Size Discount and Size Penalty

Trading Costs in Bond Markets*

Gábor Pintér — Bank of England
Chaojun Wang — Wharton
Junyuan Zou — INSEAD

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Abstract

We show that larger trades incur lower trading costs in government bond markets ("size discount"), but costs increase in trade size after controlling for clients' identities ("size penalty"). The size discount is driven by the cross-client variation of larger traders obtaining better prices, consistent with theories of trading with imperfect competition. The size penalty, driven by the within-client variation, is larger for corporate bonds and during major macroeconomic surprises as well as during COVID-19. These differences are larger among more sophisticated clients, consistent with theories of asymmetric information. We propose a trading model with bilateral bargaining and adverse selection to rationalise the co-existence of the size penalty and discount.

JEL Classification*:* G12, G14, G24

Keywords: Trading Costs, Government and Corporate Bonds, Trader Identities, Size Discount, Size Penalty

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Pinter: gabor.pinter@bankofengland.co.uk; Wang: The Wharton School, University of Pennsylvania, wangchj@wharton.upenn.edu; Zou: Finance Area, INSEAD, junyuan.zou@insead.edu.

1 Introduction

It is well documented that larger trades incur lower trading costs ("size discount") in various over-the-counter (OTC) financial markets. The size discount is consistent with theories of bilateral trading with imperfect competition, which predict that larger trades get more favourable prices because dealers' bargaining power decreases in trade size.[1] However, theories of information asymmetry and inventory imbalances predict "size penalty", in that larger trades would be executed at less favourable prices because of dealers' fear of adverse selection[2] or higher inventory costs.[3]

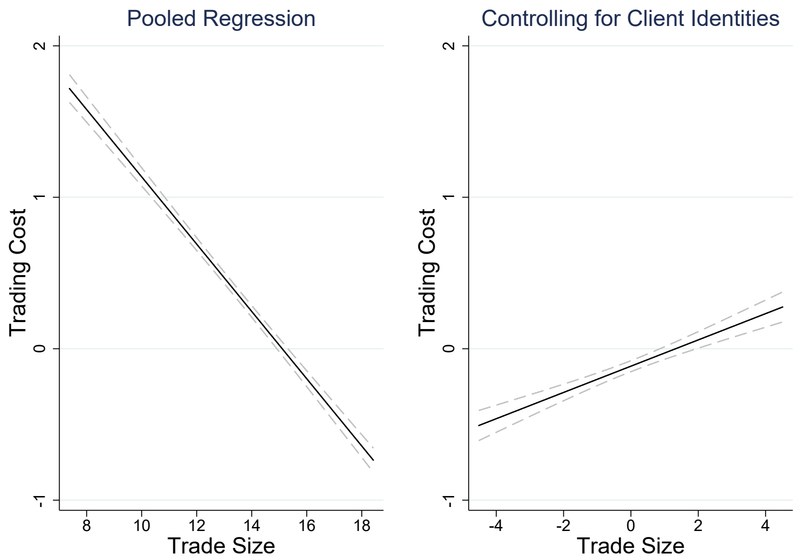
We reconcile this tension by decomposing the size-cost relationship into cross-client and within-client variations, finding size discount in the cross section and size penalty in the time series. We further analyse the drivers of the size penalty by applying differences-in-differences methods. The evidence points to an independent role of information-based theories (controlling for inventory- and liquidity-based explanations) in driving the size penalty. By studying the size-cost relationship, this paper illustrates the effects of different market frictions on trading costs. As a theoretical contribution, we present a bilateral trading model with bargaining and information asymmetry to rationalise the co-existence of the size discount and size penalty.

Our paper exploits a unique non-anonymous trade-level data to study the determinants of trading costs in UK government bond market over the period 2011-2017. The dataset covers close to the universe of secondary market transactions, and importantly, it contains the *identities of both counterparties* for each transaction. Therefore, unlike other datasets (e.g. TRACE) typically used in the literature, our dataset allows one to distinguish between client-specific characteristics (such as traders' size and type) and transaction-specific characteristics (such as trade size) in determining trading costs. Moreover, identifying clients who simultaneously trade in government bonds as well as in corporate bonds allows us to compare the size-cost relation not just across clients, but *across markets* as well.

[1] See Green, Hollifield, and Schurhoff (2007b) and the related literature.
[2] Glosten and Milgrom (1985); Kyle (1985); Easley and O'Hara (1987) among others.
[3] See Ho and Stoll (1981) and the related literature.

Our empirical analysis yields six main results. First, we show that larger trades get lower trading costs in government bond markets than smaller trades, consistent with the previous literature on the "size discount" studied in corporate bond and municipal bond markets. Second, our non-anonymous dataset allows us to decompose the size-cost relation into within-client and cross-client variation. We find that trading costs increase in trade size once we control for clients' identities, generating a "size penalty".

Figure 1: The Relation between Trade Size and Trading Costs: The Role of Traders' Identities



Notes: The Figure shows a linear regression line on the pooled, transaction-level data (left panel) and on the data after we removed client-specific averages from trading costs and trade sizes corresponding to each trade. Trading costs are measured by 4.1 (building on O'Hara and Zhou (2021)), and trade size is measured as the natural logarithm of the trade's notional. The estimated regression lines are based on around 1.24million observations. The confidence bands are based on 95% standard errors as in Gallup (2019).

These two findings are illustrated in Figure 1, which shows the relationship between trade size and trading costs in government bonds from two different model specifications. The left panel of Figure 1 plots the fitted linear regression line from a pooled regression of trading costs on trade size. The trade-level regression shows that larger trades incur lower trading costs, consistent with the findings of size discount in other OTC markets.[4] Our novel contribution is to isolate the within-client variation in the size-cost relation: the

[4]For evidence on the size discount in the US corporate bond market, see Schultz (2001), Bessembinder, Maxwell, and Venkataraman (2006), Edwards, Harris, and Piwowar (2007), Goldstein, Hotchkiss, and Sirri (2007), Hendershott and Madhavan (2015) and O'Hara, Wang, and Zhou (2018) among others. Similar evidence from the US municipal bond market is presented by Harris and Piwowar (2006) and Green, Hollifield, and Schurhoff (2007b,a) among others.

right panel of Figure 1 shows the regression line after removing the client-specific average from trading costs and trade size, showing evidence on size penalty. This suggests that the size discount is driven by the cross-client variation of larger traders facing lower trading costs and trading larger amounts, whereas the size penalty is driven by the within-client variation of the *same trader* facing higher trading costs on larger trades. This will be shown rigorously by regression analysis further below.

Third, we exploit cross-sectional variation in client types and find that the size penalty is larger for more sophisticated clients (hedge funds and asset managers), and it is smaller for less sophisticated clients (pension funds, foreign central banks, insurance companies etc.). Fourth, we additionally exploit time-series variation in the magnitude of macroeconomic surprises and find that the size penalty, faced by more sophisticated clients, is larger during informationally intensive periods such as trading days that coincide with the arrival of large macroeconomic shocks. In contrast, the size penalty faced by less sophisticated clients is similar across trading days irrespective of the magnitude of macroeconomic shocks at the time. Fifth, we also exploit cross-market variation by identifying clients who simultaneously trade in government bonds as well as in corporate bonds. We find that the size penalty is larger in corporate bonds than in government bonds, and, importantly, this difference is more pronounced amongst more sophisticated clients.

Taken together, we interpret these results as evidence that information-based explanations contribute to the heterogeneity in size penalty. To the extent that more sophisticated clients are more likely to trade on information than less sophisticated clients, the differential degree of size penalty across client types, implied by the differences-in-differences approach, is consistent with theories of asymmetric information (Glosten and Milgrom, 1985). The triple differences approach, that uses time-variation in the magnitude of macroeconomic surprises, corroborates this interpretation.

The triple differences approach using cross-market variation shows that other, inventory- and liquidity-based factors are also likely to play a role, in so far as the size penalty is larger in corporate bonds than in government bonds irrespective of client types. While corporate bonds are informationally more sensitive assets than government bonds (Brancati and Macchiavelli, 2019; Arnold and Rhodes, 2020), liquidity and inter-dealer intermediation is also considerably smaller in the UK corporate bond market than in the government bond market. This makes it more costly for corporate bond dealers to execute trades with large size (Chen, Lesmond, and Wei, 2007), which could explain the larger size penalty in corporate bonds. However, assuming that the liquidity effect of a large corporate bond trade should be the same irrespective of the sophistication of the client initiating the trade, the larger increase in size penalty among more sophisticated clients is consistent with the presence of informational channels over and above what is explained by liquidity-based mechanisms.

Our sixth result is that a more sophisticated client performs better on larger trades than on smaller trades, with performance measured as the trade's ability to predict future price movements. In contrast, we find that within-client variation in trade size is uncorrelated with trading performance for the group of less sophisticated clients. This is an important cross-check as it strengthens the information-based interpretation of the results implied by the triple differences approach.

In our analysis, we use various combinations of fixed effects in order to control for other forces that may drive the size-cost relation. For example, the size penalty can also be driven by an inventory imbalance channel: a large-sized trade is more likely to cause skewed dealer inventory imbalance. Therefore, the dealer would be forced to cover its resulting inventory cost by charging a higher trading cost (Ho and Stoll, 1981), generating a size penalty. While this force is likely to be present in the data, there are at least two reasons why we interpret our results as being driven by additional, information-based factors over and above this inventory channel. First, our trade-level regressions include dealer-day fixed effects that control for the linear effects of any daily shock to dealers' inventory which could drive the size-cost relation. Second, inventory-based mechanisms alone are less likely to explain the heterogeneity in the size penalty across more sophisticated and less sophisticated clients. However, it could still be that if dealers' inventory cost functions are sufficiently convex and if more sophisticated clients systematically trade larger amounts than less sophisticated clients, then the heterogeneity in the size penalty across client types could be explained by inventory channels. However, this possibility is rejected in our sample, as we find that, if anything, more sophisticated clients seem to trade in smaller sizes.

Moreover, the size penalty could be affected by the strength of the trading relationship between clients and dealers (Di Maggio, Franzoni, Kermani, and Sommavilla, 2019; Barbon, Maggio, Franzoni, and Landier, 2019; Hendershott, Li, Livdan, and Schurhoff, 2020). However, larger trades are typically executed by counter-parties with stronger trading relationship, and trading costs also tend to be lower at dealers with whom a given client has a more enduring relationship. While mechanisms related to relationship trading may explain some of the cross-client pattern of size discount, they are less likely to explain the size penalty and its heterogeneity across client types. Nevertheless, we include in our regressions client-dealer fixed effects to control for the linear effect of trading relationships.

We also revisit the size-cost relation during the COVID-19 period, as presented in Section 5. This provides an ideal setting for performing a cross-check on a different sample, as this analysis exploits a more recent dataset (2018-2020), compared to the one (2011-2017) used to obtain our baseline results. We continue to find significant size penalty in this more recent dataset, and additionally show evidence on an increased size penalty during the financial market turmoil in March 2020, which is particularly strong for the group of more sophisticated clients. We show that this result also holds after controlling for the selling pressure of more sophisticated clients such as asset managers – a well established feature of the COVID-19 crisis.[5]

Our empirical results highlight that controlling for traders' identity is crucial for understanding trading costs in non-anonymous OTC markets. In centralised exchanges, where client identity is not revealed before the trade, client identity is not relevant for the estimation of trading costs. However, in OTC markets, client identity is observable

[5]See 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 (2021) among others.

to dealers and naturally enters dealers' pricing function. Without information on clients' identity and by simply looking at the relationship between trade size and trading costs in a pooled regression, one could easily under-estimate the incremental cost when a trader increases trade size.

In the final, theoretical section of the paper, we present a bilateral trading model with bargaining and information asymmetry to rationalise the co-existence of the size discount and penalty. The model builds on the standard CARA-normal setting with strategic traders as in Kyle (1985) and risk aversion Subrahmanyam (1991) with the addition of a liquidity component. Importantly, we show how one can introduce into this framework of asymmetric information a simple bargaining game (building on Rubinstein (1982) and Hoel (1987)) which can generate both the size discount and the size penalty. This model could be a building block for analysing strategic bilateral trading under asymmetric information in decentralised markets.

Related Literature We contribute to both the theoretical and empirical literature on OTC markets.

Our paper builds on two mains strands of the empirical literature. First, we draw on previous studies on the determinants of trading costs in corporate (Schultz, 2001; Bessembinder, Maxwell, and Venkataraman, 2006; Edwards, Harris, and Piwowar, 2007; Goldstein, Hotchkiss, and Sirri, 2007; Feldhutter, 2012; Hendershott and Madhavan, 2015; O'Hara and Zhou, 2021) and municipal bond markets (Harris and Piwowar, 2006; Green, Hollifield, and Schurhoff, 2007b,a; Li and Schürhoff, 2019). We contribute to this literature by isolating the role of clients' identities in driving the relationship between trading costs and trade size, and to combine this client-level heterogeneity with other variations in our unique dataset to develop our empirical tests. Second, we contribute to the empirical literature on informed trading in government and corporate bond markets (Brandt and Kavajecz, 2004; Green, 2004; Kondor and Pinter, 2019; Hendershott, Kozhan, and Raman, 2020; Czech, Huang, Lou, and Wang, 2021). Compared to these studies, we focus on how analysing the size-cost relation in bond markets can reveal the presence of informed trading.

Our empirical results are able to inform the theoretical literature on OTC markets. Specifically, our evidence on the size penalty is consistent with previous models featuring asymmetric information (Kyle, 1985; Easley and O'Hara, 1987; Seppi, 1990). Our evidence on the size discount is consistent with clients facing price discrimination from dealers, possibly because of the heterogeneity in their bargaining power or search intensity (Duffie, Gârleanu, and Pedersen, 2005; Lagos and Rocheteau, 2009; Pinter and Uslu, 2021).

Accordingly, our theoretical contribution is to combine insights from these two literatures and to present a simple model that includes both bilateral bargaining and information asymmetry. Combining these two features is, in general, a hard theoretical problem. In most papers, prices are either monopolistically or competitively offered by an uninformed party to an informed party.[6] This simple price-setting mechanism avoids signalling and screening, at the expense of not being able to achieve surplus splitting between the two parties.[7] We circumvent the technical difficulty of bargaining under asymmetric information, by showing that a trader with both liquidity and informational trading motives would perfectly reveal her joint trading motive through her order size in a linear-pricing equilibrium without bargaining delay. Our model jointly predicts within-client size penalty and across-client size discount. Each of the two channels can be conveniently shut down, in which case the model reduces to a standard model with remaining feature explaining either size penalty or size discount.

