, then its trading performance increases by 2.6bps. The results are similarly strong when we focus on a client's connections only with dealer banks; and the results are also robust to using the unweighted trading performance instead of the volume-weighted performance measure. For example, Panel B of Table 4 shows that if a client increases the number of its dealer connections by one, then its unweighted trading performance increases by 2.9bps over the five-day horizon. Last but not least, we find little evidence that the variation in a client's trading volume in a certain bond on a given day would affect its trading performance.

Moreover, to assess the persistence of the effect of client connections, we gradually increase

Figure 1: Connections and Performance over 0-25 day Horizons



Notes: The left panel plots the estimated β coefficients from our client-day-bond regression 3.3, up to a 25-day horizon ($T = 25$), using the volume-weighted performance variable as the regressand, measured in %-points. The right panel plots the estimated β coefficients from our client-day regression 3.2. Connections are measured against dealer banks. We include the natural logarithm of the pound trade volume of each client ("Volume") as a control. To reduce noise, we winsorise the sample at the 1%-level. The dashed lines denote the 90% confidence bands based on robust standard errors, using two-way clustering at the day and client level.

the trading horizon up to 25 days ($T = 25$), and re-estimate our baseline regressions both at the client-day level (3.2) and the client-bond-day level (3.3). In Figure 1, we present the estimated βs for the two sets of models using the volume-weighted performance measure, together with the 90% confidence bands. There are two main takeaways from this picture. First, irrespective of which regression specification we use, the effect of connections on connections is persistent with no signs of reversal. This is consistent with connections proxying private information about bond fundamentals. Second, the effects at the client-day-bond level are about five times larger than those at the client-day level. This suggests that asset-level heterogeneity plays an important role for informational trading in corporate bond markets, particularly when compared to government bond markets (Kondor and Pinter, 2019). In the next section, we present a number of additional tests to support the information-based interpretation of our findings.

4 Testing for Informational Effects

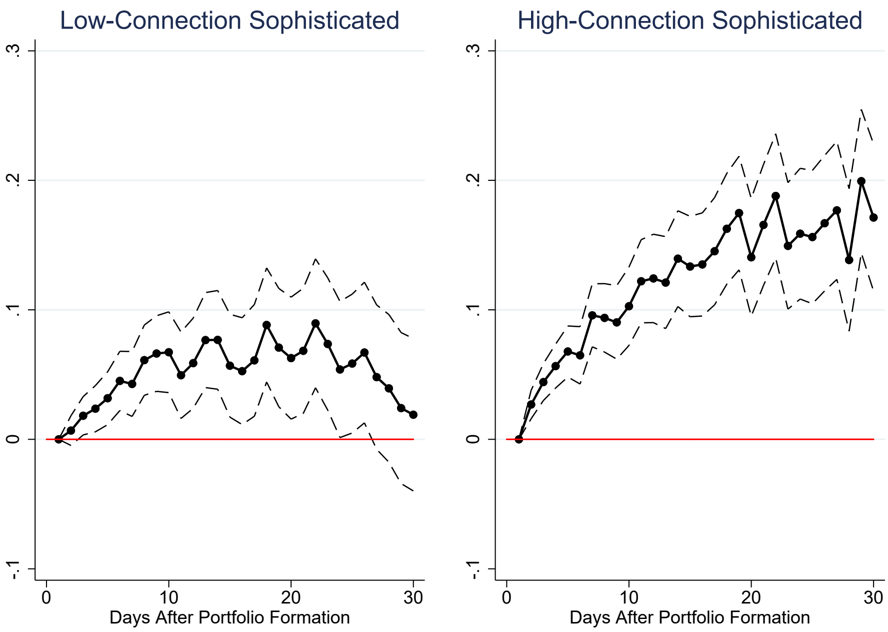
4.1 High-connection Order Flow as a Proxy for Informed Order Flow

To test the informational role of connections, we first estimate whether the order flow initiated by clients with above-average connection levels can predict future bond returns. Building on Czech, Huang, Lou, and Wang (2020), we proceed in four steps. For each client, we first sort trading days into two buckets depending on whether the given client had more or fewer connections on a given day compared to her sample average. Second, we compute the aggregate order flow in each bond of both 'high-connection' and 'low-connection' client types. It is important to emphasise that this order flow sorting is based on the within-client variation of connections, as opposed to sorting clients based on characteristics that only vary in the cross-section. More precisely, the order flow of a given client appears half of the time in the 'high-connection' order flow category, and the other half of the time in the 'low-connection' category. Third, we sort all corporate bonds (around 2,900 bonds in our sample) on each trading day into deciles based on the aggregate order flow of clients with either low or high connections. Fourth, we construct a long-short portfolio that buys the top decile and sells the bottom decile, and compute cumulative daily returns of these portfolios for up to thirty days.

Table 5 and Figure 2 show the cumulative daily returns of the long-short portfolios. The left panel of Figure 2 shows that order flows of the 'low-connection' client type positively forecast bond returns in the following five to ten days, followed by a complete reversal after thirty days. In stark contrast, the right panel of Figure 2 shows that the order flows of the 'high-connection' client type positively forecast corporate bond returns for up to thirty days. For example, the return spread between the top and bottom decile sorted by order flows of the 'high-connection' client type is 6.8bps after five days, which then grows to 10.3bps and 17.1bps after ten and thirty days, respectively.

This result helps to address concerns that our baseline results might be picking up 'high-connection' clients generating temporary demand pressures which would affect their subsequent trading performance. The difference in the persistence of portfolio returns in Figure 2 suggests that 'high-connection' order flow is indeed more likely to proxy informed trading rather than temporary demand pressures, consistent with the information-based interpretation of our

Figure 2: Long-Short Portfolio Returns



Notes: This figure plots the cumulative returns of the long-short portfolio based on the order flow of 'high-connection' and 'low-connection' client types for a 30-day horizon ($T = 30$) measured in %- points. More precisely, the bonds are equally sorted into ten groups on each trading day based on the aggregate order flow of clients with either 'low' or 'high' connections compared to their sample average. To reduce noise, we winsorise the sample at the 1%-level. The dashed lines denote the 90% confidence bands based on robust standard errors.

baseline regression results.

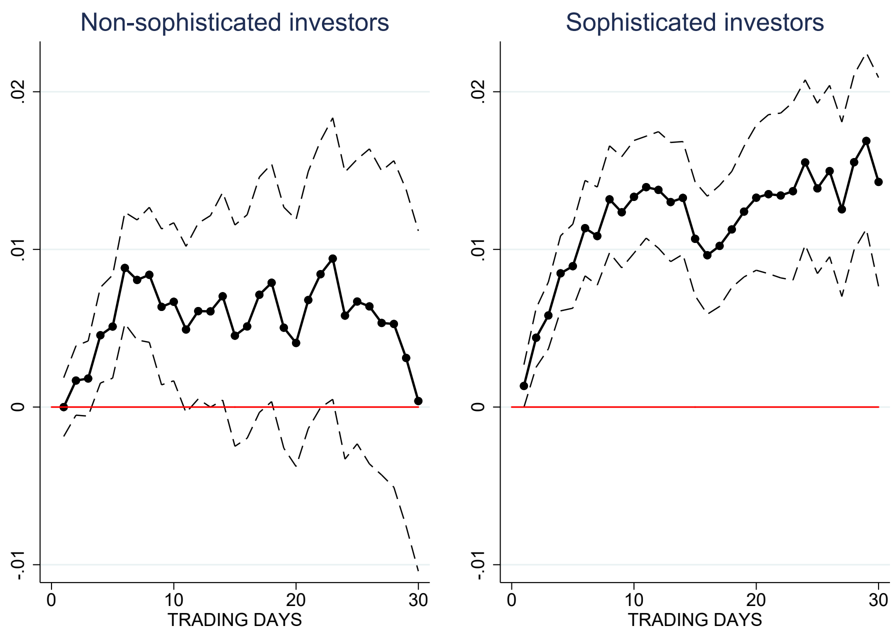
4.2 Sophisticated Client Connections and Bond Performance

Building on the long-short portfolio results, we now test whether time-variation in the total number of client connections in the market can predict bond returns. For each bond/day combination, we measure the number of connections separately for sophisticated as well as non-sophisticated investors. Consistent with our previous classification, we consider asset managers and hedge funds as sophisticated investors; and classify non-dealer banks, insurers and pension funds as non-sophisticated investors (see also Czech, Huang, Lou, and Wang, 2020). We estimate the following daily panel regression:

$$|\log(Price_{j,t+1+T}) - \log(Price_{j,t+1})| = \beta \times TotalConnections_{j,t} + Vol_{j,t} + \mu_{j,year} + \varepsilon_{j,t}, \quad (4.1)$$

where $|\log(Price_{j,t+1+T}) - \log(Price_{j,t+1})|$ is the absolute return of bond j between day $t+1$ and day $t+1+T$. $TotalConnections_{j,t}$ is the total number of client connections (against all investors) for bond j on day t; $Vol_{j,t}$ denotes the trading volume in bond j on day t; $\mu_{j,year}$ are bond-year fixed effects. We use $T = 30$, i.e. we look at absolute return effects in the 30-day window after the aggregate client connection measurement. Standard errors are clustered at the bond level.

Figure 3: Predicting Bond Returns with (Non-)Sophisticated Client Connections



Notes: This figure plots the estimated β coefficients from regression 4.1 up to a 30-day horizon ($T = 30$), using the volume-weighted absolute log-return variable as the regressand, measured in %-points. The independent variable is the total number of client connections (against all investors) for bond j on day t. We include as a control the natural logarithm of the pound trade volume in each instrument ("Volume"). To reduce noise, we winsorise the sample at the 1%-level. The dashed lines denote the 90% confidence bands based on robust standard errors, clustered at the bond level.

As shown in Table 6 and Figure 3, we find a significant difference in future bond return dynamics for the total non-sophisticated client connections compared to sophisticated client connections. For instance, the left panel of Figure 3 shows that if the number of *non-sophisticated* client connections for a given bond increases by one, then its weighted absolute return increases by 0.5bps in the following five days, followed by a complete reversal after thirty days. In contrast, the right panel of Figure 3 shows that if the number of *sophisticated* client connections for a given bond increases by one, then its weighted absolute return increases by 1.3bps in the following ten days, without any sign of reversal after thirty days. Therefore, the results are consistent with our prior that the total number of sophisticated client connections in the market should be informative about future bond returns.

4.3 *Credit Default Swap Holdings*

As a further test, we explore the relation between client connectivity and trading performance depending on the client's CDS holdings written on the issuer of the traded bond. As in 3.3, we test whether clients perform better when trading a bond with more dealers compared to trading a different bond with fewer dealers on the same day, with the important difference that we now include an interaction term with an indicator variable for the client's CDS holdings. Our prior is that CDS investors are better informed about the credit risk of the issuer, which is the primary determinant of credit spreads in normal market conditions (see, for example, Ericsson, Jacobs, and Oviedo, 2009; Hasan, Liu, and Zhang, 2016). Therefore, we expect that the informational role of connections is more pronounced for investors who hold CDS contracts written on the bond issuer, compared to investors without this information edge. We estimate the following daily panel regression:

$$\begin{aligned} Performance^{T}_{i,j,t} = \beta_1 \times ClientConnections_{i,j,t} + \beta_2 \times ClientConnections_{i,j,t} \times CDS_{i,z,m} \\ + Vol_{i,j,t} + \alpha_{i,t} + \mu_{j,year} + \varepsilon_{i,j,t}, \end{aligned} \tag{4.2}$$

where $Performance^{T}_{i,j,t}$ is the trading performance of client i on day t at horizon T; $ClientConnections_{i,j,t}$ is the number of counterparties (either against all investors or only against dealer banks) the given client is connected to on day t for bond j; $CDS_{i,z,m}$ is an indicator variable equal to one if client i holds a CDS contract (either long or short) on the issuer z of bond j in month m; $Vol_{i,j,t}$ controls for the trading volume of client i on day t for bond j; $\alpha_{i,t}$ and $\mu_{j,year}$ are client-day and bond-year fixed effects. Throughout the analysis, we again compute standard errors with two-way clustering at the client and day level.

The main coefficient of interest in 4.2 is β_2, which captures the relation between bond-specific client connectivity and trading performance depending on the client's CDS holdings written on the issuer of the traded bond. Table 7 reports the results. We find a positive relation between our CDS-client connectivity interaction term and trading performance for the five-day trading horizon. Importantly, this result remains robust when we control for client-day fixed effects, i.e. clients (who hold CDS contracts written on the bond issuer) perform better when trading a bond with more dealers compared to trading a different bond with few dealers on the same day. The economic magnitude of our results is also significant. For instance, Panel A of Table 7 shows that if a CDS-holding client increases the number of its connections by one, then its weighted trading performance increases by 2bps over five days.

Overall, these results are consistent with our prior that investors can gain an information advantage when they trade and hold CDS contracts written on a bond issuer, and these CDS investors profit from this edge by hiding their information through increasing their connections. Importantly, the results are also consistent with prior studies about the leading informational role of the CDS market with respect to the bond market (Norden and Weber, 2004; Forte and Pena, 2009) and the predominance of informed institutional investors in the CDS market (Das, Kalimipalli, and Nayak, 2014).

4.4 Rating Categories

As an additional test, we now explore the relation between client connectivity and trading performance depending on the bond credit rating. Higher-rated bond issuers tend to differ in many aspects from lower-rated firms. For example, lower credit quality firms have more complex debt structures, using multiple tiers of debt (Rauh and Sufi, 2010). Investment-grade issuers, in contrast, tend to have much simpler debt structures. By definition, credit ratings should reflect all such sources of credit risk, including information uncertainty and information asymmetry. Lu, Chen, and Liao (2010) confirm that measures of information uncertainty and asymmetry increase with lower credit ratings. Therefore, we hypothesise that the role of client connections is more pronounced for trades in bonds with more uncertain and volatile fundamentals, i.e. high-yield bonds.

Building on 3.3, we interact our connectivity variable with indicator variables for investment-grade and high-yield bonds. We estimate the following daily panel regression:

$$\begin{aligned} Performance^{T}_{i,j,t} = \beta_1 \times ClientConnections_{i,j,t} + \beta_2 \times ClientConnections_{i,j,t} \times IG_{j,t} \\ + \beta_3 \times ClientConnections_{i,j,t} \times HY_{j,t} + Vol_{i,j,t} + \alpha_{i,t} + \mu_{j,year} + \varepsilon_{i,j,t}, \quad (4.3) \end{aligned}$$

where $Performance^{T}_{i,j,t}$ is the trading performance of client i on day t at horizon T; $ClientConnections_{i,j,t}$ is the number of counterparties (either against all investors or only against dealer banks) the given client is connected to on day t for bond j; $IG_{j,t}$ and $HY_{j,t}$ are indicator variables equal to one if bond j has an investment-grade (above BB+) or high-yield (below BBB-) rating on day t; $Vol_{i,j,t}$ controls for the trading volume of client i on day t for bond j; $\alpha_{i,t}$ and $\mu_{j,year}$ are client-day and bond-year fixed effects.

The main coefficients of interest in 4.3 are β_2 and β_3 which capture the relation between bond-specific client connectivity and trading performance for investment-grade and high-yield bonds, respectively. The control group is the group of unrated bonds, for which the effect is captured in β_1. Table 8 reports the rating category interaction results. We find a strong and positive relation between bond-specific client connectivity and trading performance for high yield bonds, which is statistically significant up to ten days for both types of performance measures. Importantly, this result survives when we control for client-day fixed effects, i.e. clients perform better when trading a high-yield bond with more dealers compared to trading a different bond with fewer dealers on the same day. Perhaps unsurprisingly, we do not find a statistically significant effect for investment-grade or unrated bonds.

These results are consistent with our prior that the information asymmetry and uncertainty is significantly higher for high-yield bonds compared to investment-grade bonds. This higher information asymmetry enables sophisticated investors to gain an information advantage over non-sophisticated investors, and the sophisticated investors profit from this edge by hiding their information through increasing their connections. The muted effect for unrated bonds is probably due to a lower information asymmetry for these bonds, given the trend that many large multinationals merely rely on the reputation of the firm and issue bonds without rating to reduce expenses for rating agency fees.

The economic magnitude of our results is large. For instance, Panel A of Table 8 shows that if a client increases the number of its connections by one for high-yield bonds, then its weighted trading performance increases by 8.3bps over the five-day horizon. The high-yield bond results are similarly strong when we focus on a client's connections only with dealer banks; and the results are also robust to using the unweighted trading performance instead of the volume-weighted performance measure. For example, Panel B of Table 8 shows that if a client increases the number of its dealer connections by one for high-yield bonds, then its unweighted trading performance increases by 10.5bps over the five-day horizon.

Overall, the results show that our connection effects are concentrated in the high-yield segment of the corporate bond market. This is consistent with the higher information asymmetry (Lu, Chen, and Liao, 2010) and complexity (Rauh and Sufi, 2010) of speculative-grade firms, hence strengthening the information-based interpretation of our results.

4.5 Macroeconomic Announcements

The arrival of big macroeconomic surprises are obvious candidates for informationally intensive days that could be used to further test the informational role of connections. For example, monetary policy news change asset prices through affecting both the risk-free portion of discount rates and risk premia around FOMC announcements (Bernanke and Kuttner, 2005; Lucca and Moench, 2015; Abdi and Wu, 2018; Cieslak, Morse, and Jorgensen, 2019). Moreover, the cash-flow effects of monetary shocks on firms can also be highly heterogeneous, depending on leverage, firm age (Bahaj, Foulis, Pinter, and Surico, 2018), size (Gertler and Gilchrist, 1994) among other characteristics. Therefore, private information about companies may interact with the arrival of public information about the state of the economy, which may provide trading opportunities for informed traders. To test this hypothesis, we estimate whether connections are more important for trading performance during macroeconomic announcements.

Macroeconomic news hit markets almost constantly, some of which may contain only a small surprise component or little relevance for asset prices. It is therefore important to identify trading days on which macroeconomic news truly surprised markets and moved prices non-trivially. To do so, we build on the high-frequency methodology of Swanson and Williams (2014a,b) to identify the surprise component of macroeconomic announcements and its effect on bond prices.[8] We sort trading days into two groups depending on whether the magnitude of the macroeconomic surprise on the given day is smaller or bigger than the sample average.

We then re-estimate a variant of our baseline model 3.3, in which we interact connections with an indicator variable for days with small/big macroeconomic surprises. We present the results in Tables 9 (at client-day level) and 10 (at client-day-instrument level). We find a statistically significant and economically large effect for trading days with large macroeconomic

[8]The method uses historical tick data to compute the change in the 3-year interest rate in a tight window (five minutes before and five minutes after) around the release of both nominal and real news from both the UK and the US. See Eguren-Martin and McLaren (2015) for further details.

surprises, compared to small macro-surprise days. For example, Panel A of Table 9 shows that trading with an additional dealer leads to a 3.6bps increase in trading performance (over a five-day horizon) on days with large surprises, compared to a statistically insignificant 0.5bps on days with only small macro-surprises.

Overall, our macro-news test shows that our connection effect is concentrated on informationally intensive days. This finding adds an important dimension to our previous results, since we can now show that increased connections lead to higher trading performance for informationally sensitive (i) clients (4.2 and 4.3), (ii) bonds (4.4) and, finally, (iii) days (4.5).

4.6 Bond Price Dispersion

In over-the-counter markets one often observes a variety of prices for the same asset in a given time period. Similar to macroeconomic announcements, these high price dispersion days may provide lucrative trading opportunities for informed traders. To test this, we estimate whether connections are more important for trading performance during days with high price dispersion.

Since price dispersions in larger trades reveal more reliable insights, we follow Jankowitsch, Nashikkar, and Subrahmanyam (2011) to calculate the volume-weighted measure of price dispersion:

$$d_{j,t} = \sqrt{\frac{1}{\sum_{k=1}^{K_{j,t}} Vol_{j,k,t}} \times \sum_{k=1}^{K_{j,t}} (p_{j,k,t} - \bar{p}_{j,t})^2 \times Vol_{j,k,t}}, \tag{4.4}$$

where $d_{j,t}$ is the price dispersion measure on day t for bond j, $Vol_{j,k,t}$ is the volume of trade k in bond j, $p_{j,k,t}$ is the price of trade k in bond j, and $\bar{p}_{j,t}$ is the volume-weighted average price of bond j across all trades on that day. As for the macroeconomic announcements, we sort trading days into two groups depending on whether the daily average of our price dispersion measure across all bonds is smaller or larger than the sample average. We then interact this indicator variable for low/high price dispersion trading days with our connectivity measure, using our baseline model 3.3.

Table 11 shows the results. Consistent with our prior, we find that the relation between connections and trading performance is stronger and more significant on days with high bond price dispersion. The economic magnitude of the effect is also large. Panel A of Table 11 shows that trading with an additional dealer significantly increases trading performance by 4.6bps (over a ten-day horizon) on days with high price dispersion. Importantly, we do not find we an effect of similar economic and statistic significance for days with low price dispersion.

One possible concern with our results in this section and 4.5 is that high price dispersion and macro-surprise days are correlated with periods of bond market illiquidity, which may lead to a mechanical increase in connections as client try to obtain their desired risk profile. Furthermore, these illiquid periods may also coincide with funding liquidity strains for sophisticated traders, for instance due to investor redemptions (Dick-Nielsen, Feldhutter, and Lando, 2012; Goldstein, Jiang, and Ng, 2017). However, the inclusion of client-day fixed effects mitigate these concerns, as it allows us to control for such time-varying, client-specific shocks. Therefore, our results further emphasise that investors use transactions with multiple dealers as a means of concealing private information, particularly during periods with high price dispersion.

4.7 Connections around Rating Changes

Changes in bond ratings are obvious candidates for informationally intensive bond-specific events that could be used to further test the informational role of connections. To the extent that rating changes move prices and that certain market participants – who are likely to be sophisticated investors – have private information about impending rating changes, we now explore the dynamics of connections around rating changes to further reinforce our interpretation of the baseline results. We conduct this analysis in three steps. First, we document the estimated price effects of rating changes in our sample. Second, we show that high-connection clients make more profitable trades during the days leading up to the rating change. Third, we document how the connection dynamics of both sophisticated and unsophisticated investors evolve around rating changes.

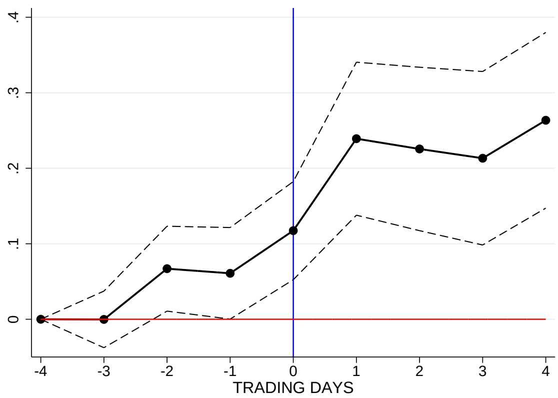
To measure the price of effect of rating changes, we collapse our dataset at the day-instrument level and analyse the cumulative price changes in a small window around rating changes. When it comes to rating upgrade/downgrade events for a given bond, we use the earliest rating change date out of all three rating agencies within the month of the upgrade/downgrade. This ensures that we capture the earliest possible information sensitive day, when better informed investors (who trade before the rating change) may profit from price jumps in the upgraded/downgraded bond.

In total, we have about 600 rating changes in our sample. For this analysis, we exclude trading days on which none of the bonds experienced rating changes from our sample. Specifically, we estimate the following panel regression:

$$|\log(Price_{j,t-4+T}) - \log(Price_{j,t-4})| = \beta^T \times RatingChange_{j,t} + \mu_t + \delta_{j,year} + \varepsilon_{j,t}, \tag{4.5}$$

where the dependent variable the absolute value of price changes, μ_t is a day FE, and $\delta_{j,year}$ is a bond-year FE, and $T = 1, 2, \ldots T$ denotes the horizon of cumulative returns. We use $T = 8$, i.e. we look at return effects of rating changes in the 8-day window around the rating announcement. Our independent variable is $RatingChange_{j,t}$, which is equal to one when any bond of the given issuer experienced a rating change on day t. Figure 4 shows the results with the vertical blue line indicating the day of the rating change. We find that the largest price effect takes place on the day after the rating change announcement, when the cumulative return reaches a peak of around 25bps compared to the base price (measured as the average transaction price four days before the rating change). Moreover, we find that prices start drifting about three days before rating change announcements, suggesting that at least some rating changes are anticipated. This is consistent with previous evidence from the US corporate bond market (Holthausen and Leftwich, 1986; Goh and Ederington, 1993; May, 2010).

