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Dealers, information and liquidity provision in safe assets

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Abstract

In this paper, we empirically study the role of information in safe asset liquidity crises, using the 2022 UK LDI crisis as a laboratory. Contrary to traditional adverse selection models, which predict higher liquidity costs due to the presence of informed traders, we find that dealers initially reduce liquidity costs for informed investors, and subsequently raise costs and reduce liquidity for the broader market. We interpret this as evidence of dealers seeking to learn from informed investors and then restricting liquidity as they process this information. We also document that dealers exploit their informational advantage in anonymous interdealer markets and that similar dynamics are present in other crises. These patterns reverse when central bank interventions restore market liquidity, thereby mitigating the effects of dealers' information chasing and their liquidity reallocation.

Key words: Adverse selection, information, OTC markets, liquidity, banks.

JEL classification: D82, E44, G12, G14, G15, G21.

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1 Introduction

Safe assets have been at the center of several major financial crises, from government bonds in the pandemic-era "Dash for Cash" and the 2023 US Banking Crisis to repurchase agreements during the Global Financial Crisis. This is surprising, as safe assets are generally expected to provide stability in times of stress. Stress and illiquidity in the markets for safe assets can pose a threat to market functioning and the broader economy (Gorton, 2017; Duffie, 2020).

Research on safe asset crises has primarily focused on investors' fire sales, which drain liquidity from the market (Ma et al., 2022; Czech et al., 2022; Alfaro et al., 2024). In contrast, studies on dealers have emphasized factors such as balance sheet constraints (Duffie et al., 2023), funding costs (O'Hara and Zhou, 2021), or the liquidity supplied by dealers' clients (Kruttli et al., 2023a). In this paper, we ask whether information plays a role in dealers' liquidity provision during safe asset crises and if so, how and why? Adverse selection models of trading, like those by Treynor (1971) and Kyle (1985), suggest that when dealers cannot distinguish between informed and uninformed investors, they raise liquidity costs to mitigate the risk of trading against informed investors. However, government bonds are usually traded in bilateral over-the-counter (OTC) markets where dealers know the identity of their counterparties. Models closer to this institutional setup, such as those on information chasing, predict that if dealers can identify informed investors, they might *lower* liquidity costs to learn from them (Naik et al., 1999; Pinter et al., 2022). For instance, in a typical large bilateral transaction, an investor may request a two-sided quote from a dealer, concealing the trade's direction until the agreement is reached. By offering discounted quotes, the dealer can gain insights into the investor's beliefs about the asset, allowing dealers to better position themselves in future trades.

To shed light on the role of information in safe asset liquidity crises, we study the 2022 UK LDI Crisis. The UK has a large, generally safe and liquid government bond market, with a dealer-based over-the-counter market structure similar to other major government bond markets, including the United States and Japan. The 2022 LDI crisis started on September 23, when Chancellor Kwasi Kwarteng unveiled the expansionary "Mini-Budget" in the UK Parliament, triggering a sharp rise in gilt yields. Over the following days, investors—particularly pension funds and liability-driven investment (LDI) funds—faced a cycle of margin calls, bond sales to raise liquidity, and further yield spikes, worsening the liquidity crisis (Alfaro et al., 2024). As a result, bond prices collapsed and 30-year gilt yields surged by 130bps in just a few days. As the crisis deepened, the Bank of England intervened on September 28 with a temporary backstop, set to end on October 14, which successfully halted the fire-sale spiral and allowed pension funds to reduce their repo leverage (Hauser, 2023; Alexander et al., 2023). This episode, like previous safe asset crises, again highlighted the growing importance of non-bank financial institutions (NBFIs) for financial stability (Czech et al., 2021a).

Our analysis relies on the regulatory MiFID II data for transactions in the UK government bond market. This dataset is highly granular and comprehensive, allowing us to distinguish the role of information from other factors like dealer balance sheet constraints or trading relationships. The dataset provides key details such as trade direction, price, quantity, and identifiers for both the buyer and seller. This level of detail is crucial. Unlike other bond transaction datasets—like TRACE in the US—our data allows us to track both sides of the transaction, enabling us to carefully control for a host of potentially confounding variation. For instance, we can account for which clients maintain stronger relationships with dealers or provide them with more liquidity.

Moreover, the high-frequency nature of the trade data also allows us to perform our analysis in very narrow time windows, further refining our comparisons between trades. Specifically, we analyze trading patterns within the same dealer and the same security in a 30-minute time window. This enables us to control for factors such as changes in the demand for specific securities and financial conditions (e.g., interest rate expectations or risk aversion). Importantly, we focus on how dealers allocate liquidity costs across their clients while holding constant broader dealer-level factors, including balance sheet constraints.

Our main empirical strategy proceeds in two stages. First, we study dealers' pricing strategies during the crisis. We define a trade as benefiting from discounted liquidity if an investor receives a better price from a given dealer compared to a similar trade in the same bond in the same 30-minute time window. Following the literature, we assume that dealers infer an investor's informational advantage from their recent trading returns, categorizing informed investors as those in the top tercile of asset managers and hedge funds, while classifying all others as uninformed.[1] We employ a two-way fixed effects model to compare the trade costs dealers impose on informed investors versus their other clients, both before and during the crisis. To validate this methodology, we present time-varying estimates to assess the parallel trends assumption and ensure that our classification of informed investors does not capture other potential drivers of discounted liquidity.

In the second stage, we examine how dealers adjust their behavior after trading with informed investors, focusing on changes in pricing, liquidity provision, and trading strategies. We do so by comparing dealers with higher versus lower informed order flow. However, dealers' informed order flow is endogenous, reflecting the outcome of decisions by both dealers and clients. To address potential endogeneity, we use a shift-share instrumental variable based on dealers' pre-crisis trading patterns. We also control for clients' demand for liquidity through investor-time fixed effects, allowing us to directly compare the liquidity supplied by two dealers—one with more informed order flow and one with less—for the same investor.

[1] We obtain qualitatively similar results when using clients' subsequent performance during the crisis or evaluating performance based on comparable past crises. These findings suggest a degree of persistence in investors' trading ability.

In our first set of results, we find that dealers significantly reduced liquidity costs for informed investors, consistent with theories that predict information chasing by dealers. This pattern is evident in the raw data, which reveals both an absolute decline in trade costs and a relative decline compared to uninformed investors, as shown in Table 1. Even in our most conservative econometric model, informed investors faced trade costs that were on average 20bps lower than those of uninformed investors at the height of the crisis. This is an economically large effect, especially in a market where pre-crisis trade costs averaged just 3bps, and where participants often use substantial leverage.

We use a range of controls and fixed effects to rule out alternative explanations. For instance, by controlling for the prior trading volumes between clients and dealers, we show that our results are not driven by pre-existing relationships. Additionally, we account for instances where clients provide liquidity to dealers, confirming that while dealers compensate clients for liquidity provision in such instances, it does not explain the observed cost reductions. Furthermore, using dealer-time fixed effects—comparing the trade costs of different clients with the same dealer in the same 30-minute time period—and controlling for dealer inventory, we ensure that balance sheet constraints do not account for our findings. Importantly, we also show that dealers do not provide discounts on shorter maturity bonds, which are less likely to be information sensitive. We also document that dealers provided discounts precisely to the best performing trades during the crisis. This behavior aligns with a dealer learning process, where dealers strategically offer better liquidity terms to informed traders early in the crisis to gather valuable information.

In the second set of results, we study how dealers adjust their behavior based on the market segment, balancing the need to maintain client relationships with the opportunity to exploit information asymmetries. We find that dealers with more informed order flow increase liquidity costs for uninformed investors in the dealer-to-client market by 10bps, while reducing their net trading volumes by one quarter of a standard deviation. This suggests that as the crisis progresses, dealers increasingly restrict liquidity provision to less informed investors. Additionally, we demonstrate that dealers profit from their informational edge in anonymous interdealer markets. However, central bank interventions eventually reverse these effects by restoring overall market liquidity. We also extend our analysis to the COVID-19 Dash for Cash episode, where we observe similar patterns of dealer behavior, indicating that these dynamics are not unique to the 2022 LDI crisis.

Our findings are consistent with the prior literature on "information chasing", which suggests that dealers may offer more favorable trading terms to informed investors in exchange for private information. Our results extend this literature by highlighting a reallocation of liquidity by dealers that benefits informed participants at the expense of the broader market. We are the first to provide evidence that information chasing can contribute to liquidity crises, using novel data that allows us to disentangle this channel from dealer-client relationships and dealer balance sheet constraints. The results underline the importance of understanding how market structures affect the incentives of key intermediaries in response to information asymmetry, particularly in times of crisis.

The role of information in dealers' liquidity provision is not mutually exclusive with other factors such as balance sheet constraints or trading networks, but it offers different predictions for market outcomes and distinct policy implications. For instance, if dealers restrict liquidity solely due to balance sheet constraints, the variation in liquidity provision should primarily be explained by dealer-level factors, such as regulatory buffers or funding costs. This would imply that temporary measures like regulatory forbearance or central bank lending facilities could ease liquidity shortages during crises. In contrast, the informational perspective predicts that variation in the supply of liquidity is driven by its allocation to certain counterparties *within* a given dealer. Addressing this informational channel would require policy tools such as *ex ante* market design reforms (e.g., enhancing price transparency or enabling anonymous trading) or interventions to influence investor beliefs and expectations (Dang et al., 2020; Abreu and Brunnermeier, 2003).

The remainder of the paper is structured as follows: Section 2 reviews the relevant literature on liquidity crises and informed trading in government bond markets. Section 3 describes the data and methodology used in our analysis and presents the key stylized facts from the 2022 LDI crisis, including evidence of dealers' liquidity redistribution. Section 4 details the main empirical analysis of dealers' pricing strategies as well as robustness checks that rule out alternative explanations. Section 5 explores dealer behavior after trading with informed investors. Section 6 extends the analysis to the Covid-19 Dash for Cash crisis episode. Section 7 concludes.

2 Literature Review

This study builds upon several key areas of research, particularly those concerning safe asset crises, information and liquidity dynamics, market making, and informed trading within government bond markets. Below, we summarize the most relevant literature across these domains.

Recent financial crises, such as the global Dash for Cash episode during the COVID-19 pandemic (2020) and the LDI crisis in the UK (2022), have revealed the potential for significant illiquidity and market dysfunction in traditionally safe and liquid government bond markets. A growing body of research has begun to explore the mechanisms behind these episodes and the associated policy responses. Several empirical studies point to fire sales by large institutional investors as key contributors to financial stress and illiquidity during both the

Dash for Cash and the 2022 LDI crisis.[2]

In theory, arbitrageurs—including specialized investors and market makers—are expected to absorb temporary selling pressure, i.e. "leaning against the wind". However, their capacity to do so is often constrained by several factors, limiting their ability to stabilize markets.[3] For instance, Duffie et al. (2023) provide empirical evidence that dealer capacity constraints—such as balance sheet limitations driven by regulations and internal risk management—exacerbate liquidity shortages in the US Treasury market. In their analysis, when dealer balance sheets are near their limits, their ability to intermediate decreases, leading to heightened illiquidity. Pinter (2023) demonstrates that strategic delays by hedge funds seeking to time market entry before policy interventions exacerbated market stress during the 2022 LDI crisis.

In contrast to this existing work, our research identifies and examines an alternative amplification mechanism rooted in how dealers allocate liquidity during market turmoils. While previous studies emphasize market-making constraints, we argue that dealers' information chasing—particularly how they distribute liquidity among clients—can also amplify illiquidity during crises. This distinction is crucial because different amplification channels may suggest varying policy implications. For example, if dealers' information chasing exacerbates illiquidity, alternative anonymous market structures, similar to interdealer markets, might help mitigate these dynamics.

Our research is also connected to the substantial literature on the relationship between liquidity and information. One of the earliest models linking liquidity pricing to information asymmetry is presented by Treynor (1971), who shows that market makers charge a spread to compensate for the risk of trading with informed investors. Kyle (1985) builds on this

[2] For research on the COVID-19 Dash for Cash, see Vissing-Jorgensen (2021); Ma et al. (2022); Czech et al. (2022); for the 2022 LDI crisis, see Alfaro et al. (2024); Pinter (2023).