The remainder of the paper is organised as follows. Section 2 develops the testable hypotheses; Section 3 describes the data sources and provides summary statistics; Section 4 presents the empirical results; Section 5 presents an analysis of the COVID-19 period; Section 6 presents the theoretical model; Section 7 concludes.

[6] Early examples on monopolistic and competitive pricing include Gould and Verrecchia (1985); Glosten (1989) and Kyle (1985); Glosten and Milgrom (1985), respectively.

[7] In Lester, Shourideh, Venkateswaran, and Zetlin-Jones (2018), the price can either be competitive or monopolistic with an exogenous probability. While not focusing on surplus splitting, Du and Zhu (2017) studies a bilateral double-auction model with information asymmetry in which the price is set by a double auction between two traders.

2 Hypothesis Development

In this section, we build on the existing theoretical literature to formulate our testable hypotheses.

Hypothesis 1 (Size Discount)**.** *Trading costs are smaller for larger trades, and this is driven by the cross-client variation of larger clients facing lower costs than smaller clients.*

The size discount is a well documented empirical pattern in various OTC markets.[8] The early literature conjectures that the size discount can be due to dealers' fixed costs of executing a trade or due to large clients' stronger bargaining power. Our cross-client variation in Hypothesis 1 isolates bargaining power from fixed costs as a driver of the size discount. More formally, Green, Hollifield, and Schurhoff (2007a) estimates a bargaining model using trade size as a proxy for bargaining power. Using more granular data with partial trader identities, recent papers show that larger traders have more dealer connections and stronger relationship with their dealers.[9]

Other forces such as asymmetric information[10] and inventory imbalances (Ho and Stoll, 1981) could generate the time-series phenomenon of size penalty in OTC markets. One would therefore expect that controlling for clients' identities (thereby controlling for the cross-client variation in average bargaining power) would likely make both information- and inventory-based mechanisms dominate. This could then give rise to observed patterns of size penalty, assuming that time-variation in bargaining power is sufficiently weak.[11]

[8] Schultz (2001); Edwards, Harris, and Piwowar (2007); Bessembinder, Maxwell, and Venkataraman (2006) find evidence of size discount in the US corporate bond market, Harris and Piwowar (2006); Green, Hollifield, and Schurhoff (2007a) in the US municipal bond market, Loon and Zhong (2016) in the index CDS market.

[9] In the US corporate bond market, for example, Hendershott, Li, Livdan, and Schurhoff (2020) shows that larger insurance companies trade in larger quantities with dealers and they also trade with more dealers. Di Maggio, Kermani, and Song (2017) shows that dealers charge lower spreads to dealers with whom they have the strongest ties and more so during periods of market turmoil. O'Hara, Wang, and Zhou (2018) finds that an insurance company will receive a better price if it trades more actively with a given dealer. Bernhardt, Dvoracek, Hughson, and Werner (2005) develops a model of relationship trading to explain size discount in an OTC market.

[10] Grossman and Stiglitz (1980), Kyle (1985, 1989), and Vives (2008) provide theoretical benchmarks for mechanisms based on adverse selection. More recently, Lester, Shourideh, Venkateswaran, and Zetlin-Jones (2018) and Chen and Wang (2020) develop dynamic models of market making under adverse selection risk. Pinter, Wang, and Zou (2020) shows that size penalty is a robust prediction even when dealers have incentive to chase informed orders.

[11] It has been shown that factors that affect bargaining power, such as the structure of trading networks,

Hypothesis 2 (Size penalty)**.** *A given client faces higher trading costs on larger trades than smaller trades.*

As mentioned above, mechanisms related to both asymmetric information and inventory imbalance can generate a size penalty. To tell these two forces apart, we introduce an additional variation in our unique dataset: we distinguish between more sophisticated clients (such as hedge funds and mutual funds) and less sophisticated clients (such as insurance companies, pension funds etc.). We build on the assumption that more sophisticated clients are more likely to trade on private information, subjecting dealers to more information asymmetry, while less sophisticated clients are more likely to trade for hedging purposes.[12] On the other hand, a dealer facing clients who seek to offload a large quantity of assets would be subject to the same inventory cost, irrespective of whether the client is more or less sophisticated. Cross-sectional variation in client types would therefore generate heterogeneity in the size penalty that is less likely to be explained by dealers' inventory imbalance. This is summarised by Hypothesis 3.

Hypothesis 3 (Client Heterogeneity)**.** *The size penalty is bigger for more sophisticated clients compared to less sophisticated clients.*

To provide further analysis of the driving forces behind the time-series pattern of the size penalty, we also exploit time-series variation in the magnitude of macroeconomic surprises. Previous literature has shown that macroeconomic announcements increase price volatility and invite informed trading in government bond markets (Ederington and Lee, 1993; Green, 2004). This is consistent with the theoretical models which show that a trader can use leaked information and make trading profits during these informationally intensive periods (Brunnermeier, 2005). Since informed trading is more likely to happen and price movements are larger during informationally intensive periods, we expect the size penalty to be more pronounced during these periods. Moreover, the difference in

tend to be stable over time. Recent empirical work has shown that OTC markets have a stable core-periphery network structure, and these markets feature persistent trading relationships. Li and Schürhoff (2019) provides evidence on municipal bonds, Di Maggio, Kermani, and Song (2017) on corporate bonds, Afonso, Kovner, and Schoar (2014) provide evidence on federal funds.

[12] See Kondor and Pinter (2019), Czech and Pinter (2020) and Czech, Huang, Lou, and Wang (2021) for recent evidence.

size penalty (across trading days with small and large macro surprises) is expected to be larger for more sophisticated clients, who are likely to possess private information relevant to the event.

Hypothesis 4. *The size penalty is larger during informationally intensive days (such as large macroeconomic surprises), and this difference is more pronounced in the case of more sophisticated clients.*

We also exploit cross-market variation (comparing corporate and government bond trades of the same client) to analyze the driving forces behind the time-series pattern of the size penalty. The corporate bond market and the government bond market differ in at least two important dimensions. First, corporate bonds have idiosyncratic cashflow risk on top of the interest rate risk associated with government bonds (Longstaff, Mithal, and Neis, 2005). This, ceteris paribus, would provide larger room for informed trading in the corporate bond market. Second, corporate bonds are less liquid than government bonds (Chen, Lesmond, and Wei, 2007). According to the search literature, inventory concerns are likely to be more prominent when market liquidity is lower (Garleanu and Pedersen, 2007). As argued above, both the information- and inventory-based explanations could generate a more severe size penalty in the corporate bond market. Therefore, in order to isolate the informational channel, we combine the cross-market variation with heterogeneity in client types (similar to Hypothesis 4). Since informational effects are likely to be more pronounced in the case of more sophisticated clients, we expect any differential effect of the size penalty (across the two markets) to be larger for more sophisticated clients compared to less sophisticated clients.

Hypothesis 5. *The size penalty is larger in corporate bonds than in government bonds, and this difference is more pronounced in the case of more sophisticated clients.*

To further test for the informational mechanism behind the size penalty, we construct a measure of informativeness at the client-day level and test whether clients perform better when trading larger amounts. We measure the informativeness of a client's trade by the future price impact of the trade (Hasbrouck, 1991; Collin-Dufresne, Junge, and Trolle, 2020). When a market maker trades with a client who possesses private information, the size of a given trade is a well-established proxy for the presence of private information.[13] This positive correlation between trade size and information content of trade holds in various market settings including the exchanges (Kyle, 1985) and OTC markets (Naik, Neuberger, and Viswanathan, 1999).

Hypothesis 6. *A given informed client performs better on larger trades than on smaller trades.*

In the rest of the paper, we test these six hypotheses and find evidence in support of each one of them.

3 Data and Summary Statistics

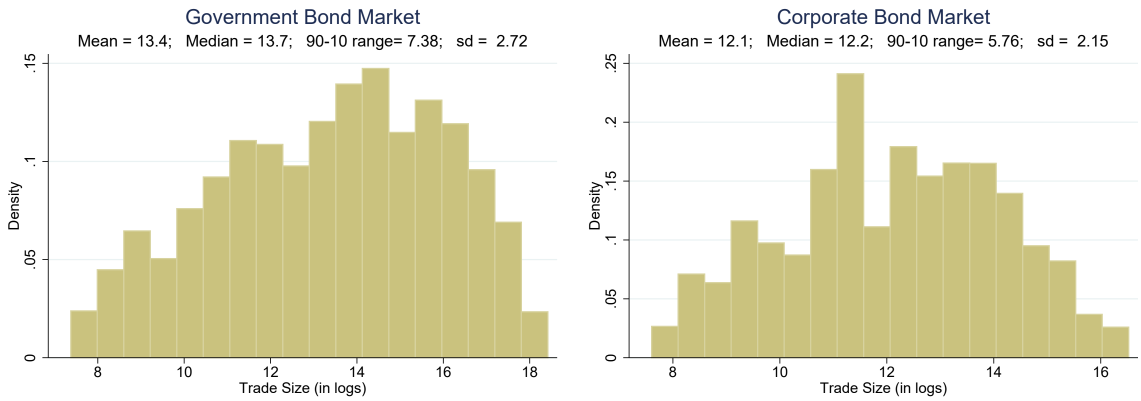
Data Source To distinguish between trade size and trader size in bond markets, one needs a detailed transaction-level dataset which contains information on the identity of both sides of a trade. The ZEN database sourced by the UK Financial Conduct Authority, contains this information along with information on the transaction time, the transaction price and quantity, the International Securities Identification Number, the account number, and buyer-seller flags, as explained in more detail in Kondor and Pinter (2019). Our sample covers the period between August 2011 and Dec 2017. Our analysis focuses on transactions that occur between clients and designated market makers, called Gilt-Edged Market Makers (GEMMs). GEMMs are the primary dealers in the UK government bond market, and the majority of client-dealer trades are intermediated by them.[14] After filtering out all duplicates, erroneous entries, we are left with approximately 1.25 million observations for government bond market trades and about 1.2 million observations for corporate bond market trades.

[13] The mechanism design literature points out that when the client has private information, any incentive compatible trading mechanism must prescribe a weakly increasing relationship between the value of the asset and the quantity bought by the trader (Myerson and Satterthwaite, 1983).

[14] GEMMs' intermediation activity is lower in corporate bonds, acting as counterparties for about 65% of all client trades in our sample. For further details on the identities of GEMMs, see https://www.dmo.gov.uk/responsibilities/gilt-market/market-participants/.

A key aspect of our empirical analysis is that we are able to see the identities of both counterparties for each transaction – a unique feature of the ZEN database as also used in Kondor and Pinter (2019), Czech and Pinter (2020) and Czech, Huang, Lou, and Wang (2021). Following these papers, we distinguish between more sophisticated clients (hedge funds and asset managers) and less sophisticated clients (pension funds, foreign central banks, commercial banks, international policy institutions, insurance companies, non-financial investors). This classification is motivated by the recent evidence on the enhanced ability of more sophisticated clients to predict future bond returns. We identify 609 clients that cover more than 90% of the trading volume between clients and dealers.

Figure 2: Trade Size Distributions



Notes: these figures summarize the size distributions on the UK government bond (left panel) and corporate bond (right panel) markets, based on trade-level data spanning the period Aug 2011 - Dec 2017. The summary statistics are based on the dataset after winsorising at the 1-99% level.

Figure 2 illustrates the size distribution for the UK government bond and corporate bond markets, along with selected summary statistics. Both the mean and the dispersion measures are larger in the government bond market. Table A.1 in Appendix provides further summary statistics. The mean and median trade size for government bonds in our sample is about £6.3million and £0.86million, suggesting a sizeable skew in the distribution. While trades in corporate bonds tend to be considerably smaller, we do not see a discernible difference in the size distribution across more and less sophisticated clients.

4 Empirical Analysis

4.1 Measurement

Building on O'Hara and Zhou (2021), our measure of trading cost for each trade v is:

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

where $P_v^\star$ is the transaction price, $\mathbf{1}_{B,S}$ is an indicator function equal to 1 when the transaction is a buy trade, and equal to -1 when it is a sell trade, and $\overline{P}$ is a benchmark price, which in our baseline is the average price of all transactions in bond k on trading day t. We multiply $Cost_v$ by 10,000 to compute costs in basis points of value. As shown below, our baseline results are robust to using four alternative ways to compute $\overline{P}$.[15]

Our baseline specification is the following trade-level regression:

$$Cost_v = \beta \times Size_v + \alpha_{k,t} + \lambda_{i,m} + \mu_{j,m} + \delta_{i,j} + \varepsilon_v, \tag{4.2}$$

where $Cost_v$ is the trading cost as computed in 4.1, $Size_v$ is the natural logarithm of the given trade's notional (in £s) and *controls* includes combinations of fixed effects at the levels of client i, dealer j, bond k, day t and month m. The key object of interest is the estimated value of β: if trading cost is the same for large and small trades, then we would expect β not to be significantly different from zero.

4.2 The Role of Trader Identity in the Size-Cost Relation

Table 1 shows the results for our baseline regression 4.2, using various specification of fixed effects. All regressions include bond-day fixed effects that aim to control for the linear effects of aggregate shocks that may affect bonds heterogeneously. For example,

[15] The four alternatives are as follows. First, we compute $\overline{P}$ as the average transaction price in bond k, trading day t and dealer j. Second, we compute $\overline{P}$ as the average transaction price in bond k, in a given part of the trading day t. Using the time stamp for each trade, we divide trades into three groups, depending on whether the transaction occurred (i) before 11am, (ii) during 11am-3pm, or (iii) after 3pm. Third, we also compute $\overline{P}$ as the average transaction price in bond k, trading day t, separately for buy and sell trades. Fourth, we also compute $\overline{P}$ as the average transaction price in bond k, trading day t, using only trades on the inter-dealer market.

trading costs tend to be larger in more illiquid bonds where average trade sizes are also different compared to more liquid bonds. With bond-day fixed effects, we aim to control for time-variation in such liquidity effects.

