Dealers, Information, and Liquidity Crises in Safe Assets*

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Abstract

In this paper, we empirically study the role of information in safe asset liquidity crises, using the 2022 UK LDI crisis as a laboratory. Contrary to traditional adverse selection models, which predict higher liquidity costs due to the presence of informed traders, we find that dealers initially reduce trade costs for informed investors, and subsequently raise costs and reduce volumes for the broader market. Importantly, the results are not driven by competition for trading relationships or compensation for client-supplied liquidity. We interpret this as evidence of dealers seeking to learn from informed investors and then restricting liquidity provision as they process this information. We also document that dealers subsequently exploit their informational advantage in anonymous interdealer markets and that similar dynamics are present in other crises. Our findings suggest that dealers' reallocation of liquidity towards informed clients during crises deepens market-wide liquidity shortages and amplifies the severity of liquidity crises.

Keywords: Adverse Selection, Information, OTC Markets, Liquidity.

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1 Introduction

Government bonds issued by advanced economies have been at the center of several major market turmoils, most recently in the pandemic-era Dash for Cash and the 2022 UK LDI crisis. This is surprising, as these bonds are generally viewed as safe assets and 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). Moreover, studies on dealers have emphasized factors such as balance sheet constraints (Duffie et al., 2023), funding costs (Brunnermeier and Pedersen, 2009; O'Hara and Zhou, 2021), or the liquidity supplied by dealers' clients (Kruttli et al., 2024).

In this paper, we ask whether information plays a role in dealers' liquidity provision during safe asset crises and if so, through which mechanisms? Adverse selection models of trading, like those by Treynor (1971) and Kyle (1985), suggest that when dealers cannot distinguish between informed and uninformed clients, 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 clients, they might *lower* liquidity costs to learn from them (see, e.g., Naik et al., 1999; Pinter et al., 2022). For instance, in a typical large bilateral transaction, an investor may request a two-sided quote from a dealer, concealing the trade's direction until the agreement is reached. By offering discounted quotes, the dealer can gain insights into the investor's beliefs about the asset, allowing dealers to better position themselves in future trades.

To study the role of information in safe asset liquidity crises, we examine the 2022 UK LDI crisis.[1] The announcement of the expansionary "Mini-Budget" on September 23 triggered a sharp rise in gilt yields, leading to margin calls on swap and repo exposures, large fire sales of government bonds by pension funds and liability-driven investment (LDI) funds, and a rapid deterioration in market liquidity (Alfaro et al., 2024). Thirty-year gilt yields rose by 130bps within days, prompting a temporary Bank of England intervention on September 28 that halted the fire sale dynamic and allowed pension funds to reduce their leverage exposures (Hauser, 2023; Alexander et al., 2023).

Our analysis relies on the regulatory MiFID II data for transactions in the UK government bond market. This dataset is highly granular and comprehensive, allowing us to distinguish the role of information from other factors like dealer balance sheet constraints or trading relationships. We also obtain 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—such as 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. Moreover, the high-frequency nature of the transaction data also allows us to perform our analysis in very narrow time windows, further refining our comparisons between trades.

Our main empirical strategy proceeds in two stages. First, we study dealers' pricing strategies during the crisis. We classify a trade as benefiting from discounted liquidity if the execution price obtained from a given dealer is more favorable than the price of an otherwise comparable trade in the same bond executed within the same 30-minute interval. Following the literature, we assume that dealers infer a client's informational advantage from their recent trading returns, categorizing informed investors as those in the top tercile of asset managers and

[1] The UK has a large, generally safe and liquid government bond market, with a dealer-based OTC market structure similar to other major government bond markets, including the United States, Germany, and Japan.

hedge funds, while classifying all others as uninformed.[2] We employ a difference-in-difference model to compare the trade costs dealers charge informed investors versus their other clients, both before and during the crisis. To validate this methodology, we present time-varying estimates to assess the parallel trends assumption and conduct extensive robustness tests to ensure that our classification of informed investors does not capture other potential drivers of trade cost discounts.

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

In our first set of results, we find that dealers substantially reduced trading costs for informed clients during the crisis, consistent with theoretical models in which dealers actively chase information. This pattern is evident in the raw data, which reveals both an absolute decline in informed investors' trade costs and a relative decline compared to uninformed clients. Even under our most conservative specification, informed investors paid, on average, 15bps less than uninformed clients at the peak of the crisis. This effect is economically large in a market where pre-crisis trading costs averaged only 3bps and where positions are typically highly leveraged. Further evidence points to an active liquidity reallocation by dealers: during

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

the crisis, the dispersion in prices is driven primarily by within-dealer variation rather than cross-dealer differences, consistent with dealers exercising discretion in reallocating liquidity across their client base.

We address alternative explanations using an extensive set of controls and fixed effects. In particular, by controlling for the trading volumes of each dealer-client pair before and after the crisis, we show that our results are not driven by pre-existing relationships or by dealers competing for future order flow. We further examine cases in which clients act as liquidity providers to dealers (see, e.g., Choi et al., 2024). While dealers compensate clients for their liquidity provision in these instances, such compensation does not explain the overall reduction in trade costs. Furthermore, using dealer-time fixed effects—comparing the trade costs of different clients with the same dealer in the same 30-minute time period—and controlling for dealer inventory, we ensure that dealers' balance sheet constraints do not account for our findings. To further validate our findings, we show that dealers charge lower trading costs on bonds that are most informationally sensitive, including longer-maturity and inflation-linked bonds. 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 lower trade costs to informed traders early in the crisis to gather valuable information.

In our second set of results, we show how dealers adjust their behavior across different market segments after trading with informed investors, balancing the need to maintain client relationships against the incentive to exploit their informational advantage. Dealers with one standard deviation higher informed order flow increase transaction costs for uninformed clients in the dealer-to-client market by approximately 10bps, while reducing their daily net and gross trading volumes by about 0.15 standard deviations for bonds subject to the greatest fire-sale pressure. These findings indicate that, as market stress intensifies, informed dealers adopt increasingly defensive market-making strategies and restrict liquidity provision to less informed clients. Consistent with reputational concerns in the non-anonymous dealer-to-client market, informed dealers primarily monetize their informational advantage through generating trading profits in the anonymous interdealer market.

We further examine the nature of the information used by informed clients and learned by dealers. Trading by informed clients and dealers predicts subsequent pension fund and LDI fund (PFLDI) order flows, whereas uninformed trading does not, suggesting that their informational advantage reflects the ability to anticipate which bonds will come under selling pressure by the PFLDI sector. We also show that central bank interventions mitigate these effects by restoring aggregate market liquidity and weakening dealers' incentives to chase information. Finally, we extend the analysis to the pandemic-era Dash for Cash episode and document similar patterns of dealer behavior, indicating that these dynamics are not specific to the 2022 LDI crisis.

While the informational channel in dealers' liquidity provision does not preclude alternative mechanisms—such as balance sheet constraints or network effects—it yields distinct empirical predictions and carries separate implications for market design and regulatory policy. 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 alone can 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 broader interventions aimed at shaping investor beliefs and expectations (Abreu and Brunnermeier, 2003; Dang et al., 2020).

Related literature. Our paper relates to three literatures. First, this study contributes to the extensive literature on adverse selection and, within that literature, to the growing evidence on information chasing. One of the earliest models linking transaction costs 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. Glosten and Milgrom (1985) and Kyle (1985) build on this intuition, developing widely used models that formalize 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), and Bilan et al. (2023) demonstrate that informed investors, in fact, face lower trade costs in FX, equity, and CDS markets, respectively.[3] These findings indicate that standard adverse selection models may not fully capture the nuanced behavior of dealers in markets where they can distinguish between informed and uninformed clients.