Figure 4: Cumulative Returns Around Rating Changes

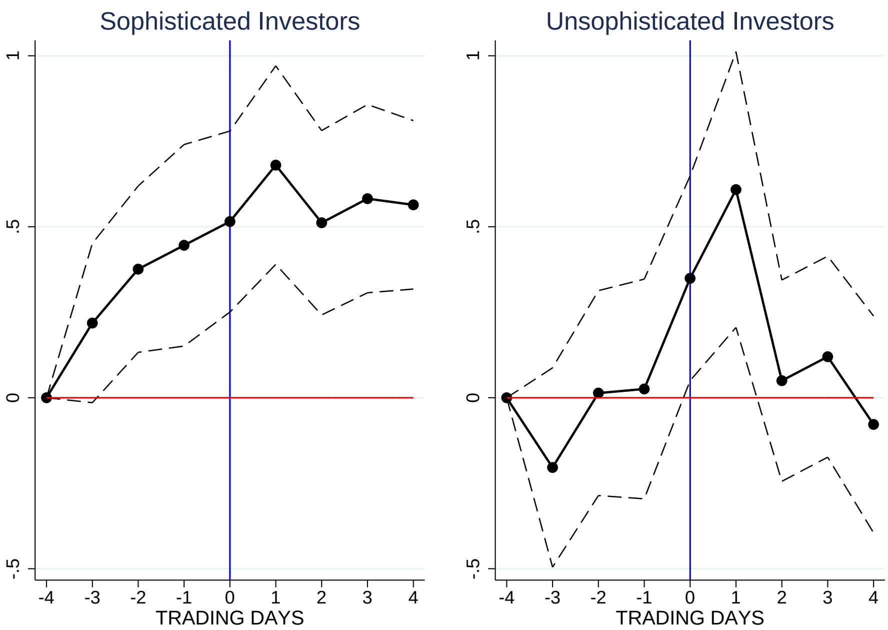


Notes: Figure 4 plots the estimated β coefficients from regression 4.5 during the 8-day window around rating changes. The dataset is collapsed at the instrument-day level, and we exclude trading days on which none of the bonds experienced a rating change. We end up with about 20,000 observations. The dashed lines denote 90% confidence bands, based on robust standard errors, using clustering at the bond level.

We now analyse whether trades of clients with more connections are more profitable during periods *leading up to* rating changes compared to trades outside this time window. To address this, we use our baseline sample at the client-day level and construct an indicator variable equal to one (zero) when the given client has more (fewer) connections on a given trading day compared to her sample average. We construct another variable indicating all transactions that happen during the 5-day window leading up to a bond rating change. Then we estimate another variant of our performance regression at the client-day-bond level, and check whether the interaction between the high-connection indicator variable and the rating change indicator variable is economically and statistically significant.

The results are presented in Table 12, using both types of connection and performance measures. We find that the effects are significant: the 6-8 day trading performance of high-connections clients is about 15-20bps higher during periods leading up to a bond rating change compared to periods without a rating change. This provides another piece of evidence on the informational nature of variations in connections.

Figure 5: Dynamics of Connections Around Rating Changes



Notes: Figure 5 plots the estimated β coefficients from a modified version of panel regression 4.5, where the the dependent variable is the cumulative change in connections of sophisticated (left panel) and unsophisticated (right panel) investors. The dashed lines denote 90% confidence bands, based on robust standard errors clustered at the bond level.

Moreover, a natural proposition is that sophisticated investors have the ability to predict rating changes. Indeed, recent evidence (Christophe, Ferri, and Hsieh, 2010; Henry, Kisgen, and Wu, 2015; Guo and Wu, 2019) shows that the short-selling activity of sophisticated investors can accurately predict rating changes. Building on these results, we check whether one can detect any differences between sophisticated and unsophisticated investors regarding the dynamics of their connections around rating changes. Figure 5 shows the estimated β coefficients from a modified version of regression 4.5, in which we replace the dependent variable (absolute log-returns) with the cumulative changes in the number of dealer connections of sophisticated investors (left panel) and unsophisticated investors (right panel).

Consistent with the dynamics of the price effect (Figure 4), the large impact of rating changes on the connections of both types of clients occurs on the trading day following the rating change. However, there is an important difference between the two types of investors: sophisticated investors start increasing their connections about three days prior to the announcement, and this drift mirrors the pre-announcement price drift shown by Figure 4; in contrast, unsophisticated investors only start to increase their connections on the day of the announcement. To put it differently, connections of sophisticated clients predict the rating announcement, whereas connections of unsophisticated clients react to it. These results are consistent with informed clients increasing their connections in order to slice profitable trades across multiple dealers to reduce price impact; whereas the behaviour of unsophisticated clients is more consistent with the liquidity effects of rating changes, as analysed by Ellul, Jotikasthira, and Lundblad (2011) and Bao, OHara, and Zhou (2018) amongst others.

5 Controlling for Dealer Characteristics and Further Robustness Checks

We argued so far that the observed pattern of clients systematically increasing their connections when they perform better is a sign that they have private information about future price changes. An alternative explanation of our baseline findings is that private information is in the possession of dealer banks (Li and Song 2019, 2020; Glode and Opp 2020; Brancaccio, Li, and Schurhoff 2020), and dealers pass on the information - either intentionally or unintentionally - to their clients. This could happen directly via close client-dealer relationships (Di Maggio, Franzoni, Kermani, and Sommavilla 2019; Barbon, Maggio, Franzoni, and Landier 2019), or less directly through uninformed clients eliciting information from dealers by making small offers (Golosov, Lorenzoni, and Tsyvinski, 2014).

To control for these mechanisms, we proceed as follows. We collapse our dataset at the client-dealer-day level and compute, as additional controls, the total daily trading volume for each dealer j ($DealerVol_{j,t}$) as well as the total daily number of client connections of each dealer ($DealerConnections_{j,t}$). We then estimate the following regression at the client-dealer-day level:

$$\begin{aligned} Performance^T_{i,t} =& \beta \times ClientConnections_{i,t} + Vol_{i,t} \\ &+ DealerVol_{j,t} + DealerConnections_{j,t} + \alpha_i + \lambda_j + \mu_t + \varepsilon_{i,j,t}, \end{aligned} \tag{5.1}$$

where λ_j is a dealer fixed effect and the other terms are the same as in our baseline regression 3.2. The assumption underlying 5.1 is that daily variation in dealers' volume and their connections captures some of the time-variation in the informedness of dealers which could potentially confound our interpretation of the performance-connection relation. If our baseline regression 3.2 is picking up that private information is flowing from informed dealers to clients, then we would expect the estimated β in 5.1 to be significantly different from our baseline results in Table 2.

In a more conservative specification, we also include a dealer-day fixed effect, $\delta_{j,t}$, which absorbs the linear effect of any time-varying, dealer-specific shocks on client performance and connections. Notwithstanding, this control set could not rule non-linear confounds: it might still be that dealers pass on their information to selected (and not all) clients – those that the dealer has a stronger trading relationship with (Di Maggio, Franzoni, Kermani, and Sommavilla 2019; Barbon, Maggio, Franzoni, and Landier 2019). We therefore go a step further and rank each client i trading with dealer j in terms of trading volume in month m. We then place each client-month-dealer observation in one of three buckets $r = \{1, 2, 3\}$, with the third bucket containing the closest client-dealer relationships. We then run the following regression:

$$Performance^T_{i,t} = \beta \times ClientConnections_{i,t} + Vol_{i,t} + \alpha_i + \delta_{j,t,r} + \varepsilon_{i,j,t}, \tag{5.2}$$

where $\delta_{j,t,r}$ is a dealer-day-relationship fixed effect that aims to absorb any dealer-specific shocks on a given trading day, and we allow this effect to vary across the given dealer's client base, depending on the strength of dealer j's relationship with client i in month m.

Table 13 presents the results, showing that the estimated β coefficients implied by our baseline results (Columns 1-3 of Panel A of Table 2) are little changed by the additional dealer-specific controls. We find some evidence that clients who trade with more connected dealers (Column 4 of Panel A) perform better over the 5-day horizon, consistent with the literature mentioned above. Importantly, Columns 4-6 of Panel B show that controlling for dealer-day-relationship fixed effects (i.e. dealer-day level shocks that could be heterogeneous for clients with stronger or weaker relationships with the given dealer), if anything, strengthens our baseline results.

Moreover, we conduct additional robustness tests for our main results. We test whether our results are robust to the exclusion of the most information-sensitive bonds and clients. More precisely, we first eliminate the most information-sensitive bonds (high-yield bonds) in Panel A of Table A.1. In Panel B, we exclude the most information-sensitive clients (hedge funds). Overall, Table A.1 shows that our results remain statistically and economically highly significant for both of these subsamples. Furthermore, as shown in Table A.2, our main result that clients have systematically better trading performance when trading with more dealers is also robust to various fixed effects specifications.

6 Connections in Corporate Bond vs. Government Bond Markets

An interesting question is whether one could exploit variation in connections to compare the role of private information *across different markets* rather than across different clients in the same market. However, estimating the relative importance of informed trading across different markets is empirically difficult, because the composition of clients itself can be endogenous to the type of market in question. For example, traders who find it less costly to generate information may choose to participate in markets in which private information has higher returns. This selection problem is largely mitigated in our case, as the ZEN dataset provides us with a unique opportunity to identify clients who simultaneously trade in both UK bond markets.

Therefore, we are able to extend our analysis of corporate bond markets, and contrast it to studies on government bond markets Kondor and Pinter (2019). Specifically, we can estimate how the sensitivity of performance to client connections differs between corporate and government bond markets, while controlling for unobserved heterogeneity at the client-day level, e.g. changes in clients' overall information sets.[9] We estimate the following client-time-market level regression:

$$Performance^T_{i,k,t} = \gamma \times D_k \times ClientConnections_{i,k,t} + \beta \times ClientConnections_{i,k,t} + Vol_{i,k,t} + \alpha_{i,t} + \mu_{k,t} + \delta_{i,k} + \varepsilon_{i,k,t}, \quad (6.1)$$

where $Performance^T_{i,k,t}$ is the trading performance of client i on day t at horizon T in market $k = \{GovernmentBond, CorporateBond\}$; D_k is an indicator variable equal to one for the corporate bond market and zero for the government bond market; $ClientConnections_{i,k,t}$ is the number of dealer banks the given client is connected to on day t in market k; $Vol_{i,k,t}$ controls for the trading volume of client i on day t in market k; $\alpha_{i,t}$ and $\mu_{k,t}$ are client-day and market-day fixed effects. Moreover, the term $\delta_{i,k}$ is a client-market fixed effect which plays an important role in the analysis.

The main coefficient of interest is γ, which captures the strength of the performance-connection relation in the corporate bond market relative to the government bond market. Table 14 shows the results for the volume-weighted performance (Columns 1-3) and unweighted performance (Columns 4-6) of sophisticated clients. Panel A shows the results when we exclude the client-market level fixed effect, $\delta_{i,k}$. The results show that connections in the corporate bond market are significantly more important for performance than in the government bond market, with an additional dealer connection worth about 2.6bps more in the corporate bond market (over a 15-day horizon). Importantly, the effect is statistically significant and economically large across all time horizons shown in the table.

[9] We identify 630 clients who trade in both bond markets. These clients cover more than 90% of all client trading in both markets in terms of trading volume. We identify 301 sophisticated investors (asset managers and hedge funds) and 329 unsophisticated investors (central banks, insurance companies, pension funds, commercial banks etc.) in this subsample, with sophisticated and unsophisticated clients covering about 55% and 45% of trading volume, respectively.

To reiterate, we are able to merge non-anonymous transaction-level data across the two largest fixed-income markets in the UK. However, excluding the fixed effect $\delta_{i,k}$ means that the previous results may be confounded by unobserved heterogeneity at the client-market level. For example, a client who trades in both markets may have a specialisation in one of the two markets. Our analysis of particular counterparties indeed reveals that sophisticated clients (such as macro-hedge funds) seem to be specialised in trading in the government bond market, whereas other clients (such as credit funds) have a specialisation in trading corporate bonds.

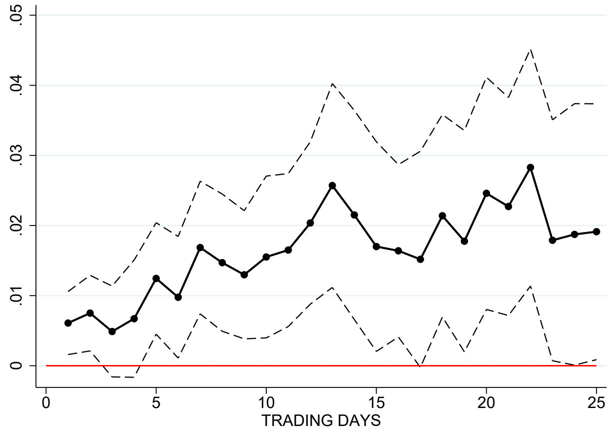
Therefore, we now include the fixed effect $\delta_{i,k}$ to control for the average effect related to such a market-level specialisation of clients, which could affect both clients' connections as well as performance. The results in Panel B of Table 14 show that connections in the corporate bond market are still significantly more important for performance than in the government bond market, with an additional dealer connection now worth about 1.7bps more in the corporate bond market (over a 15-day horizon).

In Figure 6, we plot the γ coefficients from model 6.1 for longer horizons to explore the persistence of this effect, using the sample of sophisticated investors. The effect is highly persistent for sophisticated clients, with no sign of reversal after 25 days. We find a peak effect of more than 2.8bps per added dealer connection in the corporate bond market compared to the government bond market.[10]

This cross-market analysis motivates the following question: what drives the strength of the performance-connection relation? One plausible information-based explanation is that the degree of inter-dealer competition may play a role. For example, the lower inter-dealer competition in corporate bonds may slow down information diffusion (through dealers' bid-shading), which could explain the more pronounced performance-connection relation compared to the government bond market. An alternative explanation is that the difference is due to the higher magnitude of private information in the corporate bond market, in which private information is more likely bond-specific (Hendershott, Kozhan, and Raman, 2020) compared to government bond markets. The next section formalises these ideas in a theoretical model, and designs empirical tests to disentangle both mechanisms in the data.

[10]Similar to our baseline connection effects for unsophisticated clients in Table 3, we do not find any statistically significant relative effects across the two markets for this group of clients. These results are available upon request.

Figure 6: Relative Connection Effects in Corporate vs. Government Bond Markets



Notes: Figure 6 plots the estimated γ coefficients from our client-day-market regression 6.1, up to a 25-day horizon ($T = 25$), using the volume-weighted performance variable as the regressand, measured in %-points. The sample includes 301 sophisticated clients who simultaneously trade in both the UK government bond and UK corporate bond markets. Connections are measured against dealer banks. We include the natural logarithm of the pound trade volume of each client in each market ("Volume") as a control. We also include client-day, market-day and client-market fixed effects. To reduce noise, we winsorise the sample at the 1%-level. The dashed lines denote the 90% confidence bands based on robust standard errors, using two-way clustering at the day and client level.

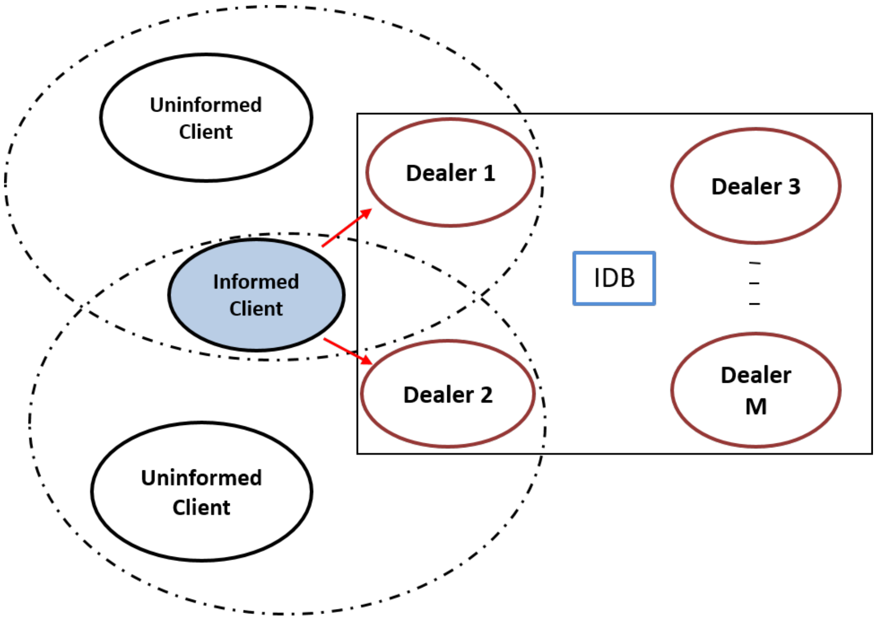
7 Testing Information-based Mechanisms: Insights from a Theoretical Model

In this section, we build a theoretical model based on Kyle (1989) to further explore the two information-based explanations for the strength of the performance-connection relation. First, we analyse whether increased client connections are more profitable in a market with a less competitive inter-dealer sector, because dealers increased strategic behaviour against one another may slow down information diffusion and lead to less revealing prices in the inter-dealer market. This, in turn, would increase clients' profits from splitting informed orders across multiple dealers. Second, accounting for the higher magnitude of private information in corporate bond markets, we check whether the performance-connection relation is more pronounced when we increase the variance of the asset's fundamental value (which the informed trader can observe). Last, we use an empirical strategy to disentangle these two mechanisms in the data.

7.1 Model Set-up

There is one asset whose payoff is $\tilde{v} \sim N(v, \sigma_v^2)$. The asset is traded by clients and dealers, with the market structure illustrated in Figure 7. There are $j = \{1, 2\}$ dealers who trade with one another as well as with clients in two stages. In the first stage, dealer j trades with N_j clients, all submitting demand schedules. In the second stage, dealers interact with one another through the inter-dealer broker (IDB) market, by submitting demand schedules (Viswanathan and Wang, 2004). The market in the first and second stages clears at price p_j and $p^\star$, respectively. Moreover, there are other dealers $i = \{3, 4, \ldots, M\}$, whose clientele we do not model. Their role is purely to provide (increasing) competition among dealers in the second stage.

Figure 7: Illustration of the Market Structure



Dealer j serves two clients $k = \{1, 2\}$, one of which may be informed. The demand of clients are denoted $d_{j,1}$ and $d_{j,2}$, whereas the demand of dealer j in stage 1 and 2 is $x_{j,1}$ and $x_{j,2}$, respectively. The market clearing condition at dealer j in stage 1 is:

$$0 = x_{j,1} + \sum_k d_{j,k} + u_j, \tag{7.1}$$

where $u_j \sim N\left(0, \sigma_{u_j}^2\right)$ captures random liquidity trading. Similarly, market clearing in stage 2 is given by:

$$0 = \sum_i x_{i,2} + \sum_i x_{j,2} + u^\star, \tag{7.2}$$

where $u^\star \sim N\left(0, \sigma_{u^\star}^2\right)$ captures random liquidity trading at the inter-dealer stage.

In our analysis, we carry out comparative statistics to compare the equilibrium allocation and profits when the informed client (highlighted by the shaded blue circle) is allowed to trade with dealer 1 and 2, instead of only trading with dealer 1.[11] We assume that the informed trader observes the asset's value v without any noise, i.e. she is perfectly informed about the asset value.

7.2 Optimisation and Equilibrium

Dealer j has the following optimisation problem over the two stages:

$$\max_{x_{j,1},x_{j,2}} U\left(\left(v - p_j\right) x_{j,1} \mid p^\star, p_j\right) + U\left(\left(v - p^\star\right) x_{j,2} \mid p^\star, p_j\right), \tag{7.3}$$

where $x_{j,1}$ and $x_{j,2}$ are the quantity demanded by dealer j in stage 1 and 2, respectively. A notable feature of the problem is that the choices are conditional on the first stage price, p_j, as well as the IDB price $p^\star$.

The optimisation problem of client k, trading with dealer j at stage 1, is:

$$\max_{d_{j,k}} \mathbb{E}\left[U\left(\left(v - p_j\right) d_{j,k} \mid \mathcal{I}_{j,k}\right)\right], \tag{7.4}$$

where $\mathcal{I}_{j,k}$ is the relevant information set on which the client conditions when submitting her demand schedule. In the case of informed clients, $\mathcal{I}_{j,k} = v$; in the case of uninformed clients, $\mathcal{I}_{j,k} = p_j$.

We focus on equilibria in which quantities demanded are linear functions of prices and the asset value. Appendix B provides further details about model derivations. The solution is standard (Kyle, 1989 and Ch. 5 of Vives, 2008): we start with a proposed strategy for traders in the form of $x = \beta_1 p + \beta_2 v$, and, through market-clearing 7.1 – 7.2, we express prices as linear functions of noise terms and the asset's fundamental value:

$$\begin{aligned} p_j &= \kappa_{1,0} + \kappa_{j,1} u_1 + \kappa_{j,2} u_2 + \kappa_{j,3} u^\star + \kappa_{j,4} v \\ p^\star &= \kappa_{\star,0} + \kappa_{\star,1} u_1 + \kappa_{\star,2} u_2 + \kappa_{\star,3} u^\star + \kappa_{\star,4} v, \end{aligned} \tag{7.5}$$

and, through the first-order conditions of dealers' and clients' optimisation problems 7.3 – 7.4,

[11] In the latter case, the informed trader's demand from dealer 2 is replaced by that of an uninformed trader.

we determine the equilibrium coefficients.

Definition *In a linear rational expectations equilibrium, traders and dealers maximise expected trading profits given correct conjectures, net order flows are consistent with the optimising behaviour of all agents (7.3 – 7.4), and the conditions for market clearing are satisfied (7.1 – 7.2).*

7.3 Theoretical Predictions

The model aims to capture the idea that equilibrium profits of informed traders are higher when they trade with more dealers, i.e. when they are more connected. To investigate this, we perform comparative statics to see how the profits of the informed change when splitting her trades across two dealers as opposed to trading with only one dealer.

Claim 1. *The gains from increasing connections from 1 to 2 fall as M rises. i.e. as inter-dealer competition increases.*

A motivation behind this claim is the empirical observation that dealers in corporate bond markets tend to specialise in intermediating certain assets, whereas the vast majority of government bond issues are traded by all major dealers. Given that we have virtually the same set of dealers in both markets, but only a few of these dealers intermediate an average corporate bond, the effective dealer competition is lower in the corporate bond market compared to gilts. This is also supported by our empirical evidence (see Tables 1 and A.3). As dealer competition falls, dealers act more strategically in the IDB market (IDB prices will be less revealing due to bid shading), which, in turn, increases the informed clients' marginal gain from splitting the trades across multiple dealers.

Another intuitive explanation is that the marginal profitability of connections increases with the magnitude of private information for a given asset (after controlling for the competitiveness of the inter-dealer market).