We move gradually from the least restrictive specification (column 1) to the most restrictive specification (column 5). Consistent with the Figure 1 above, the inclusion of client fixed effects (column 2) makes the biggest change to the estimation results by flipping the sign of the estimated effect: without client fixed effects, a one log unit increase in trade size is associated with a size discount of -0.217bp. In contrast, the inclusion of client fixed effects results in a size penalty of 0.1bp.

Table 1: Trading Costs and Trade Size in Government Bond Markets: The Role of Traders' Identities

	(1)	(2)	(3)	(4)	(5)
Trade Size	-0.217***	0.102***	0.121***	0.134***	0.158***
	(-4.04)	(3.05)	(4.01)	(4.25)	(5.19)
N	1274295	1274289	1274289	1269855	1269238
R^2	0.055	0.061	0.062	0.134	0.139
Day*Bond FE	Yes	Yes	Yes	Yes	Yes
Client FE	No	Yes	Yes	No	No
Dealer FE	No	No	Yes	No	No
Day*Dealer FE	No	No	No	Yes	Yes
Month*Client FE	No	No	No	Yes	Yes
Client*Dealer FE	No	No	No	No	Yes

Notes: this table regresses transaction performance measure on trade size and various fixed effects (4.2). The performance measures are in bp-points. 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).

In column 3, we include dealer fixed effects, motivated by the recent literature (Hollifield, Neklyudov, and Spatt, 2017) that emphasised the role of dealer-heterogeneity in determining transaction costs. In column 4, we include dealer-day fixed effects in order to control for time-variation in the tightness of balance sheet constraints of dealers and client-month fixed effects to control for lower frequency variation in client characteristics. In column 5, we include client-dealer fixed effects, motivated by Di Maggio, Franzoni, Kermani, and Sommavilla (2019) emphasising the role of client-dealer relationship in determining trading costs. The interpretation of this additional control is that it allows the comparison of trades that are executed by the same counterparties in different points in time. We find that the results are qualitatively robust to including these additional fixed effects, and are overall consistent with Hypothesis 2 of Section 2.

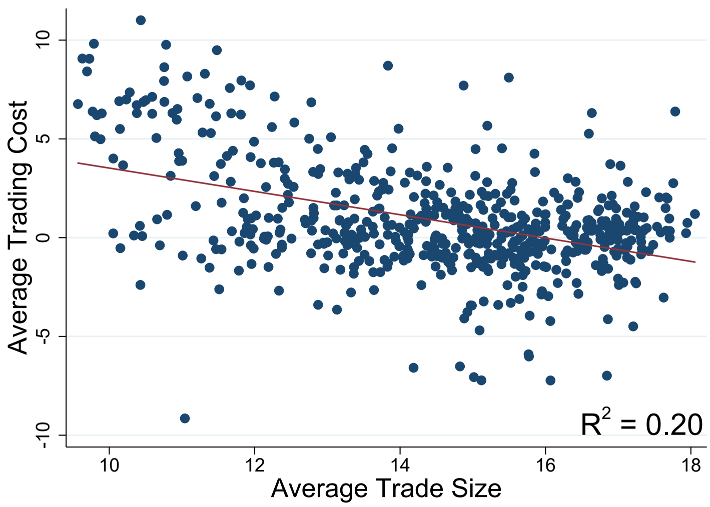
4.3 The Size Discount in the Cross-Section

We argued above that the size discount implied by pooled regressions (left panel of Figure 1) is driven by the cross-client variation of larger traders facing more favourable trading costs and trading larger amounts. To show this rigorously, we collapse our dataset at the client-level and estimate the following cross-sectional regression for client i:

$$Cost_i = \gamma \times TraderSize_i + \varepsilon_i, \tag{4.3}$$

where $Cost_i$ is the unweighted average trading cost (4.1) based on all trades of client i, and $TraderSize_i$ is measured as the natural logarithm of the average trade size of client i.

Figure 3: Trading Costs and Trader Size in the Cross-Section



Notes: this Figure shows a scatter plot of average client trading costs (vertical axis) against average trade size (horizontal axis) at the client-level. Average trading cost is the unweighted mean of our baseline cost measure 4.1 at the client-level. Average trade size is the natural logarithm of the average nominal size of a client's transactions. To reduce noise, the dataset is trimmed at 1%-level, leaving 586 observations. The estimated $\hat{\gamma} = -0.59$ with t-stat (based on robust standard error) of -9.6.

The results are summarised in Figure 3, confirming a statistically significant size discount in the cross-section. This is consistent with Hypothesis 1 of Section 2. In spite of the simplicity of the cross-sectional regression (with various other dimensions of client heterogeneity not featured), the estimated model delivers a non-negligible R^2 of 0.2. These results are robust to using an alternative measure of trader size such as clients' total monthly trading volume averaged across months. Moreover, the baseline scatter plot looks similar when we control for clients' average monthly dealer connections (Kondor and Pinter, 2019; Hendershott, Li, Livdan, and Schurhoff, 2020) as well as average monthly intensity (the log of total number of transactions) of client i (O'Hara, Wang, and Zhou, 2018). These results are shown by Figures A.1–A.2 in the Appendix.

As reviewed in the Introduction, a voluminous literature documented on the size discount as an important feature of bond trading. Figure 3 adds to this literature by isolating the source of variation in the trade-level data (i.e. the cross-client variation) that drives the documented size discount.

4.4 The Size Penalty: Exploring the Mechanisms

We now take a closer look at the within-client pattern of size-penalty documented in Section 4.2.

4.4.1 The Role of Trader Sophistication

To explore the role of heterogeneity in client types in driving the size penalty, we first divide clients into two groups based on whether the given client is of a more sophisticated type (asset manager or hedge fund) or of a less sophisticated type (pension funds, foreign central bank etc.). As argued, the underlying assumption is that former group is more likely to trade on information, than the latter group.[16] For these two groups $g = \{g_1, g_2\}$, we estimate an extended version of our baseline regression 4.2, as follows:

$$Cost_v = \sum_{w=1}^{2} \eta_w \times \mathbf{1}[i \in g_w] \times Size_v + FE + \varepsilon_v, \tag{4.4}$$

where $\mathbf{1}[i \in g_w]$ is an indicator function equal to 1 if client i belongs to group w, and 0 otherwise. We present the estimates of η_1 and η_2 adjacent to each other in the regression

[16] See Czech, Huang, Lou, and Wang (2021) for further details on the ability of more sophisticated clients to forecast bond returns.

tables and present results for tests of equality of the two coefficients.

Table 2 shows the results for the case when we estimate regression 4.2 for the more sophisticated and less sophisticated clients separately. This "diff-in-diff" (DID) approach reveals that while the cross-sectional phenomenon of size discount is present for both sets of clients (with the estimated coefficients being similar), the inclusion of client fixed effects generates a larger size penalty for the group of more sophisticated traders. The most conservative specification (column 5) shows that the size penalty is almost twice as large among more sophisticated clients (0.197) than among less sophisticated clients (0.106), consistent with Hypothesis 3 of Section 2.

Table 2: Trading Costs and Trade Size: More Sophisticated Clients vs Less Sophisticated Clients

	(1)	(2)	(3)	(4)	(5)
	Less Sophisticated Clients				
Trade Size	-0.217***	0.057	0.067	0.080*	0.106**
	(-4.14)	(1.22)	(1.46)	(1.79)	(2.29)
	More Sophisticated Clients				
Trade Size	-0.213***	0.140***	0.169***	0.183***	0.197***
	(-2.67)	(3.34)	(4.83)	(5.08)	(5.61)
p-values, eq. of coeff.	0.966	0.185	0.076	0.069	0.115
N	1271112	1271106	1271106	1264580	1263963
R^2	0.100	0.106	0.107	0.202	0.207
Day*Bond*ClientType FE	Yes	Yes	Yes	Yes	Yes
Client FE	No	Yes	Yes	No	No
Dealer*ClientType FE	No	No	Yes	No	No
Day*Dealer*ClientType FE	No	No	No	Yes	Yes
Month*Client FE	No	No	No	Yes	Yes
Client*Dealer FE	No	No	No	No	Yes

Notes: this table regresses transaction performance measure on trade size and various fixed effects. The performance measures are in bp-points. 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). The p-values correspond to the testing for the equality of coefficients.

To the extent that more sophisticated traders are more likely to trade on information, heterogeneity in the degree of size penalty across the two groups of traders is suggestive of an information-based explanation (Kyle (1985), Easley and O'Hara (1987) and others). It could still be however that more sophisticated clients face a steeper cost-size trade-off for non-informational reasons (e.g. mechanisms related to dealer inventory). Therefore, to isolate more rigorously the role of information in driving the size penalty, the next subsections extend the DID approach by adding one additional layer of "differences" related to macroeconomic surprises.

4.4.2 The Size Penalty around Macroeconomic Announcements

In this section, we estimate the role of macroeconomic announcements in affecting the degree of size-penalty. According to our Hypothesis 4, the release of large unexpected macroeconomic news leads to higher probability of informed trading (Bernile, Hu, and Tang, 2016; Du, Fung, and Loveland, 2018), so it increases the size penalty of both more and less sophisticated clients. Moreover, since more sophisticated clients have a higher likelihood to possess private information or a more accurate private interpretation of public signals, the increase in size penalty should be larger among this group of clients.

We build on the high-frequency methodology of Swanson and Williams (2014) to identify trading days when the surprise component of US and UK macroeconomic announcements were unusually high.[17] Specifically, we sort trading days into two groups $s = \{s_1, s_2\}$, based on whether the magnitude of the surprise on day t was smaller or bigger than the sample median. We estimate a modified version of our baseline regression 4.4, as follows:

$$Cost_v = \sum_{w=1}^{2} \sum_{z=1}^{2} \eta_{w,z} \times \mathbf{1}_t[t \in s_z, i \in g_w] \times Size_v + FE + \varepsilon_v, \tag{4.5}$$

where $\mathbf{1}_t[t \in s_z, i \in g_w]$ is an indicator function equal to 1 when a given trading day t belongs to group z and client i belongs to group w, and is equal to 0 otherwise; the term FE includes various combinations of fixed effects discussed above.

The results are shown in Table 3. The size penalty faced by less sophisticated clients is virtually the same irrespective of whether trading days are hit by small or large macroeconomic shocks. In contrast, the size penalty continues to be more statistically significant for sophisticated clients. Importantly, the point estimates are around 30%

[17]Our dataset is obtained from the Bank of England (building on Eguren-Martin and McLaren (2015) as used in Kondor and Pinter (2019)). 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 from the UK and the US.

Table 3: Trading Costs and Trade Size: Around Big and Small Macroeconomic News

	(1)	(2)	(3)	(4)	(5)
			Less Sophisticated Clients		
Trade Size#SmallNews	0.061	0.080	0.061	0.082*	0.104**
	(1.25)	(1.57)	(1.33)	(1.70)	(2.11)
Trade Size#LargeNews	0.067	0.069	0.066	0.075	0.107**
	(1.44)	(1.40)	(1.41)	(1.58)	(2.13)
p-values, eq. of coeff.	0.830	0.673	0.871	0.833	0.943
			More Sophisticated Clients		
Trade Size#SmallNews	0.150***	0.161***	0.141***	0.154***	0.171***
	(4.01)	(4.03)	(3.49)	(3.62)	(4.11)
Trade Size#LargeNews	0.196***	0.207***	0.202***	0.205***	0.221***
	(4.55)	(4.75)	(4.77)	(4.79)	(5.17)
p-values, eq. of coeff.	0.132	0.119	0.086	0.144	0.147
N	1182307	1178836	1179827	1176302	1175687
R^2	0.106	0.136	0.173	0.199	0.204
Day*Bond*ClientType FE	Yes	Yes	Yes	Yes	Yes
Dealer*ClientType FE	Yes	No	No	No	No
Client FE	Yes	Yes	Yes	No	No
Day*Dealer*ClientType FE	No	No	Yes	Yes	Yes
Month*Client FE	No	Yes	No	Yes	Yes
Client*Dealer FE	No	No	No	No	Yes

Notes: this table regresses trading costs (measured in bp-points) on trade size (measured as log of the nominal size of the trade in £s) interacted with indicator variables denoting whether the trading day coincides with the arrival of a large or small macroeconomic surprise compared to the median, and whether the client is more or less sophisticated. The macroeconomic surprises are constructed following the high-frequency methodology of Swanson and Williams (2014). The regression also includes various fixed effects. 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). The p-values correspond to the testing for the equality of coefficients, within a given client type.

larger on trading days with big macroeconomic surprises (0.221) compared to days with small surprises (0.171) in the most conservative specification (column 5). The statistical significance of these differences is somewhat modest, with the corresponding p-values being in the range 0.08-0.15.

The third layer of the triple differences approach, represented by the time-variation in the magnitude of macroeconomic surprises provides a stronger evidence for the presence information-based drivers of the size penalty, compared to the differences-in-differences approach of the previous subsection. Tables A.5–A.6 in Appendix show that the results are similar when we experiment with four alternative measures of trading costs as left-hand-side variables in regression 4.5.

An alternative interpretation of these results, however, is that the trading activity of clients during informationally sensitive periods may be endogenous to client type, e.g. less sophisticated clients may refrain from trading (large amounts) compared to more sophisticated clients during high-surprise days. This selection effect combined with the possibility of dealers facing more inventory risk during high-surprise days may be driving the results in Table 3. There are two ways in which we try to address this issue. First, we document how the relative presence of more and less sophisticated clients may change during low- and high-surprise days. We measure the presence of the given client group with three variables: (i) total number of daily transactions, (ii) total daily trading volume and (iii) total number of unique clients from the given group type. As shown in Table A.7 in the Appendix, we find all three measures increase during days with large macroeconomic surprises. Importantly, we find that this increase is similar across the two client groups, indicating that the selection issue may be less of a concern. Second, the next subsection will exploit cross-market variation to further analyse the source of heterogeneity in the size penalty. This alternative approach is less subject to the aforementioned selection effect, as will be discussed below, because we require clients to be present and active in both markets in a given time period.