We contribute to this literature by studying two recent episodes of severe stress in safe asset markets and showing that dealers' information-chasing behavior intensifies sharply during these periods.[4] This behavior results in a substantial reallocation of liquidity towards informed clients, exacerbating market-wide liquidity shortages and amplifying the severity of liquidity crises. Furthermore, we provide novel evidence that dealers with greater informed order flow exploit their informational advantage through trading in anonymous interdealer markets, but not in bilateral, non-anonymous dealer-to-client or dealer-to-dealer markets.

Second, by studying the 2022 UK LDI crisis and the pandemic-era Dash for Cash, we con-

[3]Other notable contributions to this literature include, among others, Glode and Opp (2016); Osler et al. (2016); Hollifield et al. (2017); Babus and Kondor (2018); Hagstromer and Menkveld (2019); Li and Schürhoff (2019); Brancaccio et al. (2020); Glode and Opp (2020); Hau et al. (2021); Pinter et al. (2022).

[4]Theoretically, it is ambiguous whether incentives to acquire information rise or fall during crises. On the one hand, higher volatility increases the potential returns to informational advantages; on the other hand, illiquidity reduces the ability to monetize such advantages (Kadan and Manela, 2025). Appendix A provides a more detailed discussion of these forces and estimates of information-gathering incentives.

tribute to the broad literature on liquidity crises. 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 LDI crisis.[5] In theory, arbitrageurs—including specialized investors and market makers—are expected to absorb temporary selling pressure by "leaning against the wind". However, their capacity to do so is often constrained by several factors, limiting their ability to stabilize markets.[6] For instance, Duffie et al. (2023) provide empirical evidence that dealer capacity constraints—such as balance sheet constraints driven by regulations and internal risk management—exacerbate liquidity shortages in the US Treasury market.

Complementing the existing literature, our paper identifies and studies an alternative amplification mechanism operating through dealers' allocation of scarce liquidity in market turmoils.[7] While previous studies emphasize market-making constraints, we argue that dealers' information chasing—particularly how they distribute liquidity among their clients—can also amplify illiquidity during crises. This distinction is crucial, because different amplification channels may suggest distinct policy implications. That is, if dealers' information chasing exacerbates illiquidity, alternative market structures—for example, all-to-all trading platforms or full post-trade transparency—might help mitigate these dynamics.

Third, we contribute to the growing literature on informed trading and information transmission in government bond markets. These markets are typically characterized by high liquidity and price formation driven largely by public information, such as macroeconomic releases

[5]For research on the COVID-19 Dash for Cash, see, e.g., Falato et al. (2021); Kargar et al. (2021); Vissing-Jorgensen (2021); O'Hara and Zhou (2021); Ma et al. (2022); Czech et al. (2022); Cesa-Bianchi et al. (2023); Huang et al. (2024); for the LDI crisis, see Alfaro et al. (2024); Pinter (2023).

[6]See, e.g., 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. (2024, 2025).

[7]Studies such as Di Maggio et al. (2017) and Jurkatis et al. (2023) demonstrate that dealers prioritize liquidity provision to their most valuable clients during stress periods.

and monetary policy announcements (Fleming and Remolona, 1999). Nonetheless, recent work shows that sophisticated investors can possess persistent informational advantages even in these settings. Such advantages may arise from superior forecasting of macroeconomic fundamentals and faster reactions to new information (Farboodi and Veldkamp, 2020), as well as from the ability to anticipate other investors' order flow (Czech et al., 2021; Kondor and Pinter, 2022). Consistent with this evidence, we show that informed clients exhibit a persistent edge in the UK gilt market, particularly profiting from their ability to anticipate which bonds are likely to experience selling pressure from distressed pension funds. Moreover, Di Maggio et al. (2019) and Barbon et al. (2019) highlight the role of dealers in disseminating information to clients. In contrast to this body of work, our study focuses on the reverse flow of information—from informed clients to dealers—and examines how this dynamic can affect dealers' liquidity provision during crises.

Outline. The remainder of the paper is structured as follows. Section 2 describes the data and methodology used in our analysis and presents the key stylized facts from the 2022 LDI crisis. Section 3 details the main empirical analysis of dealers' trade pricing strategies as well as robustness checks that rule out alternative explanations. Section 4 explores dealer behavior after trading with informed clients. Section 5 studies the source of the informational advantage of informed clients and dealers. Section 6 extends the analysis to the Covid-19 Dash for Cash episode. Section 7 concludes.

2 Data, Measurement, and Stylized Facts

2.1 Data

Our analysis draws on the regulatory MiFID II data covering all UK gilt transactions from January 2018 onward. For this study, we primarily focus on the period surrounding the

UK LDI crisis, spanning from August 2022 to October 2022. Over this period, our dataset encompasses approximately 287,000 transactions, with 120,000 occurring in the dealer-to-client market, and the remainder in the interdealer market. Our baseline sample includes transactions between 2,969 distinct legal entities and the 17 dealers who are designated Gilt-Edged Market Makers (GEMMs), covering all bonds in the gilt market.

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

Furthermore, the granular nature of the data allows us to examine trades at high frequency. In our baseline analysis, we use a 30-minute window to compare trades executed by different clients with the same dealer, which helps to eliminate confounding factors such as varying demand for specific securities, shifts in financial conditions (e.g., interest rate expectations or changes in risk aversion), and overall market dynamics. By focusing on this short time window, our analysis centers on the *allocation* of liquidity costs across the different clients of a given dealer, providing insights into how dealers distribute liquidity 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 or electronic messaging, particularly for medium or large size trades, even if they begin with an electronic quote from a trading platform. As a result, our dataset captures equilibrium outcomes and may reflect changes in the composition of investors or trade types over time. In the econometric analysis presented in Section 3, we directly address these concerns. Specifically, we hold constant our sample of investors and trade types through investor and trade-size fixed effects in order to ensure that our findings are not biased by changes in market composition or trade characteristics during the crisis. Our time-varying estimates show that the trades we compare received similar transaction costs before the crisis.

2.2 Dealers' Liquidity Provision During the Crisis

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

As shown in Figure 1, dealers' net order flow in the gilt market was negative prior to the first BoE announcement, i.e. they were net sellers of gilts. The increased selling pressure from dealers likely compounded the illiquidity in the gilt market, further amplifying financial instability. The magnitudes are economically significant, with around £2bn in net sales on a risk-adjusted basis (or £30bn in non-adjusted sales, approximately the same amount as the PFLDI sector during the crisis).

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 is calculated as the difference in log prices between the realized transaction price P_n^* and the prevailing interdealer benchmark price P_t^{ID}:[8]

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

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

2.3 Price Dispersion

Price dispersion, a widely used indicator of aggregate market illiquidity, occurs when the same bond trades at different prices across simultaneous transactions (Jankowitsch et al., 2011). The underlying intuition is that, in normal market conditions, arbitrage ensures that a security trades at similar prices across venues and counterparties. However, when arbitrageurs and dealers are constrained, securities begin to trade at increasingly divergent

[8]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.

prices. This divergence heightens the trade cost risk for investors, as the lack of price uniformity makes it more expensive and uncertain to execute transactions. Price dispersion for any given bond can be calculated as the average deviation of the realized prices P^* for transactions $n \in N$ in a time period t from the bond's average price over the same period $\bar{P}_t$, as given by equation (2):

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

Figure 3 plots the time series of price dispersion for both the interdealer market (in blue) and the dealer-to-client market (in pink).[9] 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 market volatility.