[3] See Shleifer and Vishny (1997); Gromb and Vayanos (2002); Weill (2007); Duffie (2010, 2020); Lagos et al. (2011); Abreu and Brunnermeier (2003); O'Hara and Zhou (2021); Kruttli et al. (2023a,b).

intuition, developing a widely used model that formalizes the dynamics of adverse selection in liquidity provision. However, empirical research has challenged the adverse selection narrative. Studies by Ramadorai (2008), Kacperczyk and Pagnotta (2019), Pinter et al. (2022), and Bilan et al. (2023) demonstrate that informed investors, in fact, receive better liquidity pricing in FX, equity, government bond, and CDS markets, respectively.

These findings suggest that adverse selection models may not fully capture the complexities of market maker behavior, especially in markets where dealers can identify informed and uninformed investors. Closely related to our work, Pinter et al. (2022) propose a model where market makers infer information acquisition by investors, leading to liquidity provision that favors informed investors under certain conditions. In their model, investors can signal their information—without revealing it via transaction size—in a request for a two-sided quote.

Building on this literature, our study extends these insights by exploring how dealers' pursuit of information can contribute to liquidity crises, even in the most liquid and typically safe government bond markets. We provide empirical evidence that dealers' "information chasing" can exacerbate market stress by altering liquidity dynamics during crisis periods.

Furthermore, our paper contributes to the growing literature on informed trading in government bond markets. These markets are typically characterized by high liquidity and price formation driven by publicly available information, such as macroeconomic data and monetary policy announcements (Fleming and Remolona, 1999). Nonetheless, recent research reveals that sophisticated investors often possess an informational edge, allowing them to outperform other market participants. Moreover, these studies document that even the safest assets can become information-sensitive in times of stress (Cashin et al., 2023; Czech et al., 2021b; Pinter et al., 2022). This informational advantage may stem from several factors. Sophisticated investors in government bond markets, such as macro and relative-value hedge funds, are often better at forecasting macroeconomic fundamentals and react more quickly to new information. As a result, they can anticipate other investors' order flow, gaining a strategic advantage (Czech et al., 2021b; Kondor and Pinter, 2022). This edge is one of the primary sources of returns for these investors, consistent with anecdotal evidence from the bond market.

Finally, this paper contributes to the extensive literature on market makers, particularly their management of information and client relationships during periods of market stress. Studies such as Di Maggio et al. (2017) and Jurkatis et al. (2023) demonstrate that dealers prioritize liquidity provision to their most valuable clients during crises. Di Maggio et al. (2019) and Barbon et al. (2019) further highlight the role of dealers in disseminating information to clients. In contrast to this body of work, our research focuses on the reverse flow of information—from informed investors to dealers—and examines how this dynamic can affect financial stability during crisis periods.

3 Data, Measures, and Stylized Facts

3.1 Data

Our analysis leverages the regulatory MiFID II data for UK government bond (gilt) transactions from January 2018 onwards. For this study, we primarily focus on the period surrounding the UK LDI crisis, spanning from August 2022 to October 2022. Over this period, our dataset encompasses approximately 230,000 transactions, with 124,000 occurring in the dealer-to-client market, and the remainder in the interdealer market. Our baseline sample includes transactions between 3,144 investors and the 17 dealers who are designated Gilt-Edged Market Makers (GEMMs), covering all bonds in the gilt market.

The MiFID II data is highly granular and comprehensive. It includes detailed information on each transaction, such as trade direction, price, quantity, and security identifiers, along with the identities of both counterparties involved. This counterparty information is particularly valuable, distinguishing our dataset from other commonly used government bond trade datasets, such as TRACE in the US, where counterparties are often anonymous. The ability to track both investors and dealers enables us to control for a wide range of potential confounding factors. For instance, we can account for the intensity of pre-existing trading relationships between investors and dealers.

Furthermore, the high-frequency nature of the data allows us to examine trades with fine temporal granularity. In our baseline analysis, we utilize a 30-minute window to analyze trades in the same bonds with the same dealers, which helps to eliminate confounding factors such as varying demand for specific securities, shifts in financial conditions (e.g., interest rate expectations or changes in risk aversion), and overall market dynamics. By focusing on this short time window, our analysis centers on the *allocation* of liquidity costs across the different clients of a given dealer, providing insights into how liquidity is distributed during periods of stress.

Despite its comprehensiveness, the data has certain limitations. Notably, we only observe realized transactions, meaning we do not have access to dealer quotes, investor requests for quotes, or any part of the negotiation process. Most transactions are negotiated over the phone, particularly for medium or large size trades, even if they begin with an electronic quote over a trading platform. As a result, our dataset captures equilibrium outcomes, but may reflect changes in the composition of investors or trade types over time. In the econometric analysis presented in Section 4, we directly address these concerns. Specifically, we hold constant our sample of investors and trade types to ensure that our findings are not biased by changes in market composition or trade characteristics during the crisis.

3.2 Dealers' Supply of Liquidity During the Crisis

In the lead-up to the crisis, gilt yields had been rising steadily as central banks worldwide tightened monetary policy to combat the post-pandemic surge in inflation. However, these yield increases occurred in orderly markets until the "Mini-Budget" announcement from UK Chancellor Kwasi Kwarteng on September 23, which triggered a sharp rise in gilt yields. The ensuing surge in margin calls led to fire sales by large liability-driven investors, including pension funds, contributing to the market turmoil (Alfaro et al., 2024). In response to the market stress, the Bank of England (BoE) initiated its first financial stability asset purchases of long-dated gilts on September 28. This intervention was subsequently expanded to include inflation-linked gilts on October 11, with the BoE concluding its market operations on October 14.

As shown in Figure 1, dealers' net order flow in the gilt market was negative prior to the first BoE announcement, i.e. they were net sellers of gilts. The increased selling pressure from dealers likely compounded the illiquidity in the gilt market, further amplifying financial instability. The magnitudes are economically significant, with around £2bn in net sales on a risk-adjusted basis.

In addition to a sharp decline in market depth, the cost of executing transactions also surged during the crisis. We measure these trade costs relative to the most recent interdealer price for the same bond. The interdealer market, known for its high liquidity, low transaction costs, and anonymity, allows dealers to trade with each other via interdealer brokers. These brokers provide real-time pricing streams, which dealers commonly use as benchmarks for pricing their trades with clients. Specifically, in a time period t, the trade cost for transaction $n \in N$ is calculated as the difference in log prices between the realized transaction P_n^* and the prevailing interdealer benchmark price P_t^{ID}:[4]

$$TradeCost_n = (P_n^* - P_t^{ID}) \times \mathbb{I}_{buysell}. \tag{1}$$

Figure 2 plots the volume-weighted average trade cost across the entire gilt market, expressed in basis points and using a five-day rolling average. Trade costs increased from 3bps before the mini-budget to 24bps prior to the conclusion of the BoE market intervention on October 14. Together, these charts provide evidence that dealers decreased the quantity and increased the cost of liquidity, which is consistent with an inward shift in the supply curve for market liquidity.

3.3 Price Dispersion

Price dispersion, a widely used indicator of aggregate market illiquidity, occurs when the same bond trades at different prices across simultaneous transactions (Jankowitsch et al., 2011). The underlying intuition is that, in normal market conditions, arbitrage ensures that a security trades at similar prices across venues and counterparties. However, when arbitrageurs and dealers are constrained, securities begin to trade at increasingly divergent prices. This divergence heightens the trade cost risk for investors, as the lack of price uniformity makes it more expensive and uncertain to execute transactions. Price dispersion for any given bond can be calculated as the average deviation of the realized prices P^* for transactions $n \in N$ in a time period t from the bond's average price over the same period $\bar{P}_t$, as given by equation (2):

$$PD_t = \sqrt{\frac{1}{N}\sum_{n}^{N}\left(P_n^* - \bar{P}_t\right)^2}. \tag{2}$$

[4]Throughout this paper, all prices are expressed in logs to facilitate interpretation. Averages are computed using log prices, and all calculations are scaled to basis points for comparability. Additionally, trade costs are winsorized at the 2.5% and 97.5% tails of the distribution to mitigate the impact of outliers.

Following Pinter (2023), this can be further decomposed into the the within-dealer and across-dealer dispersion using the dealer-specific average price of a bond $\ddot{P}_t$:

$$PD_t^2 = \underbrace{\frac{1}{N}\sum_n^N \left(P_n^* - \ddot{P}_t\right)^2}_{within-dealer} + \underbrace{\frac{1}{N}\sum_n^N \left(\ddot{P}_t - \bar{P}_t\right)^2}_{across-dealer}. \tag{3}$$

Across-dealer price dispersion will primarily be driven by differences in the cross-section, such as dealers' regulatory capacity to expand their balance sheet, funding costs, and client-base. Within-dealer price dispersion, on the other hand, is primarily driven by how liquidity is distributed among the dealer's clients. This can be affected by changes in the composition of the dealer's clients, such as shifts towards larger or smaller investors, or variations in the size and types of transactions. For example, dealers might quote different prices based on trade size, with larger trades potentially incurring higher costs due to liquidity constraints.

Since our primary interest lies in how dealers distribute liquidity, we focus on *within-dealer* price dispersion. Figure 3 plots the time series of price dispersion for both the interdealer market (in blue) and the dealer-to-client market (in pink).[5] Our data allows for a high-frequency calculation of this measure by comparing the prices of the same bond traded by the same dealer within a narrow 30-minute window. We then aggregate these deviations across bonds and dealers on a daily basis. This approach minimizes any distortion in the price dispersion measure arising from changes in underlying market volatility.

The figure shows that within-dealer price dispersion in dealer-to-client trades surged following the Mini-Budget announcement (black vertical line), then stabilized after the BoE announced its initial asset purchase program (red line). However, it rose again before the intervention was expanded (green line) and ultimately concluded (blue line). In contrast, the across-dealer price dispersion in the interdealer market remained relatively stable. The

[5] We only include bonds that were traded by at least two investors (in a given time window for the same dealer and bond) to ensure that the observed price dispersion is meaningful.

interdealer market's centralized and anonymous nature provides a useful comparison, as in this market dealers cannot differentiate between their counterparties. Given the interdealer market's liquidity and non-informational nature, its price dispersion provides an approximate upper bound on the proportion of dispersion attributable to fundamental volatility. This comparison helps address concerns that our price dispersion measures might simply reflect broader financial or macroeconomic volatility.

Figure 4 further breaks down the sources of price dispersion during the crisis, comparing the share attributable to the across-dealer dispersion with that from the within-dealer variation. The results show that the share of price dispersion attributable to within-dealer variation in the dealer-to-client market increased from around 25% before the Mini-Budget to over 60% at the peak of the crisis, before retracing following the BoE's intervention. This shift suggests that dealers' liquidity allocation to different clients became increasingly significant during the crisis, compared to other factors such as macroeconomic fundamentals or dealer-specific constraints like regulatory balance sheet limits. Overall, these findings indicate that during periods of market stress, dealers increasingly differentiate their trade costs across clients, reflecting a more targeted distribution of liquidity.

3.4 Definition of Informed Investors

We hypothesize that during periods of stress, dealers offer *better* trading costs to informed investors compared to others, with the goal of learning from their trades. Prior research has shown that sophisticated investors, such as hedge funds and asset managers, often possess an informational advantage in government bond markets over short- to medium-term horizons (Czech et al., 2021b; Kondor and Pinter, 2022; Pinter et al., 2022). To test this hypothesis, we follow the approach of Di Maggio et al. (2019) and measure the T-day ahead performance of a trade as follows:

$$Perf_n^T = (P^T - P_n^*) \times \mathbb{I}_{buysell}, \tag{4}$$

where P^T is the average price of the bond T days in the future and P_n^* is the price of trade n.

We further decompose this performance measure into two components: one that reflects changes in market prices and another that captures the impact of trade costs and execution. This decomposition is crucial, as our primary focus is on the cost of liquidity provided by dealers. By separating these components, we avoid conflating investors' ability to predict future bond returns with their ability to negotiate favorable trading terms from dealers:

$$Perf_n^T = \left(\underbrace{(P^T - \bar{P}_t)}_{Market\ Prices} + \underbrace{(\bar{P}_t - P_n^*)}_{Execution} \right) \times \mathbb{I}_{buysell} \tag{5}$$

where $\bar{P}_t$ is the average price of the bond on day t. Using this decomposition, equation (6) measures the trade performance after removing the transaction cost component:

$$AdjPerf_n^T = (P^T - \bar{P}_t) \times \mathbb{I}_{buysell} \tag{6}$$

Intuitively, the adjusted trade performance measure assumes that each investor transacts at the bond's average transaction price rather than their actual execution price. This adjustment removes the impact of execution costs on trading profitability, isolating the component attributable to the investor's ability to predict bond price movements. We then average each investor's performance, weighted by transaction size, and sum the daily returns.[6]

During the crisis, a subset of sophisticated investors exhibited particularly strong perfor-

[6] All the main results are robust to using i) unweighted returns to calculate performance and ii) interdealer prices to adjust for transaction costs.

mance. According to Pinter (2023), hedge funds achieved cumulative size-weighted returns exceeding 30% over the crisis period, based on their 6-day ahead trading performance. However, these superior returns were not directly observable by dealers in real time.