4.4.3 The Size Penalty in Government vs Corporate Bond Markets

In this section, we estimate whether the size penalty may be different in the corporate bond market compared to the government bond market. This cross-market analysis is made possible by a unique feature of our dataset: our ZEN dataset not only covers close-to the universe of secondary market trades in UK government bonds but also in UK corporate bonds. This allows us to identify clients who simultaneously trade in both UK bond markets on the same trading day. Identifying a common set of clients is crucial for a cross-market comparison of the size penalty, because the client composition itself can be endogenously determined by the yields, riskness, liquidity and opaqueness of the market in question (Dow, 2004). We mitigate the selection issue by restricting the sample to clients who have a non-trivial presence in both types of bond markets. Specifically, we restrict that any client in this subsample must generate at least 15% of their volume in both markets. For example, this means that we omit most foreign central banks from this exercise, as they have little presence in the UK corporate bond markets and trade almost exclusively in government bonds. Some asset managers specialize in trading in either the government bond or the corporate bond market so they are also excluded from the sample.

Possible differences in size penalty across the two markets could be due to at least three reasons. First, corporate bonds provide more opportunities for informed trading than government bonds, because of additional variation in cash-flows and default risk. Second, the corporate bond market tends to be more illiquid than the government bond market, due to the higher asset-heterogeneity and lower trading frequency of corporate bonds. Because of this, the inventory cost should be higher in the corporate bond market. A third and related reason is that inter-dealer brokers play a smaller role in the corporate bond market than in the government bond market, which would ceteris paribus increase dealers' cost of managing their corporate bond inventories. All three factors could make larger trades in corporate bond markets more costly to execute compared to government bond markets. Thereby all three factors could in theory explain why the size penalty is larger in corporate bonds than in government bonds.

The identification assumption underlying our triple differences approach is that the liquidity and inventory mechanisms should generate a differential degree of size penalty in corporate bonds vis-a-vis in government bonds, *irrespective of client type*. Therefore, if we find that the size penalty is larger for corporate bonds than in government bonds and, importantly, this increase is significantly larger for sophisticated clients than less sophisticated clients, then we can plausibly argue that information-based factors likely play a role in determining the size penalty over and above what is captured by liquidity and inventory channels, consistent with Hypothesis 5 in Section 2.

To proceed, we sort all transactions into two groups $l = \{\text{GovernmentBond}, \text{CorporateBond}\}$, based on whether the given trade occurred in the government bond or corporate bond

Table 4: Trading Costs and Trade Size: Government vs Corporate Bonds Markets

	(1)	(2)	(3)	(4)
Less Sophisticated Clients				
Trade Size#GovernmentBonds	0.078	0.093**	0.122***	0.125***
	(1.42)	(2.01)	(2.69)	(2.74)
Trade Size#CorporateBonds	0.310	0.316	0.332	0.350*
	(1.59)	(1.59)	(1.64)	(1.71)
p-values, eq. of coeff.	0.149	0.192	0.232	0.208
More Sophisticated Clients				
Trade Size#GovernmentBonds	0.152***	0.177***	0.186***	0.186***
	(3.92)	(4.70)	(5.16)	(5.11)
Trade Size#CorporateBonds	0.774***	0.749***	0.800***	0.856***
	(3.89)	(3.81)	(4.07)	(4.34)
p-values, eq. of coeff.	0.001	0.002	0.001	0.000
N	1171526	1165674	1165359	1164790
R^2	0.349	0.426	0.430	0.433
Day*Bond*ClientType FE	Yes	Yes	Yes	Yes
Client*Market FE	Yes	Yes	Yes	No
Dealer*Market*ClientType FE	Yes	Yes	Yes	No
Day*Dealer*ClientType FE	No	Yes	Yes	Yes
Month*Client FE	No	Yes	Yes	Yes
Client*Dealer	No	No	Yes	No
Client*Dealer*Market FE	No	No	No	Yes

Notes: this table regresses trading costs (measured in bp-points) on trade size (measured as log of the nominal size of the trade in £s) interacted with an indicator variable taking value 2 (1) if the trade takes place in the corporate (government) bond market. The regression also includes various fixed effects. The upper (lower) panel shows the results for less (more) sophisticated clients. 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). The p-values correspond to the testing for the equality of coefficients, within a given client type.

market. We then estimate a modified version of our baseline regression 4.4, as follows:

$$Cost_v = \sum_{w=1}^{2}\sum_{z=1}^{2} \eta_{w,z} \times \mathbf{1}[j \in l_z, i \in g_w] \times Size_v + FE + \varepsilon_v, \tag{4.6}$$

where $\mathbf{1}[j \in l_z, i \in g_w]$ is an indicator function equal to 1 when a bond j belongs to group z and client i belongs to group w, and is equal to 0 otherwise; the term FE includes various combinations of fixed effects discussed above.

The results are shown in Table 4. We find that the size penalty is significantly larger in corporate bonds than in government bonds, but only for the sophisticated group of clients. While the most conservative specification (column 4) shows that the point estimate on the size penalty is about 0.225bp larger (0.35 vs. 0.125) for less sophisticated clients, it is larger by about 0.67 (0.856 vs. 0.186) for the more sophisticated client groups. For the latter group, the statistical significance of these differences is particularly strong, with the corresponding p-values being less than 0.01. As shown by Tables A.8–A.9 in the Appendix, we obtain similar results when using four alternative definitions of trading costs. Moreover, including all clients in the analysis (irrespective of their relative trading volume in the two markets) lead to similar findings as well, as shown in Table A.10 in the Appendix.

4.4.4 Trade Size and Trading Performance

One natural test for an information-based explanation of the size penalty is to check whether clients make more profitable trades when trading larger amounts. To carry out this test, we first construct a measure of performance for each trade v and horizon T, building on Di Maggio, Franzoni, Kermani, and Sommavilla (2019):

$$Performance_v^T = \left[\ln\left(\overline{P}_T\right) - \ln\left(\overline{P}_0\right)\right] \times \mathbf{1}_{B,S}, \tag{4.7}$$

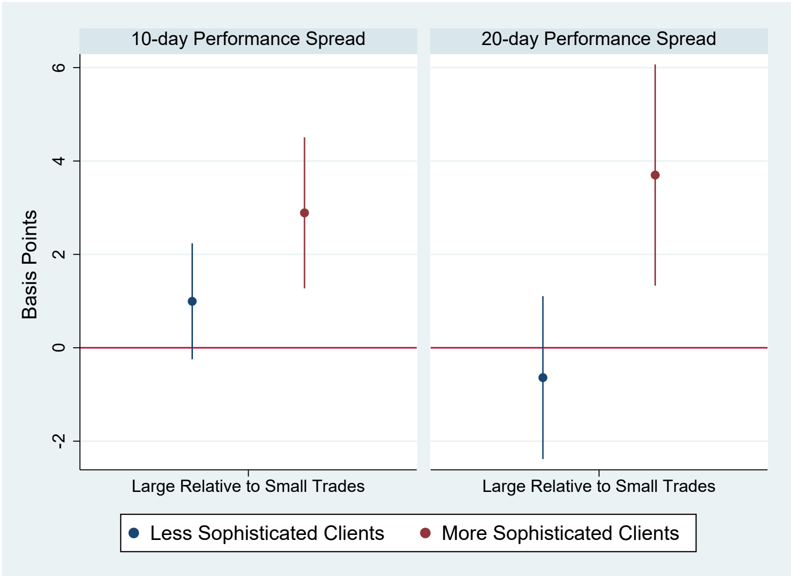
where $\overline{P}_0$ is the average price of all transactions in bond k on the day when transaction v takes place, $\overline{P}_T$ is the average transaction price T days after trade v, and $\mathbf{1}_{B,S}$ is an indicator function equal to 1 when the transaction is a buy trade, and equal to -1 when it is a sell trade.

Given that bond trading strategies tend to have multiple legs (Duarte, Longstaff, and Yu, 2007), we do not estimate trade-level regression to proxy informed trading but, instead, we collapse our dataset at the client-day level using volume weighted average of measure 4.7 for each client i, market l, and day t. We also sort trading days of each client i on each market l into three tertiles according to average trade size. For these groups $g_{i,l} = \{g_{i,l,1}, g_{i,l,2}, g_{i,l,3}\}$, we estimate the following panel regression:

$$Performance_{i,l,t}^T = \sum_{w=1}^{3} \eta_w \times \mathbf{1}_t[t \in g_{i,l,w}] + Intensity_{i,l,t} + \varepsilon_{i,l,t}, \tag{4.8}$$

where $\mathbf{1}_t[t \in g_{i,l,w}]$ is an indicator function equal to 1 on trading days t when a client i in market l belongs to group w, and is equal to 0 otherwise. It is important to emphasise

Figure 4: The Relation between Trade Size and Trading Performance



Notes: this figure plots the difference between the estimated η_3 and η_1 coefficients from regression 4.8 using performance at the 10- and 20-day horizon measured in basis points. We include as control the natural logarithm of the number of daily transactions ("Intensity"). To reduce noise, we winsorise the sample at the 1%-level and use client-day observations. The 90% confidence interval based on robust standard errors, using two-way clustering at the client and day level.

that the construction of this indicator variable primarily exploits within-client variation (in market l), i.e. we compare the performance of the same client across different trading days instead of comparing clients who systematically trade in different quantities. The term $Intensity_{i,l,t}$ in 4.8 is the log of total number of transactions of client i on day t, which aims to control for the activity of clients (O'Hara, Wang, and Zhou, 2018).

Figure 4 shows the difference between the estimated values for η_1 and η_3 for horizons $T = \{10, 20\}$ trading days, separately for more sophisticated clients (red bars) and less sophisticated clients (blue bars). The results show that, for the set of more sophisticated clients, days with large trade sizes are associated with significantly higher trading performance over the 10-20 day horizon, compared to days when *the same client* trades in the lower size tertile. In contrast, we do not observe such a size effect for less sophisticated clients.

These results can also be used to discuss alternative explanations behind the observed size penalty. For example, one may argue that the size penalty is due to differences in opinions, instead of information asymmetry.[18] According to this alternative explanation,

[18]See Aumann (1976) and the subsequent literature; Carlin, Longstaff, and Matoba (2014) presents a recent contribution.

a larger trade size may reflect a greater disagreement between the client and the dealer. For example, if the client buys a larger amount from a dealer, then this could indicate that the client is more optimistic than the dealer, leading to the client buying at a higher price. If more sophisticated clients were more likely to trade on opinions (while less sophisticated clients were more likely to trade for hedging purposes), this could explain the differential degree of size penalty across client types. However, this (non-informational) explanation would be at odds with the results presented in this section, i.e. disagreements alone may not explain why larger trades better *predict future yields changes* than smaller trades, and why this difference would be more pronounced among more sophisticated clients.

4.5 Robustness and Extensions

4.5.1 Client Type and Trade Size

A main source of variation in our empirical design is client type. A key assumption underlying the information-based interpretation of our regressions is that more sophisticated clients are different from less sophisticated clients because they are more likely to trade on information, and not because, say, they systematically trade in different quantities. To test for this, we estimate the following trade-level regression:

$$Size_v = \delta \times D_i^{Soph} + FEs + \varepsilon_v, \tag{4.9}$$

where D_i^{Soph} is a dummy variable taking value 1 is client i is an asset manager or a hedge fund and 0 otherwise.

Table A.11 in Appendix shows the results for the estimated values for δ using different combinations of fixed effects. The effects are statistically insignificant. The point estimates suggest that, if anything, more sophisticated clients seem to trade in smaller sizes. This rejects the possibility that heterogeneity in client types is simply picking up that more sophisticated clients trade in larger sizes, which could generate larger inventory costs for dealers and thereby larger size penalty.

4.5.2 Non-linearities

Moreover, we check for non-linearities and non-monotonicity in the size penalty. To that end, we re-estimate a variant of Table 2 by replacing *size* as a continuous variable with four dummy variables indicating which size quartile a given trade is located in, using the within-size variation of a client. As shown in Table A.12 in Appendix, trading costs are the largest on the trades that are in top quartile of the size distribution, using the within-client variation of trade sizes. The results continue to be more statistically and economically significant among more sophisticated clients compared to less sophisticated clients.

4.5.3 Agency Trades

As an additional test, we explore variation in *trade-type* to further investigate the possible information-based mechanism underlying the size penalty. In our baseline sample, about 20% of client-dealer trades are labelled as agency trades, with these trades structured as follows: trader B trades, on behalf of trader A, with trader C. In our sample, trader C is always a dealer; trader B (the agent) can either be a dealer or a client; and trader A is always a client that can be more or less sophisticated.[19] We now test whether a more sophisticated client A faces a differential size penalty when trading directly with dealers (non-agency trade) compared to trading with dealers via an agent (agency trade). The hypothesis is that if information-based mechanisms are at play, then the size penalty of the sophisticated client would be smaller on agency trades, because the given client could conceal her identity through agency.[20]

Table A.13 in the Appendix shows the results for the group of more sophisticated clients from a variant of regression 4.4, where we interact size with a dummy variable, indicating whether the given trade is an agency trade or not. We find that the size penalty is concentrated in non-agency trades, consistent with an information-based explanation.

[19] Our baseline sample therefore excludes the type of agency trades (typically studied in the literature) whereby (using the example above) traders A and C would be clients and trader B would be a dealer.

[20] See Smith, Turnbull, and White (2001) and the related literature.

5 COVID-19

In this last empirical section of our paper, we revisit the cost-size relation during the COVID-19 episode in the UK. The spread of the COVID-19 pandemic in early 2020 presented a major shock to the global financial system, including bond markets. Investigating the behaviour of the cost-size relation during this informationally intensive period provides an ideal opportunity to perform an out-of-sample robustness test of our baseline results. This is because more recent sample period (2018-2020) requires the use of a different dataset compared to our baseline sample (2011-2017).

In addition, a better understanding of the functioning of government bond markets after COVID-19 is interesting on its own right and it is becoming ever more important for policy design (Duffie 2020; Hauser 2020). While a growing literature has analysed the unfolding of the crisis in bond markets and the effect of subsequent central bank interventions, the majority of this literature focused on corporate bond markets in the US (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 2021 amongst others) and the UK (Czech and Pinter 2020), and there has been little transaction-level evidence on the effect of COVID-19 in government bond markets.[21]

To carry out the analysis, we employ the MiFID II bond transaction data, which covers the period from January 2018 to July 2020.[22] 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.