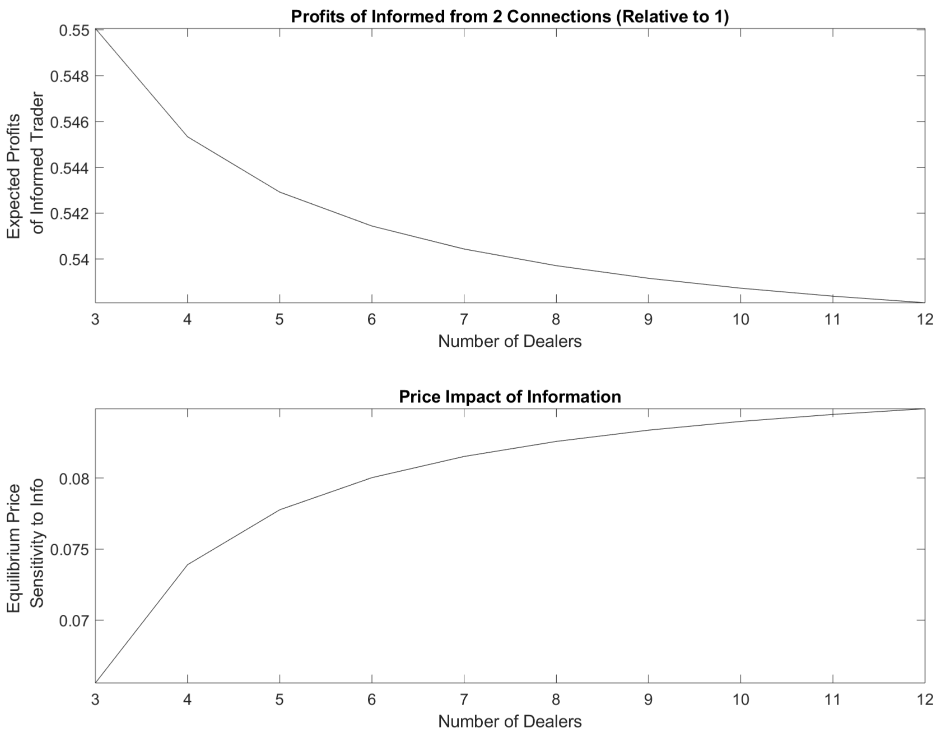
Claim 2. *The gains from increasing connections from 1 to 2 fall as σ_v shrinks, i.e. as the asset's fundamental value becomes less volatile.*

Our prior is that the information advantage of informed clients increases with the volatility of the asset's fundamental value, given that more volatile fundamentals translate into a higher magnitude of private information (Odders-White and Ready, 2008; Back, Crotty, and Li, 2018). Informed clients then profit from the higher magnitude of private information by splitting their trades across multiple dealers. This notion is supported by our empirical evidence in Table 8, and is also consistent with the less pronounced performance-connection relation in the government bond market compared to the corporate bond market (see Section 6).

7.4 Numerical Analysis

We solve the model numerically. We use the baseline values $\rho = \sigma^2_{u_1} = \sigma^2_{u_2} = \sigma^2_{u^\star} = \sigma^2_v = 1$, i.e. we assume that all dealers and clients have the same (unitary) level of risk aversion; we also assume unit volatility of noise trading in market 1 and 2 and in the IDB stage.

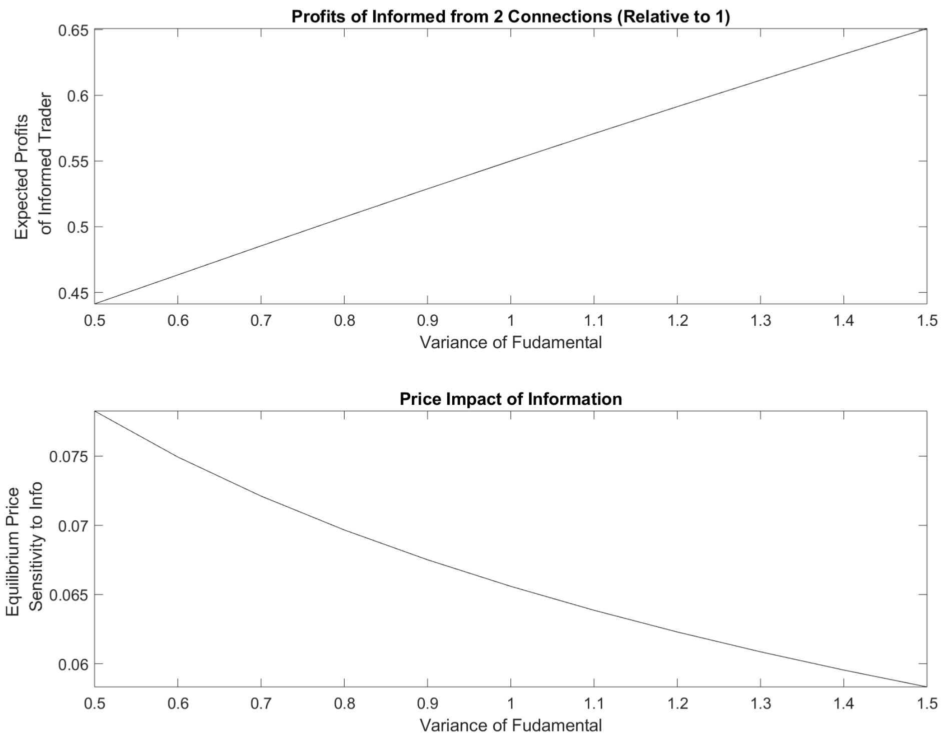
Figure 8: The Role of Inter-Dealer Competition



Notes: This figure shows numerical results from a comparative statics exercise, in which we compare (across various models) the informed trader's expected profit (upper panel) as computed by B.30 as well as the price impact of information (lower panel), denoted by $\kappa_{1,4}$ in 7.5. To construct this figure, we compute equilibria for a series of models in which the informed client is only allowed to trade with one dealer, while we gradually increase the number of dealers in the IDB market from 3 to 12 (10 models in total). Similarly, we compute equilibria for a series of models in which the informed client is allowed to trade with two dealers, while we gradually increase the number of dealers in the IDB market from 3 to 12 (10 models in total). The model parameters are $\rho = \sigma^2_{u_1} = \sigma^2_{u_2} = \sigma^2_{u^\star} = \sigma^2_v = 1$.

Figure 8 illustrates the role of inter-dealer competition in affecting the marginal profitability of increased connections. To construct this figure, we compute equilibria for a series of models in which the informed client is only allowed to trade with one dealer, while we gradually increase the number of dealers in the IDB market from 3 to 12 (10 models in total). Similarly, we compute equilibria for a series of models in which the informed client is allowed to trade with two dealers, while we gradually increase the number of dealers in the IDB market from 3 to 12 (10 models in total). We compute the difference in profits (B.30) for the 10 model pairs, which is shown by the solid line in the top panel of Figure 8. The bottom panel of the Figure shows the equilibrium value of $\kappa_{1,4}$ across the 10 model pairs.

Figure 9: The Role of the Variance of the Fundamental



Notes: This figure shows numerical results from a comparative statics exercise, in which we compare across various models the informed trader's expected profit (upper panel) as computed by B.30 as well as the price impact of information (lower panel), denoted by $\kappa_{1,4}$ in 7.5. To construct this figure, we compute equilibria for a series of models in which er increase the volatility of the asset's fundamental $\sigma_u^2 = \{0.5, 0.6, \ldots, 1.5\}$ and compute the differences in equilibrium profits and price impact for these model pairs. The model parameters are $\rho = \sigma_{u_1}^2 = \sigma_{u_2}^2 = \sigma_{u^\star}^2 = \sigma_v^2 = 1$.

The results show that increased inter-dealer competition lowers the marginal profitability of connections and increases the impact of information on prices ($\kappa_{1,4}$). This is because increased inter-dealer competition lowers the equilibrium incidence of bid-shading of dealers in the IDB stage, thereby leading to more revealing prices. Importantly, this could be an intuitive explanation for the more pronounced performance-connection relation in corporate bond markets compared to government bond markets. The empirical evidence in Table A.3 shows that inter-dealer competition in corporate bonds is indeed lower than in government bonds. For example, the market share of the most active dealer in the average gilt is only around 20% (compared to 63% for corporate bonds), and the average Herfindahl-Hirschman Index of 0.12 further indicates a much higher degree of inter-dealer competition in the government bond market.

An alternative explanation is related to the more volatile corporate bond fundamentals, which allow informed clients to acquire a larger amount of private information compared to the government bond market. We simulate this possibility by defining a grid for the volatility of the asset's fundamental $\sigma_u^2 = \{0.5, 0.6, \dots, 1.5\}$ and compute the differences in equilibrium profits and price impact for these model pairs. Figure 9 illustrates that increasing σ_u^2 raises the marginal profitability of connections and reduces the equilibrium price impact.

7.5 Empirical Strategy to Disentangle Mechanisms

We propose the following empirical strategy to quantify the relative importance of (i) inter-dealer competition vs. (ii) volatility of fundamentals for the performance-connection relation. We propose a sequential double-sorting of corporate bonds (i) first by the number of active dealers in a traded bond on a given day and (ii) then by the bond credit rating. The number of active dealers serves as a proxy for inter-dealer competition, whereas the credit rating is closely related to the uncertainty and volatility of bond fundamentals (Lu, Chen, and Liao, 2010).

We generate an indicator variable D_j, which takes four values to indicate whether the given bond is above/below the median inter-dealer competition (as measured by the number of active dealers), and - within these two groups - whether the bond's rating is above/below the median credit rating. Given D_j, we estimate the following client-day-bond level regression:

$$\begin{aligned} Performance^T_{i,j,t} = \beta_1 \times ClientConnections_{i,j,t} + \beta_2 \times ClientConnections_{i,j,t} \times D_j \\ + Vol_{i,j,t} + \alpha_{i,t} + \mu_{j,year} + \varepsilon_{i,j,t}, \quad (7.6) \end{aligned}$$

where $Performance^T_{i,j,t}$ is the trading performance of client i on day t at horizon T; and

$ClientConnections_{i,j,t}$ is the number of dealers the given client is connected to on day t for bond j. The coefficient of interest is β_2, which helps us disentangle the relative importance of the two mechanisms highlighted by our theoretical model above.

Table 15 shows the results. We find the the performance-connection effect is concentrated in the subset of bonds with higher inter-dealer competition and lower credit ratings. For example, the fifth column shows that an additional client connection increases trading performance by more than 6bps over a ten-day horizon for the group of high-dealer-competition / low-rated bonds. The effect is statistically highly significant for this subset of bonds, but not for any of the other three groups. Importantly, these results (and also the findings in Table 8) point towards a prominent role of the magnitude of private information for the performance-connection relation.

Furthermore, the results suggest that inter-dealer competition plays a less important role for the profitability of connections, thereby rejecting the first prediction of our theoretical model. This important insight is further corroborated by the results in Table 16, in which we interact our client connection measure with an indicator variable that equals one if inter-dealer competition (as measured by the number of active dealers or the HHI) is below the sample median. Contrary to our theoretical prediction, we find that lower inter-dealer competition is associated with a less significant performance-connection relation. Overall, these results help to rule to out inter-dealer competition as a major factor for the profitability of client connections.

8 A Case Study: The COVID-19 Crisis

In this final section of our paper, we present an analysis of the COVID-19 episode in the UK through the lens of our empirical framework. This analysis serves a dual purpose. First, it provides an out-of-sample test of our baseline results, as the more recent sample period (2018-2020) requires the use of a different dataset. The market volatility and fundamental uncertainty during this period provided opportunities for informed traders to generate returns from private information, which makes the COVID-19 episode an ideal setting for an out-of-sample test of our information-based explanation. Second, the analysis of the COVID-19 period in the UK, using a non-anonymous dataset, could be interesting in its own right. While there is a growing literature on the events in the US corporate bond market during COVID-19, there is little coverage on the unfolding of the crisis in corporate bond markets outside the US.[12]

We proceed by (i) providing a brief overview of the events in March 2020 in the UK corporate bond market, (ii) conducting an out-of-sample test of the connection-performance relation for informed clients, and (iii) estimating the effect of policy interventions on the connection-performance relation. To conduct this analysis, we employ the MiFID II bond transaction data, which covers the period from January 2018 to May 2020.[13] Similar to the ZEN data, the MiFID II data provide detailed information (including counterparty identifiers) on transactions in the UK corporate bond market and give us almost full coverage of the client trade universe.

Figure A.1 shows the net trading volumes of different investor types in the UK corporate bond market during the COVID-19 crisis. From February 2020 onwards, asset managers were net sellers of corporate bonds, culminating in the 'dash for cash' in March, while dealers and non-dealer banks absorbed the majority of these sales.[14] Corporate bond spreads widened considerably: sterling investment grade spreads jumped from around 120bps in mid-February to more than 280bps by March 23 (Figure A.2). For sterling high-yield bonds, the jump was even more dramatic from 430bps to around 1040bps. Furthermore, effective bid-ask spreads also widened significantly to around 70bps for investment grade bonds and more than 80bps for high yield bonds (Figure A.3). The large-scale Quantitative Easing (QE) announcement by the Bank of England on March 19 and the Federal Reserve's announcement of the Primary Market Corporate Credit Facility (PMCCF) and Secondary Market Corporate Credit Facility (SMCCF) on March 23 stopped the widening of spreads and helped to restore liquidity in the

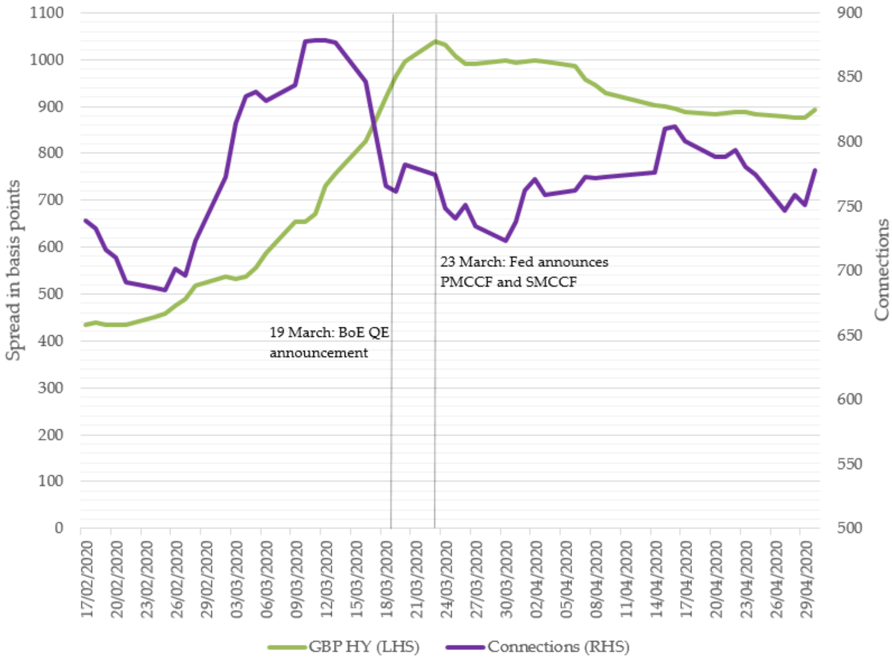
[12]The spread of the COVID-19 pandemic in early 2020 brought the global economy to a halt and exposed major vulnerabilities in the financial system, which catalysed an abrupt and extreme 'dash for cash'. US studies documented that corporate bond funds suffered huge and prolonged outflows (Falato, Goldstein, and Hortaçsu, 2020; Ma, Xiao, and Zeng, 2020), while many dealers were reluctant or unable to absorb inventory onto their balance sheets (Kargar, Lester, Lindsay, Liu, Weill, and Zuniga, 2020). As a consequence, liquidity dried up and trading costs soared (O'Hara and Zhou, 2020). Only the quick and large-scale responses by central banks around the globe helped to restore liquidity and avoid a prolonged tightening of financing conditions.

[13]The MiFID II reporting requirements became applicable on 3 January 2018. While ZEN is generally regarded as the predecessor of the MiFID II database, there are significant differences in the reporting requirements that prohibit a consistent merge of both datasets.

[14]On aggregate, asset managers' sell volumes soared to £5bn during the two 'dash for cash' weeks (March 9-23). Dealer banks were able to absorb £2.4bn of these sales, while non-dealer banks absorbed approximately £2.1bn.

secondary corporate bond market.[15]

Figure 10: Connections and Corporate Bond Spreads During the COVID-19 Crisis



Notes: This figure shows sterling-denominated high-yield bond spreads (in bps) and the ten-day rolling average of total sophisticated client connections. Sophisticated clients include asset managers and hedge funds; and connections are measured against all counterparties. The grey lines mark the Bank of England's Quantitative Easing announcement on March 19 and the Federal Reserve's announcement of the Primary Market Corporate Credit Facility (PMCCF) and Secondary Market Corporate Credit Facility (SMCCF) on March 23.

Linking these stylised facts to our empirical framework, Figure 10 presents the dynamics of high-yield corporate bond spreads along the dynamics of total sophisticated client connections (building on our analysis in Section 4.2). The figure is suggestive of a positive co-movement between market-wide connections and spreads, with the former leading the latter. Table A.4 in the appendix tests the predictive power of connections, providing evidence that connections of sophisticated clients predict one-day-ahead changes in high-yield spreads.

We acknowledge, however, that any positive correlation between connections and spreads could naturally be driven by non-informational factors such as liquidity effects due to the selling pressures in the period. We therefore undertake a more thorough, micro-level analysis of the role of connections during COVID-19, while trying to control for non-informational factors. We extend our regression model 3.3 as follows. Building on Falato, Goldstein, and Hortaçsu

[15] At a special meeting on 19 March, the Monetary Policy Committee decided to increase the Bank of England's holdings of UK government bonds and sterling non-financial investment-grade corporate bonds by £200 billion to a total of £645 billion, and to reduce the Bank Rate by 15 basis points to 0.1%. On March 23, the Federal Reserve announced the PMCCF for new bond and loan issuance and the SMCCF to provide liquidity for outstanding corporate bonds.

(2020), we first break down the COVID-19 crisis into three sub-periods: the *Build-up* period (February), the *Outbreak* period (March 1-13) and the *Peak* period (March 14-April 30). We create an indicator variable for each of these three sub-periods, and estimate the following client-time-bond regression:

$$\begin{aligned} Performance^T_{i,j,t} = &\beta_1 \times ClientConnections_{i,j,t} + Vol_{i,j,t} + \alpha_{i,t} + \mu_{j,year} + \varepsilon_{i,j,t} \\ &+ \beta_2 \times ClientConnections_{i,j,t} \times Buildup_t \\ &+ \beta_3 \times ClientConnections_{i,j,t} \times Outbreak_t \\ &+ \beta_4 \times ClientConnections_{i,j,t} \times Peak_t, \end{aligned} \tag{8.1}$$

where the coefficients β_2, β_3 and β_4 are the new terms that measure the possibly differential connections-performance relation during the different sub-periods of the crisis.

We present the regression results in Panel A of Table 17. The baseline effect of connections on the performance of sophisticated clients is still highly significant and economically large, with a peak effect of 4bps per added connection after 25 days (Column 5). This confirms that our baseline results (based on the ZEN dataset for 2011-2017) hold in more recent years as well. Regarding the three COVID sub-periods, it is striking that while we do not find any significantly different connection-performance relation for the *Build-up* or *Outbreak* period, we observe a much larger and positive effect for the *Peak* period. More precisely, we find that an additional client connection increases trading performance by up to 18bps during this period (Column 5).

There are four reasons why we reject the possibility that the stronger connection-performance relation is simply picking up liquidity effects due to selling pressures, i.e. asset mangers performing better if they increase their connections under pressure. First, regression 8.1 includes a client-day fixed effect, $\alpha_{i,t}$, that controls for the linear effect of any liquidity shock that hits a given client on any trading day. However, it can still be that selling pressure might be heterogeneous across bonds for a given client-day pair (as also emphasised by Haddad, Moreira, and Muir, 2020). To address this concern, the second point to note is that regression 8.1 includes trading volume $Vol_{i,j,t}$ to control for bond-specific selling pressures for each client i on day t. Third, selling pressures were already present during the *Build-up* and *Outbreak* periods, nevertheless the connection-performance relation is not significantly different during these periods compared to the pre-COVID period. Fourth, perhaps most importantly, the effect corresponding to the $ClientConnections_{i,j,t} \times Peak_t$ interaction term is monotonically increasing across the five time horizons and shows no sign of reversal. If higher connections merely facilitated easier and less costly trade execution by clients under selling pressure, then we would expect the effect to be concentrated in the execution component of performance. The relatively small effect for the one-day horizon enables us to dismiss the hypothesis that the effect could be driven by lower transaction costs due to order splitting during this period.

Our interpretation of the results in Panel A of Table 17 is that the large connection effects during the *Peak* period of the COVID-19 crisis can be attributed to the effect of policy announcements in the US as well as in the UK. To explore this more rigorously, we estimate the granular impact of the large-scale central bank interventions on the connection-performance relation during the *Peak* period. To that end, we create three more granular sub-periods: the *pre-BoE announcement* period (March 14-18), the *pre-Fed announcement* period (March 19-23) and the *post-Fed announcement* period (March 24-April 30). We then use these indicator variables in a variant of regression 8.1. The results are shown in Panel B of Table 17.

Consistent with our previous findings for macro-announcements, we find that the effect is concentrated on the informationally intensive days prior to the BoE and Fed announcements. The effect is statistically significant and economically huge. Column 4 shows that an additional client connection increases trading performance by more than 41bps during the *pre-BoE announcement* period, and by more than 101bps during the *pre-Fed announcement* period.[16] Conversely, we do not find any significantly differential effects for the *post-Fed announcement* period.

9 Conclusion

To conclude, our paper shows that clients' trading performance in corporate bond markets increases with the number of dealer connections, and this effect is substantially larger when exploiting the asset-level heterogeneity: clients outperform when trading a bond with more

[16]The latter result is consistent with the recent literature documenting the dominant role of US monetary policy in affecting international asset markets (Gerko and Rey, 2017; Brusa, Savor, and Wilson, 2020).

dealers compared to trading a different bond with fewer dealers at the same time. We provide a battery of empirical tests to argue for an information-based interpretation of our results.

To the best of our knowledge, our paper is also the first to compare informed trading across corporate and government bond markets. Our non-anonymous dataset enables us to identify a common set of clients who operate simultaneously in both markets. We find that informed trading is associated with stronger and more persistent performance in corporate bond markets. Our theoretical model highlights two distinctive information-based mechanisms that could explain the strength of the performance-connection relation. The model predicts that this relation is more pronounced for assets with a less competitive inter-dealer market or more volatile fundamentals. While our empirical tests reject the inter-dealer competition channel, we find strong empirical support for the mechanism related to the volatility of corporate bond fundamentals.

Our results not only provide strong evidence for the prevalence of private information in corporate bond markets, but also highlight the dynamic and endogenous nature of trading relationships in OTC markets. An interesting extension of our analysis would be to take a closer look (in the spirit of Collin-Dufresne and Fos (2015) and Baruch, Panayides, and Venkataraman (2017)) at how informed clients actually form trading positions and connections with dealers. For example, clients as well as dealers tend to have multiple trading accounts (whose identities are also observable in our dataset), so one could explore through which trading account(s) connections may form between clients and dealers. We leave this investigation for future research.

References

Abdi, F., and B. Wu (2018): "Informed Corporate Credit Market Before Monetary Policy Surprises: Explaining Pre-FOMC Stock Market Movements," Working Papers on Finance 1828, University of St. Gallen, School of Finance.

Alexander, G., and M. A. Peterson (2007): "An analysis of trade-size clustering and its relation to stealth trading," *Journal of Financial Economics*, 84(2), 435–471.

Babus, A., and P. Kondor (2018): "Trading and Information Diffusion in Over the Counter Markets," *Econometrica*, 86(5), 1727–1769.

Back, K., K. Crotty, and T. Li (2018): "Identifying Information Asymmetry in Securities Markets," *Review of Financial Studies*, 31(6), 2277–2325.

Bahaj, S., A. Foulis, G. Pinter, and P. Surico (2018): "Employment and the Collateral Channel of Monetary Policy," Discussion Papers 1832, Centre for Macroeconomics (CFM).

Bao, J., M. OHara, and X. Zhou (2018): "The Volcker Rule and corporate bond market making in times of stress," *Journal of Financial Economics*, 130(1), 95–113.

Barbon, A., M. D. Maggio, F. Franzoni, and A. Landier (2019): "Brokers and Order Flow Leakage: Evidence from Fire Sales," *Journal of Finance*, 74(6), 2707–2749.

Barclay, M. J., and J. B. Warner (1993): "Stealth trading and volatility: Which trades move prices?," *Journal of Financial Economics*, 34(3), 281–305.

Baruch, S., G. A. Karolyi, and M. L. Lemmon (2007): "Multimarket Trading and Liquidity: Theory and Evidence," *Journal of Finance*, 62(5), 2169–2200.

Baruch, S., M. Panayides, and K. Venkataraman (2017): "Informed trading and price discovery before corporate events," *Journal of Financial Economics*, 125(3), 561–588.