The figure shows that price dispersion in dealer-to-client trades surged following the Mini-Budget announcement (black vertical line), then stabilized after the BoE announced its initial asset purchase program (red line). However, it rose again before the intervention was expanded (green line) and ultimately concluded (blue line). In contrast, the price dispersion in the interdealer market remained relatively stable. The interdealer market's centralized and anonymous nature provides a useful comparison, as in this market dealers cannot differentiate between their counterparties. Given the interdealer market's liquidity and anonymity, its price dispersion provides an approximate upper bound on the proportion of dispersion attributable to fundamental volatility. This comparison helps address concerns that our price dispersion measures might simply reflect broader financial or macroeconomic volatility.

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

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

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

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 any given 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.

Figure 4 further breaks down the sources of price dispersion in the dealer-client segment during the crisis, comparing the share attributable to the across-dealer dispersion with that from the within-dealer variation. The results show that the share of price dispersion attributable to within-dealer variation in the dealer-to-client market increased from around 30% before the Mini-Budget to over 70% at the peak of the crisis, before retracing following the BoE's intervention. This shift indicates that, during the crisis, dealers' liquidity allocation across clients became substantially more important relative to dealer-level factors, such as regulatory constraints or internal risk limits. Overall, these findings indicate that during periods of market stress, dealers increasingly differentiate their trade costs across clients, reflecting a more targeted distribution of liquidity.

2.4 Performance Measures and Definition of Informed Investors

We hypothesize that during periods of stress, dealers offer *lower* 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., 2021; Kondor and Pinter, 2022). For the purposes of our analysis, we therefore assume that dealers form conjectures about which investors have an informational advantage by observing their recent trading performance.

To operationalize this, 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 forecast bond returns with trade cost discounts they may receive from dealers:

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

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

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

Intuitively, the adjusted trade performance measure assumes that each investor transacts at the bond's average transaction price rather than their actual execution price. This adjustment removes the impact of execution costs on trading profitability, isolating the component attributable to the investor's ability to predict bond price movements. We then average each investor's performance, weighted by transaction size, and sum the daily returns.[10]

During the crisis, a subset of sophisticated investors exhibited particularly strong performance. According to Pinter (2023), hedge funds achieved cumulative size-weighted returns exceeding 50% over the crisis period, based on their 3-day ahead trading performance. However, these superior returns are typically not observable by dealers in real time.

Therefore, we classify the top tercile of sophisticated investors (based on their average 3-day ahead trading performance) in the month preceding the crisis as "informed investors". Dealers are likely to perceive these investors as possessing an informational advantage, driven by their recent trading performance. The control group of "uninformed investors" includes the remaining hedge funds and asset managers, as well as other non-sophisticated investors such as pension funds, insurers or non-financial companies.

In our baseline classification, informed investors comprise 149 asset managers and 33 hedge funds, representing a subset of the 2,969 entities in the full sample. By volume, these top traders are dominated by quantitative fixed income and macro hedge funds and large bond fund managers. Appendix Table A.1 examines the persistence of investors' information advantages by regressing indicators of top-tercile trading performance on indicators from

[10] All the main results are robust to using i) unweighted returns to calculate performance and ii) interdealer prices instead of average market-wide prices in the execution cost component.

other periods. Column (2) shows that asset managers and hedge funds that outperformed in the month preceding the LDI crisis were significantly more likely to remain top performers during the turmoil, and Column (3) demonstrates that many of these same investors had also been top performers during the COVID crisis. Together, these findings indicate that informational advantages tend to be persistent for a subset of investors, consistent with sustained investments in superior information acquisition and processing.[11]

Table 1 Panel B provides basic statistics on the relative size of these informed investors. On average, they execute 427 daily trades (£5.5bn in volume), compared with 4,446 trades (£37bn) in the entire gilt market. Panel A provides the average trade costs for each market segment before and during the crisis. Informed investors have slightly higher transaction costs relative to uninformed investors before the crisis, which decrease significantly during the crisis. Uninformed clients have relatively modest pre-crisis average transaction costs, but their trade costs increase substantially during the crisis. This table provides our baseline result in its simplest form: during the crisis, dealers reduce high performing investors' trade costs, while increasing trade costs for the rest of the market.

3 Information Chasing in Crises

3.1 Information Chasing

The preceding analysis shows that during the crisis dealers restricted the supply of liquidity and raised trade costs. Moreover, we observed the increased price dispersion was driven by dealers' allocation of liquidity among their clients. However, these aggregate dynamics could still be influenced by other factors, such as shifts in the types of transactions or the profiles of investors with whom dealers are trading.

[11] Appendix Figure A.2 further shows that trading volumes of informed and uninformed investors evolve similarly around the crisis.

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 (Pinter et al., 2024). In times of market stress, if smaller investors, who typically trade less frequently, suddenly need to trade more, then this change in the composition of investors and transaction sizes could explain the variation in trade costs, rather than targeted liquidity provision by dealers.

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

$$TradeCost_n = \beta Post_t \times Informed_i + \theta Connections_{i,day} + \alpha_{d,t} + \gamma_{i,d} + Size_n \times \phi_{day} + \epsilon_n, \tag{7}$$

where $TradeCost_n$ refers to the trade cost as defined in equation (1), expressed in basis points, for transaction n in a 30-minute window t between investor i and dealer d in bond b. As defined earlier, our trade cost measure compares each transaction to the most recent interdealer price for the same bond, effectively controlling for time- and security-specific factors like changes in bond fundamentals, demand, or broader market conditions such as interest rates or risk aversion. $Post_t$ is an indicator variable that equals 1 after the crisis begins on September 23, while $Informed_i$ is an indicator variable equal to 1 if the investor is a top-performing asset manager or hedge fund (adjusted for execution performance) in the month prior to the crisis, as explained in Section 2.4. Importantly, our results remain robust across various alternative definitions, as described in the next subsection.

The data allows us to use a rich set of fixed effects to account for potentially confounding, unobserved variation. To focus on how dealers allocate liquidity among their clients, we use dealer-time fixed effects ($\alpha_{d,t}$), ensuring that our comparison is between different investors trading with the same dealer and in the same 30-minute time window. This effectively sweeps out variation from dealer-level factors such as regulatory constraints or internal risk limits. We also apply investor-dealer fixed effects ($\gamma_{i,d}$), which capture the intensity of dealer-client relationships across our sample.[12] Transaction size-day fixed effects ($Size_n \times \phi_{day}$) absorb any non-linear changes in size discounts/premia through the sample (Pinter et al., 2024).[13] Additionally, we control for the number of daily dealer connections of a given client ($Connections_{i,day}$) to account for the possibility that informed investors may split trades across multiple dealers to reduce execution costs.[14]

Private information is generally unobservable, making identification challenging. Our identification relies on two assumptions: (1) clients' prior performance can be used as a proxy for dealers' perceptions of their informational advantage, and (2) conditional on our controls, informed and uninformed clients would have faced similar trading costs in the absence of the shock.[15] In the following subsections we provide evidence to support these assumptions, including (1) time-varying estimates in support of the parallel trends assumption, (2) measuring the profitability of informed investors' trades receiving discounts, and (3) extensive robustness tests showing that our results are not driven by past or future trading relationships or compensation for clients' liquidity provision.

[12] In Section 3.3, we also control for the *time-varying* nature of trading relationships. More precisely, we rule out the possibility that the effect is driven by pre-existing relationships or competition for future, post-crisis relationships.

[13] $Size_n$ defines five transaction size categories: $<$ £1m, £1m-£5m, £5m-£10m, £10m-£25m, and $\geq$ £25m.

[14] The $Connections_{i,day}$ and size-day fixed effects help mitigate concerns that sophisticated investors strategically split 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.

[15] From an empirical standpoint, the presence of an actual informational advantage is not necessary; what matters is dealers' perception of such an advantage. Nonetheless, in equilibrium dealers could not sustainably offer trade cost discounts to clients unless doing so were ultimately profitable.

