Dealers, Information, and Liquidity Crises in Safe Assets*

Win Monroe† and Robert Czech‡

November 22, 2024

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 gather information. We also document that dealers exploit their informational advantage in anonymous interdealer markets and that similar dynamics are present in other crises. These behaviors reverse when central bank interventions restore market liquidity, thereby mitigating the effects of dealers' information chasing and reallocation of liquidity.

*We are grateful for the valuable guidance and support from Win's advisors, Marcin Kacperczyk and Jose Luis Peydro. We also received helpful feedback from Markus Bak-Hansen, Luis Brandao-Marques, David Cashin, Jamie Coen, Lauri Esala, Andrea Fabiani, Peter Hoffman, Raj Iyer, John Kandrac, Marco Macchiavelli, Marco Di Maggio, Ailsa Roell, Edu Seyde, Savitar Sundaresan, and Basil Williams, as well as conference and seminar participants at the Bank of England, European Economic Association Conference, HEC PhD Finance Workshop, and the Imperial College London PhD Economics and Finance Conference. The views expressed in this paper are those of the authors and not necessarily those of the Bank of England or its committees.

†Imperial College Business School, w.monroe19@imperial.ac.uk

‡Bank of England, robert.czech@bankofengland.co.uk

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, who act as market makers by providing liquidity through buying and selling on demand, have emphasized factors like balance sheet constraints—such as regulations (Duffie et al., 2023) and 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 insight 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 government bond (gilt) market crisis in the UK. This episode provides an excellent setting to study information in safe asset liquidity crises. In addition to having unique administrative micro-data, the UK has a large, otherwise safe and liquid government bond market, with a dealer-based OTC market structure similar to other major safe government bond markets, such as the United States and Japan. The crisis began on September 23, when Chancellor Kwasi Kwarteng unveiled the expansionary "Mini-Budget" in the UK Parliament, followed by 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, which captures almost all 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 investors 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 (30 minutes in the baseline), further refining our comparisons between trades. 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 demand for specific securities and financial conditions (e.g., interest rate expectations, 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 then use a two-way fixed effects model to compare the trade costs dealers charge informed investors versus their other clients, both before and during the crisis. To validate this approach, we provide time-varying estimates to inspect the parallel trends assumption and confirm that our classification of informed investors is not picking up other potential sources for discounted liquidity.

In the second stage, we study how dealers change their behavior after trading with informed investors, adjusting their pricing and liquidity supply and trading behavior. We do so by comparing dealers with higher versus lower informed order flow. However, a dealers' informed order flow is endogenous, reflecting the outcome of both dealer and investor decisions. To address potential endogeneity, we use a shift-share instrumental variable based on dealers' pre-crisis trading patterns. We also control for investors' demand for liquidity through investor-time fixed effects, allowing us to directly compare the liquidity supplied by two

[1] We find qualitatively similar results using future performance through the crisis and from similar past crises, consistent with there being persistence in investors trading ability.

dealers—one with more informed order flow and one with less—for the same investor.

In our first set of results, we find that dealers significantly reduced liquidity costs for informed investors, consistent with theories theories that predict information chasing. This pattern is already visible in the raw data, which shows both an absolute decline in trade costs and relative one compared with uninformed investors, as can be seen in Table 1. Even in our most demanding econometric model, informed investors faced trade costs that were on average 20 basis points (bps) 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 investors and dealers, we show that our results are not driven by pre-existing relationships. Additionally, we account for instances where investors provide liquidity to dealers, confirming that while dealers compensate for liquidity provision, it does not explain the observed cost reductions. Furthermore, using dealer-time fixed effects—comparing the trade costs of different investors 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 gilt market 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-investor relationships and dealer balance sheet constraints. The results reinforce the importance of understanding how market structure affects 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 suggests different predictions for market outcomes and has 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 gilt market 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 Dash for Cash episodes in the US, UK, and the European Union during the COVID-19 pandemic (2020) and the gilt market crisis in the UK (2022), have revealed 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 gilt market 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 US Treasury markets. In their analysis, when dealer balance sheets are near their limits, their ability to intermediate decreases, leading to heightened illiquidity. Pinter (2023) demonstrate that strategic delays by hedge funds seeking to time market entry before policy interventions exacerbated market stress during the 2022 gilt market crisis.

In contrast to this existing work, our research identifies and examines an alternative amplification mechanism rooted in how dealers allocate liquidity during market turmoil. 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 also connects 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 intu-

[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 gilt market 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).

ition, 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.

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 dealer "information chasing" can exacerbate market stress by altering liquidity dynamics during periods of crisis.

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 and 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 reacting 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); 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 times of crisis.

3 Data, Measures, and Stylized Facts

3.1 Data

Our analysis leverages MiFID II regulatory data, which covers the entire universe of UK government bond (gilt) transactions from January 2018 onwards. For this study, we primarily focus on the period surrounding the UK gilt market crisis, spanning from August 2022 to October 2022. The crisis was triggered by the "Mini-Budget" announcement from UK Chancellor Kwasi Kwarteng on September 23, which led to 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.

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 largest dealers, covering all bonds in the gilt market.

The MiFID II data is highly granular and comprehensive, capturing almost the entire universe of gilt trades. 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 a given dealer's different clients, 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 post-pandemic inflation. However, these yield increases occurred in orderly markets until the announcement of the UK Mini-Budget on September 23. The policy announcement, followed by the Chancellor's reiteration of the Mini-Budget over the subsequent weekend, triggered sharp market disruptions. In its aftermath, margin calls and forced asset sales began to escalate into a severe liquidity crisis as investors sought to deleverage their positions (Alfaro et al., 2024).

Dealers' negative net order flow (i.e. net sales) in gilts accelerated the liquidity stress, contributing to the worsening crisis. As shown in Figure 1, the increased selling pressure from dealers compounded the illiquidity in the gilt market, further amplifying financial instability. The magnitudes are economically significant, representing approximately 10% of volume over the sample.

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 taking a 5-day rolling average. Trade costs increased from 3 basis points before the mini-budget, to 24 after. 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 liquidity, occurs when the same bond trades at different prices simultaneously across 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 trade cost risk for investors, as the lack of price uniformity makes it more expensive and uncertain to execute transactions efficiently. 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 that 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 Bank of England (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, across-dealer price dispersion in the interdealer market remained relatively stable.

[5] We only include bonds that were traded at least twice by the same dealer within a given period to ensure that the observed price dispersion is meaningful.

The interdealer market's centralized and anonymous nature provides a useful comparison, as dealers in this market cannot differentiate between their counterparties. Given the interdealer market's liquidity and non-informational characteristics, its price dispersion serves as an approximate upper bound for the portion of trade cost dispersion driven by 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 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 tend to differentiate their trade costs more across clients, reflecting a more targeted distribution of liquidity.

3.4 Definition of Informed Investors

We hypothesize that during periods of crisis, 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 adjusting for transaction costs:

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

Intuitively, the adjusted trade performance measure assumes each investor only receives the average transaction price of the bond rather than the actual price they received, stripping out the role of execution costs in trading profitability, isolating the component arising from predicting the direction of bond prices. We then average each investor's performance, weighted by transaction size, and sum the daily returns.