Bernanke, B. S., and K. N. Kuttner (2005): "What Explains the Stock Market's Reaction to Federal Reserve Policy?," *Journal of Finance*, 60(3), 1221–1257.

Bernhardt, D., and E. Hughson (1997): "Splitting Orders," *Review of Financial Studies*, 10(1), 69–101.

Bernhardt, D., and B. Taub (2008): "Cross Asset Speculation in Stock Markets," *Journal of Finance*, 63(5), 2385–2427.

Bessembinder, H., S. Jacobsen, W. Maxwell, and K. Venkataraman (2018): "Capital Commitment and Illiquidity in Corporate Bonds," *Journal of Finance*, 73(4), 1615–1661.

Bessembinder, H., K. M. Kahle, W. F. Maxwell, and D. Xu (2009): "Measuring abnormal bond performance," *Review of Financial Studies*, 22(10), 4219–4258.

Brancaccio, G., D. Li, and N. Schurhoff (2020): "Learning by Trading: The Case of the US Market for Municipal Bonds ," Working paper.

Brandt, M. W., and K. A. Kavajecz (2004): "Price Discovery in the U.S. Treasury Market: The Impact of Orderflow and Liquidity on the Yield Curve," *Journal of Finance*, 59(6), 2623–2654.

Brusa, F., P. Savor, and M. Wilson (2020): "One Central Bank to Rule Them All," *Review of Finance*, 24(2), 263–304.

Chakravarty, S. (2001): "Stealth-trading: Which traders' trades move stock prices?," *Journal of Financial Economics*, 61(2), 289–307.

Choi, J., and Y. Huh (2017): "Customer Liquidity Provision : Implications for Corporate Bond Transaction Costs," Finance and Economics Discussion Series 2017-116, Board of Governors of the Federal Reserve System (U.S.).

Chowdhry, B., and V. Nanda (1991): "Multimarket Trading and Market Liquidity," *Review of Financial Studies*, 4(3), 483–511.

Christophe, S. E., M. G. Ferri, and J. Hsieh (2010): "Informed trading before analyst downgrades: Evidence from short sellers," *Journal of Financial Economics*, 95(1), 85–106.

Cieslak, A., A. Morse, and A. V. Jorgensen (2019): "Stock Returns over the FOMC Cycle," *Journal of Finance*, 74(5), 2201–2248.

Collin-Dufresne, P., and V. Fos (2015): "Do Prices Reveal the Presence of Informed Trading?," *Journal of Finance*, 70(4), 1555–1582.

Czech, R. (2019): "Credit Default Swaps and Corporate Bond Trading," *Bank of England Staff Working Paper No. 810*.

Czech, R., S. Huang, D. Lou, and T. Wang (2020): "Informed Trading in Government Bond Markets," Working paper.

Das, S., M. Kalimipalli, and S. Nayak (2014): "Did CDS trading improve the market for corporate bonds?," *Journal of Financial Economics*, 111(2), 495–525.

Dennert, J. (1993): "Price Competition between Market Makers," *Review of Economic Studies*, 60(3), 735–751.

Di Maggio, M., F. Franzoni, A. Kermani, and C. Sommavilla (2019): "The relevance of broker networks for information diffusion in the stock market," *Journal of Financial Economics*, 134(2), 419–446.

Dick-Nielsen, J., P. Feldhutter, and D. Lando (2012): "Corporate bond liquidity before and after the onset of the subprime crisis," *Journal of Financial Economics*, 103(3), 471–492.

Eguren-Martin, F., and N. McLaren (2015): "How much do UK market interest rates respond to macroeconomic data news?," *Bank of England Quarterly Bulletin*, 55(3), 259–272.

Ellul, A., C. Jotikasthira, and C. Lundblad (2011): "Regulatory pressure and fire sales in the corporate bond market," *Journal of Financial Economics*, 101(3), 596–620.

Ericsson, J., K. Jacobs, and R. Oviedo (2009): "The determinants of credit default swap premia," *Journal of financial and quantitative analysis*, 44(1), 109–132.

Falato, A., I. Goldstein, and A. Hortaçsu (2020): "Financial fragility in the COVID-19 crisis: The case of investment funds in corporate bond markets," *NBER Working Paper*.

Feldhutter, P. (2012): "The Same Bond at Different Prices: Identifying Search Frictions and Selling Pressures," *Review of Financial Studies*, 25(4), 1155–1206.

Forte, S., and J. I. Pena (2009): "Credit spreads: An empirical analysis on the informational content of stocks, bonds, and CDS," *Journal of Banking & Finance*, 33(11), 2013–2025.

Gabrieli, S., and C.-P. Georg (2014): "A network view on interbank market freezes," Discussion paper.

Garvey, R., T. Huang, and F. Wu (2017): "Why Do Traders Split Orders?," *Financial Review*, 52(2), 233–258.

Gerko, E., and H. Rey (2017): "Monetary Policy in the Capitals of Capital," *Journal of the European Economic Association*, 15(4), 721–745.

Gertler, M., and S. Gilchrist (1994): "Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms," *The Quarterly Journal of Economics*, 109(2), 309–40.

Glode, V., and C. Opp (2016): "Asymmetric Information and Intermediation Chains," *American Economic Review*, 106(9), 2699–2721.

——— (2020): "Over-the-Counter versus Limit-Order Markets: The Role of Traders Expertise," *Review of Financial Studies*, 33(2), 866–915.

Goh, J. C., and L. H. Ederington (1993): " Is a Bond Rating Downgrade Bad News, Good News, or No News for Stockholders?," *Journal of Finance*, 48(5), 2001–2008.

Goldstein, I., H. Jiang, and D. T. Ng (2017): “Investor flows and fragility in corporate bond funds,” *Journal of Financial Economics*, 126(3), 592–613.

Golosov, M., G. Lorenzoni, and A. Tsyvinski (2014): “Decentralized Trading With Private Information,” *Econometrica*, 82(3), 1055–1091.

Guo, X., and C. Wu (2019): “Short interest, stock returns and credit ratings,” *Journal of Banking & Finance*, 108(C).

Haddad, V., A. Moreira, and T. Muir (2020): “When Selling Becomes Viral: Disruptions in Debt Markets in the COVID-19 Crisis and the Fedâs Response,” NBER Working Papers 27168, National Bureau of Economic Research, Inc.

Han, S., and X. Zhou (2014): “Informed Bond Trading, Corporate Yield Spreads, and Corporate Default Prediction,” *Management Science*, 60(3), 675–694.

Hasan, I., L. Liu, and G. Zhang (2016): “The determinants of global bank credit-default-swap spreads,” *Journal of Financial Services Research*, 50(3), 275–309.

Hendershott, T., R. Kozhan, and V. Raman (2020): “Short selling and price discovery in corporate bonds,” *Journal of Financial and Quantitative Analysis*, 55(1), 77–115.

Henry, T. R., D. J. Kisgen, and J. Wu (2015): “Equity short selling and bond rating downgrades,” *Journal of Financial Intermediation*, 24(1), 89–111.

Hollifield, B., A. Neklyudov, and C. Spatt (2017): “Bid-Ask Spreads, Trading Networks, and the Pricing of Securitizations,” *Review of Financial Studies*, 30(9), 3048–3085.

——— (2020): “Volume and Intermediation in Corporate Bond Markets,” Working paper.

Holthausen, R. W., and R. W. Leftwich (1986): “The effect of bond rating changes on common stock prices,” *Journal of Financial Economics*, 17(1), 57–89.

Jankowitsch, R., A. Nashikkar, and M. G. Subrahmanyam (2011): “Price dispersion in OTC markets: A new measure of liquidity,” *Journal of Banking and Finance*, 35(2), 343–357.

Kargar, M., B. R. Lester, D. Lindsay, S. Liu, P.-O. Weill, and D. Zuniga (2020): “Corporate bond liquidity during the COVID-19 crisis,” *NBER Working Paper*.

Kedia, S., and X. Zhou (2014): “Informed trading around acquisitions: Evidence from corporate bonds,” *Journal of Financial Markets*, 18, 182–205.

Kondor, P., and G. Pinter (2019): “Clients’ Connections: Measuring the Role of Private Information in Decentralised Markets,” Cepr discussion paper.

Kyle, A. S. (1989): "Informed Speculation with Imperfect Competition," *Review of Economic Studies*, 56(3), 317–355.

Li, D., and N. Schürhoff (2019): "Dealer networks," *The Journal of Finance*, 74(1), 91–144.

Li, W., and Z. Song (2019): "Dealers as Information Intermediaries in Over-the-Counter Markets," Working paper.

——— (2020): "Expertise, Information, and Dealer-intermediated OTC Markets," Working paper.

Lu, C.-W., T.-K. Chen, and H.-H. Liao (2010): "Information uncertainty, information asymmetry and corporate bond yield spreads," *Journal of Banking & Finance*, 34(9), 2265–2279.

Lucca, D. O., and E. Moench (2015): "The Pre FOMC Announcement Drift," *Journal of Finance*, 70(1), 329–371.

Ma, Y., K. Xiao, and Y. Zeng (2020): "Mutual fund liquidity transformation and reverse flight to liquidity," *Working Paper.*

Maggio, M. D., A. Kermani, and Z. Song (2017): "The value of trading relations in turbulent times," *Journal of Financial Economics*, 124(2), 266 – 284.

Malamud, S., and M. Rostek (2017): "Decentralized Exchange," *American Economic Review*, 107(11), 3320–3362.

May, A. D. (2010): "The impact of bond rating changes on corporate bond prices: New evidence from the over-the-counter market," *Journal of Banking and Finance*, 34(11), 2822 – 2836.

Norden, L., and M. Weber (2004): "Informational efficiency of credit default swap and stock markets: The impact of credit rating announcements," *Journal of Banking & Finance*, 28(11), 2813–2843.

Odders-White, E. R., and M. J. Ready (2008): "The probability and magnitude of information events," *Journal of Financial Economics*, 87(1), 227–248.

OHara, M., Y. Wang, and A. Z. Xing (2018): "The execution quality of corporate bonds," *Journal of Financial Economics*, 130(2), 308–326.

O'Hara, M., and X. A. Zhou (2020): "Anatomy of a Liquidity Crisis: Corporate Bonds in the COVID-19 Crisis," *Journal of Financial Economics, forthcoming.*

Pagano, M. (1989): "Trading Volume and Asset Liquidity," *The Quarterly Journal of Economics*, 104(2), 255–274.

Pasquariello, P., and C. Vega (2007): "Informed and Strategic Order Flow in the Bond Markets," *Review of Financial Studies*, 20(6), 1975–2019.

Rauh, J. D., and A. Sufi (2010): "Capital structure and debt structure," *The Review of Financial Studies*, 23(12), 4242–4280.

Ronen, T., and X. Zhou (2013): "Trade and information in the corporate bond market," *Journal of Financial Markets*, 16(1), 61–103.

Swanson, E. T., and J. C. Williams (2014a): "Measuring the Effect of the Zero Lower Bound on Medium- and Longer-Term Interest Rates," *American Economic Review*, 104(10), 3154–85.

Swanson, E. T., and J. C. Williams (2014b): "Measuring the effect of the zero lower bound on yields and exchange rates in the UK and Germany," *Journal of International Economics*, 92, 2–21.

Viswanathan, S., and J. J. D. Wang (2004): "Inter-Dealer Trading in Financial Markets," *The Journal of Business*, 77(4), 987–1040.

Vives, X. (2008): *Information and Learning in Markets.* Princeton University Press.

Wei, J., and X. Zhou (2016): "Informed Trading in Corporate Bonds Prior to Earnings Announcements," *Financial Management*, 45(3), 641–674.

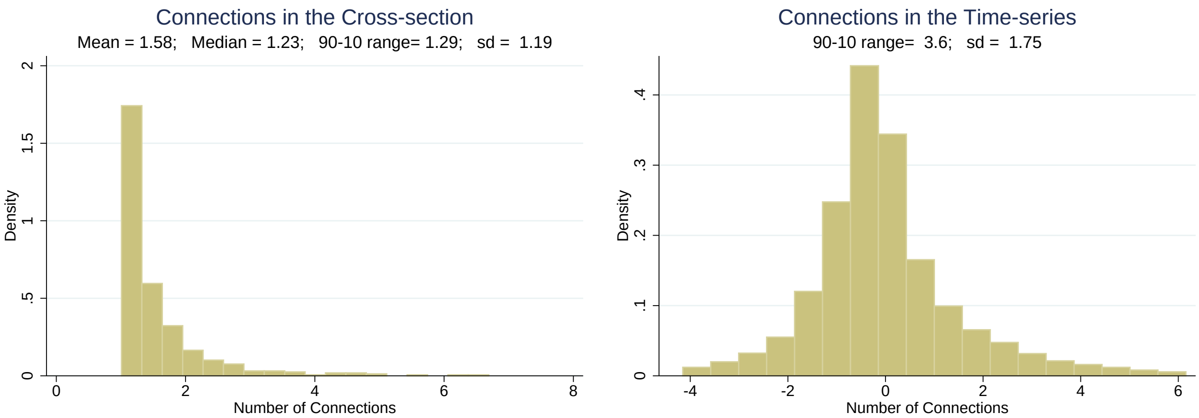
Ye, M., and W. Zhu (2020): "Strategic Informed Trading and Dark Pools," Working paper.

Zhu, H. (2014): "Do dark pools harm price discovery?," *The Review of Financial Studies*, 27(3), 747–789.

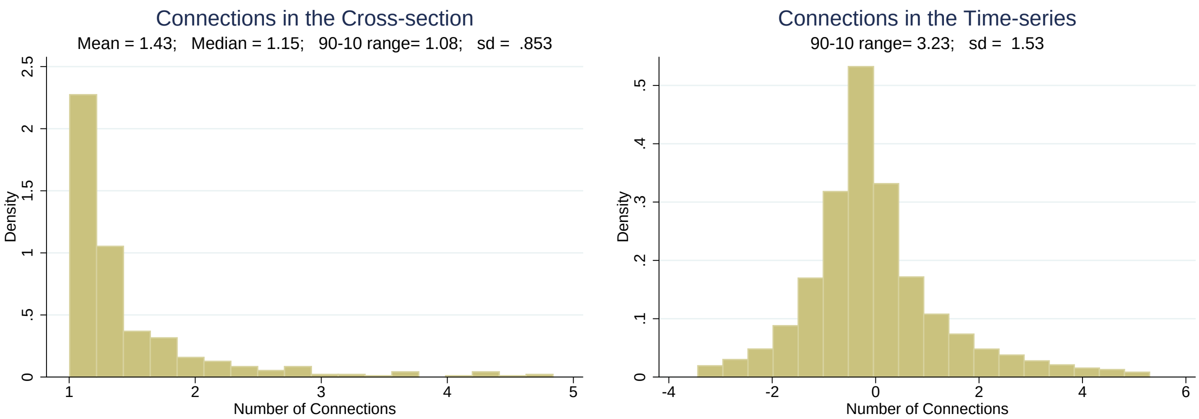
10 Figures and Tables

Figure 11: Time-series and Cross-sectional Variation in Client Connections

(a) All Connections



(b) Connections with Dealers Only



Notes: These figures summarise the cross-sectional (left side) and time-series (right side) variation in our first-order connections against all counterparties (Panel A) and against dealer banks (Panel B) measures. On the left side, we first calculate the average number of connections for each client across all her trading days; then we plot the distribution of the average across all clients. To construct the figures on the right side, we first run a panel regression to purge out client and day 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

(a) Clients' connections

	(1) Mean	(2) Median	(3) p10	(4) p90	(5) sd	(6) N
Connections (with Dealers)	2.44	1.00	1.00	6.00	2.28	133,046
Connections (all)	2.75	2.00	1.00	6.00	2.93	162,784
Number of Transactions	6.54	2.00	1.00	14.00	16.77	162,784
Volume (£ millions)	5.58	0.99	0.05	11.50	18.42	162,784

(b) Dealer Concentration

	(1) Mean	(2) Median	(3) p10	(4) p90	(5) sd
Market Share Top 1 Dealer per Bond	62.0%	57.1%	32.9%	100.0%	24.0%
Market Share Top 2 Dealers per Bond	82.1%	85.2%	57.1%	100.0%	17.0%
Market Share Top 3 Dealers per Bond	91.0%	96.1%	73.8%	100.0%	11.2%
Number of Dealers per Bond (daily)	1.74	1.00	1.00	3.00	1.05
Number of Dealers per Bond (monthly)	4.82	5.00	1.00	9.00	2.88
Herfindahl-Hirschman Index (HHI)	0.38	0.32	0.23	1.00	0.22

(c) Connections and Performance

	Excess Performance in the Cross-Section High- Minus Low-Connection Clients		Excess Performance in the Time-Series High- Minus Low-Connection Days	
	All Connections	Dealer Connections	All Connections	Dealer Connections
5-day Perf. (bps)	5.93***	8.21***	2.57***	2.59***
	(6.94)	(12.75)	(5.96)	(5.58)
10-day Perf. (bps)	5.25***	6.50***	1.58***	1.71***
	(4.40)	(7.26)	(2.65)	(2.64)
15-day Perf. (bps)	4.51***	5.72***	1.82**	2.29***
	(3.11)	(5.28)	(2.50)	(2.91)

Notes: This table reports summary statistics for our baseline sample, covering the period from September 2011 to December 2017. Panel A reports summary statistics for clients' connections and trading volumes, collapsed at the client-day level. Panel B shows different measures to quantify the concentration of G15 dealer banks in the market. The first three rows report the market shares of the one/two/three most active dealers for a particular bond in a given month. The Herfindahl-Hirschman Index (HHI) measures the market concentration for a particular bond in a given month by summing up the squared market shares of each active dealer in the market. In Panel C, Columns (1)-(2) differentiate between more connected and less connected clients by placing clients into two groups based on whether their average first-order connections are above or below the median client in the cross-section. Columns (3)-(4) place each client observation into two groups based on the within-variation of connections, i.e. depending on whether the client's first-order connections are above or below the client's own median connection measure based on the whole sample. The estimated coefficients are from individual pooled regressions of performance on the group indicator variables. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01), based on robust standard errors.

Table 2: Client Connections and Performance: Sophisticated Clients (Baseline I)

(a) Volume-weighted Trading Performance

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client	0.0035***	0.0034**	0.0042**	0.0030**	0.0040**	0.0060**
Connection	(3.00)	(2.10)	(2.23)	(2.06)	(1.98)	(2.36)
Volume	0.0005	-0.0029	-0.0076*	-0.0025	-0.0058	-0.0145***
	(0.18)	(-0.81)	(-1.83)	(-0.93)	(-1.56)	(-3.43)
N	133677	132168	131020	109968	108830	107807
R^2	0.036	0.031	0.029	0.039	0.035	0.034
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	Yes	Yes	Yes	Yes	Yes

(b) Unweighted Trading Performance

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client	0.0040**	0.0043**	0.0042*	0.0033*	0.0049*	0.0054
Connection	(2.55)	(2.06)	(1.80)	(1.73)	(1.95)	(1.64)
Volume	-0.0030	-0.0059	-0.0101**	-0.0049	-0.0079*	-0.0151***
	(-1.04)	(-1.48)	(-2.19)	(-1.65)	(-1.91)	(-3.14)
N	133677	132168	131020	109968	108830	107807
R^2	0.038	0.031	0.030	0.041	0.035	0.034
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table regresses the volume-weighted (Panel A) and unweighted (Panel B) trading performance at different time horizons on our connectivity measures (3.2). Sophisticated clients include asset managers and hedge funds. The transaction-level data is collapsed at the client-day level. The performance measures are in %-points. We include the natural logarithm of the pound trade volume of each client ("Volume") as a control. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 3: Client Connections and Performance: Unsophisticated Clients

(a) Volume-weighted Trading Performance

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client	-0.0001	0.0008	0.0005	-0.0011	0.0007	0.0013
Connection	(-0.06)	(0.61)	(0.30)	(-0.77)	(0.41)	(0.55)
Volume	0.0059***	0.0019	-0.0011	0.0065***	0.0022	-0.0014
	(2.76)	(0.71)	(-0.32)	(3.10)	(0.74)	(-0.39)
N	148205	146681	145770	121614	120530	119821
R^2	0.040	0.033	0.032	0.046	0.040	0.039
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	Yes	Yes	Yes	Yes	Yes

(b) Unweighted Trading Performance

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client	-0.0005	0.0000	0.0005	-0.0022	-0.0005	0.0012
Connection	(-0.44)	(0.00)	(0.29)	(-1.32)	(-0.25)	(0.45)
Volume	0.0045**	0.0014	-0.0011	0.0057**	0.0024	0.0001
	(2.07)	(0.48)	(-0.31)	(2.55)	(0.80)	(0.03)
N	148205	146681	145770	121614	120530	119821
R^2	0.042	0.034	0.033	0.048	0.040	0.040
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table regresses the volume-weighted (Panel A) and unweighted (Panel B) trading performance at different time horizons on our connectivity measures (3.2). Sophisticated clients include asset managers and hedge funds. The transaction-level data is collapsed at the client-day level. The performance measures are in %-points. We include the natural logarithm of the pound trade volume of each client ("Volume") as a control. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 4: Bond-specific Client Connections and Trading Performance (Baseline II)

(a) Volume-weighted Trading Performance

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client	0.0263***	0.0234**	0.0127	0.0210**	0.0355**	0.0221
Connection	(3.06)	(2.39)	(1.31)	(2.49)	(2.15)	(1.49)
Volume	-0.0091*	-0.0027	-0.0036	-0.0119**	-0.0071	-0.0095*
	(-1.87)	(-0.43)	(-0.68)	(-2.54)	(-1.09)	(-1.94)
N	372888	366848	362342	269902	264948	261550
R^2	0.330	0.331	0.337	0.356	0.361	0.369
Bond $*$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Client $*$ Day FE	Yes	Yes	Yes	Yes	Yes	Yes

(b) Unweighted Trading Performance

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client	0.0293***	0.0260***	0.0176	0.0291***	0.0432***	0.0348**
Connection	(3.45)	(2.65)	(1.56)	(3.73)	(3.05)	(2.39)
Volume	-0.0089*	-0.0015	-0.0026	-0.0117**	-0.0060	-0.0082*
	(-1.82)	(-0.24)	(-0.50)	(-2.51)	(-0.92)	(-1.69)
N	372888	366848	362342	269902	264948	261550
R^2	0.330	0.330	0.336	0.356	0.360	0.368
Bond $*$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Client $*$ Day FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table regresses the volume-weighted (Panel A) and unweighted (Panel B) trading performance at different time horizons on our connectivity measures (3.3) for sophisticated clients. Sophisticated clients include asset managers and hedge funds. The transaction-level data is collapsed at the client-day-instrument level. The performance measures are in %-points. We include the natural logarithm of the pound trade volume of the particular client in the given bond ("Volume") as a control. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 5: Long-Short Portfolio Returns based on Client Order Flow

(a) Portfolio Returns based on 'High-Connection' Order Flow

	(1) 5-day	(2) 10-day	(3) 15-day	(4) 20-day	(5) 25-day	(6) 30-day
'High-Connection'	0.0678***	0.1028***	0.1335***	0.1406***	0.1562***	0.1713***
Order Flow	(5.66)	(5.59)	(5.66)	(5.09)	(4.99)	(4.96)
Constant	0.0226***	0.0473***	0.0591***	0.1113***	0.1480***	0.1950***
	(2.69)	(3.70)	(3.60)	(5.72)	(6.85)	(8.11)
N	25922	25261	24846	24485	24377	24167
R^2	0.001	0.001	0.001	0.001	0.001	0.001

(b) Portfolio Returns based on 'Low-Connection' Order Flow

	(1) 5-day	(2) 10-day	(3) 15-day	(4) 20-day	(5) 25-day	(6) 30-day
'Low-Connection'	0.0317**	0.0673***	0.0569**	0.0627**	0.0585*	0.0190
Order Flow	(2.56)	(3.55)	(2.35)	(2.19)	(1.80)	(0.53)
Constant	0.0125	0.0241*	0.0720***	0.1107***	0.1833***	0.2475***
	(1.45)	(1.84)	(4.33)	(5.64)	(8.11)	(10.06)
N	22747	22277	21953	21728	21477	21307
R^2	0.000	0.001	0.000	0.000	0.000	0.000

Notes: This table shows the cumulative returns of the long-short portfolio based on the order flow of 'high-connection' (Panel A) and 'low-connection' (Panel B) client types for different holding periods up to thirty days, measured in %-points. More precisely, the bonds are equally sorted into ten groups on each trading day based on the aggregate order flow of clients with either 'low' or 'high' connections compared to their sample average. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors. Asterisks denote significance levels (* $p<0.1$, ** $p<0.05$, *** $p<0.01$).