First, Figure 5 estimates equation (7) as a weekly time-varying model. The figure shows that in the first week of the crisis, informed investors incurred significantly lower transaction costs than their uninformed counterparts. The effect then reverses in the following weeks. Importantly, the estimates provide evidence in support of the parallel trends assumption.

Table 2 presents the results from the pooled difference-in-difference estimation, alongside robustness checks, with standard errors clustered at the Investor-Day level. The baseline finding (column 2) reveals that, during the crisis, informed investors faced transaction costs that were about 15bps lower than those of their uninformed counterparts. In column (1), we employ less granular fixed effects and fewer controls compared to the main baseline in column (2). This demonstrates that the results are not solely driven by the demanding specification or extensive controls used in the baseline model. Column (3) shows that our findings remain robust when we employ standard errors double clustered at the investor and day levels.

While these results focus on a crisis-period indicator, they naturally raise the question of whether the value of information varies more continuously with market conditions rather than discretely around the crisis. Recent research (Kadan and Manela, 2025) has provided a methodology to estimate the value of information in markets as a function of volatility and liquidity, finding that it increases at times of financial distress and significant macroeconomic policy announcements. Following this work, column (4) replaces the *Post* indicator variable with our time-varying estimate of the value of information, standardized over the sample, and described in more detail in Appendix A. A one-standard deviation increase in the value of information is associated with informed investors facing trade costs that are 9bps lower in a given bond, relative to the dealer's other clients. This is consistent with dealers providing discounted liquidity to sophisticated clients precisely when information is most valuable.

Next, 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 therefore serve as an appropriate control group for the information channel. Table 3 re-estimates our baseline specification, but for subsamples of different bond types. The first two columns estimate an unweighted model for shorter maturity (<10y) and longer maturity buckets (≥10y) for conventional gilts, while column (3) examines the effect for inflation-linked bonds. Columns (4)-(6) rerun the regressions with trade costs weighted by trading volume. Consistent with our prior, we find economically and statistically significant effects for the longer maturity (column 5) and the inflation-linked gilt sample (column 6). These results are consistent with our information-based hypothesis.

3.1.1 Robustness Tests

Appendix Table A.2 provides robustness tests for our measure of trade costs. Column (2) modifies the benchmark used to compute trade costs in equation (1) by replacing the average interdealer price with the hourly Bloomberg bond price. Column (3) further uses the average market price across both interdealer and dealer-to-client trades, excluding trade n, and compares purchases only with purchases and sales only with sales. This measure yields a lower average trade cost level because the benchmark nets out the higher costs embedded in dealer-to-client trades, as shown in Appendix Table A.3. Consistent with this, the coefficient in column (3) of Table A.2 is smaller in magnitude but remains both statistically and economically significant.

Columns (4) and (5) of Table A.2 address the concern that informed investors may simply trade more quickly in volatile markets, which may mechanically lower trade costs relative to the benchmark. Although we do not observe the timing of dealers' quote revisions, these specifications control, respectively, for the number of minutes since the most recent interdealer trade and since the start of the 30-minute benchmark window. Column (4) shows that trading closer to the latest interdealer transaction is associated with a modest reduction (0.002bps per minute) in measured trade costs. However, the estimated coefficient on informed investors' trade costs is virtually unchanged across specifications. This robustness indicates that faster trade execution or stale benchmarks cannot explain the substantially lower trade costs offered to informed investors during the crisis.

Appendix Table A.4 studies the non-linearity of dealers' information chasing by re-estimating our baseline specification, using an indicator for daily terciles of trade costs as the dependent variable. These estimates serve as a robustness check against the possibility that increased overall trade cost dispersion could bias our results. Heightened volatility might cause transaction prices to deviate further from their benchmarks within a fixed window, potentially inflating our transaction cost measure. By scaling transaction costs relative to their daily distribution, we study whether informed investors receive larger discounts during the crisis, even after accounting for broader price dispersion. Column (1) represents the lowest tercile, column (2) the middle tercile, and column (3) the highest. Despite elevated volatility, informed investors are significantly more likely to transact in the lowest transaction-cost tercile and significantly less likely to be in the highest.

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

Appendix Table A.5 presents the results of these robustness checks. The first three columns offer variations on our main measure of T-day ahead trading performance. Columns (1)-(3) define informed investors as the top tercile of asset managers and hedge funds based on their volume-weighted 1, 3, and 5-day trading performance in the month prior to the crisis, respectively. Column (4) is the 3-day *risk-weighted* trading performance.[16] Column (5) reports results using the top tercile of cumulative crisis-period P&L and the estimates remain nearly unchanged.[17] Though not observable in real-time by dealers, our data also allows us to calculate investors' trading returns through the end of the crisis. Investors with an informational edge should be among those with the highest realized returns *ex post*. Column (6) uses 3-day-ahead returns through the end of the crisis and finds effects that remain highly statistically significant and economically large, at roughly 29bps. In column (7), we identify the top performing investors in the last liquidity crisis—the pandemic-era Dash for Cash—and the results remain robust to this alternative classification. Together, column (6) and (7) also further corroborate the persistence of investors' informational advantage, echoing results from Appendix Table A.1 in the prior section.

Overall, these tests provide evidence that the main results are robust to a wide range of alternative definitions and measurements and support our interpretation that dealers offer lower liquidity costs to high-performing sophisticated investors during crises, consistent with our hypothesis of dealers' information-chasing behavior.

3.2 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

[16]The calculation of the weights for the risk-weighted performance measure 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.

[17]P&L is calculated using realized cash flows and valuing cumulative changes in inventory (normalized by trading volume). This measure may better capture inventory valuation effects. All variables use the prevailing average market prices to exclude the effect of favorable execution terms, although unadjusted results are similar.

plausibility of this assumption. To investigate this, we examine whether the trades receiving dealer discounts indeed yield higher returns. For dealers, offering discounts must provide some advantage to be sustainable in equilibrium. If this advantage stems from the informational edge gained through these trades, then discounted trades should, on average, generate higher returns than those without discounts.

We define trades that receive substantial discounts as those in the lowest daily tercile of trade costs, using the indicator variable $Low(TradeCost)_n$ 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:

$$\begin{aligned} AdjPerf(Informed)_n^T = &\beta_w Low(TradeCost)_n \times \alpha_w + \mu_{d,day} + \gamma_{i,d} \\ &+ Size_n \times \phi_{day} + \theta Connections_{i,day} + \epsilon_n, \end{aligned} \tag{8}$$

where α_w is a week indicator variable, $\mu_{d,day}$ are dealer-day fixed effects, and the remaining variables are defined as before. The coefficients β_w therefore measures the average return on a discounted trade by an informed client in week w, relative to other trades executed by the same dealer on the same day, and benchmarked to the week preceding the crisis. Standard errors are clustered at the investor and dealer level. A positive β thus indicates higher relative returns on discounted trades in week w.

Figure 6 illustrates the 3-day ahead profitability (adjusted for execution costs following equation (6)) for trades that receive trade cost discounts.[18] We find that trades with the lowest trade costs outperform by almost six percentage points in the first week of the crisis—the same week during which dealers provide the largest discounts to informed clients.[19]

[18]We obtain nearly identical results when we use the 1- or 5-day trading performance.

[19]We also observe a few episodes in late August and mid-October, outside the core crisis period, in which discounted trades underperformed ex post, reflecting the weaker link between short-horizon returns and trade informativeness outside the main stress episode.

Importantly, the rich set of fixed effects rules out the possibility that the trade profitability is driven by established client-dealer relationships, clients' order splitting, or differential trade sizes.