During the crisis, a subset of sophisticated investors exhibited particularly strong performance. 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". These informed investors are likely perceived by dealers to have an edge based on their recent 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.[6]

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 higher transaction costs before the crisis, which decrease significantly during the crisis. Uninformed clients have comparable pre-crisis average transaction costs, but they 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 and aggregate size.

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

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 within-dealer 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 engaging.

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, 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 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 a binary variable that equals 1 after the crisis begins on September 23, while $Informed_i$ is an indicator 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 described earlier. This classification remains robust across various alternative definitions.

The richness of our data allows us to use fine-grained 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. 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 transaction size composition. Additionally, we control for the number of dealers an investor trades with daily ($Connections_{it}$) to address potential strategic behavior where investors might split trades across multiple dealers to reduce liquidity costs rather than trade on information.[7]

Private information is generally unobservable, making identification challenging. Our identifying assumptions are (1) that prior investor 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 crisis shock, after conditioning

[7]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.

on our controls.[8] In the following subsections we provide evidence to support theses 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 that our results are not driven by trading relationships or compensation for investors' liquidity provision.

Figure 6 estimates equation 7 as a weekly time-varying model and provides evidence in support of the parallel trends assumption. The figure also 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.

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 15bps lower than their uninformed counterparts. This effect is pronounced but short-lived. 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 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 (1) reproduces the baseline for comparison. Column (2) alters the 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

[8]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.

lower, reflecting the fact that the full-market benchmark includes higher average transaction 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 informational channel. Table 7 re-estimates our baseline specification, but for sub-samples 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 sophisticated investors' trades in forecasting short-term price movements (Czech et al., 2021b). However, recognizing that alternative measures of superior trading 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. Column (1) shows the baseline 3-day ahead trading performance. Column (2) extends this to 5-day ahead performance, while column (3) introduces a risk-weighted version of the 3-day ahead trading performance, which adjusts for risk-adjusted volumes.[9]

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, 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.[10] Column (4) reports the funds' cumulative P&L during the crisis, normalized by trading volume, and finds nearly identical results.

Identifying informed investors is a complex and state-dependent process, as different investors may have informational advantages at different times. For example, macro hedge funds may

[9]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.

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

have an edge during crises, while relative value funds might outperform in more stable conditions. Ideally, we would analyze a comparable episode in the same market with the same investors to observe how they performed, revealing their informational advantage in a similar context.

The COVID-19 Dash for Cash offers such an episode: a period marked by macroeconomic stress, policy uncertainty, and a liquidity crisis in the gilt market. In Column (5), we use the top tercile of sophisticated investors based on their performance during the Dash for Cash and find nearly identical results. This aligns with prior research, which highlights that different investors possess distinct sources of informational edge (Czech et al., 2021b). This may explain why dealers tend to pursue information from investors they believe have state-specific informational advantages.

4.1.2 Non-Linearity

We hypothesize that the mechanism we propose is highly non-linear. Informed investors represent a small subset of high-performing traders with information that is significantly more valuable than the savings they receive from improved liquidity costs. Therefore, we expect dealers to offer substantial incentives in the form of lower trade costs.

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

These estimates also provide additional robustness against the possibility that increased overall trade cost dispersion could skew our results. Specifically, heightened volatility could cause transaction prices to deviate more from their benchmarks within a fixed window, potentially inflating our transaction cost measure. By scaling transaction costs within their daily distribution, we confirm that informed investors still benefit from lower costs, even amid 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 dummy 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:

$$AdjPerf(Informed)^{T}_{idbn} = \beta_t Date_t \times Low(TradeCost)_{in} + \mu_{dt} + \gamma_{id} + Size_n + \epsilon_{idbn}. \quad (9)$$

A positive coefficients β captures the average returns of a discounted trade compared with 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.[11] 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 much of the variation stemming from alternative explanations for the pricing 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 supported by empirical research (Di Maggio et al., 2017). Additionally, some investors might be compensated for supplying liquidity to the market, effectively acting as shadow dealers. While these mechanisms are not mutually exclusive with our proposed explanation, 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,

[11] 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.[12] 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 sales pressure. While we do not dismiss the possibility 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 purchases of 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, we would expect dealer discounts to be con-

[12] 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—a key spillover channel to broader market liquidity in our hypothesis.

centrated 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.[13] 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 investor purchases. Column (2) excludes all investor purchases, but our main coefficient remains virtually unchanged.

Next, we examine which types of investors are receiving discounts, specifically comparing our informed investor classification with measures that could indicate investors' role in supplying liquidity to dealers. Investors trading frequently with dealers could potentially serve as a release valve for dealers in an imbalanced market. In column (3), we account for the log of daily gross volume between each investor-dealer pair to assess this possibility. Next, to directly address dealers' potential balance sheet constraints and the sales pressure from distressed investors, we include daily investor-dealer net volume (in millions of GBP) as a control in column (4). 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 (5) 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 (Alfaro et al., 2024). The results again indicate that net liquidity supply does not account for our measure of investors' informational edge.

Finally, we study which dealers provide discounts. Column (6) controls for the interaction

[13] This exclusion covers gilts with maturities of 10-19 years from the mini-budget announcement (September 23) to the end of the sample, 20+ year gilts from the mini-budget until the BoE's initial asset purchases on September 18, and inflation-linked gilts until October 11, when the BoE expanded its asset purchases to include these bonds.

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 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) 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 investors' 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 $InformedShare_{dt}$ as a given dealer's share of trading volume with informed clients:

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

where Q_{idt} is the gross volume traded between investors 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.

Using the lagged $InformedShare_{dt-1}$ 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 $Y_{idbt} \in \{TradeCost, TradeProfits\}$. The main identification challenge in estimating this model is that $InformedShare_{dt-1}$ reflects the outcome of both dealer and investor 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 investor's quantity of trading with a particular dealer can be expressed as a product of that investor'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:

$$\widehat{InformedShare}_{dt} = \frac{\sum_i^{I_d} \widehat{Q_{idt}} \times Informed_i}{\sum_i^{I_d} \widehat{Q_{idt}}}, \tag{12}$$

This instrument captures the time-varying share of informed order flow to a dealer, while excluding any variation caused by changes in investor-dealer 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 correlated 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 improvement 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 representing approximately a 3X increase in the pre-crisis cost of liquidity.

Table 13 provides a further analysis on which types of investors face higher trade costs by re-estimating equation 7, using an indicator for the highest daily tercile of trade costs as the dependent variable. The results show that larger investors and those who trade more frequently are more likely to receive higher trade costs. However, when we assess the potential impact of bargaining power and trading relationships—quantified by the proportion of a dealer's business represented by an investor and the share of an investor's trades handled by that dealer—we find no consistent pattern influencing these liquidity costs.

5.3 Dealers' Trading

The previous analysis shows that during the 2022 gilt market crisis, dealers strategically shifted liquidity costs away from sophisticated investors to access 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 9 presents the estimated coefficients for trade profitability over 1-, 3-, and 5-day horizons (in black, red, and green, respectively) based on equation 4. The top 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 bottom panel reveals that dealers with a one standard deviation higher informed order flow outperform less informed ones by 50 to 75bps per trade 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 more information absorb more or less 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, $NetVolume_{d,t}$ is the net volume a dealer trades in a day, scaled by each dealer's standard deviation. In the most stringent specification, a one standard deviation increase in the share of a dealer's informed order flow leads to approximately a one quarter 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.