Table 6: (Non-)Sophisticated Client Connections and Bond Performance

(a) Sophisticated Client Connections and Bond Performance

	(1) 5-day	(2) 10-day	(3) 15-day	(4) 20-day	(5) 25-day	(6) 30-day
Sophisticated Connections	0.0089***	0.0133***	0.0107***	0.0133***	0.0139***	0.0143***
	(5.52)	(6.14)	(4.86)	(4.75)	(4.22)	(3.55)
Volume	0.0024**	0.0010	0.0017	0.0022	-0.0031	-0.0036
	(2.22)	(0.65)	(0.83)	(0.92)	(-1.06)	(-1.23)
N	193904	191588	188892	187637	186103	184929
R^2	0.329	0.362	0.389	0.411	0.422	0.426
Bond $*$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes

(b) Non-Sophisticated Client Connections and Bond Performance

	(1) 5-day	(2) 10-day	(3) 15-day	(4) 20-day	(5) 25-day	(6) 30-day
Non-Sophisticated Connections	0.0051**	0.0067**	0.0045	0.0041	0.0067	0.0004
	(2.57)	(2.19)	(1.06)	(0.85)	(1.22)	(0.06)
Volume	0.0025**	0.0019	0.0027	0.0015	-0.0024	-0.0056*
	(2.35)	(1.29)	(1.44)	(0.62)	(-0.94)	(-1.85)
N	147597	145262	143901	142625	141150	140494
R^2	0.349	0.386	0.414	0.437	0.442	0.447
Bond $*$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table regresses the volume-weighted absolute log-returns at different time horizons on the total number of sophisticated (Panel A) and unsophisticated (Panel B) client connections for a given bond (4.1). The transaction-level data is collapsed at the day-instrument level. The absolute log-returns are measured in %-points. We include the natural logarithm of the daily pound trade volume in the given bond ("Volume") as a control. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors clustered at the instrument level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 7: Credit Default Swap Interaction and Trading Performance

(a) Volume-weighted Trading Performance

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client	0.0063	0.0141	-0.0008	-0.0070	0.0358*	-0.0069
Connection	(0.57)	(0.93)	(-0.04)	(-0.40)	(1.86)	(-0.22)
Client	0.0171**	0.0181*	0.0132	0.0193**	0.0139	0.0122
Connection ∗ CDS	(2.48)	(1.83)	(1.00)	(2.17)	(1.30)	(0.84)
Volume	-0.0122***	-0.0007	-0.0068	-0.0148***	-0.0039	-0.0086
	(-2.73)	(-0.13)	(-1.52)	(-3.52)	(-0.68)	(-1.22)
N	169136	165705	162261	121720	118931	116262
R^2	0.340	0.338	0.345	0.370	0.372	0.383
Bond ∗ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Client ∗ Day FE	Yes	Yes	Yes	Yes	Yes	Yes

(b) Unweighted Trading Performance

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client	0.0077	0.0126	-0.0009	0.0051	0.0454**	0.0058
Connection	(0.65)	(0.73)	(-0.05)	(0.30)	(2.31)	(0.19)
Client	0.0165***	0.0160	0.0079	0.0173**	0.0097	0.0031
Connection ∗ CDS	(2.59)	(1.47)	(0.56)	(2.19)	(0.85)	(0.21)
Volume	-0.0119***	0.0006	-0.0056	-0.0147***	-0.0034	-0.0075
	(-2.59)	(0.11)	(-1.23)	(-3.47)	(-0.59)	(-1.05)
N	169136	165705	162261	121720	118931	116262
R^2	0.340	0.335	0.343	0.370	0.369	0.382
Bond ∗ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Client ∗ Day FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table regresses the volume-weighted (Panel A) and unweighted (Panel B) trading performance at different time horizons on our connectivity measures (3.3) for sophisticated clients, interacted with an indicator variable equal to one if the client holds credit default swaps (CDS) written on the bond issuer in the month of the transaction. Sophisticated clients include asset managers and hedge funds. The transaction-level data is collapsed at the client-day-instrument level. The performance measures are in %-points. We include the natural logarithm of the pound trade volume of the particular client in the given bond ("Volume") as a control. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 8: Rating Category Interaction and Trading Performance

(a) Volume-weighted Trading Performance

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client	0.0157	0.0093	0.0075	0.0007	-0.0079	-0.0017
Connection	(1.19)	(0.57)	(0.64)	(0.05)	(-0.31)	(-0.07)
Client	-0.0008	0.0002	-0.0049	0.0047	0.0193	0.0083
Connection ∗ IG	(-0.06)	(0.01)	(-0.36)	(0.31)	(0.90)	(0.40)
Client	0.0671***	0.0859***	0.0501	0.0935***	0.1666***	0.1017
Connection ∗ HY	(3.75)	(3.22)	(1.40)	(2.90)	(4.44)	(1.54)
Volume	-0.0091*	-0.0026	-0.0035	-0.0119**	-0.0071	-0.0095*
	(-1.87)	(-0.43)	(-0.68)	(-2.54)	(-1.09)	(-1.94)
N	372888	366848	362342	269902	264948	261550
R^2	0.330	0.331	0.337	0.356	0.361	0.369
Bond ∗ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Client ∗ Day FE	Yes	Yes	Yes	Yes	Yes	Yes

(b) Unweighted Trading Performance

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client	0.0154	0.0085	0.0078	0.0058	-0.0024	0.0079
Connection	(1.01)	(0.44)	(0.53)	(0.43)	(-0.11)	(0.37)
Client	0.0040	0.0061	0.0021	0.0074	0.0215	0.0102
Connection ∗ IG	(0.27)	(0.31)	(0.13)	(0.52)	(1.03)	(0.53)
Client	0.0707***	0.0852***	0.0537	0.0992***	0.1700***	0.1118*
Connection ∗ HY	(3.67)	(2.60)	(1.43)	(3.12)	(4.16)	(1.79)
Volume	-0.0089*	-0.0015	-0.0026	-0.0116**	-0.0060	-0.0082*
	(-1.82)	(-0.24)	(-0.50)	(-2.51)	(-0.92)	(-1.69)
N	372888	366848	362342	269902	264948	261550
R^2	0.330	0.330	0.336	0.356	0.360	0.368
Bond ∗ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Client ∗ Day FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table regresses the volume-weighted (Panel A) and unweighted (Panel B) trading performance at different time horizons on our connectivity measures (3.3) for sophisticated clients, interacted with an indicator variable for investment-grade (IG) and high-yield (HY) corporate bonds. Sophisticated clients include asset managers and hedge funds. The transaction-level data is collapsed at the client-day-instrument level. The performance measures are in %-points. We include the natural logarithm of the pound trade volume of the particular client in the given bond ("Volume") as a control. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 9: Client Connections and Performance During Macroeconomic Announcements

(a) Volume-weighted Trading Performance

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client Connection ∗ Small Surprise	0.0029**	0.0020	0.0015	0.0022	0.0026	0.0033
	(2.04)	(1.01)	(0.68)	(1.16)	(1.01)	(1.08)
Client Connection ∗ Large Surprise	0.0028**	0.0038**	0.0059***	0.0028*	0.0048**	0.0081***
	(2.32)	(2.29)	(2.96)	(1.86)	(2.27)	(2.83)
Volume	0.0001	-0.0028	-0.0082*	-0.0036	-0.0069*	-0.0159***
	(0.03)	(-0.74)	(-1.87)	(-1.27)	(-1.80)	(-3.62)
N	123089	122023	121367	101096	100317	99676
R^2	0.037	0.032	0.031	0.040	0.036	0.036
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	Yes	Yes	Yes	Yes	Yes

(b) Unweighted Trading Performance

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client Connection ∗ Small Surprise	0.0030*	0.0026	0.0025	0.0019	0.0034	0.0043
	(1.70)	(1.07)	(0.87)	(0.84)	(1.07)	(1.05)
Client Connection ∗ Large Surprise	0.0037**	0.0050**	0.0060**	0.0039*	0.0065**	0.0073**
	(2.32)	(2.33)	(2.43)	(1.87)	(2.40)	(2.07)
Volume	-0.0034	-0.0057	-0.0108**	-0.0062**	-0.0092**	-0.0169***
	(-1.14)	(-1.37)	(-2.25)	(-2.04)	(-2.14)	(-3.40)
N	123089	122023	121367	101096	100317	99676
R^2	0.039	0.032	0.031	0.042	0.036	0.036
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table regresses the volume-weighted (Panel A) and unweighted (Panel B) trading performance at different time horizons on our connectivity measures (3.2) for sophisticated clients, interacted with an indicator variable for low-surprise macro-news announcements ("Small Surprise") and large-surprise macro-news announcements ("Large Surprise"). Sophisticated clients include asset managers and hedge funds. The transaction-level data is collapsed at the client-day level. The performance measures are in %-points. We include the natural logarithm of the pound trade volume of each client ("Volume") as a control. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 10: Bond-specific Client Connections and Performance During Macro-Announcements

(a) Volume-weighted Trading Performance

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client Connection ∗	0.0141	0.0132	0.0074	0.0055	0.0209	0.0251
Small Surprise	(1.59)	(1.25)	(0.53)	(0.50)	(1.17)	(1.16)
Client Connection ∗	0.0349***	0.0319**	0.0185	0.0364***	0.0476**	0.0234
Large Surprise	(3.35)	(2.36)	(1.38)	(3.08)	(2.12)	(1.34)
Volume	-0.0089*	-0.0024	-0.0028	-0.0118**	-0.0078	-0.0094*
	(-1.71)	(-0.35)	(-0.50)	(-2.34)	(-1.09)	(-1.76)
N	348304	343427	339972	251624	247542	245013
R^2	0.330	0.332	0.337	0.356	0.363	0.370
Bond ∗ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Client ∗ Day FE	Yes	Yes	Yes	Yes	Yes	Yes

(b) Unweighted Trading Performance

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client Connection ∗	0.0183**	0.0170	0.0149	0.0113	0.0221	0.0308
Small Surprise	(2.13)	(1.51)	(1.08)	(1.06)	(1.25)	(1.42)
Client Connection ∗	0.0361***	0.0318**	0.0177	0.0462***	0.0604***	0.0392***
Large Surprise	(3.31)	(2.28)	(1.42)	(4.12)	(3.22)	(2.60)
Volume	-0.0088*	-0.0013	-0.0020	-0.0116**	-0.0069	-0.0083
	(-1.66)	(-0.18)	(-0.34)	(-2.31)	(-0.96)	(-1.56)
N	348304	343427	339972	251624	247542	245013
R^2	0.330	0.331	0.336	0.356	0.362	0.368
Bond ∗ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Client ∗ Day FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table regresses the volume-weighted (Panel A) and unweighted (Panel B) trading performance at different time horizons on our connectivity measures (3.3) for sophisticated clients, interacted with an indicator variable for low-surprise macro-news announcements ("Small Surprise") and large-surprise macro-news announcements ("Large Surprise"). Sophisticated clients include asset managers and hedge funds. The transaction-level data is collapsed at the client-day-instrument level. The performance measures are in %-points. We include the natural logarithm of the pound trade volume of each client ("Volume") as a control. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 11: Bond-specific Client Connections and Price Dispersion

(a) Volume-weighted Trading Performance

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client Connection ∗	0.0195**	0.0163	0.0144	0.0139	0.0179	0.0237
Low Price Dispersion	(2.57)	(1.23)	(1.24)	(1.31)	(0.64)	(1.14)
Client Connection ∗	0.0309***	0.0280***	0.0116	0.0254**	0.0461***	0.0212
High Price Dispersion	(2.73)	(2.87)	(1.03)	(2.21)	(2.96)	(1.27)
Volume	-0.0091*	-0.0027	-0.0036	-0.0119**	-0.0071	-0.0095*
	(-1.87)	(-0.43)	(-0.69)	(-2.54)	(-1.09)	(-1.94)
N	372888	366848	362342	269902	264948	261550
R^2	0.330	0.331	0.337	0.356	0.361	0.369
Bond ∗ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Client ∗ Day FE	Yes	Yes	Yes	Yes	Yes	Yes

(b) Unweighted Trading Performance

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client Connection ∗	0.0233***	0.0233*	0.0232*	0.0207*	0.0262	0.0344*
Low Price Dispersion	(2.94)	(1.78)	(1.92)	(1.88)	(1.03)	(1.70)
Client Connection ∗	0.0334***	0.0277***	0.0139	0.0343***	0.0534***	0.0350**
High Price Dispersion	(3.01)	(2.75)	(1.00)	(3.12)	(3.71)	(2.13)
Volume	-0.0089*	-0.0015	-0.0026	-0.0117**	-0.0060	-0.0082*
	(-1.82)	(-0.24)	(-0.50)	(-2.50)	(-0.91)	(-1.69)
N	372888	366848	362342	269902	264948	261550
R^2	0.330	0.330	0.336	0.356	0.360	0.368
Bond ∗ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Client ∗ Day FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table regresses the volume-weighted (Panel A) and unweighted (Panel B) trading performance at different time horizons on our connectivity measures (3.3) for sophisticated clients, interacted with an indicator variable for days with low bond price dispersion ("Low Price Dispersion") and high bond price dispersion ("High Price Dispersion"). The price dispersion measure is the root mean squared difference between the traded prices of a particular bond and its respective trade-weighted market price, weighted by trading volume (see Jankowitsch, Nashikkar, and Subrahmanyam (2011) for more details on this measure). Sophisticated clients include asset managers and hedge funds. The transaction-level data is collapsed at the client-day-instrument level. The performance measures are in %-points. We include the natural logarithm of the pound trade volume of each client ("Volume") as a control. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 12: Client Connections and Performance around Bond Rating Changes

(a) Volume-weighted Trading Performance

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	6-day	7-day	8-day	6-day	7-day	8-day
High-Connection Days ∗ Rating Change	0.1459*	0.2113**	0.2143**	0.1369*	0.1509*	0.1933*
	(1.78)	(2.33)	(2.06)	(1.89)	(1.76)	(1.90)
High-Connection Days	-0.0009	-0.0141	-0.0087	0.0120	-0.0072	-0.0072
	(-0.13)	(-1.48)	(-0.80)	(1.50)	(-0.82)	(-0.63)
Rating Change	-0.1440**	-0.2022***	-0.2447***	-0.1391**	-0.1670***	-0.2266***
	(-2.27)	(-2.85)	(-3.10)	(-2.43)	(-2.68)	(-3.44)
Volume	-0.0075	-0.0060	-0.0028	-0.0090	-0.0080	-0.0047
	(-1.31)	(-0.94)	(-0.47)	(-1.57)	(-1.24)	(-0.76)
N	171080	171264	170122	155256	155554	154484
R^2	0.074	0.072	0.072	0.076	0.075	0.074
Bond ∗ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Client ∗ Year FE	Yes	Yes	Yes	Yes	Yes	Yes

(b) Unweighted Trading Performance

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	6-day	7-day	8-day	6-day	7-day	8-day
High-Connection Days ∗ Rating Change	0.1542*	0.2212**	0.2303**	0.1387*	0.1521*	0.2006**
	(1.96)	(2.51)	(2.30)	(1.95)	(1.81)	(2.03)
High-Connection Days	-0.0004	-0.0137	-0.0086	0.0118	-0.0079	-0.0080
	(-0.06)	(-1.40)	(-0.77)	(1.47)	(-0.88)	(-0.68)
Rating Change	-0.1373**	-0.1964***	-0.2393***	-0.1341**	-0.1627***	-0.2227***
	(-2.23)	(-2.81)	(-3.08)	(-2.36)	(-2.63)	(-3.46)
Volume	-0.0064	-0.0049	-0.0016	-0.0079	-0.0068	-0.0033
	(-1.15)	(-0.77)	(-0.26)	(-1.39)	(-1.06)	(-0.54)
N	171080	171264	170122	155256	155554	154484
R^2	0.074	0.073	0.072	0.077	0.076	0.074
Bond ∗ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Client ∗ Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table regresses the volume-weighted (Panel A) and unweighted (Panel B) trading performance at different time horizons on an indicator variable “High-Connection” that takes value 1 (0) if the given client has more (fewer) connections on the given trading day than its sample average, interacted with an indicator variable “Rating Change” indicating bond-day level observations that occur during the 5-day window before the given bond experiences a rating change (either upgrade or downgrade). The sample includes only sophisticated clients. The transaction-level data is collapsed at the client-day-instrument level. The performance measures are in %-points. We include the natural logarithm of the pound trade volume of each client (“Volume”) as a control. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 13: Client Connections and Performance: Controlling for Dealer Characteristics

(a) Dealer Fixed Effects & Dealers' Connections and Volumes

	(1) 5-day	(2) 10-day	(3) 15-day	(4) 5-day	(5) 10-day	(6) 15-day
Client Connection	0.0041***	0.0044**	0.0060**	0.0041***	0.0044**	0.0060**
	(2.92)	(2.34)	(2.44)	(2.96)	(2.35)	(2.47)
Client Volume	-0.0126***	-0.0164***	-0.0269***	-0.0126***	-0.0164***	-0.0270***
	(-3.44)	(-2.89)	(-4.22)	(-3.44)	(-2.88)	(-4.23)
Dealer Volume				-0.0002	-0.0010	0.0040
				(-0.05)	(-0.24)	(0.75)
Dealers' Connections				0.0004*	0.0001	0.0002
				(1.75)	(0.39)	(0.49)
N	297618	295607	293979	297618	295607	293979
R^2	0.043	0.039	0.037	0.043	0.039	0.037
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Dealer FE	Yes	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	Yes	Yes	Yes	Yes	Yes

(b) Dealer-Day & Dealer-Day-Relation Fixed Effects

	(1) 5-day	(2) 10-day	(3) 15-day	(4) 5-day	(5) 10-day	(6) 15-day
Client Connection	0.0044***	0.0045**	0.0062**	0.0051***	0.0051**	0.0069***
	(3.13)	(2.42)	(2.58)	(3.43)	(2.45)	(2.60)
Client Volume	-0.0132***	-0.0165***	-0.0277***	-0.0155***	-0.0182***	-0.0287***
	(-3.60)	(-2.92)	(-4.33)	(-3.88)	(-2.92)	(-4.20)
N	296090	294073	292476	280631	278570	276963
R^2	0.111	0.106	0.105	0.205	0.199	0.197
Dealer $*$ Day FE	Yes	Yes	Yes	No	No	No
Dealer $*$ Day $*$ Relation FE	No	No	No	Yes	Yes	Yes
Client FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table regresses the volume-weighted trading performance at different time horizons on connections of sophisticated clients (asset managers and hedge funds). The transaction-level data is collapsed at the client-dealer-day level. The performance measures are in %-points. We include the natural logarithm of the pound trade volume of each client ("Client Volume") as a control in all regressions. In Columns 4-6 of Panel A, we add the natural logarithm of the pound trade volume of each dealer ("Dealer Volume") as well as the total daily number of client connections of each dealer ("Dealers' Connections") as additional controls. Columns 1-3 of Panel B include a dealer-day fixed effect, and Columns 4-6 of the same panel include a dealer-day-relationship fixed effect, where relationship $r = \{1, 2, 3\}$ captures the strength of client-dealer relationships based on realised monthly trading volumes. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 14: Performance-Connection Relation in Corporate vs. Government Bond Markets

(a) Without Client-Market Fixed Effects

	Volume-weighted Performance			Unweighted Performance		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client Connection ∗	0.0217***	0.0252***	0.0259***	0.0159**	0.0166**	0.0160**
Corporate Bond Markets	(3.24)	(3.23)	(3.23)	(2.29)	(2.34)	(2.24)
Client Connection	-0.0089**	-0.0048	-0.0068	-0.0064	-0.0051	-0.0066
	(-2.12)	(-0.86)	(-1.14)	(-1.61)	(-1.01)	(-1.43)
Volume	0.0060	0.0046	0.0095*	0.0036	0.0038	0.0071
	(1.62)	(1.00)	(1.75)	(1.03)	(0.84)	(1.43)
N	94524	93566	92646	94524	93566	92646
R^2	0.530	0.531	0.530	0.525	0.529	0.528
Market ∗ Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Client ∗ Market FE	No	No	No	No	No	No
Client ∗ Day FE	Yes	Yes	Yes	Yes	Yes	Yes

(b) With Client-Market Fixed Effects

	Volume-weighted Performance			Unweighted Performance		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client Connection ∗	0.0125**	0.0155**	0.0170*	0.0092**	0.0084	0.0062
Corporate Bond Markets	(2.58)	(2.21)	(1.87)	(2.00)	(1.30)	(0.75)
Client Connection	-0.0081**	-0.0024	-0.0033	-0.0055*	-0.0024	-0.0026
	(-2.51)	(-0.47)	(-0.49)	(-1.84)	(-0.49)	(-0.42)
Volume	0.0116***	0.0108**	0.0126**	0.0095***	0.0104**	0.0109**
	(3.33)	(2.32)	(2.13)	(3.01)	(2.40)	(2.06)
N	94494	93534	92618	94494	93534	92618
R^2	0.536	0.536	0.535	0.533	0.535	0.533
Market ∗ Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Client ∗ Market FE	Yes	Yes	Yes	Yes	Yes	Yes
Client ∗ Day FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table regresses the volume-weighted (Columns 1-3) and unweighted (Columns 4-6) client trading performance at different time horizons on our connectivity measures (6.1). The sample is restricted to a subset of clients who trade simultaneously in both corporate bond and government bond markets. The transaction-level data is collapsed at the client-day-market level. A client-market fixed effect is excluded in Panel A and included in Panel B. The performance measures are in %-points. We include the natural logarithm of the pound trade volume of the particular client in the given market ("Volume") as a control. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 15: Dealer Concentration and Rating Categories

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client	0.0167	0.0094	0.0063	0.0055	0.0039	0.0070
Connection	(1.31)	(0.60)	(0.53)	(0.36)	(0.13)	(0.29)
Client Connection ∗	0.0100	0.0195	0.0199	0.0135	0.0339	0.0309
More Dealers & High Rating	(0.78)	(1.10)	(1.25)	(0.95)	(1.37)	(1.33)
Client Connection ∗	0.0326**	0.0465***	0.0266	0.0385**	0.0617***	0.0278
More Dealers & Low Rating	(2.44)	(2.83)	(1.50)	(2.09)	(2.83)	(1.04)
Client Connection ∗	-0.0034	-0.0000	-0.0047	-0.0024	0.0129	0.0005
Fewer Dealers & High Rating	(-0.28)	(-0.00)	(-0.31)	(-0.16)	(0.51)	(0.02)
Client Connection ∗	0.0035	-0.0023	-0.0139	-0.0061	-0.0059	-0.0301
Fewer Dealers & Low Rating	(0.25)	(-0.13)	(-0.81)	(-0.46)	(-0.35)	(-1.26)
Volume	-0.0092*	-0.0028	-0.0037	-0.0120**	-0.0074	-0.0097**
	(-1.90)	(-0.46)	(-0.72)	(-2.57)	(-1.12)	(-1.98)
N	372888	366848	362342	269902	264948	261550
R^2	0.330	0.331	0.337	0.356	0.361	0.369
Bond ∗ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Client ∗ Day FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table regresses the volume-weighted trading performance at different time horizons on our connectivity measures (3.3) for sophisticated clients. Sophisticated clients include asset managers and hedge funds. The connection measure is interacted with indicator variables equal to one if the number of active dealers in the given bond is below (above) the sample median across all bonds in the month of the transaction; and, within these two groups, the rating of the bond is below (above) the median in the month of the transaction. The group of unrated bonds is the control group in this regression. The transaction-level data is collapsed at the client-day-instrument level. The performance measures are in %-points. We include the natural logarithm of the pound trade volume of each client ("Volume") as a control. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 16: Dealer Concentration Interaction and Trading Performance