To be clear, our findings do not imply that dealers systematically incur offsetting losses when taking the opposite side of these trades, given their rapid inventory turnover (often less than one day). Moreover, as we demonstrate below, access to informed order flow generates substantial benefits for dealers. Specifically, it enables more careful inventory management and facilitates gains in subsequent transactions, including profits realized through trading in the anonymous interdealer market. Overall, the findings are consistent with the hypothesis that dealers are able to identify potentially informative trades and offer cheap liquidity to sophisticated investors to gather valuable information.

3.3 Alternative Hypotheses

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

3.3.1 Competition for Trading Relationships

The first alternative explanation we consider is whether our results are driven by dealers competing for valuable future trading relationships.[20] Prior research shows that dealers offer more favorable liquidity terms to their most valuable clients (Di Maggio et al., 2017; Jurkatis et al., 2023). This behavior raises the possibility that our results reflect changes in competition for future trading relationships that are not absorbed by the fixed effects in our baseline specification. To examine this channel, we conduct two sets of tests. First, we horse-race our informed investor classification against standard proxies for the value of dealer–client relationships. Second, we test whether, *ex post*, investors reallocate trading volume toward dealers that provided discounted liquidity during the crisis. If competition for future trading relationships were driving our results, these variables should attenuate the coefficient of interest in both settings.

Table 4 includes controls for common measures of trading relationships, demonstrating that the time-varying components of these factors do not drive our results. 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 client size, measured by turnover in the pre-crisis period, as a proxy for client value, with similar results. Column (3) includes the number of trades of a given client (sometimes referred to as trade intensity) in the pre-crisis period, 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

[20] Here, we define the value of 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 from future trading with the *same client*. This distinction is crucial because, for dealers to monetize the "payment" of information in exchange for trade cost discounts, they must trade against other, less informed clients or dealers—i.e. a key spillover channel to broader market liquidity.

baseline results are not driven by the average or time-varying effects of trading relationships.

Next, we compute the share of each client's trading allocated to each dealer, measured both by trading volume and by the number of trades. Specifically, we calculate the change in these shares by comparing the six months following the crisis with the six months preceding it. For example, the change in trading volume Q between investor i and dealer d is given by:

$$\Delta Q_{i,d} = 100 \times \frac{\sum_{t=Nov2022}^{T=Mar2023} Q_{i,d,t}}{\sum_{d \in D} \sum_{t=Nov2022}^{T=Mar2023} Q_{i,d,t}} - \frac{\sum_{t=Apr2022}^{T=Aug2022} Q_{i,d,t}}{\sum_{d \in D} \sum_{t=Apr2022}^{T=Aug2022} Q_{i,d,t}}. \tag{9}$$

Thus, if an investor traded 25% of its volume with a given dealer prior to the crisis and 40% afterward, $\Delta Q_{i,d}$ equals 15%. We define $\Delta Trades_{i,d}$ analogously using the number of transactions. If our results were driven not by lower trade costs for information, but instead by increased competition for future trading revenues, these variables–and their interactions with the crisis indicator variable–should absorb our coefficient of interest. Table 5 includes these controls in columns (2) and (3), yet the coefficient of interest remains effectively unchanged. Taken together, these results provide strong evidence that our informed client classification is not inadvertently capturing dealers' discounts during the crisis.

3.3.2 Clients' Liquidity Provision

Another alternative hypothesis is that the clients we classify as having an informational edge are instead being compensated for providing liquidity in a one-sided market (see, e.g., Kruttli et al., 2024). Specifically, these investors might be acting as shadow dealers if traditional dealers are unwilling or unable to absorb clients' selling pressure. While we do not dismiss the possible existence of this mechanism, we provide evidence that it does not explain our findings. If our categorization of informed investors was inadvertently capturing the compensation for clients' 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 6 excludes bonds being "fire sold" by pension funds and LDI funds (PFLDIs). We classify a bond as being fire-sold by the PFLDI sector when it falls within the top tercile of net sales volume from this sector. If the investors we classify as informed were being compensated for purchasing bonds offloaded by PFLDIs to dealers, we would expect dealer discounts to be concentrated in those specific bonds. Instead, the results show that our findings are not driven by the segments of the market where liquidity was most urgently needed. Another possibility is that clients provide liquidity to dealers—but not in the bonds under fire sale pressure—thereby easing balance sheet constraints. If our results were driven by this more general client-supplied liquidity, then we should expect dealer discounts to be concentrated in client purchases. Column (2) excludes all client purchases, but our main coefficient remains largely unchanged.

Next, we examine which types of clients are receiving discounts, contrasting our informed investor classification with alternative measures that proxy for clients' liquidity provision to dealers. To directly address dealers' potential balance sheet constraints and the sales pressure from distressed investors, we include daily client-dealer net volume (in £m) as a control in column (3). A positive value for this variable indicates the client net purchasing bonds from the dealer. While the significant and negative coefficient suggests that dealers offer cheaper trade costs to clients who supply liquidity, the coefficient on informed investors remains virtually unchanged from the baseline, supporting the notion that the informational channel operates independently of client liquidity supply.

Finally, we study which dealers provide discounts. Column (4) controls for the interaction of our main coefficient with dealer inventories. Inventory is calculated as the risk-adjusted net order flow over the month prior to the crisis, normalized by dealer turnover, a proxy for dealer size. Positive values indicate that dealers have increased their bond holdings, while negative values indicate inventory reduction. If dealers' need to reduce their inventories due to balance sheet constraints (such as regulatory or internal risk limits) were driving our results, then discounted liquidity costs should be primarily driven those dealers with larger inventories. If that were the case, we would expect the interaction with dealer inventories to absorb the significance of our main coefficient. However, the results show that this is not the case.

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

4 Dealers' Use of Information

4.1 Empirical Strategy

In the preceding analyses, we found that during the crisis, dealers provided substantial trade cost discounts to high-performing informed investors. If liquidity is reallocated, at least in part, to these sophisticated clients, the natural follow-up questions are: from whom is liquidity being redistributed, and how do dealers use the information they gain?

First, dealers may impose higher trade costs on less informed investors, both to cross-subsidize transaction cost discounts offered to sophisticated clients and to avoid taking positions opposite to those of these informed clients. Second, they may trade directly on the informational advantage. While the latter strategy can yield immediate profits, it carries the risk of eroding valuable client relationships and reputational capital. Therefore, in non-anonymous markets, dealers may optimally choose to increase trade costs—while refraining from exploiting their informational advantage to trade directly against clients—in order to preserve valuable client relationships.

Consistent with this notion, we hypothesize that dealers with superior information are more likely to raise trade costs—and less likely to trade on their informational advantage—in the dealer-to-client market, where counterparties are identifiable and relationships are sticky. Conversely, in anonymous interdealer markets, where reputational concerns are attenuated, informed dealers are more likely to use their informational advantage to generate trading profits.

To investigate these hypotheses, we first measure $Informed\ Share_{d,t}$ as a given dealer's share of trading volume with informed clients:

$$Informed\ Share_{d,day} = \frac{\sum_i^{I_d} Q_{i,d,day} \times Informed_i}{\sum_i^{I_d} Q_{i,d,day}}, \tag{10}$$

where $Q_{i,d,day}$ is the gross volume traded between clients i and dealer d on day 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. Panel D of Table 1 reports that, based on our benchmark definition, average daily informed order flow across dealers is 13% over the full sample, with a standard deviation of 11%.

The main identification challenge is that $Informed\ Share_{d,day}$ reflects the outcome of both dealer and client decisions. Therefore, a key concern is that factors influencing informed investors' trading activity with a dealer might also affect outcomes such as trade costs or profitability. For instance, if a dealer faces funding constraints, it might increase trade costs for reasons unrelated to information, which could, in turn, lead informed investors to reduce their trading with that dealer.