The observation that dealers with more informed order flow both raise liquidity costs and reduce the quantity supplied, compared to less informed dealers, supports the notion that information 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 gilt market 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 Germany (Barone et al., 2022; Czech et al., 2022).

Figures 10 and 11 replicate our primary findings for the Dash for Cash episode. These figures demonstrate that informed investors received more favorable trade costs compared to uninformed investors once the crisis began. Additionally, they show that within-dealer price dispersion was concentrated in the dealer-to-client market, not in the anonymous interdealer market. Collectively, these results suggest that the crisis amplification channel we identified is not unique to the 2022 gilt market crisis.

7 Conclusion

Recent market liquidity crises in traditionally safe assets have triggered the most aggressive central bank interventions in modern history, prompting researchers and policymakers to reevaluate their understanding of liquidity crises in financial systems that are increasingly shifting from bank-based to non-bank-based models. Key questions surrounding what causes and amplifies these crises, and how policy should respond, remain central to financial stability discussions.

Our findings reveal that during crises, dealers offer cheaper liquidity to high-performing, sophisticated investors while increasing liquidity costs for the broader market. We interpret this as evidence of dealers reallocating liquidity to gain insights from investors with an informational edge. Supporting this interpretation, dealers with more 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.

References

Abreu, D. and M. K. Brunnermeier (2003): "Bubbles and crashes," *Econometrica*, 71, 173–204.

Alexander, P., R. Fakhoury, T. Horn, W. Panjwani, and M. Roberts-Sklar (2023): "Financial stability buy/sell tools: a gilt market case study," *Bank of England Quarterly Bulletin*.

Alfaro, L., S. Bahaj, R. Czech, J. Hazell, and I. Neamțu (2024): "LASH risk and Interest Rates," *Bank of England Working Paper No. 1,073*.

Barbon, A., M. Di Maggio, F. Franzoni, and A. Landier (2019): "Brokers and order flow leakage: Evidence from fire sales," *The Journal of Finance*, 74, 2707–2749.

Barone, J., A. P. Chaboud, A. Copeland, C. Kavoussi, F. M. Keane, S. Searls, et al. (2022): "The Global Dash for Cash in March 2020," *Federal Reserve Bank of New York*.

Bilan, A., S. Ongena, and C. Pancaro (2023): "Information Chasing or Adverse Selection: Evidence from Bank CDS Trades," *Mimeo*.

Cashin, D., E. E. S. Ferris, and E. Klee (2023): "Treasury Safety, Liquidity, and Money Premium Dynamics: Evidence from Debt Limit Impasses," *Journal of Money, Credit and Banking*, 55, 1475–1506.

Czech, R., B. Gual-Ricart, J. Lillis, and J. Worlidge (2021a): "The Role of Non-bank Financial Intermediaries in the 'Dash for Cash' in Sterling Markets," *Bank of England Financial Stability Paper No. 47*.

Czech, R., S. Huang, D. Lou, and T. Wang (2021b): "Informed trading in government bond markets," *Journal of Financial Economics*, 142, 1253–1274.

Czech, R., S. Huang, D. Lou, T. Wang, et al. (2022): "An unintended consequence of holding dollar assets," *Bank of England Staff Working Paper No. 953*.

Dang, T. V., G. Gorton, and B. Holmström (2020): "The information view of financial crises," *Annual Review of Financial Economics*, 12, 39–65.

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

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

Duffie, D. (2010): "Presidential address: Asset price dynamics with slow-moving capital," *The Journal of Finance*, 65, 1237–1267.

——— (2020): "Still the world's safe haven? Redesigning the US Treasury market after the COVID-19 crisis," *Brookings Institution*.

Duffie, D., M. J. Fleming, F. M. Keane, C. Nelson, O. Shachar, and P. Van Tassel (2023): "Dealer capacity and US Treasury market functionality," *FRB of New York Staff Report No 1070*.

Fleming, M. J. and E. M. Remolona (1999): "Price formation and liquidity in the US Treasury market: The response to public information," *The Journal of Finance*, 54, 1901–1915.

Gorton, G. (2017): "The history and economics of safe assets," *Annual Review of Economics*, 9, 547–586.

Gromb, D. and D. Vayanos (2002): "Equilibrium and welfare in markets with financially constrained arbitrageurs," *Journal of Financial Economics*, 66, 361–407.

Hauser, A. (2023): "Looking through a glass onion: lessons from the 2022 LDI intervention," *Bank of England Speech*.

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

Jurkatis, S., A. Schrimpf, K. Todorov, and N. Vause (2023): "Relationship discounts in corporate bond trading," *Bank of England Staff Working Paper No. 1049*.

Kacperczyk, M. and E. S. Pagnotta (2019): "Chasing private information," *The Review of Financial Studies*, 32, 4997–5047.

Khwaja, A. I. and A. Mian (2008): "Tracing the impact of bank liquidity shocks: Evidence from an emerging market," *American Economic Review*, 98, 1413–1442.

Kondor, P. and G. Pinter (2022): "Clients' Connections: Measuring the Role of Private Information in Decentralized Markets," *The Journal of Finance*, 77, 505–544.

Kruttli, M. S., M. Macchiavelli, P. Monin, and X. A. Zhou (2023a): "Liquidity Provision in a One-Sided Market: The Role of Dealer-Hedge Fund Relations," *Unpublished Working Paper*.

Kruttli, M. S., P. Monin, L. Petrasek, and S. W. Watugala (2023b): "LTCM redux? Hedge fund Treasury trading and funding fragility," *Unpublished Working Paper*.

Kyle, A. S. (1985): "Continuous auctions and insider trading," *Econometrica*, 1315–1335.

Lagos, R., G. Rocheteau, and P.-O. Weill (2011): "Crises and liquidity in over-the-counter markets," *Journal of Economic Theory*, 146, 2169–2205.

Ma, Y., K. Xiao, and Y. Zeng (2022): "Mutual fund liquidity transformation and reverse flight to liquidity," *The Review of Financial Studies*, 35, 4674–4711.

Naik, N. Y., A. Neuberger, and S. Viswanathan (1999): "Trade disclosure regulation in markets with negotiated trades," *The Review of Financial Studies*, 12, 873–900.

O'Hara, M. and X. A. Zhou (2021): "Anatomy of a liquidity crisis: Corporate bonds in the COVID-19 crisis," *Journal of Financial Economics*, 142, 46–68.

Pinter, G. (2023): "An anatomy of the 2022 gilt market crisis," *Bank of England Staff Working Paper No. 1019*.

Pinter, G., C. Wang, and J. Zou (2022): "Information chasing versus adverse selection," *Bank of England Working Paper*.

Ramadorai, T. (2008): "What determines transaction costs in foreign exchange markets?" *International Journal of Finance & Economics*, 13, 14–25.

Shleifer, A. and R. W. Vishny (1997): "The limits of arbitrage," *The Journal of Finance*, 52, 35–55.