For the purposes of our analysis, we assume that dealers form conjectures about which investors have an informational advantage by observing their recent trading performance. To operationalize this, we classify the top tercile of sophisticated investors (based on their average 3-day ahead trading performance) in the month preceding the crisis as "informed investors". Dealers are likely to perceive these investors as possessing an informational advantage, driven by their recent trading performance. The control group of "uninformed investors" includes the remaining hedge funds and asset managers, as well as other non-sophisticated investors such as pension funds, insurers or non-financial companies.[7]

Table 2 provides basic statistics on the relative size of these investors. On average, they account for 454 trades and £5.6bn in volume each day, approximately 8% and 13% of total trades and volume, respectively. Table 1 provides the average trade costs for each market segment before and during the crisis. Informed investors have slightly higher transaction costs relative to uninformed investors before the crisis, which decrease significantly during the crisis. Uninformed clients have relatively modest pre-crisis average transaction costs, but their trade costs increase substantially during the crisis. This table provides our baseline result in its simplest form: during the crisis, dealers reduce high performing investors trade costs, while increasing trade costs for the rest of the market.

Figure 5 shows the time series of gross trading volume for both informed and uninformed investors around the crisis, normalized to the initial period. Overall, the two series move in tandem, with a noticeable rise in trading activity as the crisis begins. The informed investor series exhibits greater volatility, which can be attributed to the smaller number of investors

[7]Our results remain robust when we restrict the analysis to only sophisticated investors, or apply a range of different performance measures.

and aggregate size.

4 Information Chasing in Crises

4.1 Information Chasing - Main Results

Up to this point, we have shown that during the crisis, dealers reduce the quantity and increase the price of market liquidity. Moreover, we observed a greater rise in price dispersion in the dealer-to-client market compared to the anonymous interdealer market. However, these aggregate dynamics could still be influenced by other factors, such as shifts in the types of transactions or the profiles of investors with whom dealers are trading.

For instance, during normal market conditions, dealers often offer better prices to larger investors or for larger transactions, as part of a strategy to invest in profitable future trading relationships. In times of market stress, if smaller investors, who typically trade less frequently, suddenly need to trade more, then this change in the composition of investors and transaction sizes could explain the variation in trade costs, rather than targeted liquidity provision by dealers.

Our econometric analysis aims to address these concerns by examining whether informed investors receive significantly lower trade costs compared to other investors, while controlling for potential confounding factors. The granularity of our data allows us to analyze liquidity costs at very high frequency and to carefully exclude much of the potentially confounding variation. To achieve this, we estimate the following two-way fixed effects model:

$$TradeCost_{idbn} = \beta Post_t \times Informed_i + \theta Connections_{i,day} + \alpha_{dt} + \gamma_{id} + Size_n + \epsilon_{idbn}, \quad (7)$$

where $TradeCost_{idbn}$ refers to the trade cost as defined in equation (1), expressed in basis points, for transaction n in a 30-minute window t between investor i and dealer d in bond b. As defined earlier, our trade cost measure compares each transaction to the most recent interdealer price for the same bond, effectively controlling for time- and security-specific factors like changes in bond fundamentals, demand, or broader market conditions such as interest rates or risk aversion. $Post_t$ is an indicator variable that equals 1 after the crisis begins on September 23, while $Informed_i$ is an indicator variable equal to 1 if the investor is a top-performing asset manager or hedge fund (adjusted for execution performance) in the month prior to the crisis, as explained in Section 3.4. Importantly, our results remain robust across various alternative definitions, as described below.

The granularity of our data allows us to use a rich set of fixed effects to account for potentially confounding, unobserved variation. To focus on how dealers allocate liquidity among their clients, we use dealer-time fixed effects (α_{dt}), ensuring that our comparison is between different investors within the same dealer and the same 30-minute time window. We also apply investor-dealer fixed effects (γ_{id}), which capture the intensity of dealer-client relationships across our sample.[8] Transaction-size fixed effects ($Size_v$) account for small (<£100,000), medium (£100,000 $<$ Size $<$ £1,000,000), and large (>£1,000,000) trades, absorbing any variation due to changes in the composition of transaction sizes.[9] Additionally, we control for the number of daily dealer connections of a given investor ($Connections_{i,day}$) to account for the possibility that investors might split trades across multiple dealers to reduce liquidity costs.[10]

Private information is generally unobservable, making identification challenging. Our identi-

[8]In Section 4.3, we also control for the time-varying value of trading relationships.

[9]The results do not change when we control for more granular size categories or when using a continuous measure, for example the natural logarithm of transaction size.

[10]The $Connections_{i,day}$ and size fixed effects help mitigate concerns that sophisticated investors strategically divide their trades to lower transaction costs. However, such behavior could also indicate an attempt to disguise an informational advantage, which might absorb some of the effect we are examining (Kondor and Pinter, 2022). If this were the case, it would bias the results against finding a significant effect. Yet, our empirical analysis shows nearly identical results when these controls are excluded.

fying assumptions are (1) that investors' prior performance is indicative of dealers' perception of investors' informational advantage and (2) that informed and uninformed investors would have continued to receive similar trade costs in absence of the shock, after conditioning on our controls.[11] In the following subsections we provide evidence to support these assumptions, including (1) time-varying estimates in support of the parallel trends assumption, (2) measuring the profitability of informed investors' trades receiving discounts, and (3) extensive robustness tests showing that our results are not driven by trading relationships or compensation for investors' liquidity provision.

First, Figure 6 estimates equation (7) as a weekly time-varying model. The figure shows that in the first week of the crisis, informed investors incurred significantly lower transaction costs than their uninformed counterparts. The effect then reverses in the following weeks. Importantly, the estimates also provide evidence in support of the parallel trends assumption.

Table 5 presents the results from the pooled two-way fixed effects estimation, alongside robustness checks, with standard errors clustered at the investor-day level. The key finding (column 2) reveals that, during the crisis, informed investors faced transaction costs that were 15bps lower than those of their uninformed counterparts. In column (1), we employ less granular fixed effects and fewer controls compared to the main baseline in column (2). This demonstrates that the results are not solely driven by the strict specification or extensive controls used in the baseline model. Column (3) re-estimates the baseline, weighting the sample by transaction size. Finally, column (4) re-estimates the baseline, but only within the subset of asset managers and hedge funds, confirming that the effect is not driven by this group being favored clients of dealers.

Table 6 provides robustness tests for our measure of trade costs. Column (2) alters the

[11] Strictly speaking, from an empirical perspective, there need not be any actual informational advantage, only the perception of it by dealers. However, in equilibrium, it would not be sustainable for dealers to consistently provide discounts to investors if it was not profitable.

benchmark for calculating trade costs in equation (1) by using the hourly Bloomberg bond price. Furthermore, column (3) applies the average price across the full market (both interdealer and dealer-to-client transactions), excluding the current transaction. As expected, the estimated coefficient in column (3) is lower, reflecting the fact that the full-market benchmark includes higher average transaction costs (rather than only the low interdealer trade costs), which are then compared to a given trade.

Finally, we study the results across bond maturity and type. Given the nature of the crisis, it is plausible that dealers are seeking information about fiscal outcomes or fire sales, both of which should predominantly affect longer maturity bonds or inflation-linked bonds (Alfaro et al., 2024). Thus, shorter maturity bonds should be less information sensitive and can act as a control group for the information channel. Table 7 re-estimates our baseline specification, but for subsamples of different bond types. The first two columns estimate an unweighted model for shorter maturity (<10y) and longer maturity buckets (≥10y) for conventional gilts, while column (3) examines the effect for inflation-linked bonds. Columns (4)-(6) rerun the regressions with trade costs weighted by trading volume. Consistent with our prior, we find economically and statistically significant effects for the longer maturity (column 5) and the inflation-linked gilt sample (column 6). Importantly, the absence of a significant result in the shorter maturity sample supports our informational hypothesis.

Overall, these findings provide strong evidence that dealers offer lower liquidity costs to high-performing sophisticated investors during crises, consistent with our hypothesis of dealers' information-chasing behavior.

4.1.1 Alternative Measures of Information

Our measure of informed investors identifies a distinct subset of investors who outperformed in the month leading up to the crisis. This approach is based on prior research that highlights the predictive power of top-performing investors' trades in forecasting short-term price movements (Czech et al., 2021b). However, recognizing that alternative measures of superior trading ability could also be valid, we re-estimate our baseline specification using a variety of such measures.

Table 8 presents the results of these robustness checks. The first three columns offer variations on our main measure of T-day ahead trading performance. Columns (1)-(3) define informed investors as the top tercile of asset managers and hedge funds based on their money-weighted 1, 3, and 5-day trading performance in the month prior to the crisis, respectively. Column (4) is the 3-day trading performance, weighted by risk-adjusted volumes.[12]

Our baseline measure of trading performance is straightforward and widely adopted in the literature. Intuitively, it reflects how well an investor's trade in a particular bond predicts short-term price movements, regardless of whether the investor is trading on the level or slope of interest rates, or engaging in relative value trades. However, our data's richness allows us to explore more comprehensive performance measures, such as total profits and losses (P&L). Compared to the first measure, P&L better captures realized cash flows and changes in inventory valuation throughout the sample period.

For each investor i, we calculate the bond-by-bond P&L as follows:

$$P\&L_i = \sum_{b}^{B_i} \left(\underbrace{\sum Q_b^S P_b^S - \sum Q_b^B P_b^B}_{Realized\ Cash-flows} + \underbrace{\left(\sum Q_b^B - \sum Q_b^S\right) \times P_{bT}}_{Inventory\ Valuation} \right), \tag{8}$$

where Q^B and Q^S are the quantities bought and sold, and P^B and P^S are the corresponding transaction prices, with inventory revalued at the final price P_T at the end of the sample.[13]

[12] The risk-weighted performance calculation follows Duffie et al. (2023) C.1. It scales nominal net order flow by DVO1 and implied rate volatility, normalized to monthly 95% Value-at-Risk.

[13] We use the prevailing average market prices to exclude the effect of favorable execution terms, although unadjusted results are similar.

Column (5) reports the funds' cumulative P&L during the crisis, normalized by trading volume, and finds nearly identical results.

Though not observable in real-time by dealers, our data allows us to calculate investors' trading returns through the end of the crisis. Investors' with an informational edge should be among those with the highest realized returns *ex post*. Column (6) uses the 3-day ahead returns through the end of the crisis and finds similar results.

Finally, in Column (7), we also identify the top performing investors in the last liquidity crisis—the 2020 COVID "Dash for Cash." The COVID-19 Dash for Cash was another period marked by macroeconomic stress, policy uncertainty, and a liquidity crisis in the gilt market. Together, Column (6) and (7) may suggest there is some persistence in investors' informational edge. These findings align with the notion that a subset of high-performing, sophisticated investors possesses superior skills in identifying and processing relevant information, enabling them to consistently outperform their less sophisticated counterparts.

4.1.2 Non-Linearity

We hypothesize that our proposed mechanism is highly non-linear. High-performing investors likely possess information that is significantly more valuable relative to the lower transaction costs they receive from dealers. Consequently, dealers are incentivized to offer them substantial benefits in the form of reduced trading costs.

Table 9 tests this hypothesis by re-estimating our baseline specification, using daily terciles of trade costs as the dependent variable. Column (1) represents the lowest tercile, column (2) the middle tercile, and column (3) the highest. The results indicate that informed investors gravitate toward the lower end of the trade cost distribution during the crisis.

These estimates also serve as a robustness check against the possibility that increased overall trade cost dispersion could bias our results. In particular, heightened volatility might cause transaction prices to deviate further from their benchmarks within a fixed window, potentially inflating our transaction cost measure. By scaling transaction costs relative to their daily distribution, we confirm that informed investors continue to benefit from lower costs, even in the presence of broader price dispersion.

4.2 Trade Informativeness

Our interpretation of the results so far suggests that dealers offer discounted liquidity to high-performing sophisticated investors to gain access to private information. While private information is generally unobservable, the granularity of our data allows us to assess the plausibility of this assumption. To investigate this, we examine whether the trades receiving dealer discounts indeed yield higher returns. For dealers, offering discounts must provide some advantage to be sustainable in equilibrium. If this advantage stems from the informational edge gained through these trades, then discounted trades should, on average, generate higher returns than those without discounts.