To address these concerns, we adopt a shift-share instrumental variable approach. We start by noting that any given client's quantity of trading with a particular dealer can be expressed as a product of that client's total trading volume and the share of that total allocated to the dealer: $Q_{i,d,day} = Q_{i,day} \times Share_{i,d,day}$. 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 $Q_{i,d,day} = 5$ million, $Q_{i,day} = 20$ million, and $Share_{i,d,day} = 0.25$.

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

$$\widehat{Informed\ Share}_{d,day} = \frac{\sum_i^{I_d} \widehat{Q_{i,d,day}} \times Informed_i}{\sum_i^{I_d} \widehat{Q_{i,d,day}}}. \tag{11}$$

This instrument captures the time-varying daily share of informed order flow to a dealer, while excluding any variation caused by changes in dealer-client matching after the crisis begins. Appendix Table A.6 presents the first stage at the dealer-day level, with and without fixed effects. The instrument is highly significant and explains a substantial portion of the variation in dealers' informed share, with an F-statistic ranging from 16.9 to 488.9 depending on the specification, indicating its strength as an instrument.

The primary identifying assumption is that dealers with more informed order flow would have behaved similarly to dealers with less informed order flow, conditional on controls, in absence of the crisis. While this counterfactual is not directly observable, we provide standard time-varying estimates to support this assumption. Moreover, alongside other controls, we include dealer fixed effects to mitigate concerns that the instrumental variable captures fundamental dealer characteristics such as business models or risk appetites, rather than exposure to informed order flow.

4.2 Higher Trade Costs

We apply this approach to study how dealers price trades with *uninformed* clients by estimating the following time-varying specification:

$$TradeCost_n = \beta \ InformedShare_{d,day-1} \times \alpha_w + \gamma_d + Size_n \times \phi_{day} + \theta_{i,day} + \epsilon_n, \qquad (12)$$

where $InformedShare_{d,day-1}$ is instrumented using the shift–share measure defined in the previous section and enters with a one-day lag. Unlike earlier specifications, this model does not permit dealer-time fixed effects, but we still incorporate dealer and transaction size-day fixed effects. A key feature in this analysis is the inclusion of investor-day fixed effects, which control for variations in liquidity demand (Khwaja and Mian, 2008). This allows for a more precise comparison between two dealers—one with a higher informed order flow and the other with a lower flow—serving the same investor on the same day, thus holding liquidity demand constant. Standard errors are clustered at the dealer-day level.

Figure 7 presents the time-varying coefficients from the 2SLS estimation for dealer-to-client trades. In the first week of the crisis, dealers with a one-standard-deviation higher informed order flow on day t increase trade costs for uninformed investors in the dealer-to-client market by an average of 10bps on the following day. Economically, this effect corresponds to an approximately threefold increase relative to average pre-crisis trade costs (see Panel A of Table 1). In the pre-crisis period, we find no statistically significant differences, nor any systematic trends, between dealers with high and low informed order flow, supporting the parallel trends assumption.

4.3 Dealers' Trading Performance

The previous analysis shows that during the 2022 LDI crisis, dealers strategically reduced trade costs for sophisticated investors to gain access to their information, and subsequently raised trade costs for uninformed investors in the dealer-to-client market. But do dealers utilize this information to generate trading profits? We hypothesize that dealers are more likely to exploit this information in the anonymous interdealer market, where the risk of damaging relationships is limited, rather than in the non-anonymous dealer-to-client market.

To explore this, we estimate the following time-varying model of dealers' trading performance for both the dealer-to-client and interdealer markets:

$$AdjPerf_n^T = \beta \ InformedShare_{d,day-1} \times \alpha_w + \gamma_d + \theta_{day} + \epsilon_n, \tag{13}$$

again using the lagged instrumental variable approach for dealers' share of informed order flow as outlined in equation (11). The regressions control for dealer and day fixed effects and standard errors are clustered on the dealer-day level.

Figure 8 presents the estimated coefficients for trading returns over a 3-day horizon based on equation (4).[21] The left panel shows that more informed dealers do not earn significant profits by trading against uninformed investors in the dealer-to-client market at any point during the sample. However, the right panel reveals that dealers with a one standard deviation higher informed order flow outperform less informed dealers by 60bps per trade in the interdealer market during the crisis. These coefficients are economically significant, particularly in a market with approximately £200bn in weekly trading volume. In both cases, the pre-crisis estimates provide evidence that support the parallel trends assumption.

[21] We obtain nearly identical results if we use 1- or 5-day trading performance.

4.4 Liquidity Supply

We have established that dealers with a higher share of informed order flow increase the cost of liquidity provision to uninformed clients and earn higher profits. We next examine how these dealers adjust the quantities they intermediate and the extent to which they absorb positions onto their balance sheets. That is, during a period of fire sales and stress, do dealers with higher informed order flow absorb more or less of the selling pressure? Do they intermediate more or less?

Figure 9 begins this analysis by plotting net and gross trading volumes for dealers with high versus low shares of informed order flow, defined as those in the top and bottom terciles, respectively. Panel (a) shows that dealers with high informed order flow sell larger quantities on a net basis than dealers with lower informed order flow, particularly prior to the first Bank of England intervention. Panel (b) shows that these more informed dealers also exhibit consistently lower gross intermediation volumes throughout the crisis.

To better identify and quantify the effect of informed order flow on dealers' liquidity provision, we aggregate the data to the dealer-day level and estimate the following model:

$$Volume_{d,day} = \beta Post_{day} \times InformedShare_{d,day-1} + \gamma InformedShare_{d,day-1} + \alpha_{day} + \epsilon_{d,day}, \tag{14}$$

where $Volume_{d,day} \in \{NetPurchases_{d,day}, GrossVolume_{d,day}\}$ is dealer d's daily net order flow (i.e., bond purchases minus sales) or daily gross order flow (i.e. bond purchases plus sales). Both dependent variables are standardized. The indicator variable $Post_{day}$ equals one after the onset of the crisis on September 23, 2022. As before, $InformedShare_{d,day-1}$ is standardized and measures the dealer's share of informed order flow using the shift–share instrument in equation (11). We include dealer and day fixed effects, and standard errors are clustered at the dealer–day level.

Table 7 examines the effect of dealers' informed order flow on net bond purchases during the crisis across a range of specifications. Columns (1) and (2) report results using standardized net purchases in nominal and risk-adjusted terms, respectively. Column (3) re-estimates the model using the inverse hyperbolic sine transformation of nominal net purchases. Columns (4)–(6) repeat these specifications for the subsample of fire-sale bonds (defined as those bonds in the top tercile of net sales by the PFLDI sector). In the full sample, dealers with higher informed order flow tend to purchase fewer bonds on net, although the statistical significance is generally weak. Focusing on fire-sale bonds, a one standard deviation increase in informed order flow is associated with a reduction of 0.15 standard deviations in net purchases (statistically significant at the 5% level). These findings indicate that more informed dealers substantially reduce their net purchases, particularly in bonds subject to the most acute fire-sale pressure.

Table 8 presents analogous regressions using dealers' gross trading volumes. Columns (1)–(3) show no statistically significant relationship between informed order flow and volumes in the full sample of gilts. In contrast, columns (4)–(6) indicate that, within the subsample of fire-sale bonds, dealers with higher informed order flow reduce their gross trading volumes during the crisis relative to less informed counterparts. The economic magnitudes mirror those for net purchases: a one standard deviation increase in informed order flow is associated with a roughly 0.15 standard deviation decline in gross trading volumes for bonds subject to the most acute fire-sale pressure (again statistically significant at the 5% level).

The finding that more informed dealers raise liquidity costs, scale back net purchases, and reduce intermediation relative to less informed dealers is consistent with an inward shift of the liquidity supply curve driven by greater informed order flow. The concentration of these effects in bonds subject to the most acute fire-sale pressure further supports an information-based channel for the contraction in liquidity.