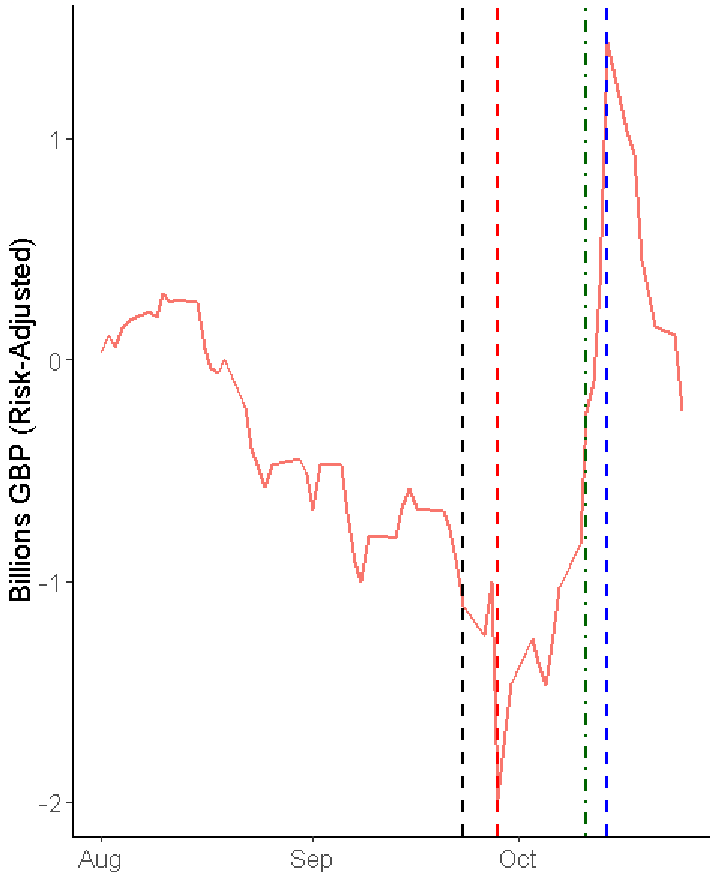
Treynor, J. (1971): "The only game in town," *Financial Analysts Journal*, 27, 12–14.

Vissing-Jorgensen, A. (2021): "The Treasury market in spring 2020 and the response of the Federal Reserve," *Journal of Monetary Economics*, 124, 19–47.

Weill, P.-O. (2007): "Leaning against the wind," *The Review of Economic Studies*, 74, 1329–1354.

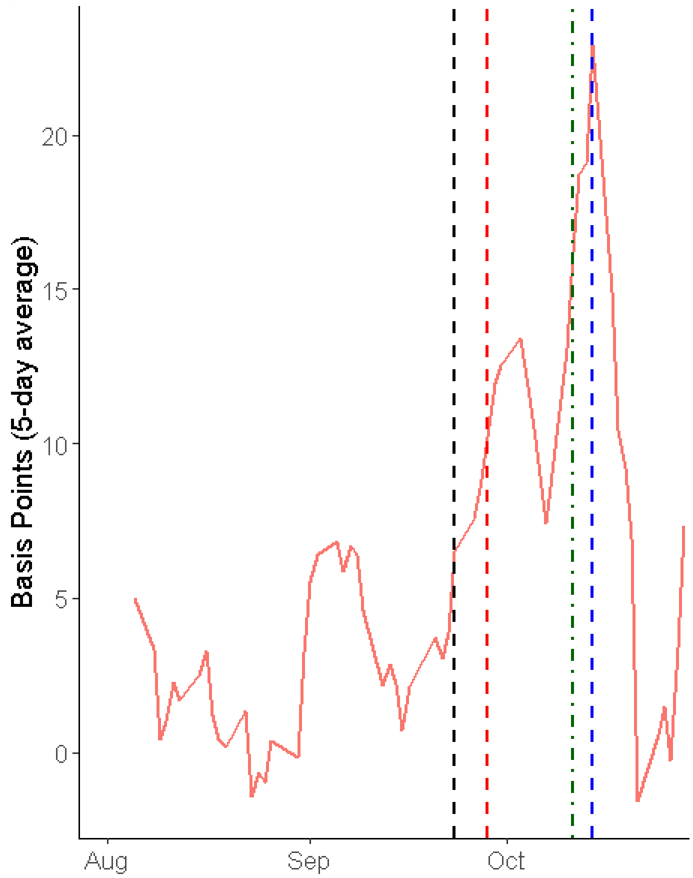
Figures and Tables

Figure 1 Cumulative Dealer Net Order Flow



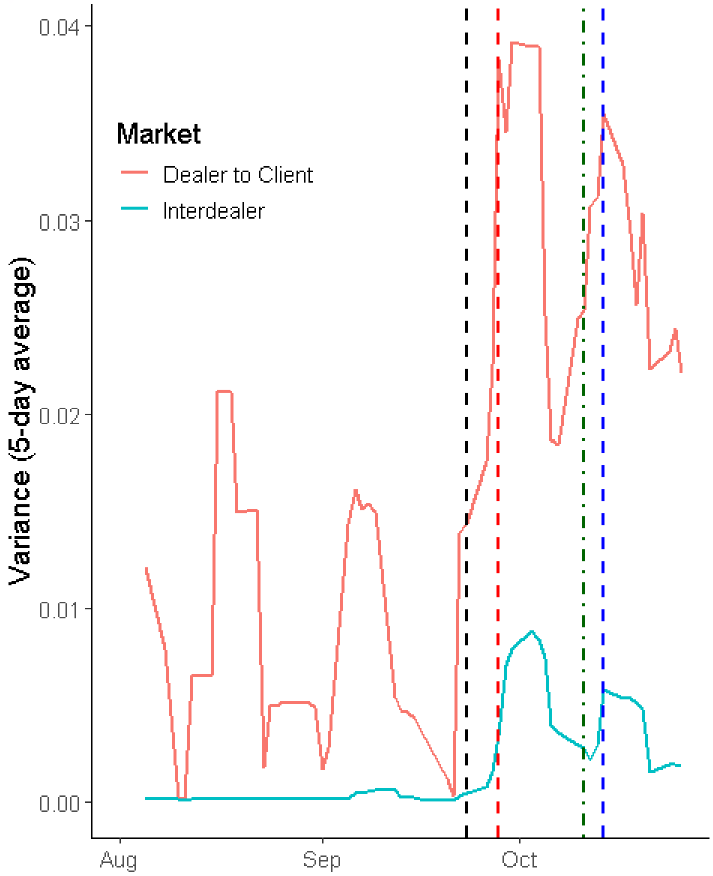
Note: The graph plots the cumulative net order flow of dealers in the gilt market. When it is increasing (decreasing), dealers are net buying (selling). The black line indicates the mini-budget announcement September 23 2022, the red line indicates the start of BoE asset purchases September 28. The green line indicates the expansion of asset purchases on October 11. And the blue line indicates the conclusion of the BoE market intervention 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. and essentially scales nominal net order flow by DVO1 and implied rate volatility, normalized to monthly 95% Value-at-Risk. Charting non-adjusted net dealer order flow is qualitatively similar.