The following analysis serves two purposes. First, we check whether size penalty continues to hold in a different and more recent sample, and whether we continue to find a more pronounced effect for more sophisticated clients, thereby providing additional

[21] For a theoretical analysis of COVID-19 crisis in US government bond markets, see He, Nagel, and Song (2021).

[22] 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.

Table 5: Trading Costs and Trade Size: During and Outside COVID-19

	(1)	(2)	(3)	(4)
Less Sophisticated Clients				
Trade Size#OutsideCOVID-19	0.261***	0.257***	0.251***	0.214***
	(4.20)	(4.43)	(4.26)	(3.56)
Trade Size#DuringCOVID-19	0.404*	0.301	0.274	0.273
	(1.81)	(1.62)	(1.43)	(1.57)
p-values, eq. of coeff.	0.525	0.808	0.903	0.737
More Sophisticated Clients				
Trade Size#OutsideCOVID-19	0.318***	0.294***	0.311***	0.329***
	(6.92)	(6.81)	(7.80)	(8.45)
Trade Size#DuringCOVID-19	0.581**	0.611***	0.635***	0.652***
	(2.22)	(2.86)	(3.12)	(3.40)
p-values, eq. of coeff.	0.271	0.121	0.096	0.080
N	1143362	1142116	1141464	1114966
R^2	0.146	0.194	0.203	0.262
Day*Bond FE	Yes	Yes	Yes	Yes
Dealer FE	Yes	No	No	No
Month*Client FE	Yes	Yes	Yes	No
Day*Dealer FE	No	Yes	Yes	Yes
Client*Dealer FE	No	No	Yes	No
Client*Dealer*Month FE	No	No	No	Yes

Notes: this table regresses transaction performance measure on trade size and various fixed effects. The performance measures are in bp-points. 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). The p-values correspond to the testing for the equality of coefficients, within a given client type.

tests for Hypotheses 2-4 of our paper. Second, we explore how the size penalty might have changed during the unprecedented COVID-19 crisis period. To this end, we sort all the trades into two groups $c = \{c_1, c_2\}$ based on whether the trade occurred during March 2020 or outside this month. We then estimate the following regression:

$$Cost_v = \sum_{w=1}^{2} \sum_{z=1}^{2} \eta_{w,z} \times \mathbf{1}_t[t \in c_z, i \in g_w] \times Size_v + FE + \varepsilon_v, \tag{5.1}$$

where $\mathbf{1}_t[t \in c_z, i \in g_w]$ is an indicator function equal to 1 when a trading day t belongs to group z and client i belongs to group w, and is equal to 0 otherwise; the term FE includes various combinations of fixed effects discussed above.

Table 5 shows the results from estimating regression 5.1, first for the group of less sophisticated (upper panel), and then for more sophisticated clients (lower panel). We continue to find that more sophisticated clients face a larger size penalty than less sophisticated clients during normal times, with the difference being about 0.1bp (0.214 vs. 0.329) according to the most conservative specification in column (4). This difference is similar to our baseline based on the Zen data for 2011-2017. Importantly, we find that the size penalty increases considerably during the COVID crisis and this increase is more pronounced for more sophisticated clients (0.652) compared to the other client type (0.273) – consistent with Hypothesis 4 and Table 3 above.

Table 6: Trading Costs and Trade Size: During and Outside COVID-19

	(1)	(2)	(3)	(4)
More Sophisticated Clients Under More Selling Pressure				
Trade Size#OutsideCOVID-19	0.320***	0.296***	0.321***	0.339***
	(5.59)	(5.84)	(7.03)	(7.47)
Trade Size#DuringCOVID-19	0.605**	0.637***	0.647***	0.644***
	(2.23)	(2.99)	(3.15)	(3.05)
p-values, eq. of coeff.	0.226	0.098	0.098	0.138
N	483475	482910	482819	476606
R^2	0.153	0.212	0.217	0.261
More Sophisticated Clients Under Less Selling Pressure				
Trade Size#OutsideCOVID-19	0.348***	0.314***	0.313***	0.311***
	(6.66)	(5.73)	(5.89)	(5.93)
Trade Size#DuringCOVID-19	0.576	0.475	0.511*	0.664***
	(1.53)	(1.58)	(1.80)	(3.11)
p-values, eq. of coeff.	0.535	0.602	0.494	0.114
N	206443	205745	205629	200467
R^2	0.241	0.325	0.333	0.393
Day*Bond FE	Yes	Yes	Yes	Yes
Dealer FE	Yes	No	No	No
Month*Client FE	Yes	Yes	Yes	No
Day*Dealer FE	No	Yes	Yes	Yes
Client*Dealer FE	No	No	Yes	No
Client*Dealer*Month FE	No	No	No	Yes

Notes: this table regresses transaction performance measure on trade size and various fixed effects. The performance measures are in bp-points. 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). The p-values correspond to the testing for the equality of coefficients, within a given client type.

We acknowledge however that these results could be driven by the fact that our group of more sophisticated clients mainly consists of asset managers who could have been under severe selling pressure as documented by the recent literature.[23] Therefore, we try

[23] See 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 (2021) amongst others.

to control for the possible contribution of selling pressure to the increase in the size penalty of more sophisticated clients during the COVID-19 crisis by adding an additional layer of differences to our research design. Specifically, we sort our group of more sophisticated clients into two subgroups based on the cumulative signed order flow in March 2020, and we then estimate our cost-size regression separately for these two subgroups.

Table 6 shows the results. Based on the point estimates, we find that while the increase in size-penalty was large for clients under selling pressure (0.664 vs. 0.339), there is still a similarly larger increase in the size penalty for clients who were under less selling pressure (0.664 vs. 0.311).

Note also that the regressions include client-dealer-month fixed effects that aim to control for relationship effects during turbulent times (Di Maggio, Franzoni, Kermani, and Sommavilla, 2019). In addition the regressions include dealer-day fixed effects in order to control for time-variation in the tightness of balance sheet constraints of dealers – an important feature of this period (Duffie, 2020).

6 A Model of Bilateral Trading

In this section, we develop a simple bilateral trading model, featuring both information asymmetry and heterogeneous bargaining power, that jointly predicts within-client size penalty and across-client size discount. Each of the two channels can be conveniently shut down, in which case the model reduces to a standard model with the remaining feature explaining either size penalty or size discount.

A client seeks to trade a risky asset with a dealer. The value of the asset, v, has an unconditional distribution $N\left(0, \frac{1}{\tau_v}\right)$. The client observes a noisy signal, $s = v + \varepsilon$, before the trade. The noise ε is normally distributed, $N\left(0, \frac{1}{\tau_\varepsilon}\right)$. The client has an initial asset position of x, following a normal distribution $N\left(0, \frac{1}{\tau_x}\right)$. The dealer does not observe the client's signal, s, or her initial position, x. The random variables v, ε and x are jointly independent. The client has a CARA utility function with risk aversion γ. The initial risky asset position x gives the client a liquidity motive to trade, while the signal

s gives her an informational motive. The client's preference and information follow the standard CARA-normal setting with strategic traders as in Kyle (1985) and risk aversion as in Subrahmanyam (1991), with the addition of a liquidity component, x, added to her trading motive. The dealer is risk neutral.

A trade is conducted as follows. First, the client requests to buy q unit of the asset from the dealer ($q < 0$ means that the client requests to sell). Then, to negotiate a price, the client and the dealer engage in an infinite-horizon bargaining game with discount rate δ and a random sequence of who makes the offers. In the bargaining game, the dealer moves first to offer a price in response to the client's request. The bargaining game concludes if the client accepts the price offer, and otherwise continues to the next stage. In each subsequent stage, the client is selected to offer a price with probability η to the dealer, and the other way round with probability $1 - \eta$ as in Hoel (1987), which is adapted from the alternating offer game of Rubinstein (1982).

We consider a Perfect Bayesian Equilibrium (PBE) in which the agreed-upon price p is linear in size, $p(q) = a + \lambda q$, and the first price offer is immediately accepted. Such an equilibrium is said to be a *linear-pricing PBE without bargaining delay.* The following theorem summarises the equilibrium of the model.

Theorem 1. *When* $\left(2\,\frac{\eta}{1+\delta} - 1\right)\gamma^2\tau_v^2 - \tau_\varepsilon\tau_x\left(\tau_v + \tau_\varepsilon\right) > 0$, *there exists a unique linear-pricing PBE without bargaining delay. On the equilibrium path, the client submits an order* $q^*_\eta(s, x)$, *the dealer offers* $p^*_\eta(q) = \lambda^*_\eta q$, *and the client immediately accepts the price offer, where*

$$\lambda^*_\eta = \frac{\gamma}{2}\frac{\left(1 + \frac{\gamma^2\tau_v^2}{\tau_\varepsilon\tau_x(\tau_v+\tau_\varepsilon)}\right) + \frac{\eta}{1+\delta}\left(1 - \frac{\gamma^2\tau_v^2}{\tau_\varepsilon\tau_x(\tau_v+\tau_\varepsilon)}\right)}{\left(2\,\frac{\eta}{1+\delta} - 1\right)\frac{\gamma^2\tau_v^2}{\tau_\varepsilon\tau_x} - \left(\tau_v + \tau_\varepsilon\right)}$$

$$q^*_\eta(s, x) = \frac{\gamma}{2\lambda^*\left(\tau_v + \tau_\varepsilon\right) + \gamma}\left(\frac{\tau_\varepsilon}{\gamma}s - x\right).$$

We establish Theorem 1 by solving for a linear-pricing PBE without bargaining delay, with the key steps detailed in the following proof.

Proof. Given each signal s and initial position x, the client's expected gain from trading

q units of the asset is:

$$\frac{\tau_\varepsilon}{\tau_\varepsilon+\tau_v}s(q+x)-pq-\frac{\gamma}{2}\frac{1}{\tau_\varepsilon+\tau_v}(q+x)^2-\left[\frac{\tau_\varepsilon}{\tau_\varepsilon+\tau_v}sx-\frac{\gamma}{2}\frac{1}{\tau_\varepsilon+\tau_v}x^2\right]\equiv(p_0(q,s,x)-p)q,$$

where $p_0(q,s,x)$ is the client's reservation price:

$$p_0(q,s,x)=\gamma\frac{1}{\tau_\varepsilon+\tau_v}\left(\frac{\tau_\varepsilon}{\gamma}s-x\right)-\frac{\gamma}{2}\frac{1}{\tau_\varepsilon+\tau_v}q. \tag{6.1}$$

Anticipating an equilibrium price $p(q)$ without bargaining delay, the client chooses size q to maximize her expected trading gain. Her first order condition is $p_0(q,s,x)-p(q)+\left(\frac{\partial p_0(q,s,x)}{\partial q}-\frac{\partial p(q)}{\partial q}\right)q=0$ which, together with a linear equilibrium price function $p(q)=a+\lambda q$, can be used to obtained the client's optimal demand q:

$$q=\frac{\gamma}{2\lambda\left(\tau_\varepsilon+\tau_v\right)+\gamma}\left(\frac{\tau_\varepsilon}{\gamma}s-x\right)-\frac{\tau_\varepsilon+\tau_v}{2\lambda\left(\tau_\varepsilon+\tau_v\right)+\gamma}a. \tag{6.2}$$

With this optimal choice q, the client's expected gain $(p_0(q,s,x)-p)q$ from trading can be written as:

$$(p_0(q,s,x)-p)q=\left(\frac{2\lambda\left(\tau_\varepsilon+\tau_v\right)+\gamma}{\tau_\varepsilon+\tau_v}-\frac{\gamma}{2}\frac{1}{\tau_\varepsilon+\tau_v}+\lambda\right)q^2, \tag{6.3}$$

which shows that the client's expected gain from trading depends on her signal s and initial endowment x only through her requested size q. This equilibrium property renders the ensuing bargaining game one with complete information. Therefore, the solution of Hoel (1987) applies, whereby the dealer offers price $p\left(q\right)$ which is immediately accepted by the client:

$$p\left(q\right)=\frac{\eta}{1+\delta}p_1(q)+\left(1-\frac{\eta}{1+\delta}\right)p_0(q), \tag{6.4}$$

where $p_1\left(q\right)$ is given by:

$$p_1(q)=\mathbb{E}[v|q]=\frac{2\lambda\left(\tau_v+\tau_\varepsilon\right)+\gamma}{\tau_v+\tau_\varepsilon+\frac{\gamma^2\tau_v^2}{\tau_\varepsilon\tau_x}}q+\frac{\tau_v+\tau_\varepsilon}{\tau_v+\tau_\varepsilon+\frac{\gamma^2\tau_v^2}{\tau_\varepsilon\tau_x}}a. \tag{6.5}$$

In 6.5, $p_1(q)$ can be viewed as the competitive price, which gives the dealer zero expected profit.[24] In equilibrium, the dealer's price offer is anticipated by the client. Therefore, substituting 6.1 and 6.5 into 6.4, and matching coefficients yields $a = 0$, while rearranging gives the solution for λ:

$$\lambda = \frac{\gamma}{2} \frac{\left(1 + \frac{\gamma^2 \tau_v^2}{\tau_\varepsilon \tau_x (\tau_v + \tau_\varepsilon)}\right) + \frac{\eta}{1+\delta}\left(1 - \frac{\gamma^2 \tau_v^2}{\tau_\varepsilon \tau_x (\tau_v + \tau_\varepsilon)}\right)}{\left(2\frac{\eta}{1+\delta} - 1\right)\frac{\gamma^2 \tau_v^2}{\tau_\varepsilon \tau_x} - (\tau_v + \tau_\varepsilon)}. \tag{6.6}$$

To verify that the size choice q in 6.2 given by the client's FOC indeed maximizes the client's expected gain, we check the client's second order condition $2\lambda(\tau_v + \tau_\varepsilon) + \gamma > 0$, which is equivalent to $[2\eta/(1+\delta) - 1]\gamma^2\tau_v^2 - \tau_\varepsilon\tau_x(\tau_v + \tau_\varepsilon) > 0$. ■

The key property allowing for a tractable bargaining solution is that the client's expected gain from trading 6.3 (and thereby the client's reservation price p_0) does not directly depend on s and x but only through the requested size q. Even though the client's liquidity motive x and informational motive s are not uniquely determined by her requested size q, the aggregate motive is. This nice equilibrium property renders the ensuing bargaining game one with complete information, so that the solution of Hoel (1987) applies.