We define trades that receive substantial discounts as those in the lowest daily tercile of trade costs, using the indicator variable $Low(TradeCost)_{in}$ from the previous section. We then examine whether the discounted trades outperform other trades by estimating the following regression on the subset of informed investors:

$$AdjPerf(Informed)^{T}_{idbn} = \beta_t Date_t \times Low(TradeCost)_{in} + \mu_t + Size_n + \epsilon_{idbn}. \qquad (9)$$

A positive coefficients β captures the average returns of a discounted trade compared to all other trades, relative to the week before the crisis. Figure 7 illustrates the 1-, 3-, and 5-day ahead profitability (adjusted for execution costs following equation (6)) for trades that receive low liquidity costs compared to other trades over time. We find that trades with the lowest liquidity costs outperform by roughly four percentage points in the first week of the crisis—the same week during which dealers provide the most discounted liquidity to these investors.[14] These findings are consistent with the hypothesis that dealers identify potentially informative trades and offer cheap liquidity to sophisticated investors to gather valuable information.

4.3 Alternative Hypotheses

Our baseline regression already controls for a number of alternative explanations for the trade costs investors receive, such as investor type, trade size, and their relationship with dealers. For instance, if larger or more frequent traders are more valuable clients and typically benefit from lower-cost liquidity, the investor and investor-dealer fixed effects absorb these average effects. However, it is possible that the importance of these factors changes over time. For example, dealer-client relationships may become more significant during periods of market stress, as shown by prior research (Di Maggio et al., 2017). Additionally, some investors might be compensated for supplying liquidity to the market, effectively acting as shadow dealers. These mechanisms are not mutually exclusive with our proposed explanation and we do not claim they are entirely absent. However, in this section, we provide strong evidence that these channels are not the primary drivers of our results.

4.3.1 Relationships

A potential concern with our baseline results is that dealers grant discounted liquidity to their most valuable clients, consistent with previous studies (Di Maggio et al., 2017; Jurkatis et al., 2023). Table 10 includes controls for common measures of trading relationships,

[14] We also observe two additional periods, late August and mid-October, where, to a lesser extent, dealers discount less profitable trades. These coincide with periods of high uncertainty from rapidly rising yields in August and the end of the BoE's asset purchases in October.

demonstrating that the time-varying components of these factors do not drive our results.[15] In column (1), we control for the investor's share of the dealer's trading business in the pre-crisis period as a proxy for potential future trading revenue. Column (2) uses investor size, measured by turnover in the pre-period, as a proxy for client value, with similar results. Column (3) includes the number of trades (sometimes referred to as trade intensity), while column (4) controls for all of these factors simultaneously. In each case, the coefficient for informed traders remains virtually unchanged, strongly suggesting that our baseline results are not driven by the average or time-varying effects of trading relationships.

4.3.2 Investors' Liquidity Provision

A final alternative hypothesis is that the investors we classify as having an informational edge are instead being compensated for providing liquidity in a one-sided market. Specifically, these investors might be acting as shadow dealers if traditional dealers are unwilling or unable to absorb clients' selling pressure. While we do not dismiss the possible existence of this mechanism, we provide evidence that it does not explain our findings. If our categorization of informed investors was inadvertently capturing the compensation for investors' supply of liquidity to dealers, we would expect this to be reflected in the transaction types, investor behavior, and dealer positions.

First, we examine the type of transactions receiving discounts. Column (1) of Table 11 excludes bonds being "fire sold" by pension funds and liability-driven investors. If the investors we classify as informed were being compensated for purchasing bonds offloaded by distressed pension and LDI funds (PFLDI), we would expect dealer discounts to be

[15] Here, we define relationships as the potential revenue from future transactions. While our focus is on information rather than relationships in this traditional sense, one could interpret our mechanism as valuing a trading relationship because of the potential information an investor may reveal, rather than direct revenues. This distinction is crucial because, for dealers to monetize the "payment" of information in exchange for liquidity, they must trade against uninformed investors—i.e. a key spillover channel to broader market liquidity.

concentrated in those specific bonds. Instead, the results show that our findings are not driven by the segments of the market where liquidity was most urgently needed.[16] Another possibility is that investors provide liquidity to dealers—but not in the bonds under fire sale pressure—thereby easing balance sheet constraints. If our results were driven by this more general client-supplied liquidity, then we should expect dealer discounts to be concentrated in client purchases. Column (2) excludes all client purchases, but our main coefficient remains largely unchanged.

Next, we examine which types of investors are receiving discounts, specifically comparing our informed investor classification with measures that could indicate clients' role in supplying liquidity to dealers. To directly address dealers' potential balance sheet constraints and the sales pressure from distressed investors, we include daily client-dealer net volume (in millions of GBP) as a control in column (3). This measure suggests that dealers provide cheaper liquidity to investors who supply net liquidity, but the coefficient on informed investors remains virtually unchanged from the baseline, supporting the notion that the informational channel operates independently of client liquidity supply. Column (4) refines this further by using the inverse hyperbolic sine of daily investor-dealer net volume, which serves a similar function compared to a log transformation but can also accommodate negative values. The results again indicate that net liquidity supply does not explain our proposed mechanism.

Finally, we study which dealers provide discounts. Column (5) controls for the interaction of our main coefficient with dealer inventories. Inventory is calculated as the risk-adjusted net order flow over the month prior to the crisis, normalized by dealer turnover in the pre-period, a proxy for dealer size. Positive values indicate that dealers have increased their bond holdings, while negative values indicate inventory reduction. If dealers' need to reduce their inventories due to balance sheet constraints (such as regulatory or internal risk limits)

[16] We classify a bond as being fire-sold by the PFLDI sector when it falls within the top tercile of net sales volume from this sector.

were driving our results, then discounted liquidity costs should be primarily driven those dealers with larger inventories. If that were the case, we would expect the interaction with dealer inventories to absorb the significance of our main coefficient. However, the results show that this is not the case.

Taken together, these tests strongly suggest that our baseline results are not driven by clients' supply of liquidity to dealers during the crisis.

5 Dealers' Use of Information

5.1 Empirical Strategy

In the preceding analyses, we found that during the crisis, dealers were significantly more likely to provide cheaper liquidity to informed investors. If liquidity is redistributed, at least in part, to these informed investors, the natural follow-up questions are: from whom is liquidity being redistributed, and how do dealers use the information they gain?

Once dealers acquire this information, they have two main ways to extract value. First, they can charge higher liquidity costs to other investors. Second, they can trade on the acquired information. While trading against clients may generate immediate profits, it risks damaging dealer-client relationships and reputations. In contrast, charging higher liquidity costs preserves relationships but requires a degree of market power to be effective.

We hypothesize that dealers with more information are more likely to raise trade costs (and less likely to trade on their information advantage) in dealer-to-client transactions, where counterparties are known, compared to the anonymous interdealer market. Conversely, we expect that informed dealers are more likely to profit from their informational edge by trading in the interdealer market rather than the dealer-to-client market.

To investigate these hypotheses, we first measure $Informed\ Share_{dt}$ as a given dealer's share of trading volume with informed clients:

$$Informed\ Share_{dt} = \frac{\sum_i^{I_d} Q_{idt} \times Informed_i}{\sum_i^{I_d} Q_{idt}}, \tag{10}$$

where Q_{idt} is the gross volume traded between clients i and dealer d in period t, I_d is the set of investors a particular dealer d trades with, and $Informed_i$ is the indicator for informed investors, as before. Table 4 shows that by our benchmark definition the average daily informed order flow across dealers is 13% over the full sample with a standard deviation of 11%.

Using the lagged $Informed\ Share_{dt-1}$ from the previous trading day, we then estimate a model of the following form, separately for dealer-to-client and interdealer markets:

$$Y_{idbn} = \beta_t Date_t \times InformedShare_{dt-1} + Controls + \epsilon_{idbn}, \tag{11}$$

where $Y_{idbn} \in \{Trade\ Cost, Performance\}$. The main identification challenge in estimating this model is that $Informed\ Share_{dt-1}$ reflects the outcome of both dealer and client decisions. A key concern is that factors influencing informed investors' trading activity with a dealer might also affect trade costs or profitability. For instance, if a dealer faces funding constraints, it might increase trade costs for reasons unrelated to information, which could, in turn, lead informed investors to reduce their trading with that dealer.

To address these concerns, we adopt a shift-share instrumental variable approach. We start by noting that any given client's quantity of trading with a particular dealer can be expressed as a product of that client's total trading volume and the share of that total allocated to the dealer: $Q_{idt} = Q_{it} \times Share_{idt}$. That is, if an investor i trades £20m in total on a given day across several dealers and 5 million of that is with dealer d, then $Q_{idt} = 5$ million, $Q_{it} = 20$

million, and $Share_{idt} = 0.25$.

To construct the instrument, we then fix these shares to their pre-crisis averages: $\widehat{Q_{idt}} = Q_{it} \times Share_{id,pre}$, so that we have the following:

$$\widehat{Informed\ Share}_{dt} = \frac{\sum_i^{I_d} \widehat{Q_{idt}} \times Informed_i}{\sum_i^{I_d} \widehat{Q_{idt}}}. \tag{12}$$

This instrument captures the time-varying share of informed order flow to a dealer, while excluding any variation caused by changes in dealer-client matching after the crisis begins. Table 12 presents the first stage at both the dealer-day and trade level, with and without fixed effects. The instrument is highly significant and explains a substantial portion of the variation in dealers' informed share, with an F-statistic ranging from 14.8 to 500.2 depending on the specification, indicating its strength as an instrument.

5.2 Higher Trade Costs

We estimate equation (11) for trade costs for uninformed investors in the dealer-to-client market. Unlike previous specifications, we cannot include dealer-time fixed effects in this model, but we still incorporate dealer, time, and transaction size fixed effects. A key feature in this analysis is the inclusion of investor-day fixed effects, which control for variations in liquidity demand (Khwaja and Mian, 2008). This allows for a more precise comparison between two dealers—one with a higher informed order flow and the other with a lower flow—serving the same investor on the same day, thus holding liquidity demand constant.

Figure 8 presents the time-varying coefficients from the 2SLS estimation for dealer-to-client trades. During the crisis, dealers with a one standard deviation higher informed order flow on the previous day increase trade costs for uninformed investors in the dealer-to-client market by 10bps the following day. Economically, this represents an approximately threefold increase relative to the pre-crisis trade costs. Figure 9 runs the regression again, but using an indicator variable capturing whether a dealer is in the top or bottom tercile of informed order flow. It shows that more informed dealers raise trade costs relative to other dealers (left panel), while less informed dealers reduce them (right panel).

Table 13 provides a further analysis on which types of clients face higher trade costs by re-estimating equation (7), using an indicator variable for the highest daily tercile of trade costs as the dependent variable. The results show that larger clients and those who trade more frequently are more likely to face higher trade costs. An examination of the potential impact of bargaining power and trading relationships—measured by the proportion of a dealer's turnover attributable to a specific client and the share of a client's trading volume executed through that dealer—reveals no systematic evidence of these factors influencing liquidity costs.

5.3 Dealers' Trading Performance

The previous analysis shows that during the 2022 LDI crisis, dealers strategically reduced liquidity costs for sophisticated investors to gain access to their information, which they then leveraged to raise trade costs for uninformed investors in the dealer-to-client market. But how do dealers utilize this information? Prior research suggests that dealers use it to trade against uninformed investors (Pinter et al., 2022). We further hypothesize that dealers are more likely to exploit this information in the anonymous interdealer market, where the risk of damaging relationships or reputations is minimized, rather than in the non-anonymous dealer-to-client market.

To explore this, we re-estimate equation (7), using the instrumental variable approach for dealers' informed order flow as outlined in equation (12). Importantly, the regressions control for dealer and time fixed effects.

Figure 10 presents the estimated coefficients for trading returns over 1-, 3-, and 5-day horizons (in black, red, and green, respectively) based on equation (4). The left panel shows that more informed dealers do not earn significant profits by trading against uninformed investors in the dealer-to-client market at any point during the sample. However, the right panel reveals that dealers with a one standard deviation higher informed order flow outperform less informed dealers by 30 to 60bps per trade in the interdealer market during the crisis. These coefficients are economically significant, particularly in a market with approximately £200bn in weekly trading volume.