Figure 2 Trade Costs



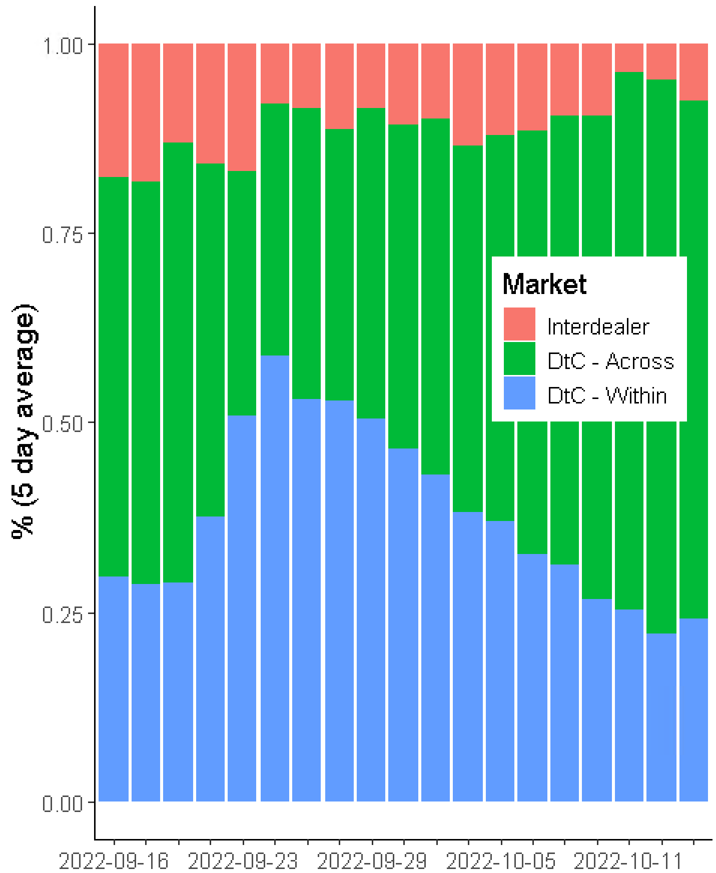
Note: The chart plots the volume-weighted average trade cost across the entire gilt market. The black line indicates the mini-budget announcement September 23 2022, the red line indicates the start of BoE asset purchases September 28. The green line indicates the expansion of asset purchases on October 11. And the blue line indicates the conclusion of the BoE market intervention October 14. Trade costs are calculated as the log difference in transaction prices with the most recent interdealer price for the same bond, scaled to basis points, and then taking the 5 day-rolling average.

Figure 3 DEALER-TO-CLIENT AND INTERDEALER PRICE DISPERSION



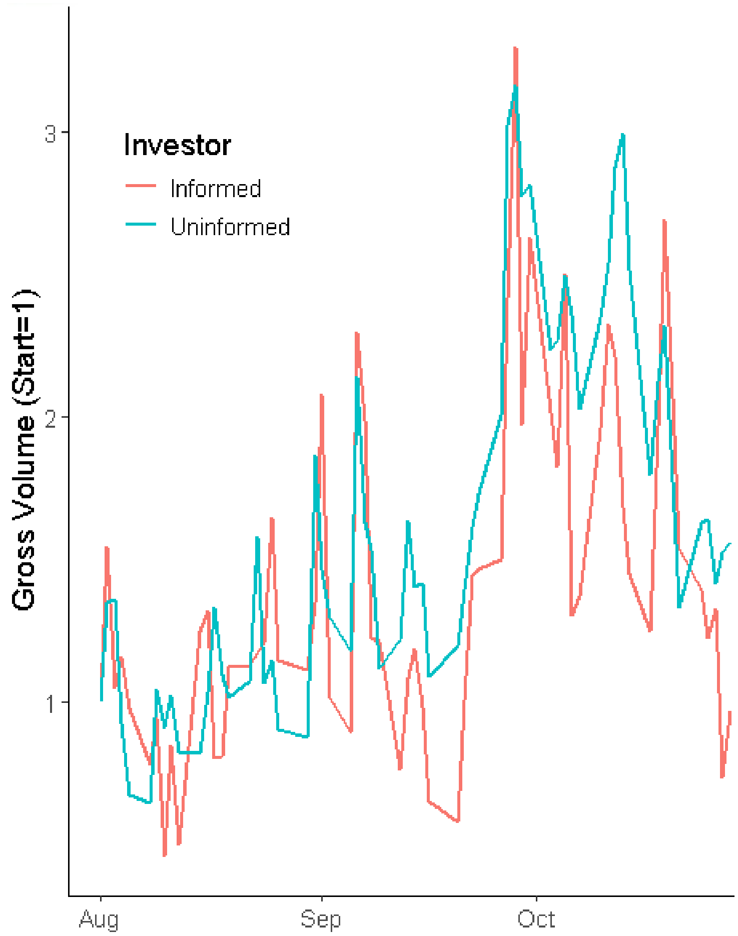
Note: The chart plots the within-dealer price dispersion, as decomposed in equation (4), for the same bond in the same 30 minute interval in the dealer-to-client and interdealer markets. The deviations are summed up across bonds and dealers and then plotted as a 5-day rolling average. The black line indicates the mini-budget announcement September 23 2022. The red line indicates the start of BoE asset purchases September 28. The green line indicates the expansion of asset purchases on October 11. And the blue line indicates the conclusion of the BoE market intervention October 14.

Figure 4 Share of Total Price Dispersion



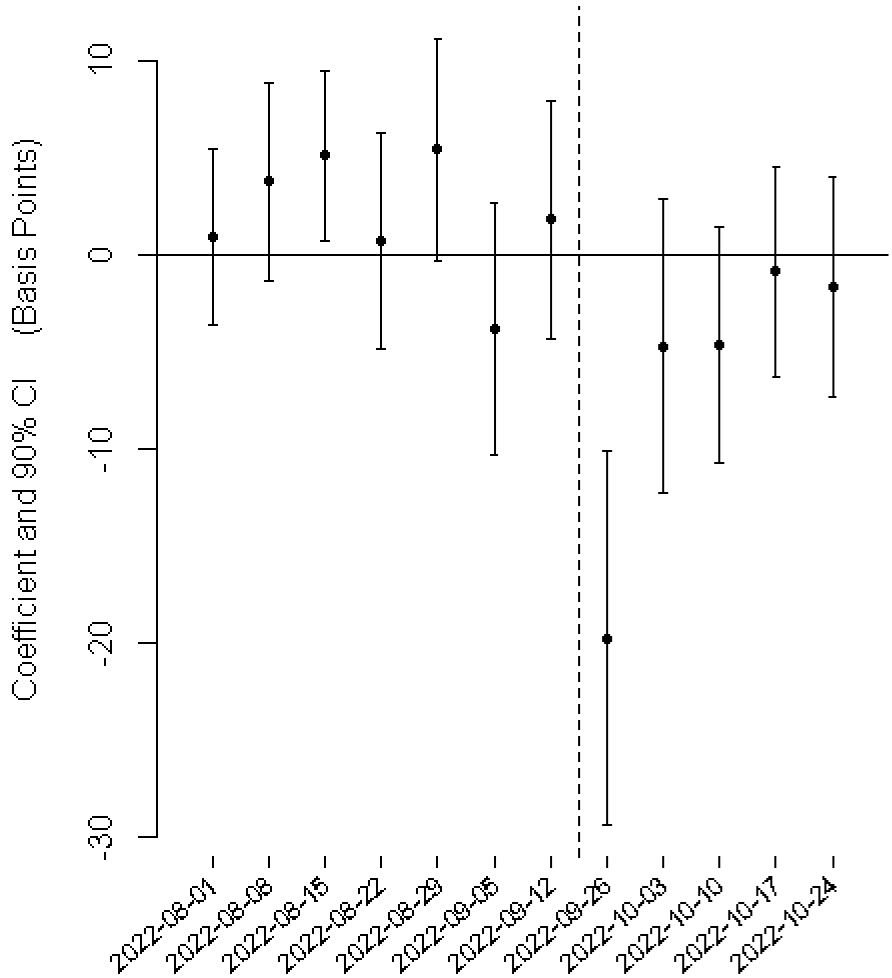
Note: The chart plots share of total price dispersion coming from the interdealer market and the dealer-to-client market, with the latter split out between across-dealer and within-dealer price dispersion, as decomposed in equation (4). The deviations are summed up across bonds and dealers, and divided by total dispersion, to be expressed as shares, and then plotted as a 5-day rolling average.