The model simultaneously explains within-client size penalty and across-client size discount:

Proposition 2. *(Within-client size penalty) In the linear-pricing PBE without delay, the trading cost $|p(q)| = \lambda|q|$ of a given client with bargaining power η is linearly increasing with her requested size $|q|$.*

Next, we compare two clients with heterogeneous bargaining powers $\eta < \eta'$ to generate size discount.

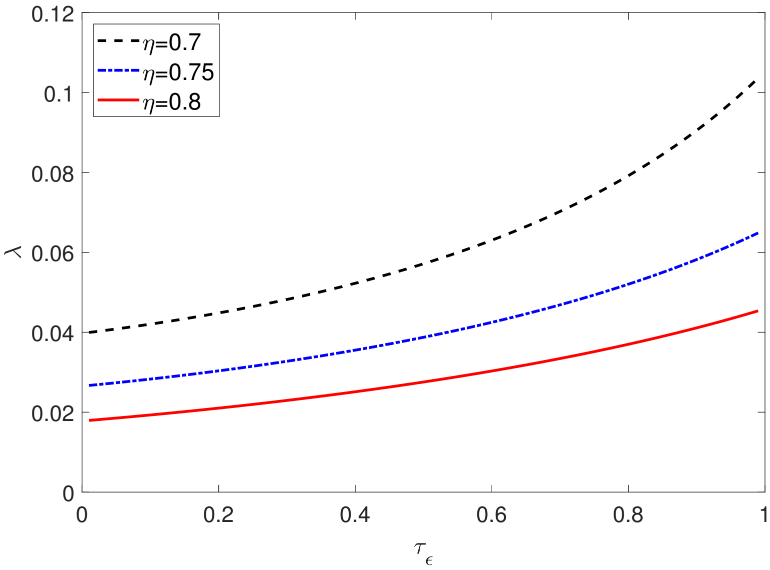
Proposition 3. *(Across-client size discount) In the linear-pricing PBE without delay, a client with higher bargaining power η has a larger average trade size $\mathbb{E}|q|$, while facing a lower average trading cost $\mathbb{E}|p|$.*

[24] To derive the conditional expectation $\mathbb{E}[v|q]$, we use the projection theorem. For that, note that the covariance between the asset value and trade size is $Cov[v,q] = (\tau_\varepsilon/\tau_v)/[2\lambda(\tau_\varepsilon + \tau_v) + \gamma]$, and the variance of the trade size is $Var[q] = [\gamma/(2\lambda(\tau_\varepsilon + \tau_v) + \gamma)]^2\left[(\tau_\varepsilon/\gamma)^2/\tau_\varepsilon + (\tau_\varepsilon/\gamma)^2/\tau_v + 1/\tau_x\right]$.

The above result follows immediately from the fact the average trade size $\mathbb{E}|q|$ is decreasing in $\lambda(\eta)$, while the average trading cost $\mathbb{E}|p|$ is increasing in $\lambda(\eta)$. On the other hand, $\lambda(\eta)$ is decreasing in bargaining power η.

To highlight the novel features of the model, we perform simple comparative statics to explore the relationship between bargaining power and the size penalty as shown in Figure 5.

Figure 5: Bargaining Power, Signal Precision and Size Penalty



Notes: this figure plots the value of λ (computed by 6.6) for different values of $\tau_\epsilon = [0.01 : 0.01 : 0.99]$ and of $\eta = \{0.7, 0.75, 0.8\}$. The rest of the parameters are $\gamma = 0.2$, $\tau_v = 2$, $\tau_x = 0.1$, $\delta = 0.01$ so that the second order condition, $[2\eta/(1+\delta) - 1]\gamma^2\tau_v^2 - \tau_\varepsilon\tau_x(\tau_v + \tau_\varepsilon) > 0$, is always satisfied.

The Figure plots the values of λ (vertical axis), as computed by 6.6, for different values of τ_ε (horizontal axis). We trace out the relationship for three different values $\eta = \{0.7, 0.75, 0.8\}$, as shown by the dashed, dotted and solid lines, respectively. All three lines are monotonically increasing: the larger the precision of the signal (τ_ε) the larger the size penalty becomes. The intuition is similar to Kyle (1985): the more precise the informed client's signal, the more informative her trade becomes, which makes the dealer revise the price more aggressively when considering trading a given quantity during the bargaining process. Moreover, one possible way to connect our client-type variation in the data with the model is to regard more sophisticated clients as having higher values of τ_ε, so that this simple theoretical framework could rationalise why more sophisticated clients face a higher size penalty in the data than less sophisticated clients.

Furthermore, the τ_ε-λ relation largely depends on the client's bargaining power, η, as shown by the different lines in Figure 5: lowering η is associated with an upward shift in the curve, which means that the size penalty becomes stronger as the client's bargaining power becomes weaker. In addition, we also find evidence for increased convexity in the τ_ε-λ relation as the client's bargaining power decreases, which means that the size penalty becomes increasingly sensitive to the precision of private information. This highlights some of the rich interactions between informational and trading frictions that this simple model can generate, and which goes beyond the regression design of our empirical model. Our companion paper (Pinter, Wang, and Zou, 2021) presents a structural estimation of a version of this model (in the spirit of Odders-White and Ready (2008)) in order to explore the model's predictions further.

7 Conclusion

To conclude, our paper revisited the relation between trade size and trading costs – one of the main questions in the literature on financial markets. In our empirical design, we were able to observe clients' identities as well as their simultaneous trading activities in government and corporate bond markets. These unique features of our empirical design allowed us to reconcile some of the tension in the vast literature on the size-cost relation. Our results reveal that controlling for traders' identity is crucial for understanding the drivers of trading costs in non-anonymous over-the-counter markets. In addition, combining this client-level variation with variations in client-type, macroeconomic news and bond markets highlights the different forces that drive the size-cost relation.

There are at least two interesting avenues for future research. First, analysing these competing forces in a more structural framework is necessary to provide a sharper characterisation of the drivers of the size-cost relation and to quantify the relative importance of the different channels. The theoretical model presented in this paper could be regarded as a first step into that direction. In ongoing work (Pinter, Wang, and Zou, 2021) we are attempting to modify this model so that structural estimation on our trade-level data would be possible. Second, one could consider the aggregate implications of our empirical analysis. For example, one could estimate how time-series variation in either the size discount or the size penalty is related to variation in aggregate bid-ask spreads and yields in government and corporate bond markets. This could tighten the link between our analysis and the literature on the term structure of interest rates.

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Online Appendix

A Additional Tables

Table A.1: Summary Statistics on Trade Size

	(1) N	(2) Mean	(3) p10	(4) p50	(5) p90	(6) sd
			Trade Size (£s)			
Government Bonds						
All Clients	1274548	7825263	12856	850000	2.07e+07	4.56e+07
Less Sophisticated Clients	601157	8569644	15000	1000000	2.50e+07	4.58e+07
More Sophisticated Clients	673391	7160731	11000	600000	1.86e+07	4.55e+07
Corporate Bonds						
All Clients	1227954	1228126	9000	200000	2850000	6111960
Less Sophisticated Clients	561528	1283479	9000	100000	2600000	7350338
More Sophisticated Clients	666426	1181485	9000	263000	3000000	4827430

Notes: This table reports summary statistics for our baseline sample, covering the period from August 2011 to December 2017. Trade size is measured as the nominal size of the transaction in £s. The summary statistics is split based on client types (more sophisticated = asset managers + hedge funds; and less sophisticated = pension funds, insurance companies, foreign central banks, commercial banks, other non-financials) as well as markets (government bond vs corporate bonds).

Table A.2: Trading Costs and Trade Size in Government Bond Markets: Alternative Cost Measures

	(1)	(2)	(3)	(4)	(5)
Alternative Cost Measure I: Using Day-Bond-Dealer Average for $\overline{P}$					
Trade Size	-0.103***	0.061**	0.068***	0.077***	0.085***
	(-3.70)	(2.35)	(2.71)	(2.99)	(3.20)
N	973952	973948	973948	969689	968913
R^2	0.061	0.065	0.065	0.126	0.132
Alternative Cost Measure II: Using Day-Bond-Within Day Average for $\overline{P}$					
Trade Size	-0.180***	0.097***	0.115***	0.131***	0.149***
	(-3.80)	(3.75)	(5.14)	(6.04)	(7.33)
N	1261480	1261474	1261474	1256983	1256358
R^2	0.052	0.063	0.064	0.133	0.139
Alternative Cost Measure III: Using Day-Bond-Sell/Buy Average for $\overline{P}$					
Trade Size	-0.220***	0.100***	0.119***	0.132***	0.156***
	(-4.09)	(3.00)	(3.96)	(4.21)	(5.16)
N	1271266	1271260	1271260	1266824	1266209
R^2	0.003	0.010	0.011	0.087	0.093
Alternative Cost Measure IV: Using Average IDB prices for $\overline{P}$					
Trade Size	-0.184***	0.151***	0.173***	0.185***	0.212***
	(-3.41)	(4.47)	(5.58)	(5.91)	(6.91)
N	1232310	1232304	1232304	1227792	1227163
R^2	0.060	0.066	0.066	0.138	0.143
Day*Bond FE	Yes	Yes	Yes	Yes	Yes
Client FE	No	Yes	Yes	No	No
Dealer FE	No	No	Yes	No	No
Day*Dealer FE	No	No	No	Yes	Yes
Month*Client FE	No	No	No	Yes	Yes
Client*Dealer FE	No	No	No	No	Yes

Notes: this table regresses transaction performance measure on trade size and various fixed effects. The four different performance measures are in bp-points. The first measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t and dealer j. The second measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, in a given part of the trading day t. Using the time stamp for each trade, we divide trades into three groups, depending on whether the transaction occurred (i) before 11am, (ii) during 11am-3pm, or (iii) after 3pm. The third measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t, separately for buy and sell trades. The fourth measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t, using only trades on the inter-dealer market. 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: Trading Costs and Trade Size in Government Bond Markets Using Weighted Regressions: Alternative Cost Measures

	(1)	(2)	(3)	(4)	(5)
Baseline Cost Measure					
Trade Size	-0.321***	0.085**	0.119***	0.117***	0.146***
	(-9.27)	(2.26)	(3.30)	(3.90)	(4.76)
N	1274295	1274289	1274289	1269855	1269238
R^2	0.321	0.319	0.319	0.458	0.468
Alternative Cost Measure I: Using Day-Bond-Dealer Average for $\overline{P}$					
Trade Size	-0.127***	0.091***	0.102***	0.076***	0.090***
	(-5.47)	(2.97)	(3.34)	(2.70)	(3.10)
N	973952	973948	973948	969689	968913
R^2	0.313	0.303	0.303	0.443	0.456
Alternative Cost Measure II: Using Day-Bond-Within Day Average for $\overline{P}$					
Trade Size	-0.253***	0.065**	0.097***	0.110***	0.136***
	(-8.64)	(2.25)	(3.49)	(4.37)	(5.15)
N	1261480	1261474	1261474	1256983	1256358
R^2	0.319	0.321	0.322	0.459	0.469
Alternative Cost Measure III: Using Day-Bond-Sell/Buy Average for $\overline{P}$					
Trade Size	-0.324***	0.084**	0.118***	0.115***	0.144***
	(-9.35)	(2.23)	(3.27)	(3.83)	(4.72)
N	1271266	1271260	1271260	1266824	1266209
R^2	0.278	0.276	0.276	0.424	0.435
Alternative Cost Measure IV: Using Average IDB prices for $\overline{P}$					
Trade Size	-0.309***	0.122***	0.156***	0.153***	0.188***
	(-8.60)	(3.04)	(4.02)	(4.68)	(5.63)
N	1232310	1232304	1232304	1227792	1227163
R^2	0.317	0.319	0.320	0.457	0.467
Day*Bond FE	Yes	Yes	Yes	Yes	Yes
Client FE	No	Yes	Yes	No	No
Dealer FE	No	No	Yes	No	No
Day*Dealer FE	No	No	No	Yes	Yes
Month*Client FE	No	No	No	Yes	Yes
Client*Dealer FE	No	No	No	No	Yes

Notes: this table regresses transaction performance measure on trade size and various fixed effects. Each observation is weighted by the inverse of the total number of transactions of the given client. The four different performance measures are in bp-points. The first measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t and dealer j. The second measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, in a given part of the trading day t. Using the time stamp for each trade, we divide trades into three groups, depending on whether the transaction occurred (i) before 11am, (ii) during 11am-3pm, or (iii) after 3pm. The third measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t, separately for buy and sell trades. The fourth measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t, using only trades on the inter-dealer market. 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.4: Trading Costs and Trade Size in Government Bond Markets: More Sophisticated Clients vs Less Sophisticated Clients, Using Alternative Cost Measures