5 Source of Information Advantage

This section analyzes the nature of the information possessed by sophisticated clients and dealers. A priori, acquiring an informational advantage over other participants in the government bond market appears challenging, given the market's depth and liquidity. Nevertheless, periods of heightened volatility, such as the 2022 LDI crisis, create opportunities for sophisticated investors to exploit profitable trading opportunities. One important channel operates through the ability to anticipate and front-run the demand of other market participants (Czech et al., 2021). We therefore hypothesize that informed investors are better able to identify bonds exposed to fire-sale pressure from distressed pension funds and LDI funds (PFLDIs), and that dealers infer this information from the order flow of these sophisticated clients.

To examine this mechanism, we aggregate order flow at the group-bond-day level across four mutually exclusive groups (excluding PFLDIs): informed investors, uninformed investors, informed dealers, and uninformed dealers. Consistent with our earlier classification, informed investors comprise the top tercile of asset managers and hedge funds, while informed dealers are those in the top tercile of informed order flow, as defined in equation (10). For each group, order flow is defined as purchases minus sales and scaled by the bond's average pre-crisis trading volume.

Following Czech et al. (2021), we test whether trades by informed investors and dealers predict subsequent order flow from the PFLDI sector. Specifically, we estimate the following panel regression:

$$PFLDI\ Order\ Flow_{t+1:t+5,b} = \beta \times Order\ Flow_{t-4:t,b,g} + \phi_t + \theta_b + \epsilon_{t+1:t+5,b}, \tag{15}$$

where the dependent variable is the aggregate net order flow of the PFLDI sector in bond b

over the next five trading days. The main independent variable of interest is the lagged order flow of each of the other four groups in the same bond in the previous week. We include bond fixed effects (θ_b) and time fixed effects (ϕ_t) to account for bond-specific characteristics and market-wide movements.

Table 9 reports the regression results. Order flow from informed clients and informed dealers positively and significantly predicts subsequent trading by the PFLDI sector, whereas flows from uninformed participants do not. A net order flow of one pound by informed investors (dealers) predicts 17 (9) pence of net order flow in the same bond by PFLDIs in the following week. A natural interpretation is that sophisticated investors process information more quickly and trade ahead of fire sales. The predictive relation is stronger for informed clients than for informed dealers, consistent with informed clients having a stronger informational advantage. Overall, the evidence suggests that sophisticated clients and dealers are better able to identify bonds that subsequently come under selling pressure from distressed investors, particularly PFLDIs in our setting.

6 External Validity: COVID-19 Dash for Cash

The preceding analysis focuses on the most recent major liquidity disruption in the UK gilt market, the 2022 LDI crisis. While the mechanism linking information acquisition and liquidity provision is conceptually general, one might be concerned that the LDI episode represents an idiosyncratic stress event. External validation is constrained by limited data availability, particularly for the United States. However, our dataset contains a second episode of severe stress in the UK gilt market. During the COVID-19 pandemic, the gilt market experienced a severe liquidity stress – the so-called "Dash for Cash" – which occurred alongside similar crises in the U.S. Treasury and euro area sovereign bond markets (Barone et al., 2023; Czech et al., 2022).

Our main findings also replicate during the Dash for Cash episode. Figure 10 shows that, at the onset of the crisis, dealers offered significantly lower trade costs (with discounts of up to 7bps) to high-performing, sophisticated investors. Moreover, Figure 11 further shows that dealers with more informed order flow sold more bonds on a net basis during the early stage of the pandemic, absorbing less of clients' selling pressure. This pattern reverses in the days prior to the Bank of England's intervention on March 19. Taken together, these results indicate that information chasing and the crisis amplification channel identified in our analysis are not unique to the 2022 LDI crisis.

7 Conclusion

In this paper, we investigate the role of information in safe asset liquidity crises, with a focus on the 2022 UK LDI crisis. Our findings reveal that during crises, dealers offer cheaper liquidity to high-performing, sophisticated clients. We interpret this as evidence of dealers shifting their liquidity provision to informed investors to gain insights from their informational edge. Supporting this interpretation, dealers with a higher informed order flow raise trade costs for less informed clients, reduce their market-wide trading volumes, and leverage their informational advantage to generate trading profits in anonymous interdealer markets. We further document that the informational advantage of sophisticated clients and dealers is linked to their ability to anticipate which bonds are likely to experience selling pressure from distressed pension funds. Importantly, these dynamics were also evident during the COVID-19 Dash for Cash and therefore not unique to the 2022 LDI crisis.

Our results thus emphasize the critical role that information plays in liquidity crises, even within safe asset markets. Our findings also suggest that market design reforms—such as introducing central clearing of safe assets or enabling anonymous trading via all-to-all platforms—may be able to curb dealers' information-chasing behavior and the reallocation of liquidity towards informed clients during stress periods.