Figure 5 Trading Volume: Informed vs. Uninformed Clients



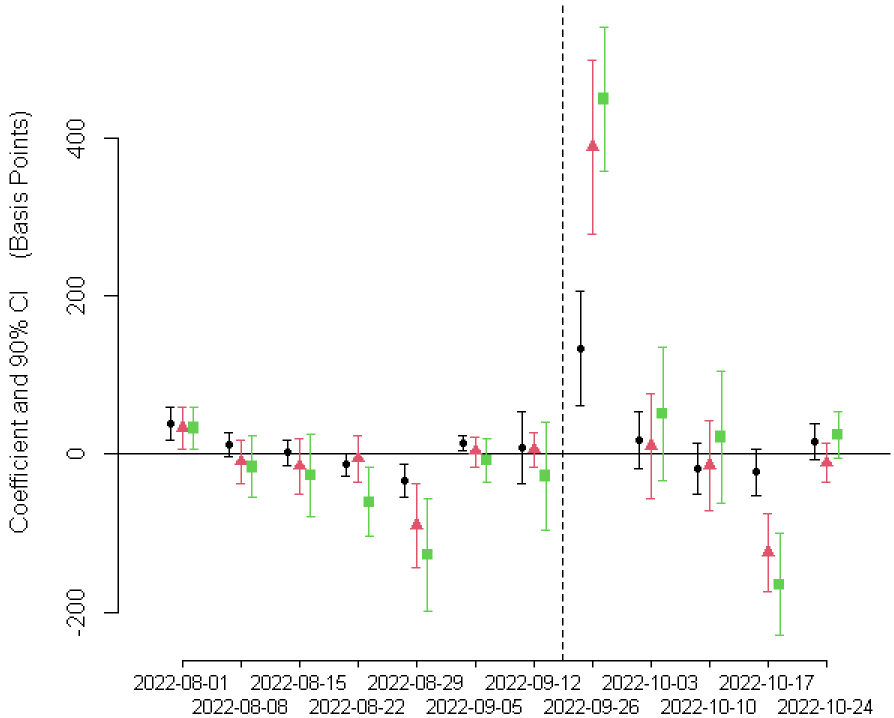
Note: The figure shows the daily gross volume of trading by informed and uninformed investors over the sample, normalized to the first period.

Figure 6 Time-varying Trade Costs for Informed Investors



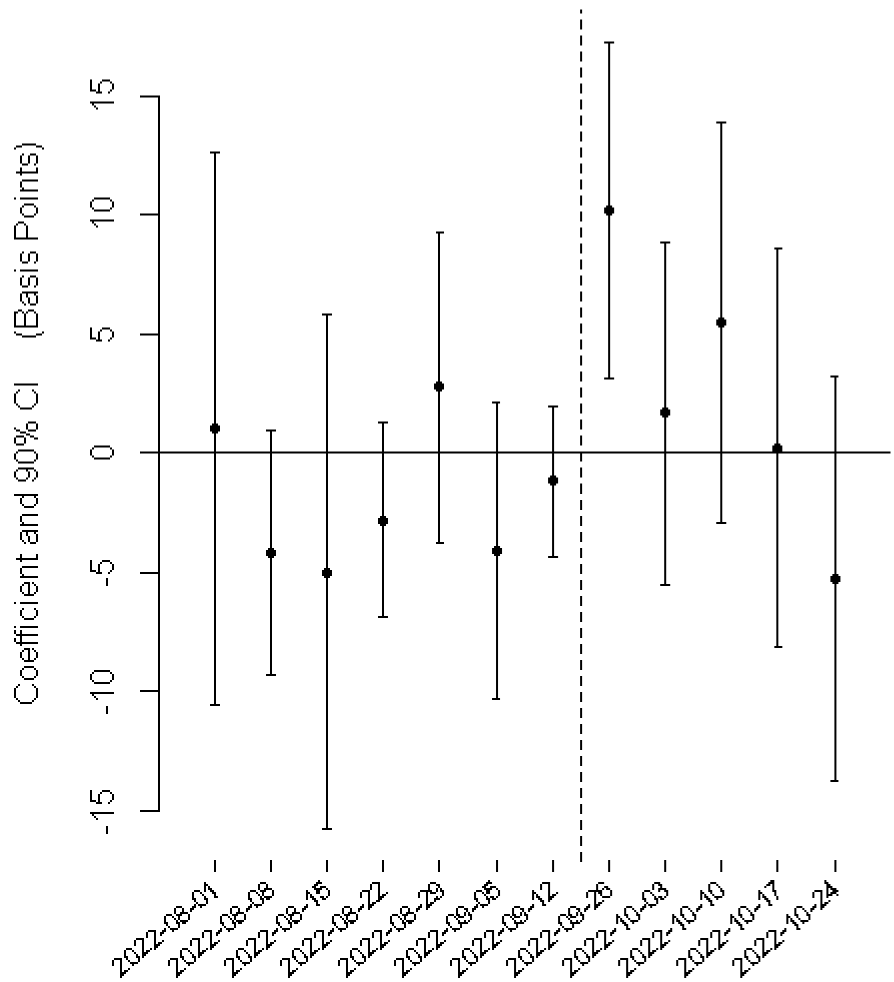
Note: The figure depicts estimates of the transaction costs that an informed investor receives relative to an uninformed investor for the same bond, expressed in basis points. The omitted baseline date is the week before the crisis. The black dashed line indicates the mini-budget announcement, sparking the start of the crisis September 23 2022. It is estimated using equation 7 and controls for 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 receive 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, sparking the start of the crisis September 23 2022.