5.4 Liquidity Supply

We have established that informed dealers increase the cost of liquidity compared to less informed dealers. But how do these dealers adjust the quantities they supply? That is, during a period of fire sales and stress, do dealers with higher informed order flow absorb more or less of the selling pressure? To investigate this, Table 14 shows the effect of dealers' informed order flow on their net bond purchases during the crisis, across a range of increasingly demanding specifications. Specifically, it re-estimates equation (10) using the instrument from equation (12), aggregated at the dealer-day level. The dependent variable, $NetPurchases_{d,t}$ is dealers' daily net order flow (i.e., bond purchases minus their bond sales each day), scaled by the given dealer's standard deviation of net purchases. In the baseline specification with day fixed effects, a one standard deviation increase in the share of a dealer's informed order flow leads to an approximately one third standard deviation reduction in their net bond purchases. Quantitatively and qualitatively similar results are obtained when using risk-adjusted net volume, the inverse hyperbolic sine of net volume, and indicator variables for positive vs. negative net purchases. We also study the non-linearity of the effect, using indicator variables for the high and low terciles of the dependent and independent variables in columns (3)-(6). The result show that more informed dealers are less likely to be net buyers and more likely to be net sellers of gilts.

The observation that better informed dealers both raise liquidity costs and reduce their net purchases, compared to less informed dealers, supports the notion that an increase in the informed order flow induces an inward shift in the market liquidity supply curve.

6 External Validity: COVID-19 Dash for Cash

The previous analysis has focused on the most recent major liquidity crisis in the UK gilt market, namely the 2022 LDI crisis. A reasonable concern is that the dynamics we identified may be unique to that specific event. While granular data for other large markets that have experienced liquidity crises, such as the US, is limited, our dataset does include another relevant episode in the UK. During the COVID-19 pandemic, the government bond market experienced a similar liquidity crisis, known as the Dash for Cash, which occurred alongside comparable crises in the US and the eurozone (Barone et al., 2022; Czech et al., 2022).

Figures 11 and 12 replicate our primary findings for the Dash for Cash episode. The figures indicate that informed investors experienced more favorable trading costs relative to uninformed investors following the onset of the crisis. Moreover, the results highlight that price dispersion was predominantly confined to the dealer-to-client market, with minimal evidence of such dispersion in the anonymous interdealer market. Collectively, these results suggest that the crisis amplification channel we identified is not unique to the 2022 LDI crisis.

7 Conclusion

In this paper, we investigate the role of information in safe asset liquidity crises, with a focus on the 2022 UK LDI crisis. Our findings reveal that during crises, dealers offer cheaper liquidity to high-performing, sophisticated clients while increasing trade costs for the broader market. We interpret this as evidence of dealers shifting their liquidity provision to informed investors to gain insights from their informational edge. Supporting this interpretation, dealers with a higher informed order flow raise trade costs for other clients, and also leverage their informational advantage in anonymous interdealer markets. Importantly, these dynamics were also evident during the COVID-19 Dash for Cash. Our results emphasize the critical role that information plays in liquidity crises, even within markets for safe assets. Our findings also suggest that market design reforms—such as introducing central clearing of safe assets or enabling anonymous trading via all-to-all platforms—may be able to curb dealers' information-chasing behavior and the reallocation of liquidity during crises.

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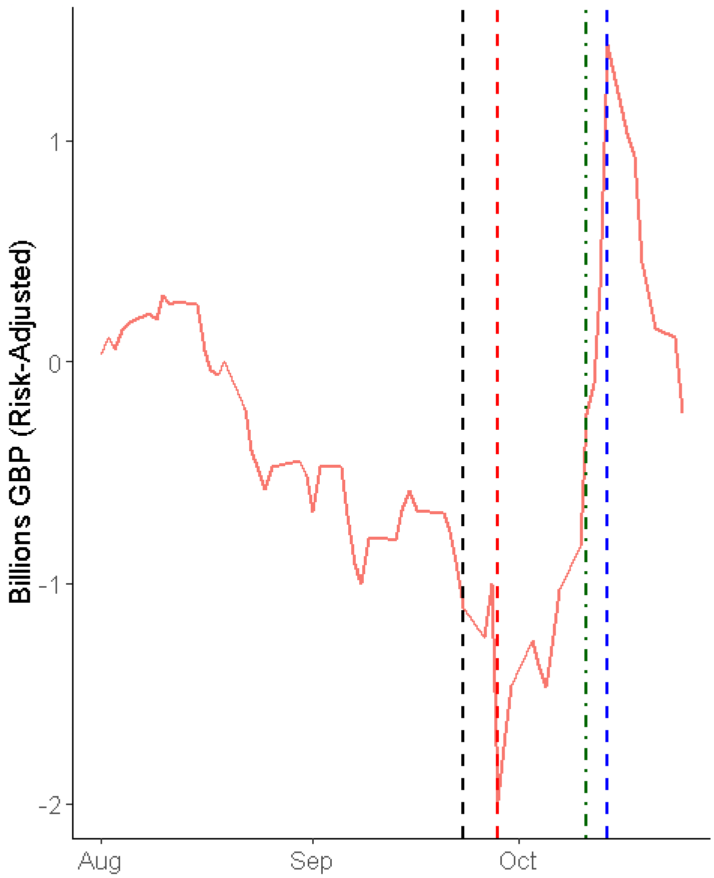
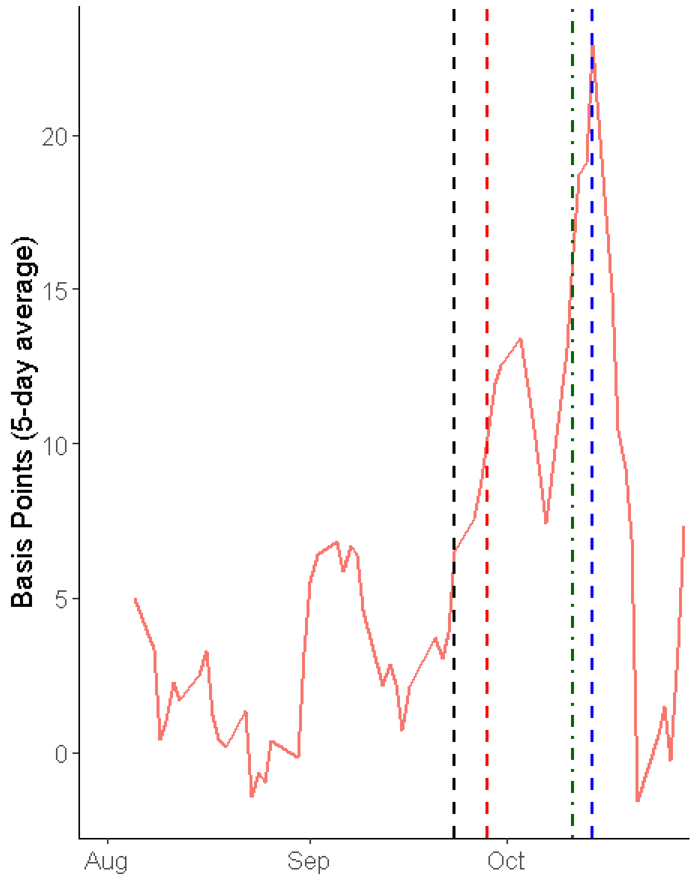
Figures and Tables

Figure 1 Cumulative Dealer Net Order Flow



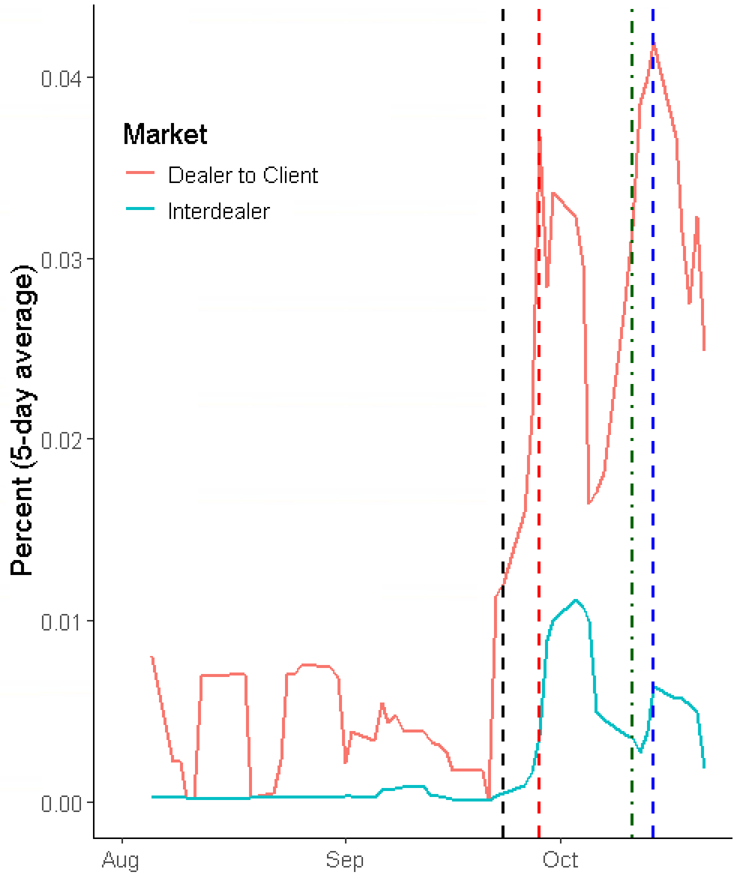
Note: The graph plots the cumulative net order flow of dealers in the gilt market. When it is increasing (decreasing), dealers are net buying (selling). The black line indicates the mini-budget announcement on September 23, the red line indicates the start of the BoE asset purchases on September 28. The green line indicates the expansion of the asset purchases on October 11. And the blue line indicates the conclusion of the BoE market intervention on October 14. The measure is risk-adjusted, so that the interpretation is net units of risk absorbed by dealers. The calculation follows Duffie et al. (2023) C.1., scaling nominal net order flow by DVO1 and implied rate volatility, normalized to monthly 95% Value-at-Risk.

Figure 2 Trade Costs



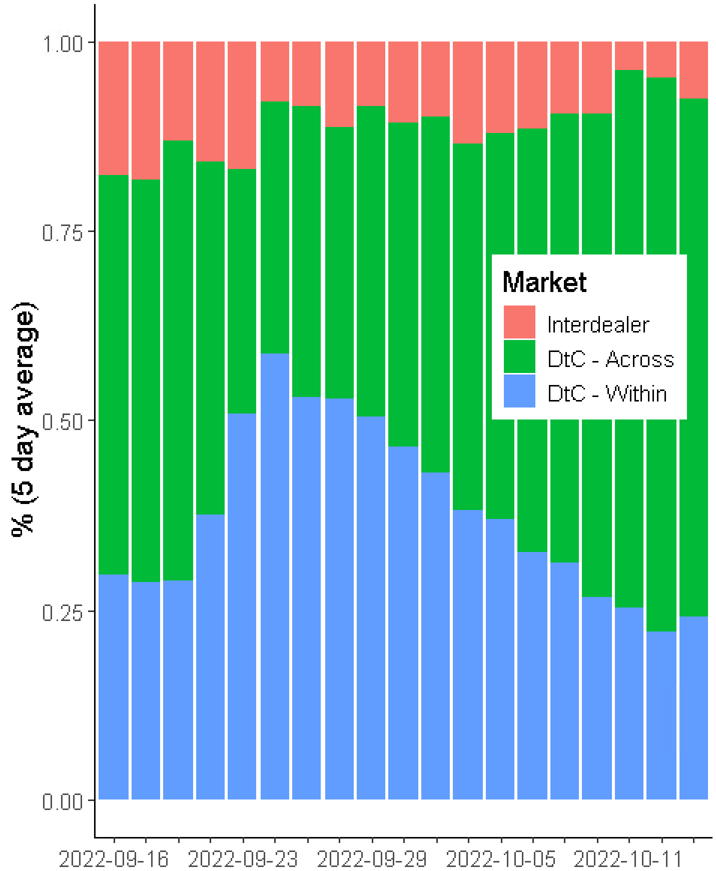
Note: The chart plots the volume-weighted average trade costs across the entire gilt market. The black line indicates the mini-budget announcement on September 23, the red line indicates the start of the BoE asset purchases on September 28. The green line indicates the expansion of the asset purchases on October 11. The blue line indicates the conclusion of the BoE market intervention on October 14. Trade costs are calculated as the log difference of the transaction price with the prevailing interdealer benchmark price for the same bond, scaled to basis points, and then using a 5 day-rolling average.