	(1)	(2)	(3)	(4)	(5)
Alternative Cost Measure I: Using Day-Bond-Dealer Average for $\overline{P}$					
Trade Size#LessSophisticated	-0.132***	0.009	0.016	0.026	0.037
	(-3.98)	(0.21)	(0.37)	(0.63)	(0.86)
Trade Size#MoreSophisticated	-0.073*	0.108***	0.118***	0.125***	0.130***
	(-1.89)	(4.25)	(4.76)	(4.59)	(4.68)
p-values, eq. of coeff.	0.243	0.048	0.037	0.043	0.070
N	965894	965890	965890	958302	957486
R^2	0.109	0.112	0.112	0.195	0.201
Alternative Cost Measure II: Using Day-Bond-Within Day Average for $\overline{P}$					
Trade Size#LessSophisticated	-0.188***	0.052	0.064*	0.088**	0.111***
	(-4.10)	(1.35)	(1.75)	(2.55)	(3.10)
Trade Size#MoreSophisticated	-0.171**	0.130***	0.155***	0.168***	0.178***
	(-2.42)	(4.43)	(6.86)	(8.12)	(8.98)
p-values, eq. of coeff.	0.840	0.105	0.032	0.045	0.097
N	1257860	1257854	1257854	1251253	1250635
R^2	0.096	0.107	0.108	0.198	0.204
Alternative Cost Measure III: Using Day-Bond-Sell/Buy Average for $\overline{P}$					
Trade Size#LessSophisticated	-0.218***	0.057	0.067	0.079*	0.104**
	(-4.14)	(1.20)	(1.44)	(1.75)	(2.24)
Trade Size#MoreSophisticated	-0.218***	0.137***	0.166***	0.181***	0.195***
	(-2.73)	(3.29)	(4.81)	(5.09)	(5.65)
p-values, eq. of coeff.	0.997	0.203	0.085	0.072	0.115
N	1267885	1267879	1267879	1261353	1260735
R^2	0.051	0.058	0.059	0.160	0.165
Alternative Cost Measure IV: Using Average IDB prices for $\overline{P}$					
Trade Size#LessSophisticated	-0.191***	0.111**	0.120**	0.131***	0.159***
	(-3.57)	(2.15)	(2.39)	(2.60)	(3.01)
Trade Size#MoreSophisticated	-0.182**	0.175***	0.209***	0.226***	0.244***
	(-2.24)	(4.37)	(6.19)	(6.99)	(7.74)
p-values, eq. of coeff.	0.924	0.322	0.141	0.106	0.167
N	1230452	1230446	1230446	1223760	1223136
R^2	0.107	0.112	0.112	0.208	0.212
Day*Bond*ClientType FE	Yes	Yes	Yes	Yes	Yes
Client FE	No	Yes	Yes	No	No
Dealer*ClientType FE	No	No	Yes	No	No
Day*Dealer*ClientType FE	No	No	No	Yes	Yes
Month*Client FE	No	No	No	Yes	Yes
Client*Dealer FE	No	No	No	No	Yes

Notes: this table regresses transaction performance measure on trade size interacted with client type dummies as well as various fixed effects (regression 4.4). The four different performance measures are in bp-points. The first measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t and dealer j. The second measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, in a given part of the trading day t. Using the time stamp for each trade, we divide trades into three groups, depending on whether the transaction occurred (i) before 11am, (ii) during 11am-3pm, or (iii) after 3pm. The third measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t, separately for buy and sell trades. The fourth measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t, using only trades on the inter-dealer market. 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 (* $p<0.1$, ** $p<0.05$, *** $p<0.01$). The p-values correspond to the testing for the equality of coefficients.

Table A.5: Trading Costs and Trade Size in Government Bond Markets: Big vs Small Macroeconomic News, Using Alternative Cost Measures

	(1)	(2)	(3)	(4)	(5)
Alternative Cost Measure I: Using Day-Bond-Dealer Average for $\overline{P}$					
Less Sophisticated Clients					
Trade Size#SmallNews	0.005	0.023	0.019	0.035	0.044
	(0.12)	(0.52)	(0.45)	(0.78)	(0.95)
Trade Size#LargeNews	0.018	0.024	0.010	0.015	0.028
	(0.39)	(0.54)	(0.23)	(0.33)	(0.60)
p-values, eq. of coeff.	0.610	0.960	0.723	0.476	0.565
More Sophisticated Clients					
Trade Size#SmallNews	0.114***	0.114***	0.110***	0.113***	0.122***
	(3.62)	(3.62)	(3.49)	(3.48)	(3.76)
Trade Size#LargeNews	0.127***	0.125***	0.139***	0.133***	0.141***
	(4.70)	(4.42)	(4.62)	(4.07)	(4.15)
p-values, eq. of coeff.	0.591	0.631	0.343	0.479	0.498
N	901677	897696	898657	894597	893772
R^2	0.112	0.142	0.164	0.194	0.199
Alternative Cost Measure II: Using Day-Bond-Within Day Average for $\overline{P}$					
Less Sophisticated Clients					
Trade Size#SmallNews	0.065	0.088**	0.072**	0.097***	0.120***
	(1.64)	(2.14)	(2.00)	(2.60)	(3.11)
Trade Size#LargeNews	0.065*	0.080**	0.065*	0.084**	0.110***
	(1.81)	(2.15)	(1.84)	(2.36)	(2.93)
p-values, eq. of coeff.	0.987	0.654	0.733	0.487	0.600
More Sophisticated Clients					
Trade Size#SmallNews	0.147***	0.164***	0.147***	0.161***	0.173***
	(5.51)	(6.46)	(5.70)	(6.81)	(7.64)
Trade Size#LargeNews	0.163***	0.173***	0.164***	0.170***	0.181***
	(6.12)	(6.52)	(6.35)	(6.91)	(7.53)
p-values, eq. of coeff.	0.422	0.627	0.386	0.633	0.649
N	1170316	1166823	1167791	1164241	1163626
R^2	0.107	0.138	0.169	0.196	0.201
Day*Bond*ClientType FE	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	No	No	No	No
Dealer*ClientType FE	Yes	Yes	Yes	No	No
Day*Dealer*ClientType FE	No	No	Yes	Yes	Yes
Month*Client FE	No	Yes	No	Yes	Yes
Client*Dealer FE	No	No	No	No	Yes

Notes: this table regresses transaction performance measure on trade size interacted with client type and macroeconomic surprise dummies as well as various fixed effects (regression 4.5). The four different performance measures are in bp-points. The first measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t and dealer j. The second measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, in a given part of the trading day t. Using the time stamp for each trade, we divide trades into three groups, depending on whether the transaction occurred (i) before 11am, (ii) during 11am-3pm, or (iii) after 3pm. The third measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t, separately for buy and sell trades. The fourth measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t, using only trades on the inter-dealer market. 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). The p-values correspond to the testing for the equality of coefficients.

Table A.6: Trading Costs and Trade Size in Government Bond Markets: Big vs Small Macroeconomic News, Using Alternative Cost Measures

	(1)	(2)	(3)	(4)	(5)
Alternative Cost Measure III: Using Day-Bond-Sell/Buy Average for $\overline{P}$					
Less Sophisticated Clients					
Trade Size#SmallNews	0.062	0.081	0.062	0.082*	0.104**
	(1.26)	(1.57)	(1.36)	(1.71)	(2.10)
Trade Size#LargeNews	0.067	0.068	0.064	0.073	0.105**
	(1.40)	(1.36)	(1.35)	(1.52)	(2.06)
p-values, eq. of coeff.	0.876	0.634	0.936	0.788	0.987
More Sophisticated Clients					
Trade Size#SmallNews	0.145***	0.156***	0.138***	0.151***	0.168***
	(3.91)	(3.96)	(3.44)	(3.57)	(4.08)
Trade Size#LargeNews	0.194***	0.206***	0.201***	0.205***	0.221***
	(4.56)	(4.81)	(4.80)	(4.84)	(5.23)
p-values, eq. of coeff.	0.112	0.099	0.082	0.130	0.134
N	1179331	1175860	1176855	1173330	1172712
R^2	0.058	0.090	0.129	0.157	0.162
Alternative Cost Measure IV: Using Average IDB prices for $\overline{P}$					
Less Sophisticated Clients					
Trade Size#SmallNews	0.125**	0.147**	0.126**	0.148***	0.175***
	(2.25)	(2.52)	(2.43)	(2.73)	(3.08)
Trade Size#LargeNews	0.118**	0.117**	0.113**	0.119**	0.153***
	(2.33)	(2.19)	(2.24)	(2.31)	(2.80)
p-values, eq. of coeff.	0.803	0.343	0.651	0.351	0.508
More Sophisticated Clients					
Trade Size#SmallNews	0.166***	0.182***	0.163***	0.177***	0.197***
	(4.16)	(4.33)	(4.10)	(4.31)	(4.86)
Trade Size#LargeNews	0.254***	0.267***	0.253***	0.260***	0.279***
	(5.95)	(6.10)	(6.37)	(6.45)	(7.00)
p-values, eq. of coeff.	0.017	0.017	0.033	0.049	0.052
N	1146316	1142804	1143736	1140154	1139534
R^2	0.112	0.141	0.179	0.205	0.210
Day*Bond*ClientType FE	Yes	Yes	Yes	Yes	Yes
Client FE	Yes	No	No	No	No
Dealer*ClientType FE	Yes	Yes	Yes	No	No
Day*Dealer*ClientType FE	No	No	Yes	Yes	Yes
Month*Client FE	No	Yes	No	Yes	Yes
Client*Dealer FE	No	No	No	No	Yes

Notes: this table regresses transaction performance measure on trade size interacted with client type and macroeconomic surprise dummies as well as various fixed effects (regression 4.5). The four different performance measures are in bp-points. The first measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t and dealer j. The second measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, in a given part of the trading day t. Using the time stamp for each trade, we divide trades into three groups, depending on whether the transaction occurred (i) before 11am, (ii) during 11am-3pm, or (iii) after 3pm. The third measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t, separately for buy and sell trades. The fourth measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t, using only trades on the inter-dealer market. 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). The p-values correspond to the testing for the equality of coefficients.

Table A.7: Client Activity During Days with Big and Small Macroeconomic Surprises

	(1) Average Daily Transactions	(2) Average Daily Volume (£s)	(3) Average Daily Number of Clients	(4) Number of Days
Less Sophisticated Clients				
Small Surprise Days	361	3.46e+09	69	737
Big Surprise Days	391	3.83e+09	72	757
More Sophisticated Clients				
Small Surprise Days	402	3.24e+09	70	737
Big Surprise Days	433	3.49e+09	73	757

Notes: This table reports summary statistics on the activity of different client types on days with small and big macroeconomic surprises. The data covers the period from August 2011 to December 2017. The classification of small and big surprise days builds on the high-frequency methodology of Swanson and Williams (2014): we identify trading days when the surprise component of US and UK macroeconomic announcements were high, by sort trading days into two groups, based on whether the magnitude of the surprise on day t was smaller or bigger than the sample median.

Table A.8: Trading Costs and Trade Size in Government vs Corporate Bond Markets: Using Alternative Cost Measures

	(1)	(2)	(3)	(4)
Alternative Cost Measure I: Using Day-Bond-Dealer Average for $\overline{P}$				
Less Sophisticated Clients				
Trade Size#GovernmentBonds	0.066*	0.079**	0.097**	0.108***
	(1.75)	(2.05)	(2.37)	(2.65)
Trade Size#CorporateBonds	0.201	0.112	0.107	0.113
	(1.50)	(0.76)	(0.71)	(0.72)
p-values, eq. of coeff.	0.247	0.797	0.940	0.970
More Sophisticated Clients				
Trade Size#GovernmentBonds	0.116***	0.127***	0.132***	0.134***
	(4.50)	(4.58)	(5.07)	(4.98)
Trade Size#CorporateBonds	0.377**	0.342**	0.360**	0.360**
	(2.52)	(2.22)	(2.23)	(2.17)
p-values, eq. of coeff.	0.074	0.142	0.142	0.155
N	790073	783440	783038	782305
R^2	0.360	0.433	0.437	0.440
Alternative Cost Measure II: Using Day-Bond-Within Day Average for $\overline{P}$				
Less Sophisticated Clients				
Trade Size#GovernmentBonds	0.099**	0.108***	0.141***	0.146***
	(2.28)	(2.71)	(3.70)	(3.83)
Trade Size#CorporateBonds	0.263	0.298*	0.299*	0.310*
	(1.53)	(1.72)	(1.70)	(1.70)
p-values, eq. of coeff.	0.268	0.216	0.318	0.316
More Sophisticated Clients				
Trade Size#GovernmentBonds	0.144***	0.169***	0.171***	0.177***
	(5.14)	(6.94)	(7.50)	(7.70)
Trade Size#CorporateBonds	0.730***	0.705***	0.717***	0.728***
	(4.56)	(4.67)	(4.62)	(4.55)
p-values, eq. of coeff.	0.000	0.000	0.000	0.000
N	1036375	1029952	1029616	1028996
R^2	0.357	0.436	0.441	0.445
Day*Bond*ClientType FE	Yes	Yes	Yes	Yes
Client*Market FE	Yes	Yes	Yes	No
Dealer*Market*ClientType FE	Yes	Yes	Yes	No
Day*Dealer*ClientType FE	No	Yes	Yes	Yes
Month*Client FE	No	Yes	Yes	Yes
Client*Dealer	No	No	Yes	No
Client*Dealer*Market FE	No	No	No	Yes

Notes: this table regresses transaction performance measure on trade size interacted with client type and bond market dummies as well as various fixed effects (regression 4.6). The four different performance measures are in bp-points. The first measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t and dealer j. The second measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, in a given part of the trading day t. Using the time stamp for each trade, we divide trades into three groups, depending on whether the transaction occurred (i) before 11am, (ii) during 11am-3pm, or (iii) after 3pm. The third measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t, separately for buy and sell trades. The fourth measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t, using only trades on the inter-dealer market. 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). The p-values correspond to the testing for the equality of coefficients.