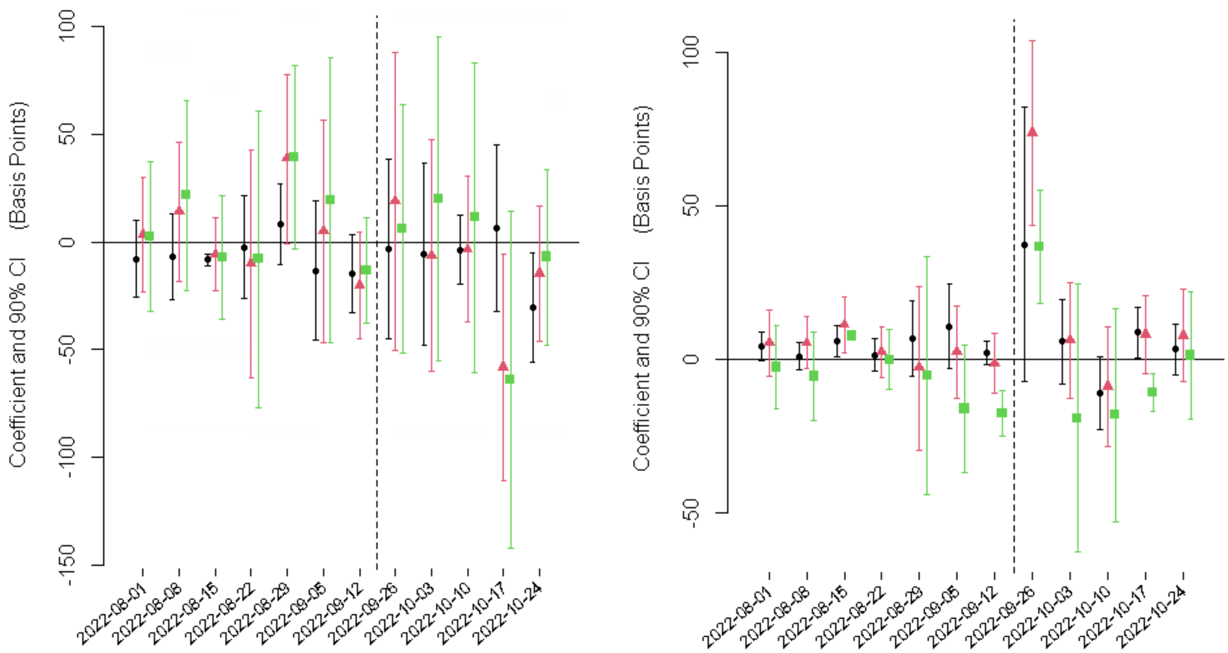
Figure 8 Informed Dealers—Trade Costs



Note: The figure shows the estimates of the sensitivity of trade costs of uninformed investors to dealers informed order flow for dealer-to-client trades, 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 and standard errors are clustered at the dealer and day level. The black dashed line indicates the mini-budget announcement, sparking the start of the crisis September 23 2022.

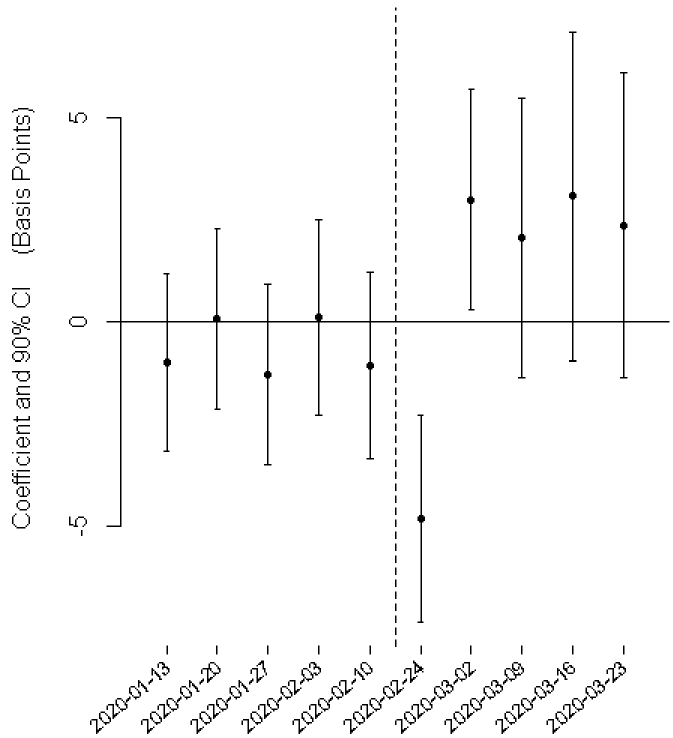
Figure 9 Informed Dealers—Trading Performance

(a) Dealer-to-Client **(b)** Interdealer



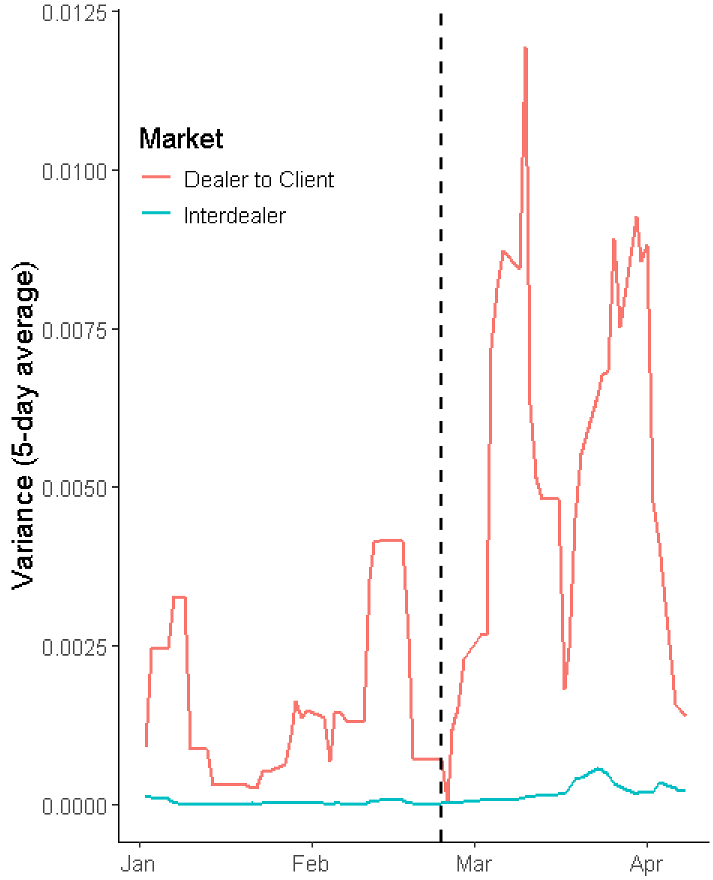
Note: The figured depicts time-varying estimates of the trading returns to dealers with more informed investor order flow in the dealer-to-client (left) and interdealer market (right), using equation 11. Trades are evaluated over 1, 3, and 5 days (black, red, and green, respectively). Dealers' share of informed order flow is lagged one day and instrumented as in equation 12. The regression controls for dealer and time fixed effects and standard errors are clustered at the dealer and day level. The black dashed line indicates the mini-budget announcement, sparking the start of the crisis September 23 2022.

Figure 10 Liquidity Costs for Informed Investors during Dash for Cash



Note: The figure depicts estimates of the within dealer transaction costs that an informed investor receives relative to an uninformed investor for the same bond at the same time, 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 start of the financial panic on February 24 2020. The omitted baseline date is the week before the crisis begins.

Figure 11 Price Dispersion during Dash for Cash



Note: The chart plots the within-dealer price dispersion, as decomposed in equation 3, for the same bond in the same 30 minute interval in the dealer-to-client and interdealer markets during the COVID-19 Dash for Cash. The deviations are summed up across bonds and dealers and then plotted as a 5-day rolling average. The black line indicates the start of the financial panic on February 24 2020.

Table 1 Investor 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 by investors before and during the crisis, expressed in basis points. Trade costs are calculated following equation 1, using interdealer prices as the benchmark.