Figure 3 Price Dispersion in the Dealer-Client and Interdealer Markets



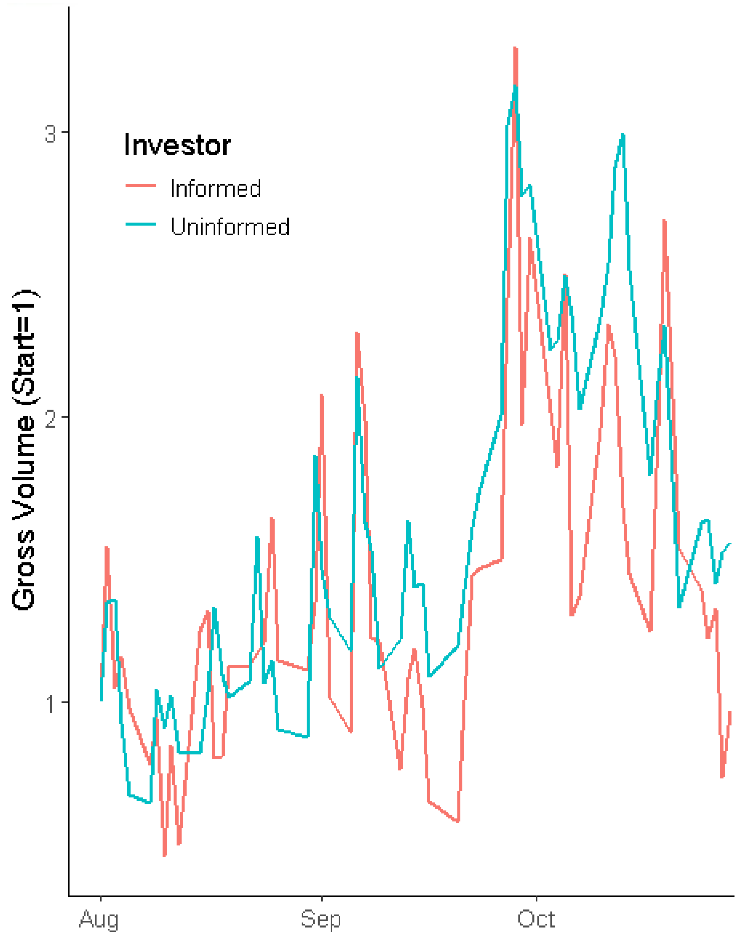
Note: The chart plots the within-dealer price dispersion in the dealer-to client market and the across-dealer price dispersion in the interdealer market, as described in equation (3). The deviations are summed up across bonds and dealers and then plotted as a five-day rolling average. The black line indicates the mini-budget announcement on September 23. The red line indicates the start of the BoE asset purchases on September 28. The green line indicates the expansion of the asset purchases on October 11. The blue line indicates the conclusion of the BoE market intervention on October 14.

Figure 4 Share of Total Price Dispersion



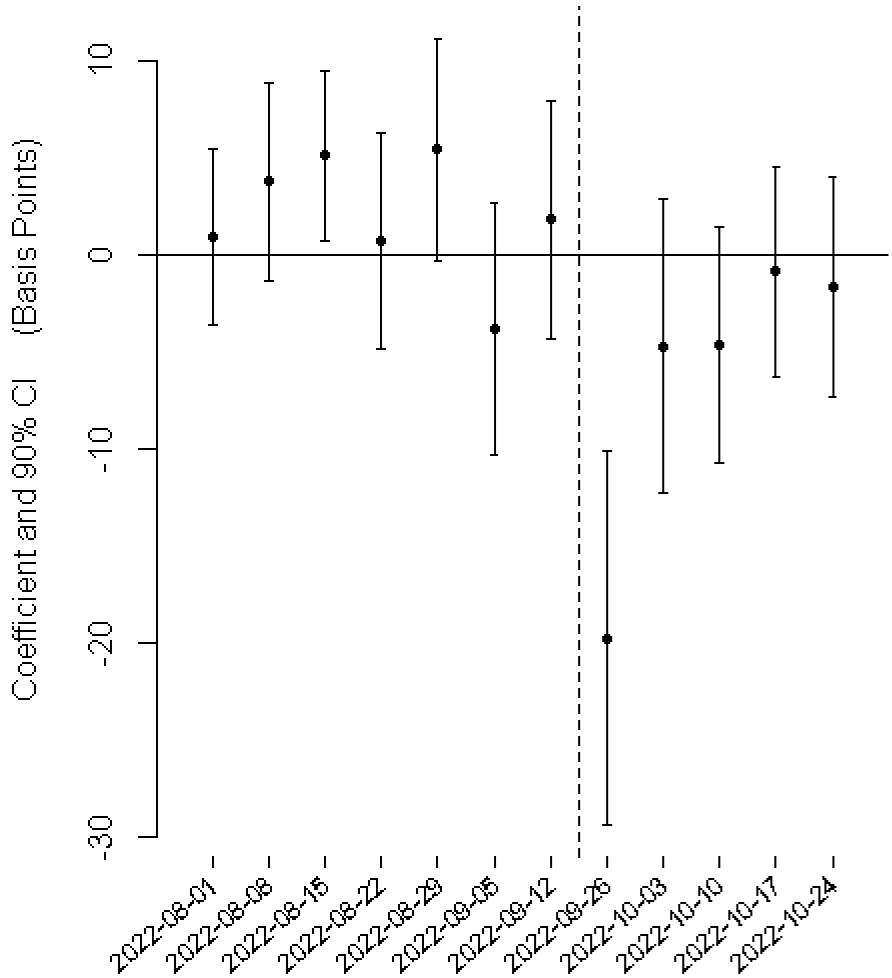
Note: The chart plots the shares of total price dispersion coming from the interdealer market and the dealer-to-client market, with the latter split out between across-dealer and within-dealer price dispersion, as described in equation (3). The deviations are summed up across bonds and dealers, then divided by total price dispersion, and plotted as a five-day rolling average.

Figure 5 Trading Volume: Informed vs. Uninformed Clients



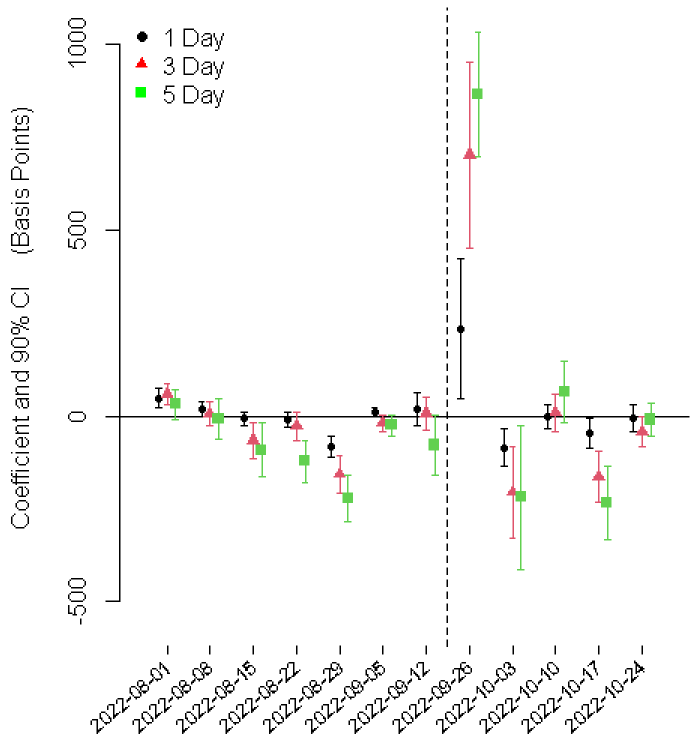
Note: The figure shows the daily gross volume of trading by informed and uninformed investors over the sample, normalized to the pre-crisis period.

Figure 6 Time-varying Trade Costs for Informed Investors



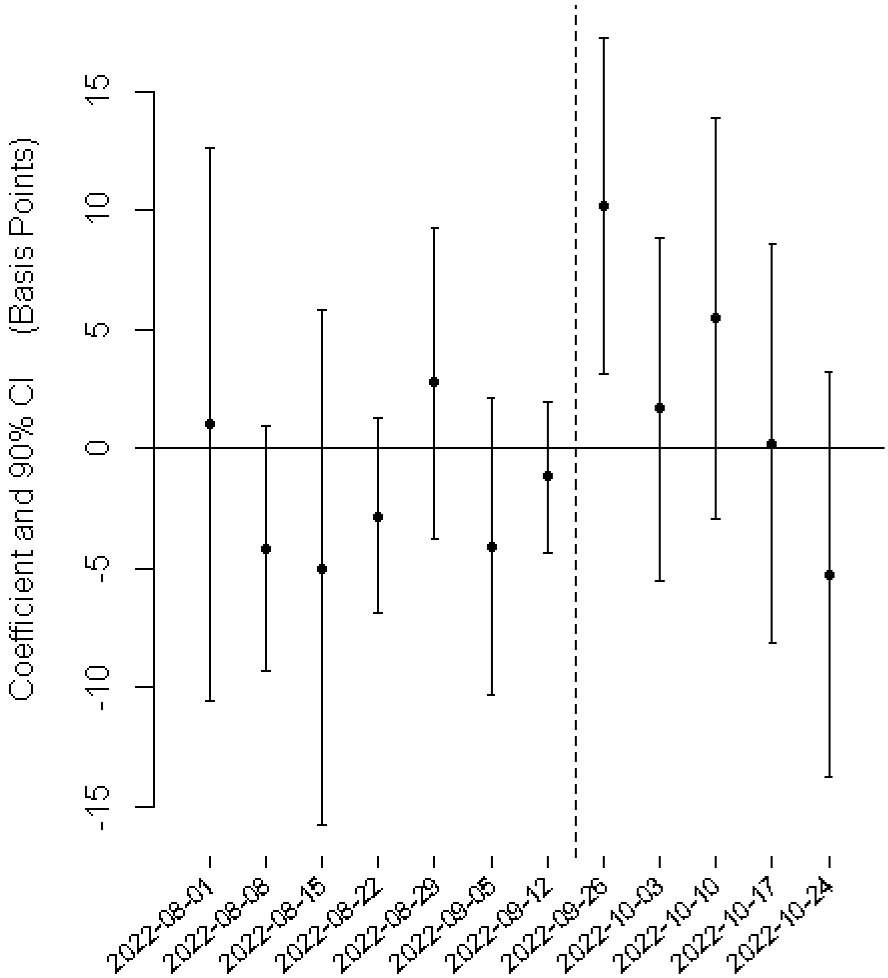
Note: The figure depicts estimates of the transaction costs for informed investors relative to uninformed investors in the same bond, expressed in basis points. The omitted baseline time period is the week before the crisis. The black dashed line indicates the mini-budget announcement on September 23, which triggered the crisis. The coefficients are estimated using equation (7), using volume-weighted trade costs, and controlling for the number of clients' dealer connections as well as dealer-time, investor-dealer and transaction size fixed effects.

Figure 7 TRADE INFORMATIVENESS



Note: The figure depicts time-varying estimates of the returns to informed investors' trades which received low trade costs from dealers, using equation (9). Trades are evaluated over 1, 3, and 5 days (black, red, and green, respectively). Low trade costs are defined as being in the lowest tercile of daily trade costs. The regression controls for dealer-time, investor-dealer, and size fixed effects. The black dashed line indicates the mini-budget announcement on September 23, which triggered the crisis.