(a) Number of Active Dealers

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client	0.0357***	0.0377***	0.0247*	0.0246***	0.0417***	0.0285*
Connection	(3.96)	(3.61)	(1.84)	(2.98)	(2.73)	(1.74)
Client Connection ∗	-0.0183***	-0.0277***	-0.0224**	-0.0113**	-0.0204**	-0.0209**
Fewer Dealers	(-5.49)	(-4.53)	(-2.36)	(-2.18)	(-2.35)	(-2.04)
Volume	-0.0095**	-0.0032	-0.0038	-0.0117**	-0.0069	-0.0091*
	(-1.97)	(-0.51)	(-0.73)	(-2.48)	(-1.04)	(-1.86)
N	368088	362140	357730	268933	263959	260607
R^2	0.331	0.332	0.338	0.356	0.362	0.369
Bond ∗ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Client ∗ Day FE	Yes	Yes	Yes	Yes	Yes	Yes

(b) Herfindahl-Hirschman Index (HHI)

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client	0.0289***	0.0275***	0.0192*	0.0217**	0.0372**	0.0244
Connection	(3.17)	(2.67)	(1.77)	(2.55)	(2.27)	(1.59)
Client Connection ∗	-0.0064*	-0.0098**	-0.0142**	-0.0022	-0.0066	-0.0097
High HHI	(-1.76)	(-2.04)	(-2.51)	(-0.43)	(-0.94)	(-1.49)
Volume	-0.0094*	-0.0030	-0.0036	-0.0118**	-0.0070	-0.0092*
	(-1.94)	(-0.48)	(-0.70)	(-2.54)	(-1.07)	(-1.88)
N	368088	362140	357730	268933	263959	260607
R^2	0.331	0.332	0.338	0.356	0.362	0.369
Bond ∗ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Client ∗ Day FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table regresses the volume-weighted trading performance at different time horizons on our connectivity measures (3.3) for sophisticated clients. Sophisticated clients include asset managers and hedge funds. In Panel A, the connection measure is interacted with an indicator variable equal to one if the number of active dealers in the given bond is below the sample median across all bonds in the month of the transaction. In Panel B, the connection measure is interacted with an indicator variable equal to one if the bond's market concentration - measured by the Herfindahl-Hirschman Index (HHI) - is above the sample median across all bonds in the month of the transaction. The transaction-level data is collapsed at the client-day-instrument level. The performance measures are in %-points. We include the natural logarithm of the pound trade volume of the particular client in the given bond ("Volume") as a control. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 17: Client Connections and Performance During the COVID-19 Crisis

(a) Evolution of the Crisis

	(1) 1-day	(2) 5-day	(3) 10-day	(4) 15-day	(5) 25-day
Client Connection	0.0206***	0.0240***	0.0250***	0.0312***	0.0399***
	(11.38)	(6.35)	(5.20)	(4.33)	(4.65)
Client Connection ∗ Build-up	0.0039	-0.0277	-0.0296	-0.1440*	-0.1065
	(0.61)	(-1.56)	(-0.82)	(-1.84)	(-1.32)
Client Connection ∗ Outbreak	-0.0246	-0.1561	-0.2585	-0.1750	-0.1431
	(-1.34)	(-1.30)	(-1.32)	(-0.93)	(-1.12)
Client Connection ∗ Peak	0.0187	0.0556*	0.1098**	0.1426**	0.1824**
	(1.60)	(1.68)	(2.31)	(2.35)	(2.33)
Volume	-0.0066***	-0.0109***	-0.0210***	-0.0243***	-0.0376***
	(-4.03)	(-2.83)	(-4.04)	(-3.09)	(-3.57)
N	212070	199131	192582	189215	182090
R^2	0.403	0.444	0.442	0.446	0.437
Bond ∗ Year FE	Yes	Yes	Yes	Yes	Yes
Client ∗ Day FE	Yes	Yes	Yes	Yes	Yes

(b) March Announcements

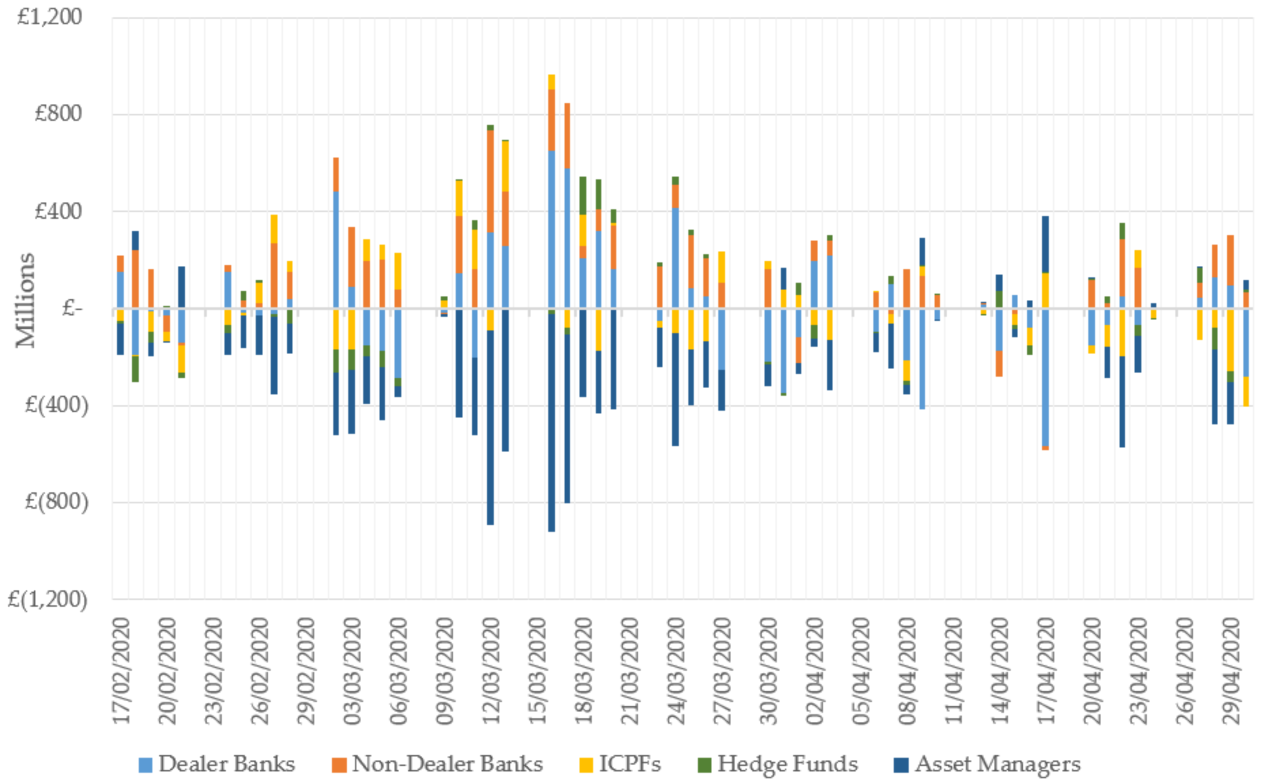
	(1) 1-day	(2) 5-day	(3) 10-day	(4) 15-day	(5) 25-day
Client Connection	0.0201***	0.0185***	0.0168**	0.0189**	0.0310***
	(11.34)	(4.76)	(2.53)	(2.17)	(3.44)
Client Connection ∗ pre-BoE	-0.0181	0.0746	0.3397***	0.4149**	0.4684***
	(-0.25)	(0.53)	(3.03)	(2.21)	(3.39)
Client Connection ∗ pre-Fed	0.1304***	0.3639***	0.6375***	1.0178***	0.8714***
	(3.32)	(10.87)	(6.64)	(5.28)	(6.33)
Client Connection ∗ post-Fed	0.0115	0.0302	0.0446	0.0270	0.0669
	(1.24)	(0.91)	(1.22)	(0.73)	(0.97)
Volume	-0.0065***	-0.0109***	-0.0207***	-0.0239***	-0.0375***
	(-3.97)	(-2.82)	(-4.00)	(-3.01)	(-3.53)
N	212070	199131	192582	189215	182090
R^2	0.403	0.444	0.442	0.446	0.437
Bond ∗ Year FE	Yes	Yes	Yes	Yes	Yes
Client ∗ Day FE	Yes	Yes	Yes	Yes	Yes

Notes: This table regresses the volume-weighted trading performance at different time horizons on our connectivity measures (3.3) for sophisticated clients. Sophisticated clients include asset managers and hedge funds; and connections are measured against all counterparties. In Panel A, the connection measure is interacted with indicator variables equal to one for the "Build-up" (February), "Outbreak" (March 1-13) and "Peak" (March 14 - April 30) periods of the COVID-19 Crisis. In Panel B, the connection measure is interacted with indicator variables equal to one for the "pre-BoE" (March 14-18), "pre-Fed" (March 19-23) and "post-Fed" (March 24 - April 30) announcement periods of the COVID-19 Crisis. The transaction-level data is collapsed at the client-day-instrument level. The performance measures are in %-points. We include the natural logarithm of the pound trade volume of each client ("Volume") as a control. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Online Appendix

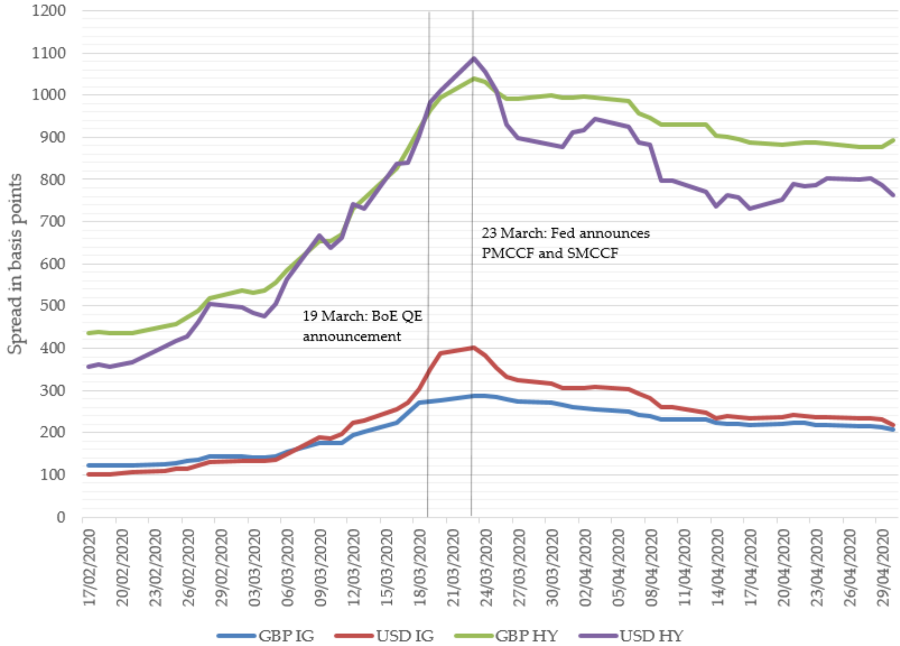
A Empirical Appendix

Figure A.1: Net Trading Volumes During the COVID-19 Crisis



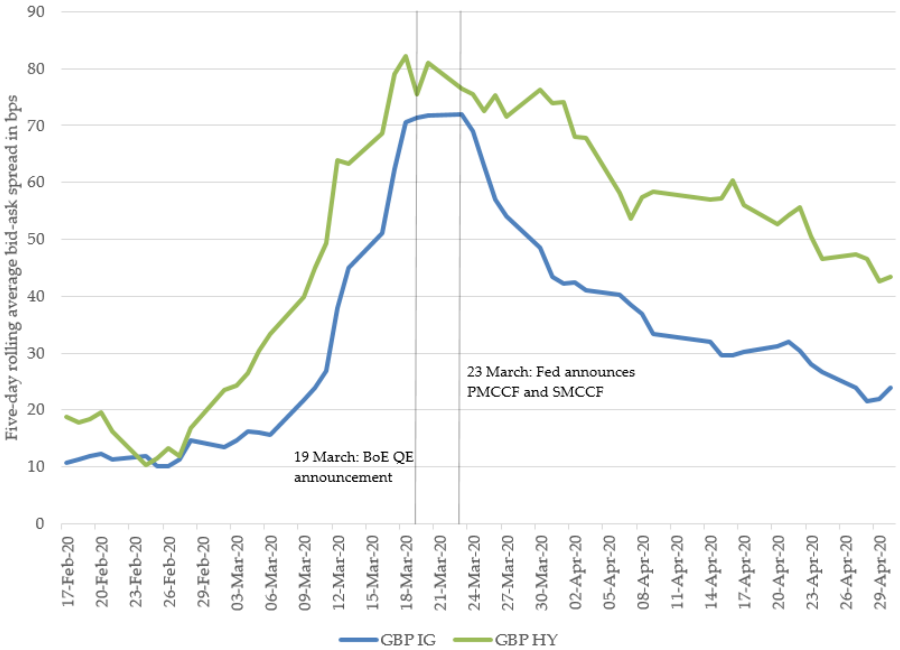
Notes: This figure shows the aggregated daily net trading volumes of different investor types in the UK corporate bond market during the COVID-19 Crisis (February-April 2020). The figure shows trading volumes of the following five investor types: dealer banks, non-dealer banks, insurance companies and pension funds (ICPFs), hedge funds, and asset managers. We omit other less prominent investor types, such as private equity funds. The trading volumes are aggregated across all firms belonging to a given investor type; and the volumes are converted to pound sterling using daily exchange rates.

Figure A.2: Corporate Bond Spreads During the COVID-19 Crisis



Notes: This figure shows the average daily quoted corporate bond spreads (in bps) over government bond yields with similar maturity for the following four groups: sterling-denominated investment-grade bonds (GBP IG), dollar-denominated investment-grade bonds (USD IG), sterling-denominated high-yield bonds (GBP HY), and dollar-denominated high-yield bonds (USD HY). The grey lines mark the Bank of England's Quantitative Easing announcement on March 19 and the Federal Reserve's announcement of the Primary Market Corporate Credit Facility (PMCCF) and Secondary Market Corporate Credit Facility (SMCCF) on March 23.

Figure A.3: Corporate Bond Bid-Ask Spreads During the COVID-19 Crisis



Notes: This figure shows the five-day rolling average effective bid-ask spreads (in bps) for sterling-denominated investment-grade (GBP IG) and high-yield bonds (GBP HY). The effective bid-ask spreads are calculated using the MiFID II transaction data and weighted by transaction volumes. The grey lines mark the Bank of England's Quantitative Easing announcement on March 19 and the Federal Reserve's announcement of the Primary Market Corporate Credit Facility (PMCCF) and Secondary Market Corporate Credit Facility (SMCCF) on March 23. To reduce noise, we winsorise the sample at the 1%-level.

Table A.1: Bond-specific Client Connections: Subsample Analysis

(a) Subsample excluding High-Yield Bonds

	Weighted Performance			Unweighted Performance		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client	0.0193**	0.0154	0.0116	0.0220***	0.0193**	0.0170**
Connection	(2.31)	(1.61)	(1.40)	(2.59)	(2.06)	(2.04)
Volume	-0.0103**	-0.0060	-0.0070	-0.0100**	-0.0052	-0.0062
	(-2.16)	(-0.97)	(-1.50)	(-2.12)	(-0.86)	(-1.35)
N	315972	311044	307587	315972	311044	307587
R^2	0.340	0.345	0.352	0.339	0.343	0.350
Bond ∗ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Client ∗ Day FE	Yes	Yes	Yes	Yes	Yes	Yes

(b) Subsample excluding Hedge Funds

	Weighted Performance			Unweighted Performance		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client	0.0255***	0.0233**	0.0144	0.0283***	0.0262**	0.0196*
Connection	(2.86)	(2.27)	(1.40)	(3.21)	(2.54)	(1.65)
Volume	-0.0091*	-0.0028	-0.0042	-0.0090*	-0.0018	-0.0033
	(-1.85)	(-0.44)	(-0.82)	(-1.81)	(-0.28)	(-0.65)
N	352402	346738	342497	352402	346738	342497
R^2	0.322	0.322	0.328	0.321	0.321	0.327
Bond ∗ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Client ∗ Day FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table regresses the volume-weighted (Columns 1-3) and unweighted (Columns 4-6) trading performance at different time horizons on our connectivity measures (3.3) for different subsamples. In Panel A, we eliminate high-yield bonds from our sample, and sophisticated clients include asset managers and hedge funds. In Panel B, we eliminate hedge funds from our sample, and therefore sophisticated clients only include asset managers. The transaction-level data is collapsed at the client-day-instrument level. The performance measures are in %-points. We include the natural logarithm of the pound trade volume of the particular client in the given bond ("Volume") as a control. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table A.2: Bond-specific Client Connections: Change in Fixed Effects

(a) No Client-Day Fixed Effects

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client Connection	0.0796***	0.0754***	0.0679***	0.0373*	0.0486	0.0359
	(5.01)	(4.05)	(3.80)	(1.81)	(1.55)	(1.21)
Volume	0.0004	0.0011	0.0008	-0.0013	-0.0025	-0.0026
	(0.10)	(0.24)	(0.18)	(-0.40)	(-0.64)	(-0.59)
N	439021	432284	427326	326482	321107	317004
R^2	0.026	0.024	0.023	0.032	0.030	0.029
Bond ∗ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Client ∗ Day FE	No	No	No	No	No	No

(b) No Bond-Year Fixed Effects

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client Connection	0.0294***	0.0265**	0.0171*	0.0239**	0.0392**	0.0283**
	(3.30)	(2.53)	(1.82)	(2.47)	(2.24)	(1.97)
Volume	-0.0071	-0.0009	-0.0015	-0.0093**	-0.0048	-0.0069
	(-1.38)	(-0.13)	(-0.25)	(-2.27)	(-0.76)	(-1.47)
N	373667	367618	363152	270718	265768	262371
R^2	0.306	0.308	0.315	0.326	0.332	0.341
Bond ∗ Year FE	No	No	No	No	No	No
Client ∗ Day FE	Yes	Yes	Yes	Yes	Yes	Yes

(c) No Client-Day & Bond-Year Fixed Effects

	All Connections			Only Dealer Connections		
	(1)	(2)	(3)	(4)	(5)	(6)
	5-day	10-day	15-day	5-day	10-day	15-day
Client Connection	0.0848***	0.0851***	0.0787***	0.0457*	0.0608	0.0500
	(4.15)	(4.00)	(3.92)	(1.70)	(1.50)	(1.30)
Volume	0.0035	0.0022	0.0011	0.0022	-0.0007	-0.0022
	(0.41)	(0.27)	(0.14)	(0.52)	(-0.13)	(-0.41)
N	439684	432959	428003	327155	321818	317687
R^2	0.001	0.001	0.000	0.000	0.000	0.000
Bond ∗ Year FE	No	No	No	No	No	No
Client ∗ Day FE	No	No	No	No	No	No

Notes: This table regresses the volume-weighted trading performance at different time horizons on our connectivity measures (3.3) for sophisticated clients, using different fixed effects specifications. In Panel A, we eliminate client-day FE from our baseline specification. In Panel B, we drop bond-year FE from our baseline specification. In Panel C, we eliminate both client-day FE as well as bond-year FE from our baseline specification. Sophisticated clients include asset managers and hedge funds. The transaction-level data is collapsed at the client-day-instrument level. The performance measures are in %-points. We include the natural logarithm of the pound trade volume of the particular client in the given bond ("Volume") as a control. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table A.3: Dealer Concentration in the Government Bond Market

	(1) Mean	(2) Median	(3) p10	(4) p90	(5) sd
Market Share Top 1 Dealer per Bond	20.6%	19.1%	14.4%	28.6%	6.5%
Market Share Top 2 Dealers per Bond	35.2%	33.7%	26.8%	45.3%	8.0%
Market Share Top 3 Dealers per Bond	46.9%	45.5%	37.5%	57.7%	8.5%
Number of Dealers per Bond (daily)	10.01	10.00	6.00	13.00	2.92
Number of Dealers per Bond (monthly)	14.47	15.00	14.00	15.00	0.69
Herfindahl-Hirschman Index (HHI)	0.12	0.11	0.09	0.15	0.03

Notes: This table reports different measures to quantify the concentration of G15 dealer banks in the government bond market, similar to the corporate bond dealer concentration statistics in Panel B of Table 1. The first three rows report the market shares of the one/two/three most active dealers for a particular bond in a given month. The Herfindahl-Hirschman Index (HHI) measures the market concentration for a particular bond in a given month by summing up the squared market shares of each active dealer in the market.

Table A.4: Client Connections and Bond Spreads During the COVID-19 Crisis

(a) All Connections

	ΔInvestment-Grade Spreads			ΔHigh-Yield Spreads		
	(1)	(2)	(3)	(4)	(5)	(6)
Sophisticated Connections	-0.0004	-0.0001	0.0001	0.0010	0.0034	0.0083
	(-0.64)	(-0.13)	(0.04)	(0.46)	(1.29)	(1.15)
Sophisticated Connections ∗ Crisis	0.0008	0.0007	0.0007	0.0043**	0.0041**	0.0041**
	(1.28)	(1.29)	(1.31)	(2.35)	(2.31)	(2.34)
Sophisticated Volume		-0.1111	-0.1077		-0.9550	-0.8587
		(-0.65)	(-0.59)		(-1.62)	(-1.38)
Sophisticated Clients			-0.0007			-0.0190
			(-0.09)			(-0.71)
N	614	614	614	614	614	614
R^2	0.007	0.008	0.008	0.024	0.028	0.029

(b) Only Dealer Connections

	ΔInvestment-Grade Spreads			ΔHigh-Yield Spreads		
	(1)	(2)	(3)	(4)	(5)	(6)
Sophisticated Connections	0.0002	0.0010	0.0009	0.0036	0.0086	0.0102
	(0.14)	(0.52)	(0.25)	(0.84)	(1.27)	(0.80)
Sophisticated Connections ∗ Crisis	0.0015	0.0015	0.0014	0.0083**	0.0080**	0.0080**
	(1.34)	(1.33)	(1.37)	(2.41)	(2.40)	(2.48)
Sophisticated Volume		-0.1640	-0.1690		-1.0087	-0.9397
		(-0.59)	(-0.53)		(-1.02)	(-0.83)
Sophisticated Clients			0.0004			-0.0061
			(0.04)			(-0.14)
N	614	614	614	614	614	614
R^2	0.009	0.009	0.009	0.028	0.029	0.029

Notes: This table regresses the daily first difference of investment-grade (Columns 1-3) and high-yield (Columns 4-6) bond spreads on sophisticated client connections. We use the daily total number of sophisticated client connections; which is interacted with an indicator variable equal to one for the "Crisis" period (February-April) of the COVID-19 pandemic. Sophisticated clients include asset managers and hedge funds; and connections are measured against all counterparties in Panel A, and against dealer banks in Panel B. The spreads are measured in basis points. We include the natural logarithm of the total pound trade volume of sophisticated clients ("Sophisticated Volume") and the total number of sophisticated clients ("Sophisticated Clients") as controls as well as a constant (not shown). T-statistics in parentheses are based on robust standard errors. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

B Theoretical Appendix

In this Section, we provide a self-contained description of the model, used in Section 7 of the text, for the case when an informed client is allowed to trade with two dealers. The model is a multi-market extension of Kyle (1989) in the spirit of Bernhardt and Taub (2008) and Malamud and Rostek (2017). There is one asset whose payoff is $\tilde{v} \sim N(v, \sigma_v^2)$. The asset is traded by clients and dealers. There are $j = \{1, 2\}$ dealers who trade with one another as well as with clients in two stages. In the first stage, dealer j trades with N_j clients, all submitting demand schedules. In the second stage, dealers interact with one another through the inter-dealer broker (IDB) market, by submitting demand schedules (Viswanathan and Wang, 2004). The market in the first and second stages clears at price p_j and $p^\star$, respectively. Moreover, there are other dealers $i = \{3, 4, \ldots, M\}$, whose clientele we do not model. Their role is purely to provide (increasing) competition among dealers in the second stage.

Dealer j serves two clients $k = \{1, 2\}$, one of which may be informed. The demand of clients are denoted $d_{j,1}$ and $d_{j,2}$, whereas the demand of dealer j in stage 1 and 2 is $x_{j,1}$ and $x_{j,2}$, respectively. The market clearing condition at dealer j in stage 1 is:

$$0 = x_{j,1} + \sum_k d_{j,k} + u_j, \tag{B.1}$$

where $u_j \sim N\left(0, \sigma_{u_j}^2\right)$ captures random liquidity trading. Similarly, market clearing in stage 2 is given by:

$$0 = \sum_i x_{i,2} + \sum_i x_{j,2} + u^\star, \tag{B.2}$$

where $u^\star \sim N(0, \sigma_{u^\star}^2)$ captures random liquidity trading at the inter-dealer stage.