Table 2 Investor Trading Volumes

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

Note: The table provides statistics on the number and volume of trades by informed investors over the sample. 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 the informed 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 trades 5,870. Total and informed volumes are expressed in billions of GBP. Shares are calculated for each day, and then the average, minimum or maximum is taken across the sample.

Table 3 INVESTOR RETURNS

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 investors' 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 are the total quantity of bonds a dealer trades in a day, expressed in billions GBP. Net volume is the difference between dealer purchases and sales, daily 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 for a dealer that is with an investors categorized as informed.

Table 5 Main Results - Liquidity Costs for Informed Investors

Dependent Variable:	Trade Costs		
Model:	(1)	(2)	(3)
Variables			
Post × Informed	-18.9***	-15.4***	-13.9**
	(4.92)	(4.91)	(5.79)
Sample	All	All	AMs + HFs
Fixed-effects			
Investor	Yes		
Dealer-Time	Yes	Yes	Yes
TSize		Yes	Yes
Investor-Dealer		Yes	Yes
Connections Control		Yes	Yes
Fit statistics			
Observations	124,401	124,401	65,233
R^2	0.21	0.27	0.33

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

Note: The table estimates the within-dealer transaction costs 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, 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 × Informed	-15.4***	-15.4***	-2.37***
	(4.91)	(4.10)	(0.730)
Fixed-effects			
Dealer-Time	Yes	Yes	Yes
TSize	Yes	Yes	Yes
Investor-Dealer	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 within-dealer transaction costs 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, $TradeCost$. Column (1) reproduces the baseline for comparison. Column (2) uses the hourly Bloomberg price as the benchmark for calculating trading costs. Column (3) uses the average bond-time price in the full market, excluding this 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
Investor-Dealer	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 within-dealer transaction costs 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)-(4) 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) are volume weighted estimates.

Table 8 ALTERNATIVE MEASURES OF INFORMED INVESTORS

Dependent Variable:			Trade Cost		
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Post×Informed	-15.4***	-16.5***	-19.8***	-14.5***	-17.8***
	(3.58)	(3.68)	(3.71)	(5.44)	(5.20)
Measure:	3 Day	5 Day	Risk-Weighted	P&L	Top COVID
Fixed-effects					
Dealer-Time	Yes	Yes	Yes	Yes	Yes
Investor-Dealer	Yes	Yes	Yes	Yes	Yes
TSize	Yes	Yes	Yes	Yes	Yes
Connections Control	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	124,401	124,401	124,401	124,401	124,401
R^2	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 within-dealer transaction costs an informed investor, relative to an uninformed investor, after the crisis begins, using alternative measures of investors' informational advantage, following equation 7. Column (1) reproduces the baseline for comparison, with informed investors as the top tercile based on their money-weighted 3-day trading performance in the month prior to the crisis. Column (2) uses the 5-day trading performance. Column (3) is the 3 day trading performance, weighted by risk-adjusted units, following Duffie et al. (2023). Column (4) measures investors' performance using P&L as in equation 8. Column (5) defines informed investors as investors who had the highest 3-day ahead returns during the COVID-19 Dash for Cash.

Table 9 Non-Linearity - Liquidity Costs for Informed Investors

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
Investor-Dealer	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 receiving different levels of transaction costs (measured by equation 1) after the start of the crisis, split by 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
Investor-Dealer	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 within-dealer transaction costs an informed investor, relative to an uninformed investor, after the crisis begins, controlling for investors-dealer relationship importance, following Pinter et al. (2022). Column (1) controls for the investor's share a dealers business prior to the crisis. Column (2) controls for investors' size, proxied by the log of their turnover in the pre-period. Column (3) controls for investor intensity, measured by the log of the number of transactions in the pre-period. Column (4) controls for all of these simultaneously.

Table 11 Clients' Liquidity Provision

Dependent Variable:	Trade Cost					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Post×Informed	-19.9***	-12.5**	-14.7***	-14.1***	-11.2**	-16.1***
	(4.87)	(6.31)	(4.90)	(4.90)	(4.79)	(5.51)
ln(Client-Dealer Gross Vol)			1.98***			
			(0.700)			
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	All
Fixed-effects						
Dealer-Time	Yes	Yes	Yes	Yes	Yes	Yes
TSize	Yes	Yes	Yes	Yes	Yes	Yes
Investor-Dealer	Yes	Yes	Yes	Yes	Yes	Yes
Connections Control	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	113,410	53,148	124,401	124,401	124,401	124,401
R^2	0.30	0.49	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 within dealer transaction costs an informed investor, relative to an uninformed investor, after the crisis begins, controlling for client liquidity provision. Column (1) re-estimates equation 7 excluding purchases of bonds fire sold by the pension fund and liability driven sector. Column (2) excludes all investor purchases. Column (3) controls for the log of investor-dealer daily gross volume. Column (4) controls for investor-dealer daily net volume, in millions GBP. Column (5) controls for the inverse hyperbolic sine of investor-dealer daily net volume. Column (6) controls for the interaction of Post and Informed with dealer inventory, proxied by cumulative net dealer order flow up the day before the crisis.

Table 12 INFORMED DEALERS — FIRST STAGE

Dependent Variable:	$InformedShare$			
Model:	(1)	(2)	(3)	(4)
Variables				
$\widehat{InformedShare}$	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		Yes		Yes
Day		Yes		
Time				Yes
TSize				Yes
Day-Investor				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 from equation 10 to the instrument from equation 12. Columns (1) and (2) estimate the relationship at the dealer-day level, excluding and including fixed effects, respectively. Columns (3) and (4) do so at the trade level.

Table 13 INFORMED DEALERS AND HIGH TRANSACTION COSTS

Dependent Variable:	High(Trade Cost)			
Model:	(1)	(2)	(3)	(4)
Variables				
Post × Investor Size	0.3616*			
	(0.1862)			
Post × Investor % Dealer		-1.988		
		(10.80)		
Post × Dealer % Investor			-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 different investors receiving within dealer transaction costs in the highest daily tercile, after the start of the crisis. Column (1) interacts *Post* with Investor Size (proxied by the log of turnover prior to the crisis). Column (2) interacts *Post* with the percent of dealers' total volume they account for prior to the crisis. Column (3) uses the percen of an *investor's* volume the dealer accounts for prior to the crisis. Column (4) interacts *Post* with the log of the number of investor trades. Coefficients are scaled to percentage points.

Table 14 INFORMED DEALERS AND QUANTITY OF LIQUIDITY

Dependent Variable:	Net Volume			
Model:	(1)	(2)	(3)	(4)
Variables				
Post × L1(InformedShare)	-0.279***	-0.248***	-0.354***	-0.275***
	(0.086)	(0.073)	(0.073)	(0.078)
Fixed-effects				
Dealer		Yes		Yes
Day			Yes	Yes
Fit statistics				
Observations	863	863	863	863
R^2	0.002	0.03	0.03	0.09

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

Note: This table estimates the effect of dealers' information flow on the quantity of liquidity they supply to the market. It re-estimates equation 10 using the instrument from equation 12, but aggregated at the dealer-day level. The dependent variable $NetVolume$ is the net volume a dealer trades in a day (dealer purchases minus dealer sales), scaled by within dealer standard deviation. The independent variable and instrument are standardized.