Figure 8 Informed Dealers—Trade Costs of Uninformed Clients

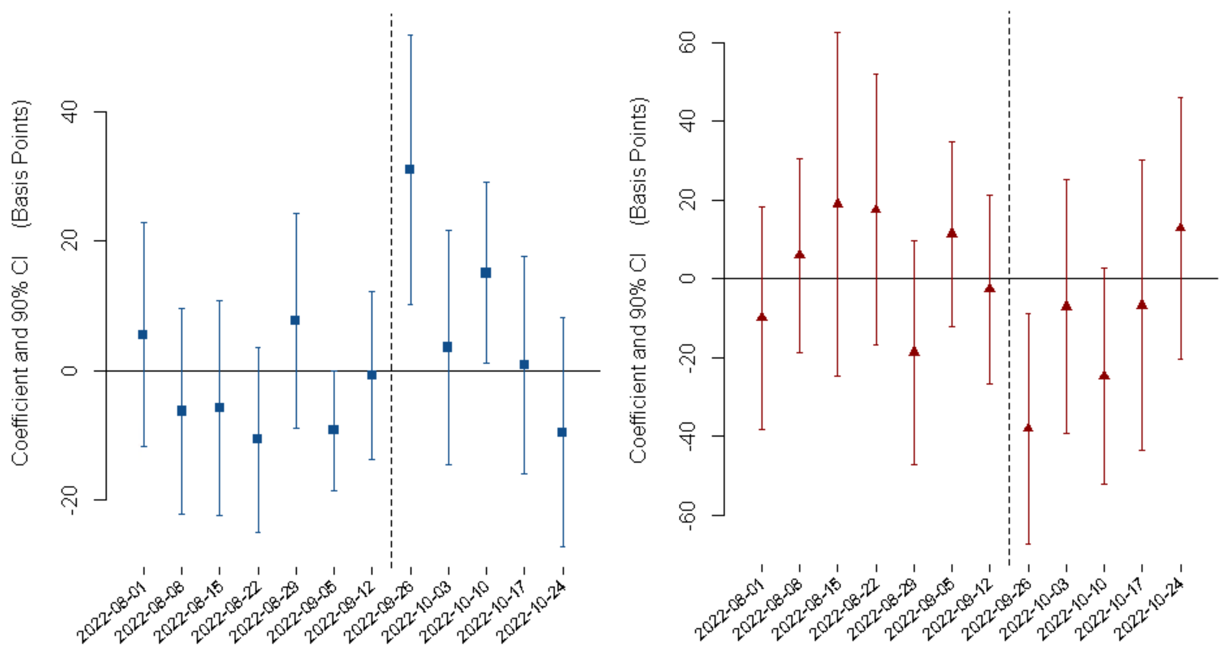


Note: The figure shows the estimates of the sensitivity of trade costs of uninformed clients to dealers' informed order flow, following equation (10). Dealers' informed order flow is instrumented as described in equation (12). The estimates control for dealer, investor-time and transaction size fixed effects. Standard errors are clustered at the dealer and day level. The black dashed line indicates the mini-budget announcement on September 23, which triggered the crisis.

Figure 9 Informed Dealers—Non-Linearity of Trade Costs

(a) Most Informed Dealers

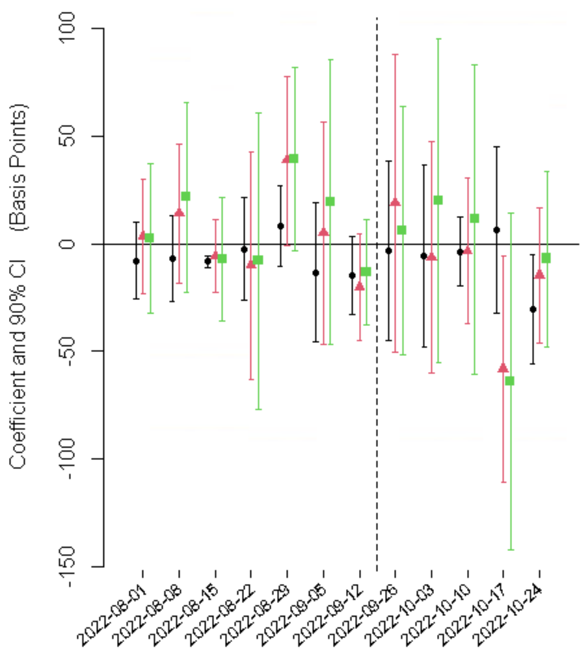
(b) Least Informed Dealers



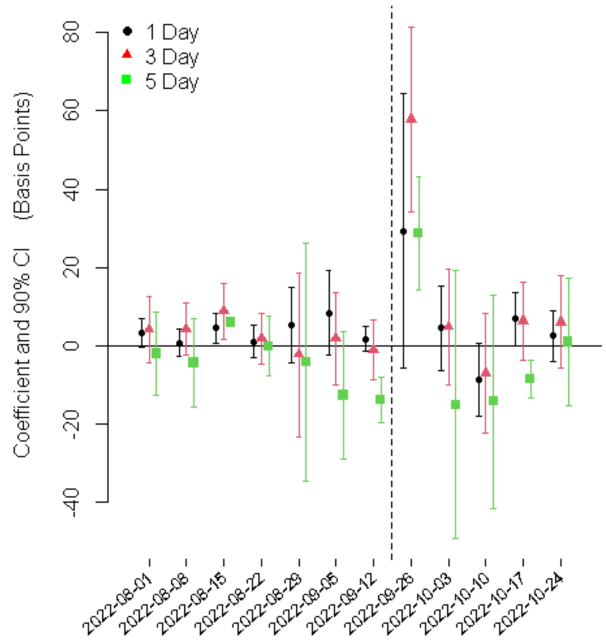
Note: The figure shows the estimates of the sensitivity of trade costs of uninformed investors to dealers' informed order flow, following equation (10), but we now replace *Informed Share* with indicator variables for the highest and lowest terciles of *Informed Share*. Dealers' informed order flow is instrumented as described in equation (12). The estimates control for dealer, investor-time and transaction size fixed effects. Standard errors are clustered at the dealer and day level. The black dashed line indicates the mini-budget announcement on September 23, which triggered the crisis.

Figure 10 Informed Dealers—Trading Performance

(a) Dealer-to-Client

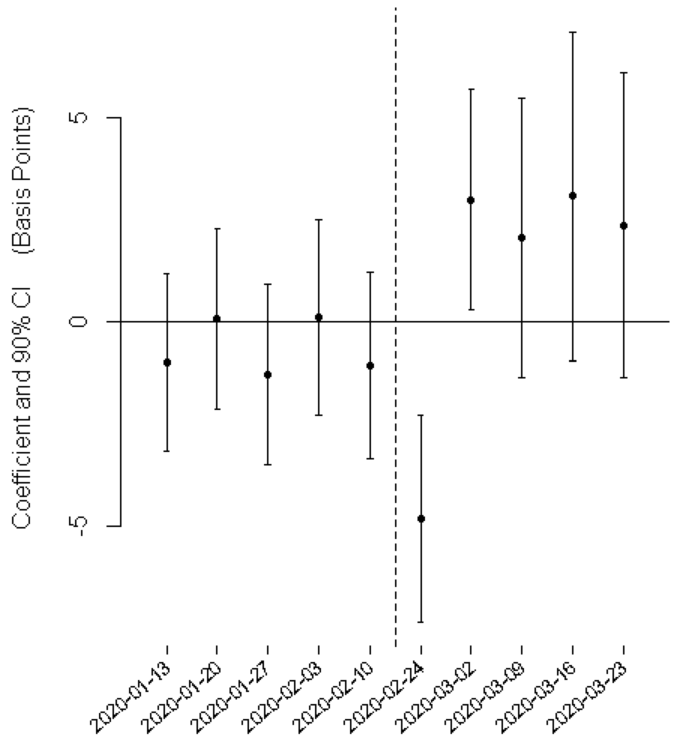


(b) Interdealer



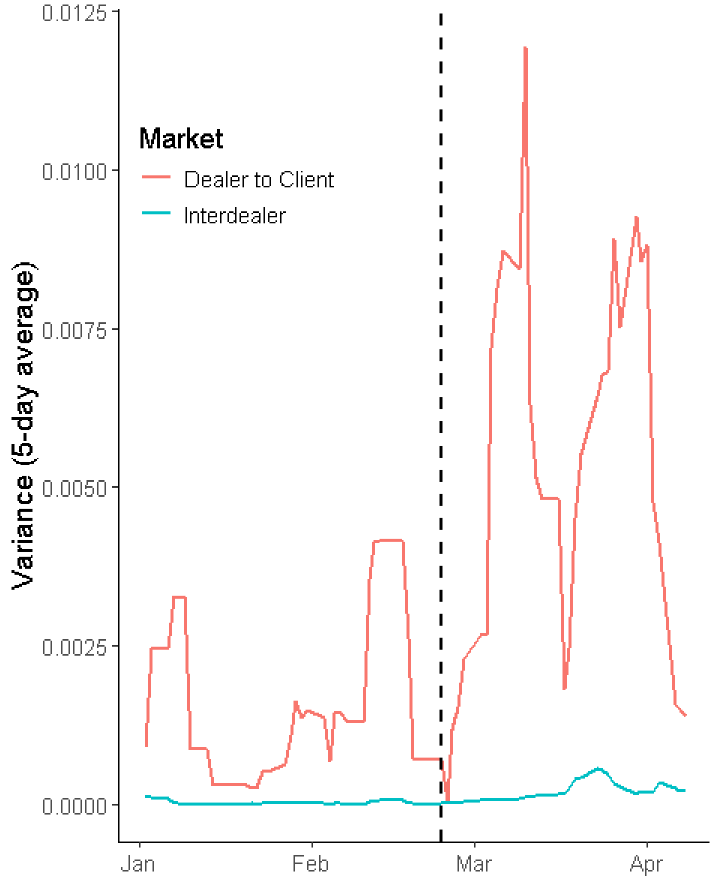
Note: The figure depicts time-varying estimates of the trading returns of dealers with higher informed investor order flow in the dealer-to-client (left) and interdealer market (right), using equation (11). Trades are evaluated over 1, 3, and 5 days (black, red, and green, respectively). Dealers' share of informed order flow is lagged one day and instrumented as in equation (12). The regression controls for dealer and time fixed effects. Standard errors are clustered at the dealer and day level. The black dashed line indicates the mini-budget announcement on September 23, which triggered the crisis.

Figure 11 Trade Costs of Informed Investors during Dash for Cash



Note: The figure depicts estimates of trade costs of informed investors relative to uninformed investors for the same bond during the COVID-19 Dash for Cash, expressed in basis points. It is estimated using equation (7) and controls for clients' dealer connections as well as dealer-time, investor-dealer, and transaction sized fixed effects. The black line indicates the appearance of the first signs of market stress on February 24, 2020. The omitted baseline time period is the week before the onset of the crisis.

Figure 12 Price Dispersion during Dash for Cash



Note: The chart plots the within-dealer price dispersion in the dealer-to client market and the across-dealer price dispersion in the interdealer market during the COVID-19 Dash for Cash, as described in equation (3). The deviations are summed up across bonds and dealers and then plotted as a 5-day rolling average. The black line indicates the appearance of the first signs of market stress on February 24, 2020.

Table 1 CLIENTS TRADE COST - WEIGHTED AVERAGE

	Pre-Crisis	**Crisis**
Informed	3.7	-2.7
Uninformed	2.7	17.9

Note: The table provides statistics on volume-weighted average trade costs of informed and uninformed clients before and during the crisis, expressed in basis points. Trade costs are calculated following equation (1), using the prevailing interdealer prices as the benchmark.

Table 2 CLIENT TRADING VOLUMES

Avg Daily	**Total**	**Informed**	**Avg Informed%**	**Min Informed%**	**Max Informed%**
Number	5,870	454	7.7%	4.8%	12.2%
Volume	45bn	5.6bn	13%	7.5%	20.6%

Note: The table provides statistics on the number and volume of trades by informed investors relative to the rest of the market. For each day in the sample, we calculate the number and volume of trading for all investors (Total) and informed investors, and then the average, minimum, and maximum share of informed investors of the total. For example, the average number of trades in a day by informed investors is 454, out of an average total number of 5,870 trades. Total and informed volumes are expressed in billions of GBP.

Table 3 CLIENT TRADING PERFORMANCE

Informed	Post	N	Mean	SD	p25	p50	p75
Uninformed	Pre-Crisis	54128	-0.34	5.03	-1.46	-0.13	0.83
Uninformed	Crisis	48453	0.35	12.74	-2.87	0.10	3.13
Informed	Pre-Crisis	12558	0.17	4.22	-1.05	0.12	1.47
Informed	Crisis	10318	1.80	13.48	-2.95	0.26	4.61

Note: The table provides statistics on clients' trading returns before and during the crisis, expressed in basis points. Returns are calculated using 3-day ahead trading returns, adjusted for execution costs following equation (6).

Table 4 DEALER STATISTICS

Variable	N	Mean	SD	p25	p50	p75
Gross Volume	882	2.22	2.10	0.73	1.78	3.09
Net Volume	882	-0.02	0.36	-0.13	-0.01	0.07
asinh(Net Volume)	882	-1.98	18.71	-19.37	-16.28	18.69
Informed Share	882	13%	11%	5%	12%	20%

Note: This table provides statistics on the dealers, calculated at the dealer-day level. Gross volumes capture the total quantity a dealer trades in a day, expressed in billions GBP. Net volume is the daily difference between dealer purchases and sales, expressed in billions GBP. asinh(Net Volume) is the inverse hyperbolic sine transformation of net volume. Informed Share is the percentage of daily gross volume of a dealer that can be attributed to trades with informed investors.