Table A.9: Trading Costs and Trade Size in Government vs Corporate Bond Markets: Using Alternative Cost Measures

	(1)	(2)	(3)	(4)
Alternative Cost Measure III: Using Day-Bond-Sell/Buy Average for $\overline{P}$				
Less Sophisticated Clients				
Trade Size#GovernmentBonds	0.071	0.086*	0.124***	0.115**
	(1.33)	(1.86)	(2.79)	(2.50)
Trade Size#CorporateBonds	0.130	0.138	0.174	0.216
	(0.61)	(0.64)	(0.79)	(0.98)
p-values, eq. of coeff.	0.744	0.786	0.799	0.601
More Sophisticated Clients				
Trade Size#GovernmentBonds	0.147***	0.176***	0.187***	0.183***
	(3.81)	(4.68)	(5.19)	(5.08)
Trade Size#CorporateBonds	0.686**	0.674**	0.750***	0.854***
	(2.48)	(2.47)	(2.76)	(3.15)
p-values, eq. of coeff.	0.043	0.060	0.037	0.012
N	1054855	1048593	1048276	1047673
R^2	0.171	0.276	0.283	0.287
Alternative Cost Measure IV: Using Average IDB prices for $\overline{P}$				
Less Sophisticated Clients				
Trade Size#GovernmentBonds	0.111*	0.125**	0.167***	0.151***
	(1.74)	(2.43)	(3.29)	(2.88)
Trade Size#CorporateBonds	0.300	0.255	0.165	0.215
	(1.38)	(1.26)	(0.80)	(1.06)
p-values, eq. of coeff.	0.362	0.496	0.992	0.741
More Sophisticated Clients				
Trade Size#GovernmentBonds	0.193***	0.209***	0.230***	0.230***
	(5.11)	(5.36)	(6.06)	(6.10)
Trade Size#CorporateBonds	0.779***	0.767***	0.809***	0.876***
	(3.85)	(3.71)	(3.87)	(4.37)
p-values, eq. of coeff.	0.002	0.006	0.005	0.001
N	768755	761318	760936	760134
R^2	0.267	0.377	0.383	0.386
Day*Bond*ClientType FE	Yes	Yes	Yes	Yes
Client*Market FE	Yes	Yes	Yes	No
Dealer*Market*ClientType FE	Yes	Yes	Yes	No
Day*Dealer*ClientType FE	No	Yes	Yes	Yes
Month*Client FE	No	Yes	Yes	Yes
Client*Dealer	No	No	Yes	No
Client*Dealer*Market FE	No	No	No	Yes

Notes: this table regresses transaction performance measure on trade size interacted with client type and bond market dummies as well as various fixed effects (regression 4.6). The four different performance measures are in bp-points. The first measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t and dealer j. The second measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, in a given part of the trading day t. Using the time stamp for each trade, we divide trades into three groups, depending on whether the transaction occurred (i) before 11am, (ii) during 11am-3pm, or (iii) after 3pm. The third measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t, separately for buy and sell trades. The fourth measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t, using only trades on the inter-dealer market. 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). The p-values correspond to the testing for the equality of coefficients.

Table A.10: Trading Costs and Trade Size: Government vs Corporate Bonds Markets: All Clients Included

	(1)	(2)	(3)	(4)
		Less Sophisticated Clients		
Trade Size#GovernmentBonds	0.077	0.083*	0.110**	0.116**
	(1.53)	(1.71)	(2.23)	(2.30)
Trade Size#CorporateBonds	0.447***	0.426***	0.353**	0.352**
	(2.87)	(2.90)	(2.43)	(2.40)
p-values, eq. of coeff.	0.007	0.008	0.055	0.067
		More Sophisticated Clients		
Trade Size#GovernmentBonds	0.174***	0.197***	0.205***	0.206***
	(4.84)	(5.40)	(5.75)	(5.74)
Trade Size#CorporateBonds	0.670***	0.705***	0.743***	0.789***
	(4.03)	(4.48)	(4.72)	(5.03)
p-values, eq. of coeff.	0.002	0.000	0.000	0.000
N	1962998	1957464	1956891	1955799
R^2	0.287	0.350	0.356	0.358
Day*Bond*ClientType FE	Yes	Yes	Yes	Yes
Client*Market FE	Yes	Yes	Yes	No
Dealer*Market*ClientType FE	Yes	Yes	Yes	No
Day*Dealer*ClientType FE	No	Yes	Yes	Yes
Month*Client FE	No	Yes	Yes	Yes
Client*Dealer	No	No	Yes	No
Client*Dealer*Market FE	No	No	No	Yes

Notes: this table regresses trading costs (measured in bp-points) on trade size (measured as log of the nominal size of the trade in £s) interacted with an indicator variable taking value 2 (1) if the trade takes place in the corporate (government) bond market. The regression also includes various fixed effects. The upper (lower) panel shows the results for less (more) sophisticated clients. 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). The p-values correspond to the testing for the equality of coefficients, within a given client type.

Table A.11: Average Trade Size of More Sophisticated Clients Relative to Less Sophisticated Clients

	(1)	(2)	(3)	(4)
More Sophisticated Clients	-0.356	-0.162	-0.120	-0.085
	(-1.39)	(-0.76)	(-0.61)	(-0.58)
N	1274295	1274295	1273531	973952
R^2	0.149	0.282	0.350	0.566
Day*Bond FE	Yes	Yes	Yes	No
Dealer FE	No	Yes	No	No
Day*Dealer FE	No	No	Yes	No
Day*Bond*Dealer FE	No	No	No	Yes

Notes: this table regresses trade size on a dummy that takes value 1 if the client is more sophisticated (asset managers and hedge funds) and 0 if they are less sophisticated (pension funds, central banks etc.) and various fixed effects. 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.12: Trading Costs and Trade Size: Non-linearities

	(1)	(2)	(3)	(4)	(5)
			Less Sophisticated Clients		
Trade Size $Q = 2$	-0.061	-0.065	-0.021	-0.029	0.015
	(-0.51)	(-0.53)	(-0.20)	(-0.27)	(0.14)
Trade Size $Q = 3$	0.247	0.221	0.224	0.225	0.285*
	(1.49)	(1.30)	(1.44)	(1.38)	(1.72)
Trade Size $Q = 4$	0.353*	0.363*	0.356*	0.390*	0.479**
	(1.81)	(1.71)	(1.86)	(1.88)	(2.24)
N	598874	596569	597365	595007	594602
R^2	0.112	0.143	0.179	0.206	0.212
			More Sophisticated Clients		
Trade Size $Q = 2$	0.008	0.030	0.084	0.071	0.084
	(0.06)	(0.19)	(0.70)	(0.60)	(0.70)
Trade Size $Q = 3$	0.242	0.257	0.301**	0.299**	0.319**
	(1.41)	(1.53)	(2.20)	(2.27)	(2.47)
Trade Size $Q = 4$	0.664***	0.693***	0.705***	0.701***	0.744***
	(3.91)	(4.02)	(4.23)	(4.06)	(4.36)
N	672232	670823	670987	669573	669361
R^2	0.102	0.132	0.172	0.198	0.203
Day*Bond FE	Yes	Yes	Yes	Yes	Yes
Client FE	No	Yes	Yes	No	No
Dealer FE	No	No	Yes	No	No
Day*Dealer FE	No	No	No	Yes	Yes
Month*Client FE	No	No	No	Yes	Yes
Client*Dealer FE	No	No	No	No	Yes

Notes: this table regresses transaction performance measure on trade size and various fixed effects. The performance measures are in bp-points. 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).

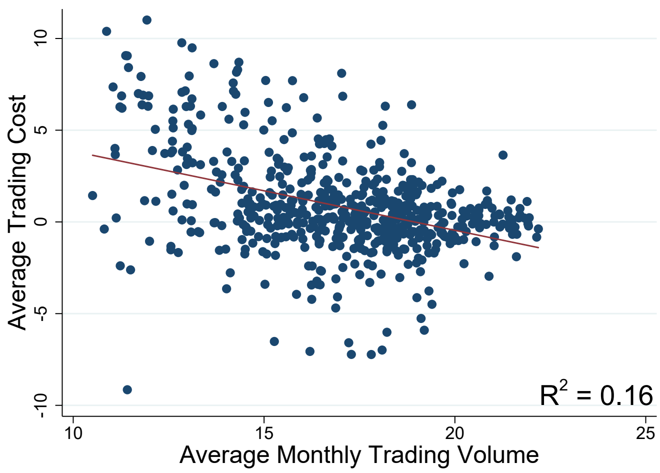
Table A.13: Trading Costs and Trade Size: Agency Trades of More Sophisticated Clients

	(2)	(3)	(4)	(5)
	Non-Agency Trades			
Trade Size	0.173***	0.194***	0.208***	0.222***
	(4.37)	(5.20)	(5.41)	(5.71)
	Agency Trades			
Trade Size	0.058	0.113*	0.078	0.079
	(0.88)	(1.72)	(1.26)	(1.29)
p-values, eq. of coeff.	0.074	0.257	0.049	0.027
N	656472	656472	647277	647029
R^2	0.159	0.160	0.282	0.286
Day*Bond	Yes	Yes	Yes	Yes
Client FE	Yes	Yes	No	No
Dealer	No	Yes	No	No
Day*Dealer	No	No	Yes	Yes
Month*Client FE	No	No	Yes	Yes
Client*Dealer FE	No	No	No	Yes

Notes: this table regresses transaction performance measure on trade size interacted with a dummy variable (taking value 1 if the given trade is an agency trade) as well as on various fixed effects. The performance measures are in bp-points. 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). The p-values correspond to the testing for the equality of coefficients.

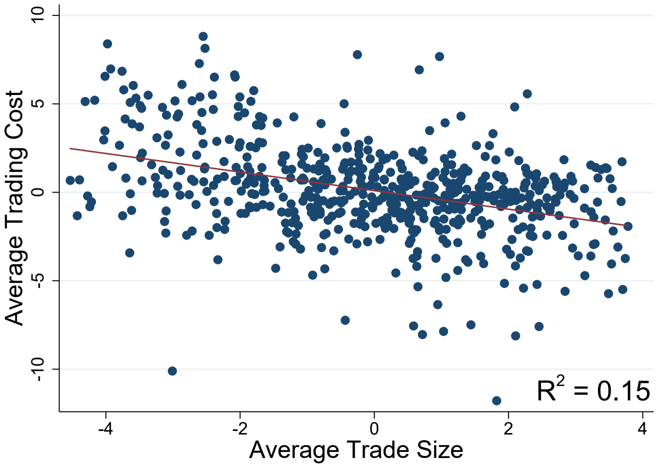
B Additional Figures

Figure A.1: Trading Costs and Trader Size in the Cross-Section



Notes: this Figure shows a scatter plot of average client trading costs (vertical axis) against average trader size (horizontal axis) at the client-level. Average trading cost is the unweighted mean of our baseline measure 4.1 at the client-level. Trader size is measured as traders' monthly trading volume average across months. To reduce noise, the dataset is trimmed at 1%-level, leaving 586 observations. The estimated $\hat{\gamma} = -0.43$ with t-stat (based on robust standard error) of -8.8.

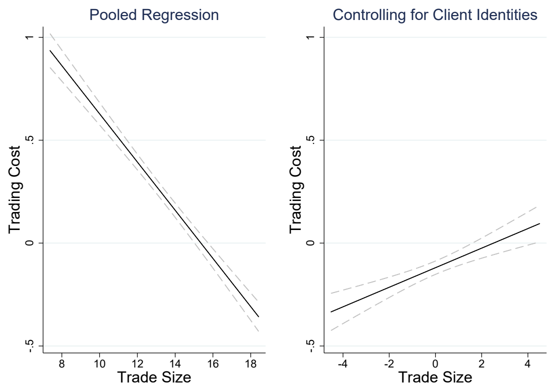
Figure A.2: Trading Costs and Trade Size in the Cross-Section: Adding Controls



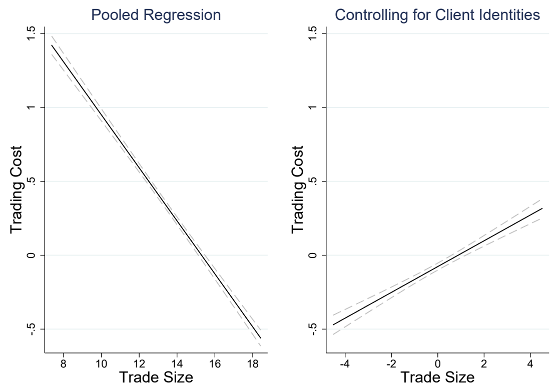
Notes: this Figure shows a scatter plot of average client trading costs (vertical axis) against average trade size (horizontal axis) at the client-level. Average trading cost is the unweighted mean of our baseline cost measure 4.1 at the client-level. Average trade size is the natural logarithm of the average nominal size of a client's transactions. To reduce noise, the dataset is trimmed at 1%-level, leaving 586 observations. The estimated $\hat{\gamma} = -0.52$ with t-stat (based on robust standard error) of -9.2.

Figure A.3: The Relation between Trade Size and Trading Costs: Using Alternative Cost Measures

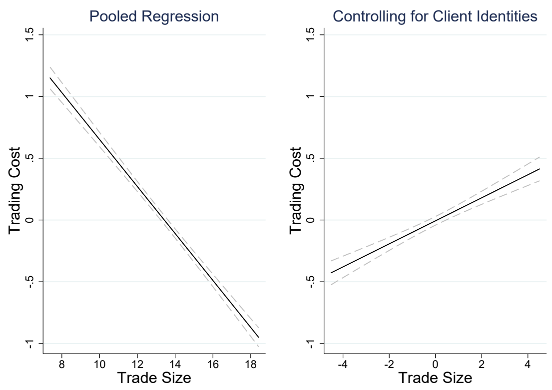
(a) Using Day-Bond-Dealer Average for $\overline{P}$



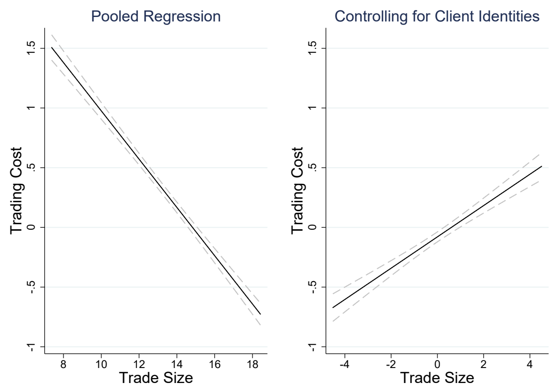
(b) Using Day-Bond-Within Day Average for $\overline{P}$



(c) Using Day-Bond-Sell/Buy Average for $\overline{P}$



(d) Using Average IDB prices for $\overline{P}$



Notes: The Figures show a linear regression line on the pooled, transaction-level data (left panel) and on the data after we removed client-specific averages from trading costs and trade size corresponding to each trade. The four different trading cost measures are measured by 4.1 (building on O'Hara and Zhou (2021)) with different definitions of $\overline{P}$, and trade size is measured as the natural logarithm of the trade's notional. The four different performance measures are in bp-points. The first measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t and dealer j. The second measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, in a given part of the trading day t. Using the time stamp for each trade, we divide trades into three groups, depending on whether the transaction occurred (i) before 11am, (ii) during 11am-3pm, or (iii) after 3pm. The third measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t, separately for buy and sell trades. The fourth measure computes $\overline{P}$ in 4.1 as the average transaction price in bond k, trading day t, using only trades on the inter-dealer market. The confidence bands are based on 95% standard errors as in Gallup (2019).