The remainder of the appendix is as follows: Subsection B.1 presents the problem of the second stage; Subsection B.2 presents the problem for the first stage; Section B.3 presents auxiliary price calculations; Section B.4 computes the relevant conditional moments; Section B.5 presents the optimality conditions; and Section B.6 presents the mapping between the conjectured demand functions and the derived counterparts.

B.1 Stage 2 problem (IDB)

In stage 2, there will be M dealers with demand functions of the following form:

$$\begin{aligned} x_{1,2} &= b_1 - c_1 p^\star + a_1 p_1 \\ x_{2,2} &= b_2 - c_2 p^\star + a_2 p_2 \\ x_{3,2} &= b_3 - c_3 p^\star \\ &= \vdots \\ x_{M,2} &= b_M - c_M p^\star, \end{aligned} \tag{B.3}$$

where $p^\star$ is the IDB price, and p_1 and p_2 are the prices that dealers 1 and 2 give to their clients in stage 1. For simplification, we assume that dealers $i = \{3, \dots M\}$ do not interact with clients and only participate in stage 2. Note that the OTC nature of the market means that dealers 1 and 2 do not see the first stage prices of the other dealer. Market clearing then gives:

$$x_{1,2} + x_{2,2} + \sum_3^M x_{i,2} + u^\star = 0. \tag{B.4}$$

B.1.1 Residual Supply Curve for Dealer 1

The residual supply curve for dealer 1 is obtained by substituting B.3 into B.4:

$$\begin{aligned} x_{1,2} + x_{2,2} + \sum_3^M x_{i,2} =& u^\star \\ x_{1,2} =& - x_{2,2} - \sum_3^M x_{i,2} + u^\star \\ x_{1,2} =& - (b_2 - c_2 p^\star + a_2 p_2) - \sum_3^M (b_i - c_i p^\star) + u^\star \\ p^\star =& \frac{x_{1,2} + \sum_2^M b_i + a_2 p_2 + u^\star}{\sum_2^M c_i}. \end{aligned}$$

B.1.2 Total Residual Supply Curve

The IDB price is given by:

$$p^\star = \frac{\sum_1^M b_i + a_1 p_1 + a_2 p_2 + u^\star}{\sum_1^M c_i}. \tag{B.5}$$

B.1.3 The Link Between IDB Price and Dealers' Prices

It will be useful to express the IDB price by adding up dealers' conjectured demand curves as well as the using market clearing condition. Given B.5, we can write the IDB price in the following form:

$$p^{\star} = y_0 + y_1 p_1 + y_2 p_2 + y_u u^{\star}, \tag{B.6}$$

so that the IDB price is a linear combination of the individual dealer prices at which clients in different markets transact.

B.1.4 Optimality Condition of Dealer 1

The profit of dealer 1 in the IDB trading stage can be written as:

$$\tilde{\pi}_1 = (v - p^{\star})\, x_{1,2}. \tag{B.7}$$

The given dealer can condition on the order flow they faced in the first round, leading to the inventory inherited $x_{1,1,}$:

$$\begin{aligned}\max_{x_{1,2}} U(\tilde{\pi}_1) &= \max_{x_{1,2}} \left[\mathbb{E}\left[((v - p^{\star})\, x_{1,2}) \mid p^{\star}, p_1\right] - \frac{\rho}{2} Var\left(((v - p^{\star})\, x_{1,2}) \mid p^{\star}, p_1\right)\right] \\ &= \max_{x_{1,2}} \left[\mathbb{E}\left[v \mid p^{\star}, p_1\right] x_{1,2} - x_{1,2}\left[\frac{x_{1,2} + \sum_2^M b_i + a_2 p_2}{\sum_2^M c_i}\right] - \frac{\rho}{2}\left(x_{1,2}\right)^2 Var\left(v \mid p^{\star}, p_1\right)\right],\end{aligned}$$

which gives:

$$0 = \mathbb{E}\left[v \mid p^{\star}, p_1\right] - \frac{x_{1,2} + \sum_2^M b_i + a_2 p_2}{\sum_2^M c_i} + \frac{x_{1,1} - x_{1,2}}{\sum_2^M c_i} - \rho x_{1,2} Var\left(v \mid p^{\star}, p_1\right). \tag{B.8}$$

Note that the second-order condition (SOC) is obtained by differentiating B.8 again wrt $x_{1,2}$, yielding:

$$\frac{2}{\sum_2^M c_i} + \rho Var\left(v \mid p^{\star}, p_1\right) > 0. \tag{B.9}$$

The FOC gives the optimal demand:

$$x_{1,2} = \frac{\mathbb{E}\left[v \mid p^{\star}, p_1\right] - p^{\star}}{\frac{1}{\sum_2^M c_i} + \rho Var\left(v \mid p^{\star}, p_1\right)}. \tag{B.10}$$

Note that while dealers do not observe signals about the asset value, their interaction with clients in the first stage gives them additional knowledge about the asset value. This element of learning is captured by the conditioning term p_1 when forming expectations about the asset value.

B.1.5 Optimality Condition of Dealer 2

The derivation of the optimal demand of dealer 2 is similar to subsection B.1.4, yielding the following condition:

$$x_{2,2} = \frac{\mathbb{E}\left[v \mid p^{\star}, p_2\right] - p^{\star}}{\frac{1}{c_1 + \sum_3^M c_i} + \rho Var\left(v \mid p^{\star}, p_2\right)}. \tag{B.11}$$

B.1.6 Optimality Condition of Dealer i

The optimal demand for other dealer $i = \{3, \ldots M\}$ is given by:

$$x_{i,2} = \frac{\mathbb{E}\left[v \mid p^{\star}\right] - p^{\star}}{\frac{1}{c_1 + c_2 + \sum_{\neq i}^M c_i} + \rho Var\left(v \mid p^{\star}\right)}. \tag{B.12}$$

Note that the main difference between the demand of dealers who do not serve clients (B.12) and the demand of those dealers who trade with clients (B.10–B.11) is that the former group of dealers can only condition their demand on the IDB price $p^{\star}$. In contrast, dealers who trade with (possibly informed) clients can condition their demand in stage 1 on prices at which clients trade.

B.2 Stage 1 Problem (Dealer j and Clients)

B.2.1 Market 1

Market clearing gives:

$$0 = x_{1,1} + d_{1,1} + d_{1,2} + u_1, \tag{B.13}$$

where $x_{1,1}$ is the demand of dealer 1, $d_{1,1}$ is the uninformed client's demand, $d_{1,2}$ is the informed client's demand and u is some random demand. We conjecture that the three demand functions are of linear form:

$$
\begin{aligned}
d_{1,1} &= -\gamma_{1,1}p_1 + \beta_{1,1} \\
d_{1,2} &= -\gamma_{1,2}p_1 + \alpha_2 v \\
x_{1,1} &= -\gamma_{M,1}p_1 + \omega_{M,1}p^{\star}.
\end{aligned}
\tag{B.14}
$$

where the parameters $\{\gamma_{1,1}, \gamma_{1,2}, \gamma_{M,1}, \beta_{1,1}, \alpha_2, \omega_{M,1}\}$ will be determined in equilibrium. The residual supply curve for dealer 1 is obtained by substituting the demand curves B.14 into B.13:

$$
\begin{aligned}
-x_{1,1} &= d_{1,1} + d_{1,2} + u_1 \\
-x_{1,1} &= \beta_{1,1} - \gamma_{1,1}p_1 - \gamma_{1,2}p_1 + \alpha_2 v + u_1 \\
p_1 &= \frac{x_{1,1} + \beta_{1,1} + \alpha_2 v + u_1}{\gamma_{1,1} + \gamma_{1,2}}.
\end{aligned}
$$

Similarly, the residual supply curve for uninformed is obtained:

$$
\begin{aligned}
-x_{1,1} &= d_{1,1} + d_{1,2} + u_1 \\
-\left(-\gamma_{M,1}p_1 + \omega_{M,1}p^{\star}\right) &= d_{1,1} - \gamma_{1,2}p_1 + \alpha_2 v + u_1 \\
p_1 &= \frac{d_{1,1} + \omega_{M,1}p^{\star} + \alpha_2 v + u_1}{\gamma_{1,2} + \gamma_{M,1}}.
\end{aligned}
$$

Similarly, residual supply curve for informed:

$$
\begin{aligned}
-x_{1,1} &= d_{1,1} + d_{1,2} + u \\
-\left(-\gamma_{M,1}p_1 + \omega_{M,1}p^{\star}\right) &= \beta_{1,1} - \gamma_{1,1}p_1 + d_{1,2} + u_1 \\
p_1 &= \frac{d_{1,2} + \beta_{1,1} + \omega_{M,1}p^{\star} + u_1}{\gamma_{1,1} + \gamma_{M,1}}.
\end{aligned}
$$

Total residual supply curve is written as:

$$
p_1 = \frac{\beta_{1,1} + \alpha_2 v + \omega_{M,1}p^{\star} + u_1}{\gamma_{1,1} + \gamma_{1,2} + \gamma_{M,1}}, \tag{B.15}
$$

where $p^\star$ can be substituted out using B.6:

$$\begin{aligned}
p_1 &= \frac{\beta_{1,1} + \omega_{M,1} p^\star + \alpha_2 v + u_1}{\gamma_{1,1} + \gamma_{1,2} + \gamma_{M,1}} \\
&= \frac{\beta_{1,1} + \omega_{M,1} \left[y_0 + y_1 p_1 + y_2 p_2 + y_u u^\star \right] + \alpha_2 v + u_1}{\gamma_{1,1} + \gamma_{1,2} + \gamma_{M,1}} \\
p_1 \left(1 - \frac{\omega_{M,1} y_1}{\gamma_{1,1} + \gamma_{1,2} + \gamma_{M,1}} \right) &= \frac{\beta_{1,1} + \omega_{M,1} \left[y_0 + y_2 p_2 + y_u u^\star \right] + \alpha_2 v + u_1}{\gamma_{1,1} + \gamma_{1,2} + \gamma_{M,1}} \\
p_1 &= \frac{\beta_{1,1} + \omega_{M,1} \left[y_0 + y_2 p_2 + y_u u^\star \right] + \alpha_2 v + u_1}{(\gamma_{1,1} + \gamma_{1,2} + \gamma_{M,1}) - \omega_{M,1} y_1}.
\end{aligned} \tag{B.16}$$

B.2.2 Market 2

The derivation for market 2 is identical to B.2.1 in the case when the informed client is present in both market 1 and market 2. In the case when the informed client has one dealer connection, then the informed client in market 2 is replaced by an uninformed client. Recall that the numerical results (Figures 8–9) in Section 7 of the text are obtained via comparative statistics whereby the equilibrium allocation and profits are compared in these two cases. In this subsection, we present the derivation for the former case, i.e. when the informed client is present in market 2.

The three demand functions are of the form:

$$\begin{aligned}
d_{2,1} &= -\gamma_{2,1} p_2 + \beta_{2,1} \\
d_{2,2} &= -\gamma_{2,2} p_2 + \alpha_3 v \\
x_{2,1} &= -\gamma_{M,2} p_2 + \omega_{M,2} p^\star.
\end{aligned} \tag{B.17}$$

where the parameters $\{\gamma_{2,1}, \gamma_{2,2}, \gamma_{M,2}, \beta_{2,1}, \alpha_2, \omega_{M,2}\}$ will be determined in equilibrium. The residual supply curve for dealer 2 is obtained by substituting the demand curves into the market clearing condition:

$$\begin{aligned}
-x_{2,1} &= d_{2,1} + d_{2,2} + u_2 \\
-x_{2,1} &= \beta_{2,1} + \alpha_3 v - \gamma_{2,1} p_2 - \gamma_{2,2} p_1 + u_2 \\
p_2 &= \frac{x_{2,1} + \beta_{2,1} + \alpha_3 v + u_2}{\gamma_{2,1} + \gamma_{2,2}}.
\end{aligned}$$

Total residual supply curve:

$$p_2 = \frac{\beta_{2,1} + \alpha_3 v + \omega_{M,2} p^\star + u_2}{\gamma_{2,1} + \gamma_{2,2} + \gamma_{M,2}}, \tag{B.18}$$

where $p^\star$ can be substituted out using B.6, $p^\star = y_0 + y_1 p_1 + y_2 p_2 + y_u u^\star$:

$$\begin{aligned} p_2 &= \frac{\beta_{2,1} + \alpha_3 v + \omega_{M,2} p^\star + u_2}{\gamma_{2,1} + \gamma_{2,2} + \gamma_{M,2}} \\ &= \frac{\beta_{2,1} + \alpha_3 v + \omega_{M,2} \left[y_0 + y_1 p_1 + y_2 p_2 + y_u u^\star\right] + u_2}{\gamma_{2,1} + \gamma_{2,2} + \gamma_{M,2}} \\ &= \frac{\beta_{2,1} + \alpha_3 v + \omega_{M,2} \left[y_0 + y_1 p_1 + y_u u^\star\right] + u_2}{(\gamma_{2,1} + \gamma_{2,2} + \gamma_{M,2}) - \omega_{M,2} y_2}. \end{aligned} \tag{B.19}$$

Substituting out the IDB price highlights a key point, namely that even if dealer 2 did not trade with an informed client ($\alpha_3 = 0$), observing both p_2 and $p^\star$ is useful for learning about the fundamental value of the asset as they depend on the informed client's action in market 1.

Note that given the price functions B.16 and B.19, all dealer prices can ultimately be written as function of (i) the asset's fundamental value, (ii) noise terms and (iii) constants:

$$\begin{aligned} p_1 &= \kappa_{1,0} + \kappa_{1,1} u_1 + \kappa_{1,2} u_2 + \kappa_{1,3} u^\star + \kappa_{1,4} v \\ p_2 &= \kappa_{2,0} + \kappa_{2,1} u_1 + \kappa_{2,2} u_2 + \kappa_{2,3} u^\star + \kappa_{2,4} v \\ p^\star &= \kappa_{\star,0} + \kappa_{\star,1} u_1 + \kappa_{\star,2} u_2 + \kappa_{\star,3} u^\star + \kappa_{\star,4} v. \end{aligned} \tag{B.20}$$

B.3 Solving for the Price Parameters

B.3.1 Local Price in Market 1

Recall the price functions B.16 and B.19:

$$\begin{aligned} p_1 &= \frac{\beta_{1,1} + \omega_{M,1} \left[y_0 + y_2 p_2 + y_u u^\star\right] + \alpha_2 v + u_1}{(\gamma_{1,1} + \gamma_{1,2} + \gamma_{M,1}) - \omega_{M,1} y_1} \\ p_2 &= \frac{\beta_{2,1} + \alpha_3 v + \omega_{M,2} \left[y_0 + y_1 p_1 + y_u u^\star\right] + u_2}{(\gamma_{2,1} + \gamma_{2,2} + \gamma_{M,2}) - \omega_{M,2} y_2}, \end{aligned}$$

and substitute to determine the coefficients in B.20. Specifically, we get:

$$
\begin{aligned}
p_1 &= \frac{\beta_{1,1} + \omega_{M,1}\left[y_0 + y_2 p_2 + y_u u^\star\right] + \alpha_2 v + u_1}{(\gamma_{1,1} + \gamma_{1,2} + \gamma_{M,1}) - \omega_{M,1} y_1} \\
&= \frac{\beta_{1,1} + \omega_{M,1}\left[y_0 + y_2\left[\frac{\beta_{2,1}+\alpha_3 v+\omega_{M,2}[y_0+y_1 p_1+y_u u^\star]+u_2}{(\gamma_{2,1}+\gamma_{2,2}+\gamma_{M,2})-\omega_{M,2}y_2}\right] + y_u u^\star\right] + \alpha_2 v + u_1}{(\gamma_{1,1} + \gamma_{1,2} + \gamma_{M,1}) - \omega_{M,1} y_1} \\
p_1 &= \frac{\frac{\beta_{1,1}+\omega_{M,1}\left[y_0+y_2\left[\frac{\beta_{2,1}+\alpha_3 v+\omega_{M,2}[y_0+y_u u^\star]+u_2}{(\gamma_{2,1}+\gamma_{2,2}+\gamma_{M,2})-\omega_{M,2}y_2}\right]+y_u u^\star\right]+\alpha_2 v+u_1}{(\gamma_{1,1}+\gamma_{1,2}+\gamma_{M,1})-\omega_{M,1}y_1}}{1-\frac{\omega_{M,1}y_2\omega_{M,2}y_1}{(\gamma_{2,1}+\gamma_{2,2}+\gamma_{M,2}-\omega_{M,2}y_2)(\gamma_{1,1}+\gamma_{1,2}+\gamma_{M,1}-\omega_{M,1}y_1)}},
\end{aligned}
$$

defining the coefficients:

$$
\begin{aligned}
\Phi_1 &\equiv \frac{(\gamma_{1,1} + \gamma_{1,2} + \gamma_{M,1}) - \omega_{M,1} y_1}{1-\frac{\omega_{M,1}y_2\omega_{M,2}y_1}{(\gamma_{2,1}+\gamma_{2,2}+\gamma_{M,2}-\omega_{M,2}y_2)(\gamma_{1,1}+\gamma_{1,2}+\gamma_{M,1}-\omega_{M,1}y_1)}} \\
\Phi_2 &\equiv (\gamma_{2,1} + \gamma_{2,2} + \gamma_{M,2}) - \omega_{M,2} y_2,
\end{aligned}
$$

we can write the price p_1 as:

$$
\begin{aligned}
p_1 &= \frac{\beta_{1,1} + \omega_{M,1}\left[y_0 + y_2\left[\frac{\beta_{2,1}+\alpha_3 v+\omega_{M,2}[y_0+y_u u^\star]+u_2}{\Phi_2}\right] + y_u u^\star\right] + \alpha_2 v + u_1}{\Phi_1} \\
&= \frac{\beta_{1,1} + \omega_{M,1}\left[y_0 + y_2\left(\frac{\beta_{2,1}+\omega_{M,2}y_0}{\Phi_2}\right)\right]}{\Phi_1} \\
&+ \frac{1}{\Phi_1} u_1 \\
&+ \frac{\omega_{M,1} y_2}{\Phi_1 \Phi_2} u_2 \\
&+ \frac{\omega_{M,1}\left(\omega_{M,2} y_2/\Phi_2 - 1\right) y_u}{\Phi_1} u^\star \\
&+ \frac{\alpha_2 + \omega_{M,1} y_2 \alpha_3/\Phi_2}{\Phi_1} v,
\end{aligned}
$$

so that the coefficients are now determined for:

$$
p_1 = \kappa_{1,0} + \kappa_{1,1} u_1 + \kappa_{1,2} u_2 + \kappa_{1,3} u^\star + \kappa_{1,4} v. \tag{B.21}
$$

B.3.2 Local Price in Market 2

Similar to the previous subsection, we now solve to determine the coefficients in B.20. Specifically, we get:

$$\begin{aligned}
p_2 &= \frac{\beta_{2,1} + \alpha_3 v + \omega_{M,2}\left[y_0 + y_1 p_1 + y_u u^\star\right] + u_2}{(\gamma_{2,1} + \gamma_{2,2} + \gamma_{M,2}) - \omega_{M,2} y_2} \\
&= \frac{\beta_{2,1} + \alpha_3 v + \omega_{M,2}\left[y_0 + y_1\left[\frac{\beta_{1,1}+\omega_{M,1}[y_0+y_2p_2+y_u u^\star]+\alpha_2 v+u_1}{(\gamma_{1,1}+\gamma_{1,2}+\gamma_{M,1})-\omega_{M,1}y_1}\right] + y_u u^\star\right] + u_2}{(\gamma_{2,1} + \gamma_{2,2} + \gamma_{M,2}) - \omega_{M,2} y_2} \\
p_2 &= \frac{\frac{\beta_{2,1}+\alpha_3 v+\omega_{M,2}\left[y_0+y_1\left[\frac{\beta_{1,1}+\omega_{M,1}[y_0+y_u u^\star]+\alpha_2 v+u_1}{(\gamma_{1,1}+\gamma_{1,2}+\gamma_{M,1})-\omega_{M,1}y_1}\right]+y_u u^\star\right]+u_2}{(\gamma_{2,1}+\gamma_{2,2}+\gamma_{M,2})-\omega_{M,2}y_2}}{1 - \frac{\omega_{M,1}y_2\omega_{M,2}y_1}{(\gamma_{2,1}+\gamma_{2,2}+\gamma_{M,2}-\omega_{M,2}y_2)(\gamma_{1,1}+\gamma_{1,2}+\gamma_{M,1}-\omega_{M,1}y_1)}},
\end{aligned}$$

defining the coefficients:

$$\begin{aligned}
\Phi_3 &\equiv \frac{(\gamma_{2,1} + \gamma_{2,2} + \gamma_{M,2}) - \omega_{M,2} y_2}{1 - \frac{\omega_{M,1}y_2\omega_{M,2}y_1}{(\gamma_{2,1}+\gamma_{2,2}+\gamma_{M,2}-\omega_{M,2}y_2)(\gamma_{1,1}+\gamma_{1,2}+\gamma_{M,1}-\omega_{M,1}y_1)}} \\
\Phi_4 &\equiv (\gamma_{1,1} + \gamma_{1,2} + \gamma_{M,1}) - \omega_{M,1} y_1,
\end{aligned}$$

we can write the price p_1 as:

$$\begin{aligned}
p_2 &= \frac{\beta_{2,1} + \alpha_3 v + \omega_{M,2}\left[y_0 + y_1\left[\frac{\beta_{1,1}+\omega_{M,1}[y_0+y_u u^\star]+\alpha_2 v+u_1}{\Phi_4}\right] + y_u u^\star\right] + u_2}{\Phi_3} \\
&= \frac{\beta_{2,1} + \omega_{M,2}\left[y_0 + y_1\left(\frac{\beta_{1,1}+\omega_{M,1}y_0}{\Phi_4}\right)\right]}{\Phi_3} \\
&\quad + \frac{\omega_{M,2} y_1}{\Phi_3 \Phi_4} u_1 \\
&\quad + \frac{1}{\Phi_3} u_2 \\
&\quad + \frac{\omega_{M,2}\left(\omega_{M,1} y_1/\Phi_4 - 1\right) y_u}{\Phi_3} u^\star \\
&\quad + \frac{\alpha_3 + \omega_{M,2} y_1 \alpha_2/\Phi_4}{\Phi_3} v,
\end{aligned}$$

so that the coefficients are now determined for:

$$p_2 = \kappa_{2,0} + \kappa_{2,1} u_1 + \kappa_{2,2} u_2 + \kappa_{2,3} u^\star + \kappa_{2,4} v. \tag{B.22}$$

B.3.3 Inter-Dealer Price

Solving the coefficients for the IDB price is then done by:

$$
\begin{aligned}
p^\star &= y_0 + y_1 p_1 + y_2 p_2 + y_u u^\star \\
&= y_0 + y_1 \left[\kappa_{1,0} + \kappa_{1,1} u_1 + \kappa_{1,2} u_2 + \kappa_{1,3} u^\star + \kappa_{1,4} v\right] \\
&\quad + y_2 \left[\kappa_{2,0} + \kappa_{2,1} u_1 + \kappa_{2,2} u_2 + \kappa_{2,3} u^\star + \kappa_{2,4} v\right] \\
&\quad + y_u u^\star,
\end{aligned}
$$

so the coefficients are:

$$
\begin{aligned}
\kappa_{\star,0} &= y_0 + \sum_i^2 y_i \kappa_{i,0} \\
\kappa_{\star,1} &= \sum_i^2 y_i \kappa_{i,1} \\
\kappa_{\star,2} &= \sum_i^2 y_i \kappa_{i,2} \\
\kappa_{\star,3} &= y_u + \sum_i^2 y_i \kappa_{i,3} \\
\kappa_{\star,4} &= \sum_i^2 y_i \kappa_{i,4},
\end{aligned}
$$

for the coefficients in :

$$
p^\star = \kappa_{\star,0} + \kappa_{\star,1} u_1 + \kappa_{\star,2} u_2 + \kappa_{\star,3} u^\star + \kappa_{\star,4} v. \tag{B.23}
$$