Table 5 MAIN RESULTS—TRADE COSTS OF INFORMED INVESTORS

Dependent Variable:			Trade Cost	
Model:	(1)	(2)	(3)	(4)
Variables				
Post × Informed	-18.9***	-15.4***	-17.7***	-13.9**
	(4.92)	(4.91)	(4.81)	(5.79)
Sample:	All	All	Volume-Weighted	AMs + HFs
Fixed-effects				
Client	Yes	-	-	-
Dealer-Time	Yes	Yes	Yes	Yes
TSize	No	Yes	Yes	Yes
Dealer-Client	No	Yes	Yes	Yes
Connections Control	No	Yes	Yes	Yes
Fit statistics				
Observations	124,401	124,401	124,401	65,233
R^2	0.21	0.27	0.40	0.33

Clustered (Investor-Day) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The table estimates the trade costs of an informed investor, relative to an uninformed investor, after the crisis begins. It is estimated using equation (7). Column (1-2) provide different specifications for the main result, with (2) being the baseline. Column (3) re-estimates the baseline, weighting the sample by transaction size. Column (4) re-estimates the baseline, but only on the sample of sophisticated investors (asset managers and hedge funds).

Table 6 Different Trade Cost Measures

Dependent Variables:	Trade Cost	Trade Cost(BBG)	Trade Cost(Mkt)
Model:	(1)	(2)	(3)
Variables			
Post $\times$ Informed	-15.4***	-15.4***	-2.37***
	(4.91)	(4.10)	(0.730)
Fixed-effects			
Dealer-Time	Yes	Yes	Yes
TSize	Yes	Yes	Yes
Dealer-Client	Yes	Yes	Yes
Connections Control	Yes	Yes	Yes
Fit statistics			
Observations	124,401	119,708	111,608
R^2	0.27	0.41	0.27

Clustered (Investor-Day) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The table estimates the trade costs of an informed investor, relative to an uninformed investor, after the crisis begins. It is estimated using equation (7), but using alternative measures for the dependent variable, *Trade Cost*. Column (1) reproduces the baseline for comparison. Column (2) uses the hourly Bloomberg price as the benchmark for calculating trade costs. Column (3) uses the average bond-time price in the entire market (incl. dealer-client trades), excluding the given transaction.

Table 7 Bond Maturity and Type

Dependent Variable:	Trade Cost					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Post × Informed	-4.89	-16.6**	-23.8	-5.87	-22.5**	-71.6**
	(3.17)	(7.75)	(20.7)	(5.17)	(9.58)	(30.1)
Bonds:	$<$10y	$\geq$10y	Inflation	$<$10y	$\geq$10y	Inflation
Weights:	Unw.	Unw.	Unw.	Volume	Volume	Volume
Fixed-effects						
Dealer-Time	Yes	Yes	Yes	Yes	Yes	Yes
TSize	Yes	Yes	Yes	Yes	Yes	Yes
Dealer-Client	Yes	Yes	Yes	Yes	Yes	Yes
Connections Control	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	44,900	47,872	31,629	44,900	47,872	31,629
R^2	0.43	0.41	0.48	0.63	0.52	0.60

Clustered (Investor-Day) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The table estimates the trade costs of an informed investor, relative to an uninformed investor, after the crisis begins. It is estimated using equation (7), splitting the sample by maturity bucket and bond type. Columns (1)-(2) and (4)-(5) use the sample of conventional gilts, split by maturity bucket. Columns (3) and (6) use the sample of inflation-linked gilts. Columns (1)-(3) provide unweighted estimates and Columns (4)-(6) show volume-weighted estimates.

Table 8 ALTERNATIVE MEASURES FOR INFORMED INVESTORS

Dependent Variable:				Trade Cost			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Post × Informed	-16.8***	-15.4***	-16.5***	-19.8***	-16.5**	-23.1***	-17.8***
	(4.82)	(4.91)	(4.95)	(4.73)	(6.54)	(4.48)	(5.96)
Measure:	1 Day	3 Day	5 Day	Risk-Weighted	P&L	Ex Post	Top COVID
Fixed-effects							
Dealer-Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TSize	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dealer-Client	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Connections Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	124,401	124,401	124,401	124,401	124,401	124,401	124,401
R^2	0.27	0.27	0.27	0.27	0.27	0.27	0.27

Clustered (Investor-Day) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The table estimates the trade costs of an informed investor, relative to an uninformed investor, after the crisis begins, using alternative measures of investors' informational advantage, following equation (7). Columns (1)-(3) define informed investors as the top tercile of asset managers and hedge funds based on their money-weighted 1, 3, and 5-day trading performance in the month prior to the crisis, respectively. Column (4) is the 3-day trading performance, weighted by risk-adjusted units, following Duffie et al. (2023). Column (5) measures investors' performance using P&L as in equation (8). Column (6) defines informed investors as the top tercile based on their 3-day ahead returns to the end of the crisis. Column (7) defines informed investors as investors who had the highest 3-day ahead returns during the COVID-19 Dash for Cash.

Table 9 Non-Linearity of Informed Investors' Trade Costs

Dependent Variables:	Low(Trade Cost)	Med(Trade Cost)	High(Trade Cost)
Model:	(1)	(2)	(3)
Variables			
Post × Informed	2.52**	1.65	-4.78***
	(1.21)	(1.15)	(1.22)
Fixed-effects			
Dealer-Time	Yes	Yes	Yes
TSize	Yes	Yes	Yes
Dealer-Client	Yes	Yes	Yes
Connections Control	Yes	Yes	Yes
Fit statistics			
Observations	125,457	125,457	125,457
R^2	0.27	0.30	0.27

Clustered (Investor-Day) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This table estimates the probability of an informed investor facing different levels of trade costs (measured by equation (1)) after the start of the crisis, split into daily terciles. Column (1) is the probability of the transaction costs being in the lowest tercile. Column (2) is the middle tercile and Column (3) is the highest tercile. Coefficients are scaled to percentage points.

Table 10 Dealer-Client Relationships

Dependent Variable:	Trade Cost			
Model:	(1)	(2)	(3)	(4)
Variables				
Post × Informed	-15.7***	-18.8***	-14.5***	-16.5***
	(5.05)	(5.09)	(4.86)	(5.29)
Post × Investor % Dealer	64.7			22.4
	(40.0)			(43.4)
Post × Investor Size		3.37***		2.25
		(0.846)		(1.41)
Post × Trade Intensity			4.15***	1.56
			(1.17)	(1.89)
Fixed-effects				
Dealer-Time	Yes	Yes	Yes	Yes
TSize	Yes	Yes	Yes	Yes
Dealer-Client	Yes	Yes	Yes	Yes
Connections Control	Yes	Yes	Yes	Yes
Fit statistics				
Observations	108,942	118,535	118,535	108,942
R^2	0.24	0.26	0.26	0.24

Clustered (Investor-Day) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The table estimates the trade costs of an informed investor, relative to an uninformed investor, after the crisis begins, controlling for dealer-client relationships, following Pinter et al. (2022). Column (1) controls for the client's share of the dealer's trading business prior to the crisis. Column (2) controls for the client's size, proxied by the log of their turnover in the pre-crisis period. Column (3) controls for client trade intensity, measured by the log of the number of transactions in the pre-crisis period. Column (4) controls for all of these measures simultaneously.

Table 11 Clients' Liquidity Provision

Dependent Variable:			Trade Cost		
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Post × Informed	-16.7***	-12.5**	-14.1***	-11.2**	-16.1***
	(4.94)	(6.31)	(4.90)	(4.79)	(5.51)
Client-Dealer Net Vol			-0.042***		
			(0.009)		
asinh(Client-Dealer Net Vol)				-0.920***	
				(0.086)	
Post × Informed × Inventory					-3.85
					(12.7)
Sample:	No Fire Sales	Sales Only	All	All	All
Fixed-effects					
Dealer-Time	Yes	Yes	Yes	Yes	Yes
TSize	Yes	Yes	Yes	Yes	Yes
Dealer-Client	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	94,396	53,148	124,401	124,401	124,401
R^2	0.32	0.49	0.27	0.27	0.27

Clustered (Investor-Day) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The table estimates the trade costs of an informed investor, relative to an uninformed investor, after the crisis begins, controlling for clients' liquidity provision. Column (1) re-estimates equation (7) excluding bonds fire sold by the pension fund and liability-driven investment fund (PFLDI) sector. Column (2) excludes all client purchases. Column (3) controls for the daily net volume for a given dealer-client pair (from the client's perspective, i.e. a positive measure indicates that the client is a net buyer), in millions GBP. Column (4) controls for the inverse hyperbolic sine of the daily dealer-client net volume. Column (5) controls for the interaction of Post and Informed with dealer inventory, proxied by dealers' cumulative net order flow up to the day before the onset of the crisis.

Table 12 Informed Dealers—First Stage

Dependent Variable:	*Informed Share*			
Model:	(1)	(2)	(3)	(4)
Variables				
$\widehat{Informed\ Share}$	1.37***	1.14***	1.65***	1.24***
	(0.235)	(0.158)	(0.241)	(0.141)
Data:	Dealer-Day	Dealer-Day	Trade Level	Trade Level
Fixed-effects				
Dealer	No	Yes	No	Yes
Day	No	Yes	No	-
Time	No	No	No	Yes
TSize	No	No	No	Yes
Day-Client	No	No	No	Yes
Fit statistics				
Observations	1,065	1,065	290,858	290,858
R^2	0.32	0.55	0.32	0.68
F-test	500.2	14.8	128.1	24.6

Clustered (Dealer-Day) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This table estimates the relationship between dealers' share of informed order flow shown in equation (10) and the instrument described in equation (12). Columns (1) and (2) estimate the relationship at the dealer-day level, excluding and including fixed effects, respectively. Columns (3) and (4) show the results at the trade level.

Table 13 Informed Dealers and High Transaction Costs

Dependent Variable:	High(Trade Cost)			
Model:	(1)	(2)	(3)	(4)
Variables				
Post × Client Size	0.3616*			
	(0.1862)			
Post × Client % Dealer		-1.988		
		(10.80)		
Post × Dealer % Client			-0.9830	
			(1.664)	
Post × Trade Intensity				0.6909***
				(0.2670)
Fixed-effects				
Dealer-Time	Yes	Yes	Yes	Yes
TSize	Yes	Yes	Yes	Yes
Fit statistics				
Observations	119,591	109,998	109,998	119,591
R^2	0.19	0.19	0.19	0.19

Clustered (Investor-Day) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This table estimates the probability of uninformed investors facing trade costs in the highest daily tercile after the start of the crisis. Column (1) interacts *Post* with client Size (proxied by the log of turnover prior to the crisis). Column (2) controls for the client's share of the dealer's trading business prior to the crisis. Column (3) controls for the client's size, proxied by the log of their turnover in the pre-crisis period. Column (4) controls for client trade intensity, measured by the log of the number of transactions in the pre-crisis period. Coefficients are scaled to percentage points.

Table 14 INFORMED DEALERS AND LIQUIDITY PROVISION

Dependent Variables:	Net Purchases		I(Top Purchases)	I(Top Sales)	Net Purchases	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Post × Info. Share_{t-1}	-0.279**	-0.354**	-0.142***	0.122**		
	(0.133)	(0.153)	(0.052)	(0.053)		
Post × High(Info. Share_{t-1})					-1.01**	
					(0.513)	
Post × Low(Info. Share_{t-1})						1.44*
						(0.794)
Fixed-effects						
Day	No	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	863	863	863	863	863	863
R^2	0.002	0.03	0.04	0.07	0.05	0.30

Clustered (Dealer-Day) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This table estimates the effect of dealers' informed order flow on their supply of liquidity to the market. It re-estimates equation (10) using the instrument from equation (12), aggregated at the dealer-day level. The dependent variable $NetPurchases$ captures the daily dealer net order flow (i.e., dealer purchases minus dealer sales), scaled by the standard deviation of the given dealer's net purchases. The independent variable and instrument are standardized. Column (1) estimates the regression without any controls and column (2) re-estimates it with day fixed effects. Column (3) uses an indicator variable equal to one for the top tercile of net dealer purchases and column (4) uses an indicator variable equal to one for the top tercile of dealer net sales. Columns (5) and (6) use indicator variables for the top and bottom terciles of dealers' informed share.