B.4 The Conditional Moments

The relevant conditioning variables are (see Ch. 5 of Vives (2008)):

$$
\begin{aligned}
\hat{z}_1 &\equiv p_1 - \kappa_{1,0} = \kappa_{1,1} u_1 + \kappa_{1,2} u_2 + \kappa_{1,3} u^\star + \kappa_{1,4} v \\
\hat{z}_2 &\equiv p_2 - \kappa_{2,0} = \kappa_{2,1} u_1 + \kappa_{2,2} u_2 + \kappa_{2,3} u^\star + \kappa_{2,4} v \\
\hat{k} &\equiv p^\star - \kappa_{\star,0} = \kappa_{\star,1} u_1 + \kappa_{\star,2} u_2 + \kappa_{\star,3} u^\star + \kappa_{\star,4} v.
\end{aligned} \tag{B.24}
$$

The conditional expectation is then:

$$
\begin{aligned}
E\left(v \mid p_1\right) &= E\left(v \mid \hat{z}_1\right) \\
&= \frac{Cov\left(v, \kappa_{1,1}u_1 + \kappa_{1,2}u_2 + \kappa_{1,3}u^{\star} + \kappa_{1,4}v\right)}{Var\left(\hat{z}_1\right)}\left(\hat{z}_1 - E\left(\hat{z}_1\right)\right) \\
&= \frac{\sigma_v^2 \kappa_{1,4}}{\kappa_{1,4}^2 \sigma_v^2 + \sum_i \kappa_{1,i}^2 \sigma_u^2}\left(p_1 - \kappa_{1,0}\right),
\end{aligned} \tag{B.25}
$$

conditional expectation in terms variances:

$$
\begin{aligned}
Var\left(v \mid p_1\right) &= E\left[E\left(v \mid p_1\right) - v\right]^2 \\
&= Var\left(v\right) - cov\left(v, p_1\right) var\left(p_1\right)^{-1} cov\left(v, p_1\right) \\
&= \sigma_v^2 - \frac{\sigma_v^2 \kappa_{1,4} \sigma_v^2 \kappa_{1,4}}{\kappa_{1,4}^2 \sigma_v^2 + \sum_i \kappa_{1,i}^2 \sigma_u^2} \\
&= \frac{\sigma_v^2\left(\kappa_{1,4}^2 \sigma_v^2 + \sum_i \kappa_{1,i}^2 \sigma_u^2\right) - \sigma_v^2 \sigma_v^2 \kappa_{1,4}^2}{\kappa_{1,4}^2 \sigma_v^2 + \sum_i \kappa_{1,i}^2 \sigma_u^2} \\
&= \frac{\sigma_u^2 \sigma_v^2 \sum_i \kappa_{1,i}^2}{\kappa_{1,4}^2 \sigma_v^2 + \sum_i \kappa_{1,i}^2 \sigma_u^2}.
\end{aligned} \tag{B.26}
$$

For Dealer 2 we get:

$$
\begin{aligned}
E\left(v \mid p_2\right) &= \frac{\sigma_v^2 \kappa_{2,4}}{\kappa_{2,4}^2 \sigma_v^2 + \sum_i \kappa_{2,i}^2 \sigma_u^2}\left(p_2 - \kappa_{2,0}\right) \\
Var\left(v \mid p_2\right) &= \frac{\sigma_u^2 \sigma_v^2 \sum_i \kappa_{2,i}^2}{\kappa_{2,4}^2 \sigma_v^2 + \sum_i \kappa_{2,i}^2 \sigma_u^2}.
\end{aligned}
$$

Similarly, for IDBs, we get:

$$
\begin{aligned}
E\left(v \mid p^{\star}\right) &= E\left(v \mid \hat{k}\right) \\
&= \frac{Cov\left(v, \hat{k}\right)}{Var\left(\hat{k}\right)}\left(\hat{k} - E\left(\hat{k}\right)\right) \\
&= \frac{\sigma_v^2 \kappa_{\star,4}}{\kappa_{\star,4}^2 \sigma_v^2 + \sum_i \kappa_{\star,i}^2 \sigma_u^2}\left(p^{\star} - \kappa_{\star,0}\right) \\
Var\left(v \mid p^{\star}\right) &= \frac{\sigma_u^2 \sigma_v^2 \sum_i \kappa_{\star,i}^2}{\kappa_{\star,4}^2 \sigma_v^2 + \sum_i \kappa_{\star,i}^2 \sigma_u^2}.
\end{aligned}
$$

Moreover, MM1 and MM2 can see both the local prices as well as the IDB prices, so they can condition on both:

$$
\begin{aligned}
E(v \mid p^{\star}, p_1) &= \begin{bmatrix} cov(v, p^{\star}) & cov(v, p_1) \end{bmatrix} \begin{bmatrix} var(p^{\star}) & cov(p^{\star}, p_1) \\ cov(p^{\star}, p_1) & var(p_1) \end{bmatrix}^{-1} \begin{bmatrix} p^{\star} - E(p^{\star}) \\ p_1 - E(p_1) \end{bmatrix} \\
&= \begin{bmatrix} \sigma_v^2 \kappa_{\star,4}, & \sigma_v^2 \kappa_{1,4} \end{bmatrix} \frac{1}{M} \Lambda_1 \begin{bmatrix} p^{\star} - \kappa_{\star,0} \\ p_1 - \kappa_{1,0} \end{bmatrix} \\
&= \delta_{1,0} + \delta_{1,1} p^{\star} + \delta_{1,2} p_1,
\end{aligned}
$$

where

$$
\Lambda_1 \equiv \begin{bmatrix} \kappa_{1,4}^2 \sigma_v^2 + \sum_i \kappa_{1,i}^2 \sigma_u^2 & -\sigma_v^2 \kappa_{\star,4} \kappa_{1,4} - \sigma_u^2 \kappa_{\star,1} \kappa_{1,1} \\ -\sigma_v^2 \kappa_{\star,4} \kappa_{1,4} - \sigma_u^2 \kappa_{\star,1} \kappa_{1,1} & \kappa_{\star,4}^2 \sigma_v^2 + \sum_i \kappa_{\star,i}^2 \sigma_u^2 \end{bmatrix},
$$

and the determinant:

$$
M = \left[\kappa_{\star,4}^2 \sigma_v^2 + \sum_i \kappa_{\star,i}^2 \sigma_u^2 \right] \left[\kappa_{\star,4}^2 \sigma_v^2 + \sum_i \kappa_{\star,i}^2 \sigma_u^2 \right] - \left[\sigma_v^2 \kappa_{\star,4} \kappa_{1,4} \right]^2 .
$$

The conditional variance is obtained as:

$$
\begin{aligned}
Var(v \mid p^{\star}, p_1) &= Var(v) - \Omega_1 \begin{bmatrix} var(p^{\star}) & cov(p^{\star}, p_1) \\ cov(p^{\star}, p_1) & var(p_1) \end{bmatrix}^{-1} \Omega_1' \\
&= \sigma_v^2 - \begin{bmatrix} \sigma_v^2 \kappa_{\star,4}, & \sigma_v^2 \kappa_{1,4} \end{bmatrix} \frac{1}{M} \Lambda_1 \begin{bmatrix} \sigma_v^2 \kappa_{\star,4}, & \sigma_v^2 \kappa_{1,4} \end{bmatrix}' .
\end{aligned}
$$

with

$$
\Omega_1 \equiv \begin{bmatrix} cov(v, p^{\star}) & cov(v, p_1) \end{bmatrix}.
$$

Similarly,

$$
\begin{aligned}
E(v \mid p^{\star}, p_2) &= \begin{bmatrix} cov(v, p^{\star}) & cov(v, p_2) \end{bmatrix} \begin{bmatrix} var(p^{\star}) & cov(p^{\star}, p_2) \\ cov(p^{\star}, p_2) & var(p_2) \end{bmatrix}^{-1} \begin{bmatrix} p^{\star} - E(p^{\star}) \\ p_2 - E(p_2) \end{bmatrix} \\
&= \begin{bmatrix} \sigma_v^2 \kappa_{\star,4}, & \sigma_v^2 \kappa_{2,4} \end{bmatrix} \frac{1}{M} \Lambda_2 \begin{bmatrix} p^{\star} - \kappa_{\star,0} \\ p_2 - \kappa_{2,0} \end{bmatrix} \\
&= \delta_{2,0} + \delta_{2,1} p^{\star} + \delta_{2,2} p_2,
\end{aligned}
$$

where

$$\Lambda_2 \equiv \begin{bmatrix} \kappa_{2,4}^2\sigma_v^2 + \sum_i \kappa_{2,i}^2\sigma_u^2 & -\sigma_v^2\kappa_{\star,4}\kappa_{2,4} - \sigma_u^2\kappa_{\star,2}\kappa_{2,2} \\ -\sigma_v^2\kappa_{\star,4}\kappa_{2,4} - \sigma_u^2\kappa_{\star,2}\kappa_{2,2} & \kappa_{\star,4}^2\sigma_v^2 + \sum_i \kappa_{\star,i}^2\sigma_u^2 \end{bmatrix},$$

and

$$\begin{aligned} Var\left(v \mid p^\star, p_2\right) &= Var\left(v\right) - \Omega_2 \begin{bmatrix} var\left(p^\star\right) & cov\left(p^\star, p_2\right) \\ cov\left(p^\star, p_2\right) & var\left(p_2\right) \end{bmatrix}^{-1} \Omega_2' \\ &= \begin{bmatrix} \sigma_v^2\kappa_{\star,4}, & \sigma_v^2\kappa_{2,4} \end{bmatrix} \frac{1}{M}\Lambda_2 \begin{bmatrix} \sigma_v^2\kappa_{\star,4}, & \sigma_v^2\kappa_{2,4} \end{bmatrix}'. \end{aligned}$$

with

$$\Omega_2 \equiv \begin{bmatrix} cov\left(v, p^\star\right) & cov\left(v, p_2\right) \end{bmatrix}.$$

B.5 Optimality Conditions

B.5.1 Market 1

The Problem of the Uninformed Given the uninformed residual supply curve:

$$p_1 = \frac{d_{1,1} + \left(\omega_{1,2} + \omega_{M,1}\right) p^\star + \alpha_2 v + u_1}{\gamma_{1,2} + \gamma_{M,1}}.$$

The profit maximisation problem is:

$$\begin{aligned} \max_{d_{1,1}} U\left(\left(v - p_1\right) d_{1,1} \mid p_1\right) &= \max_{d_{1,1}} \left[\mathbb{E}\left[\left(v - p_1\right) d_{1,1} \mid p_1\right] - \frac{\rho}{2} Var\left(\left(v - p_1\right) d_{1,1} \mid p_1\right)\right] \\ &= \max_{d_{1,1}} \left[\left(E\left(v \mid p_1\right) - \frac{d_{1,1} + \omega_{M,1} p^\star + \alpha_2 v + u_1}{\gamma_{1,2} + \gamma_{M,1}}\right) d_1 - \frac{\rho}{2}\left(d_{1,1}\right)^2 Var\left(v \mid p_1\right)\right], \end{aligned}$$

which gives the optimal informed trader 1 demand:

$$d_{1,1} = \frac{E\left(v \mid p_1\right) - p_1}{\left(\gamma_{1,2} + \gamma_{M,1}\right)^{-1} + \rho Var\left(v \mid p_1\right)}. \tag{B.27}$$

The Insider's Problem Recall that the relevant residual supply curve is written as:

$$p_1 = \frac{d_{1,2} + \beta_{1,1} + \omega_{M,1} p^\star + u_1}{\gamma_{1,1} + \gamma_{M,1}}.$$

The profit maximisation problem is then written as:

$$\max_{d_{1,2}} U\left(\left(v-p_1\right)d_2 \mid p_1,v\right) = \max_{d_{1,2}}\left[\mathbb{E}\left[\left(v-p_1\right)d_2 \mid p_1,v\right]-\frac{\rho}{2}Var\left(\left(v-p_1\right)d_2 \mid p_1,v\right)\right]$$
$$= \max_{d_{1,2}}\left[\left(E\left(v \mid p_1,v\right)-\frac{d_{1,2}+\beta_{1,1}+\omega_{M,1}p^{\star}+u_1}{\gamma_{1,1}+\gamma_{M,1}}\right)d_2-\frac{\rho}{2}\left(d_2\right)^2 Var\left(v \mid p_1,v\right)\right].$$

Similarly, insider's demand (who actually observes the asset value, therefore there is no uncertainty and corresponding variance terms) is

$$d_{1,2}=\frac{v-p_1}{\left(\gamma_{1,1}+\gamma_{M,1}\right)^{-1}}. \tag{B.28}$$

The Dealer's Problem Given the dealer's residual supply curve:

$$p_1=\frac{x_{1,1}+\beta_{1,1}+\alpha_2 v+u_1}{\gamma_{1,1}+\gamma_{1,2}},$$

the dealer's problem in stage 1 is:

$$\max_{x_{1,1}}\left[\mathbb{E}\left[\left(\left(v-p^{\star}\right)x_{1,1}\right) \mid p^{\star},p_1\right]-\frac{\rho}{2}Var\left(\left(\left(v-p^{\star}\right)x_{1,1}\right) \mid p^{\star},p_1\right)\right]$$

which gives the optimal demand:

$$x_{1,1}=\frac{E\left(v \mid p_1,p^{\star}\right)-p_1}{\left(\gamma_{1,1}+\gamma_{1,2}\right)^{-1}+\rho Var\left(v \mid p_1,p^{\star}\right)}. \tag{B.29}$$

The problem for market 2 follows the same logic, therefore we leave the derivation to the reader.

B.6 Determining the Coefficients

This subsection presents derived demand functions in compact form along the conjectured demand functions. These form a system of equations that is solved numerically for the parameters of the conjectured demand functions.

B.6.1 Market 1

For dealer 1, we have the following demand functions that are obtained after the appropriate substitutions:

$$
\begin{aligned}
x_{1,1} &= \frac{\mathbb{E}\left[v \mid p^{\star}, p_1\right] - p_1}{\left(\gamma_{1,1}+\gamma_{1,2}\right)^{-1} + \rho Var\left(v \mid p^{\star}, p_1\right)} \\
&= \frac{\delta_{1,0} + \delta_{1,1} p^{\star} + \left[\delta_{1,2} - 1\right] p_1}{\frac{1}{\gamma_{1,1}+\gamma_{1,2}} + \rho Var\left(v \mid p^{\star}, p_1\right)} \\
&= -\gamma_{M,1} p_1 + \omega_{M,1} p^{\star} \\
x_{1,2} &= \frac{\mathbb{E}\left[v \mid p^{\star}, p_1\right] - p^{\star}}{\frac{1}{\sum_2 c_i} + \rho Var\left(v \mid p^{\star}, p_1\right)} \\
&= \frac{\delta_{1,0} + \delta_{1,1} p^{\star} + \delta_{1,2} p_1 - p^{\star}}{\frac{1}{\sum_2 c_i} + \rho Var\left(v \mid p^{\star}, p_1\right)} \\
x_{1,2} &= \frac{\delta_{1,2} p_1 + \left[\delta_{1,1} - 1\right] p^{\star} + \delta_{1,0}}{\frac{1}{\sum_2 c_i} + \rho Var\left(v \mid p^{\star}, p_1\right)} \\
x_{1,2} &= b_1 - c_1 p^{\star} + a_1 p_1.
\end{aligned}
$$

The demand functions of clients can be obtained by similar substitution:

$$
\begin{aligned}
d_{1,1} &= \frac{E\left(v \mid p_1\right) - p_1}{\left(\gamma_{1,2}+\gamma_{M,1}\right)^{-1} + \rho Var\left(v \mid p_1\right)} \\
&= \frac{\frac{\sigma_v^2 \kappa_{1,4}}{\kappa_{1,4}^2 \sigma_v^2 + \sum_i \kappa_{1,i}^2 \sigma_u^2}\left(p_1 - \kappa_{1,0}\right) - p_1}{\left(\gamma_{1,2}+\gamma_{M,1}\right)^{-1} + \rho \frac{\sigma_u^2 \sigma_v^2 \sum_i \kappa_{1,i}^2}{\kappa_{1,4}^2 \sigma_v^2 + \sum_i \kappa_{1,i}^2 \sigma_u^2}} \\
&= \frac{\left[\frac{\sigma_v^2 \kappa_{1,4}}{\kappa_{1,4}^2 \sigma_v^2 + \sum_i \kappa_{1,i}^2 \sigma_u^2} - 1\right] p_1 - \frac{\sigma_v^2 \kappa_{1,4}}{\kappa_{1,4}^2 \sigma_v^2 + \sum_i \kappa_{1,i}^2 \sigma_u^2} \kappa_{1,0}}{\left(\gamma_{1,2}+\gamma_{M,1}\right)^{-1} + \rho \frac{\sigma_u^2 \sigma_v^2 \sum_i \kappa_{1,i}^2}{\kappa_{1,4}^2 \sigma_v^2 + \sum_i \kappa_{1,i}^2 \sigma_u^2}} \\
d_{1,1} &= -\gamma_{1,1} p_1 + \beta_{1,1} \\
d_{1,2} &= \frac{v - p_1}{\left(\gamma_{1,1}+\gamma_{M,1}\right)^{-1}} \\
d_{1,2} &= -\gamma_{1,2} p_1 + \alpha_2 v.
\end{aligned}
$$

B.6.2 Market 2

Similar to B.6.1, the demand function of dealer 2 in both stage 1 and 2 can be written as:

$$
\begin{aligned}
x_{2,1} &= \frac{\mathbb{E}\left[v \mid p^{\star}, p_2\right] - p_2}{\left(\gamma_{2,1} + \gamma_{2,2}\right)^{-1} + \rho Var\left(v \mid p^{\star}, p_2\right)} \\
&= \frac{\delta_{2,0} + \delta_{2,1} p^{\star} + \delta_{2,2} p_2 - p_2}{\frac{1}{\gamma_{2,1}+\gamma_{2,2}} + \rho Var\left(v \mid p^{\star}, p_2\right)} \\
&= -\gamma_{M,2} p_2 + \omega_{M,2} p^{\star} \\
x_{2,2} &= \frac{\mathbb{E}\left[v \mid p^{\star}, p_2\right] - p^{\star}}{\frac{1}{c_1+\sum_3 c_i} + \rho Var\left(v \mid p^{\star}, p_2\right)} \\
&= \frac{\delta_{2,0} + \delta_{2,1} p^{\star} + \delta_{2,2} p_2 - p^{\star}}{\frac{1}{c_1+\sum_3 c_i} + \rho Var\left(v \mid p^{\star}, p_2\right)} \\
x_{2,2} &= \frac{\delta_{2,2} p_2 + \left[\delta_{2,1} - 1\right] p^{\star} + \delta_{2,0}}{\frac{1}{c_1+\sum_3 c_i} + \rho Var\left(v \mid p^{\star}, p_2\right)} \\
x_{2,2} &= b_2 - c_2 p^{\star} + a_2 p_2.
\end{aligned}
$$

The demand functions of clients who trade with dealer 2 can be written as:

$$
\begin{aligned}
d_{2,1} &= \frac{E\left(v \mid p_2\right) - p_2}{\left(\gamma_{2,2} + \gamma_{M,2}\right)^{-1} + \rho Var\left(v \mid p_2\right)} \\
&= \frac{\frac{\sigma_v^2 \kappa_{2,4}}{\kappa_{2,4}^2 \sigma_v^2 + \sum_i \kappa_{2,i}^2 \sigma_u^2}\left(p_2 - \kappa_{2,0}\right) - p_2}{\left(\gamma_{2,2} + \gamma_{M,2}\right)^{-1} + \rho \frac{\sigma_u^2 \sigma_v^2 \sum_i \kappa_{2,i}^2}{\kappa_{2,4}^2 \sigma_v^2 + \sum_i \kappa_{2,i}^2 \sigma_u^2}} \\
&= \frac{\left[\frac{\sigma_v^2 \kappa_{2,4}}{\kappa_{2,4}^2 \sigma_v^2 + \sum_i \kappa_{2,i}^2 \sigma_u^2} - 1\right] p_2 - \kappa_{2,0} \frac{\sigma_v^2 \kappa_{2,4}}{\kappa_{2,4}^2 \sigma_v^2 + \sum_i \kappa_{2,i}^2 \sigma_u^2}}{\left(\gamma_{2,2} + \gamma_{M,2}\right)^{-1} + \rho \frac{\sigma_u^2 \sigma_v^2 \sum_i \kappa_{2,i}^2}{\kappa_{2,4}^2 \sigma_v^2 + \sum_i \kappa_{2,i}^2 \sigma_u^2}} \\
d_{2,1} &= -\gamma_{2,1} p_2 + \beta_{2,1} \\
d_{2,2} &= -\gamma_{2,2} p_2 + \beta_{2,2}.
\end{aligned}
$$

B.6.3 Market i={3,M}

Market $i = \{3, \ldots, M\}$ only features dealers who observe the IDB price:

$$
\begin{aligned}
x_{j,2} &= \frac{E\left(v \mid p^{\star}\right) - p^{\star}}{\frac{1}{\sum_{i \neq j} c_i} + \rho Var\left(v \mid p^{\star}\right)} \\
&= \frac{\frac{\sigma_v^2 \kappa_{\star,4}}{\kappa_{\star,4}^2 \sigma_v^2 + \sum_i \kappa_{\star,i}^2 \sigma_u^2}\left(p^{\star} - \kappa_{\star,0}\right) - p^{\star}}{\frac{1}{\sum_{i \neq j} c_i} + \rho \frac{\sigma_u^2 \sigma_v^2 \sum_i \kappa_{\star,i}^2}{\kappa_{\star,4}^2 \sigma_v^2 + \sum_i \kappa_{\star,i}^2 \sigma_u^2}} \\
&= \frac{\left[\frac{\sigma_v^2 \kappa_{\star,4}}{\kappa_{\star,4}^2 \sigma_v^2 + \sum_i \kappa_{\star,i}^2 \sigma_u^2} - 1\right] p^{\star} - \kappa_{\star,0} \frac{\sigma_v^2 \kappa_{\star,4}}{\kappa_{\star,4}^2 \sigma_v^2 + \sum_i \kappa_{\star,i}^2 \sigma_u^2}}{\frac{1}{\sum_{i \neq j} c_i} + \rho Var\left(v \mid p^{\star}\right)} \\
&= b_3 - c_3 p^{\star}.
\end{aligned}
$$

B.7 Computing Expected Profits of the Informed

The informed client's expected profit can be written as:

$$\mathbb{E}\left[\left(v - p_1\right) d_{1,2}\right].$$

Also, recall that the equilibrium price is:

$$p_1 = \kappa_{1,0} + \kappa_{1,1} u_1 + \kappa_{1,2} u_2 + \kappa_{1,3} u^{\star} + \kappa_{1,4} v.$$

The informed expected profits are written as follows:

$$
\begin{aligned}
E\left[\Pi\right] &= E\left[\left(v - p_1\right) d_{1,2}\right] \\
&= E\left[\left(v - p_1\right)\left(\frac{v - p_1}{\left(\gamma_{1,1} + \gamma_{M,1}\right)^{-1}}\right)\right] = E\left[\frac{v^2 + p_1^2 - 2 v p_1}{\left(\gamma_{1,1} + \gamma_{M,1}\right)^{-1}}\right] \\
&= \left[\frac{\sigma_v^2\left(1 + \kappa_{1,4}^2 - 2\kappa_{1,4}\right) + \sigma_u^2\left(\kappa_{1,1}^2 + \kappa_{1,2}^2 + \kappa_{1,3}^2\right)}{\left(\gamma_{1,1} + \gamma_{M,1}\right)^{-1}}\right] \\
&= \left[\frac{\sigma_v^2\left(1 - \kappa_{1,4}\right)^2 + \sigma_u^2\left(\kappa_{1,1}^2 + \kappa_{1,2}^2 + \kappa_{1,3}^2\right)}{\left(\gamma_{1,1} + \gamma_{M,1}\right)^{-1}}\right].
\end{aligned}
\tag{B.30}
$$

The numerical analysis above explores how $E\left[\Pi\right]$ in B.30 changes across different equilibria.