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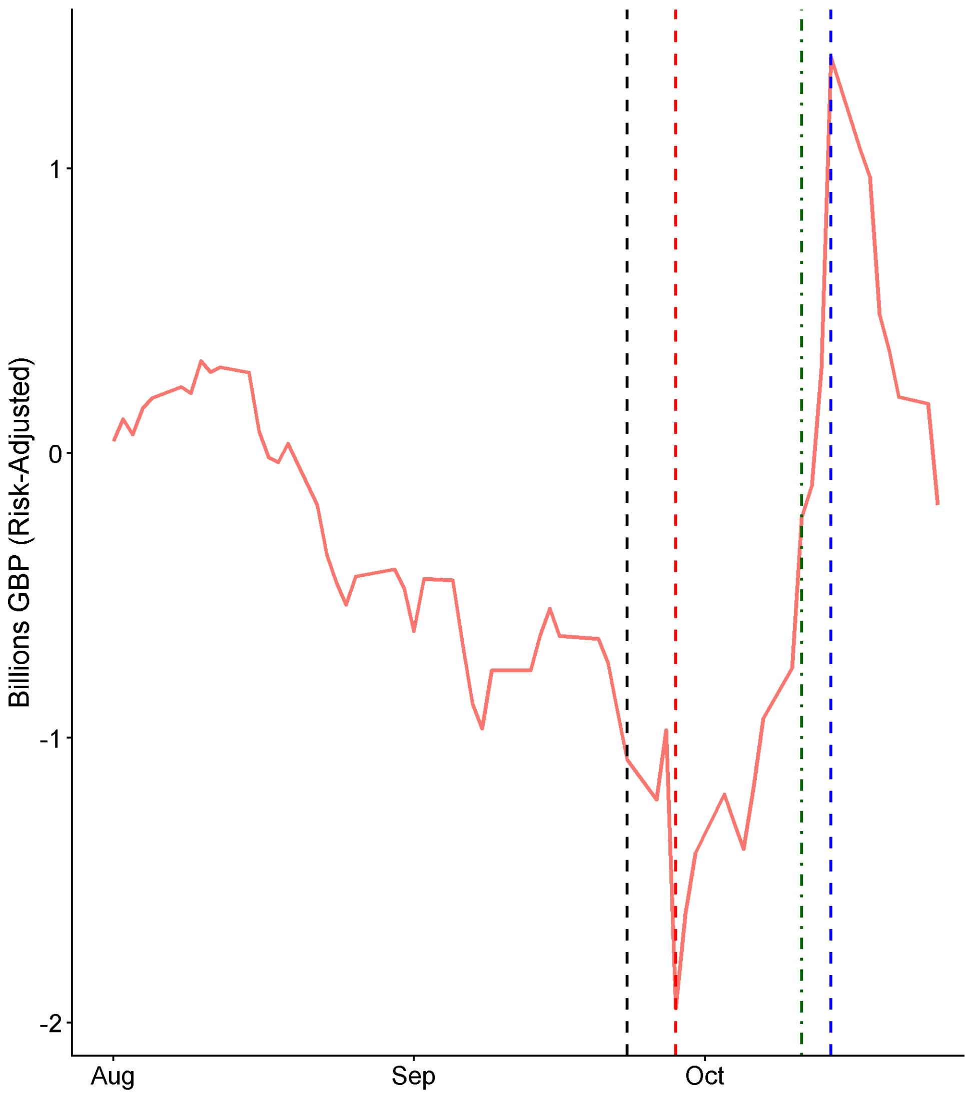
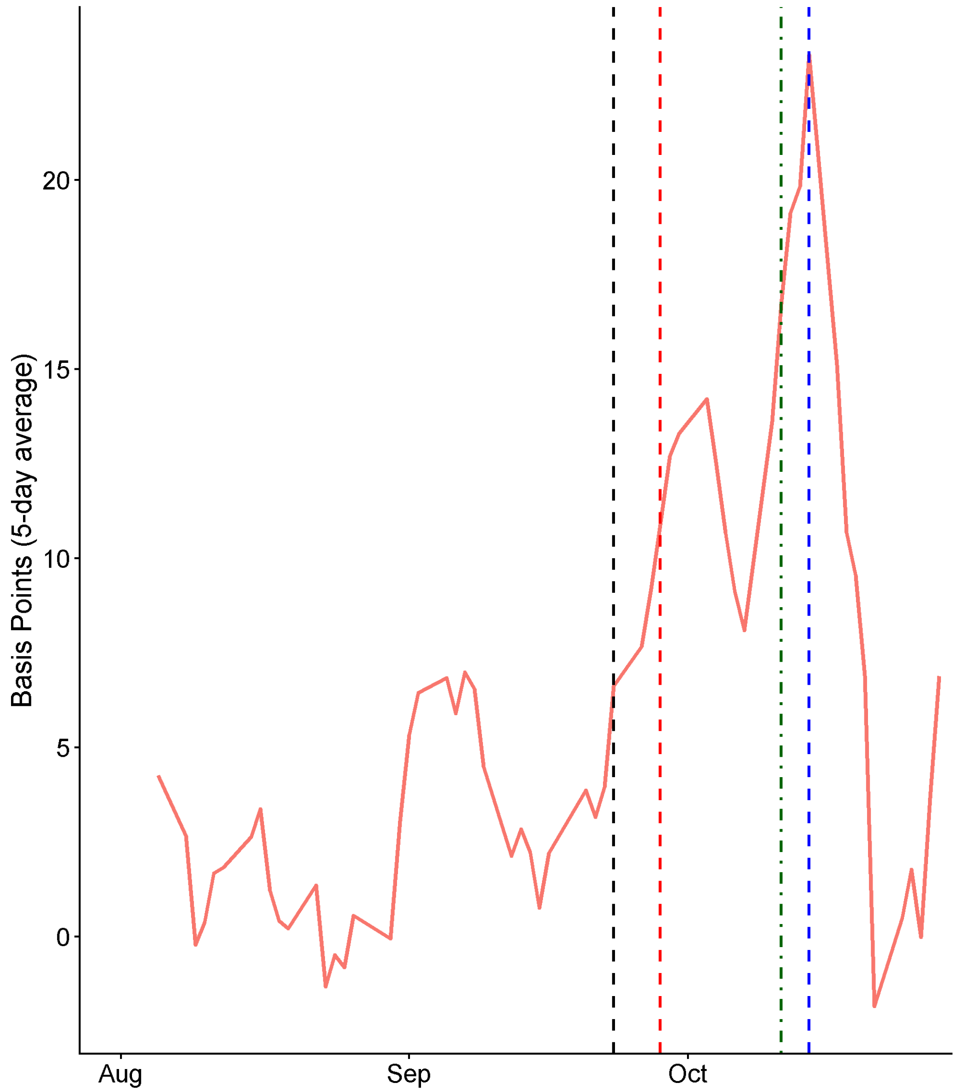
Figures and Tables

Figure 1 Cumulative Dealer Net Order Flow



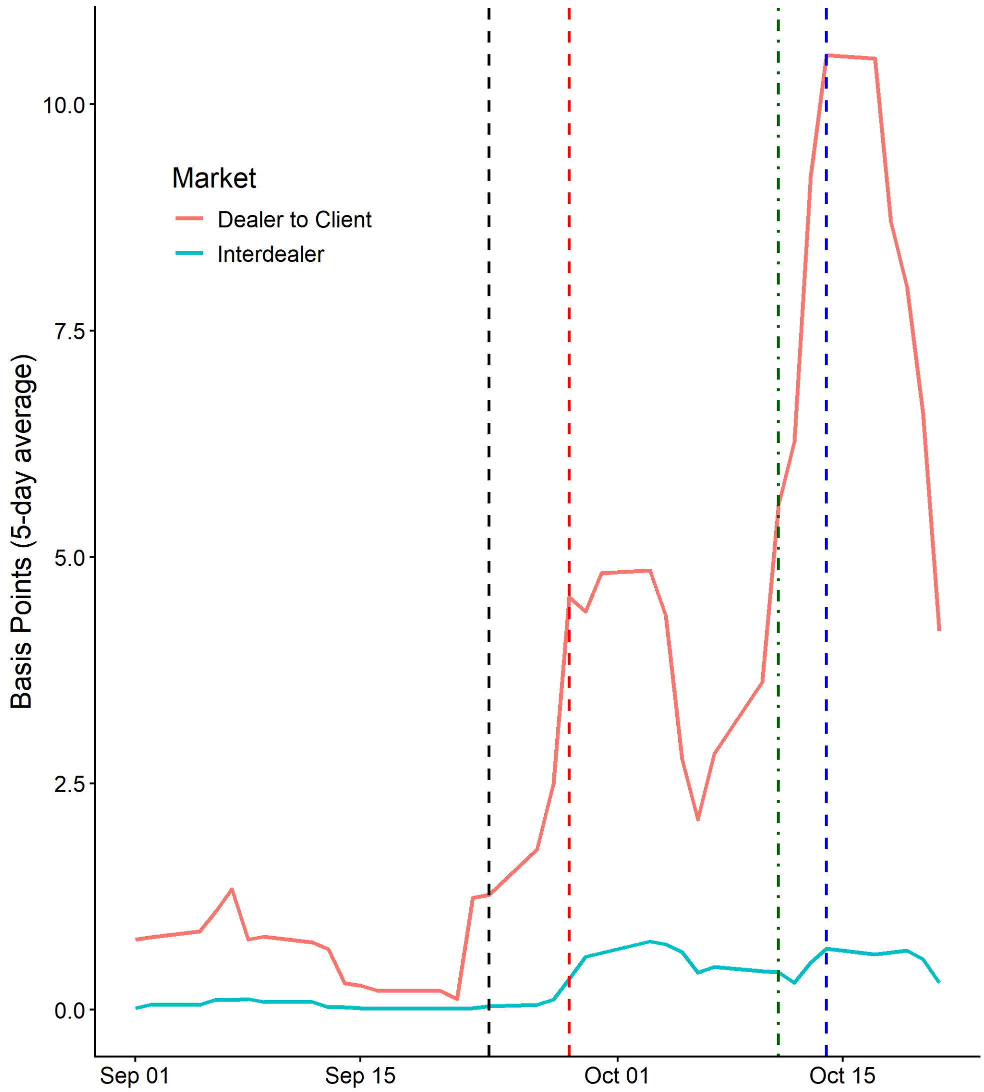
Note: The figure plots the cumulative net order flow of dealers in the gilt market. When it is increasing (decreasing), dealers are net buying (selling). The black line indicates the mini-budget announcement on September 23, the red line indicates the start of the BoE asset purchases on September 28.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

Figure 2 TRADE COSTS



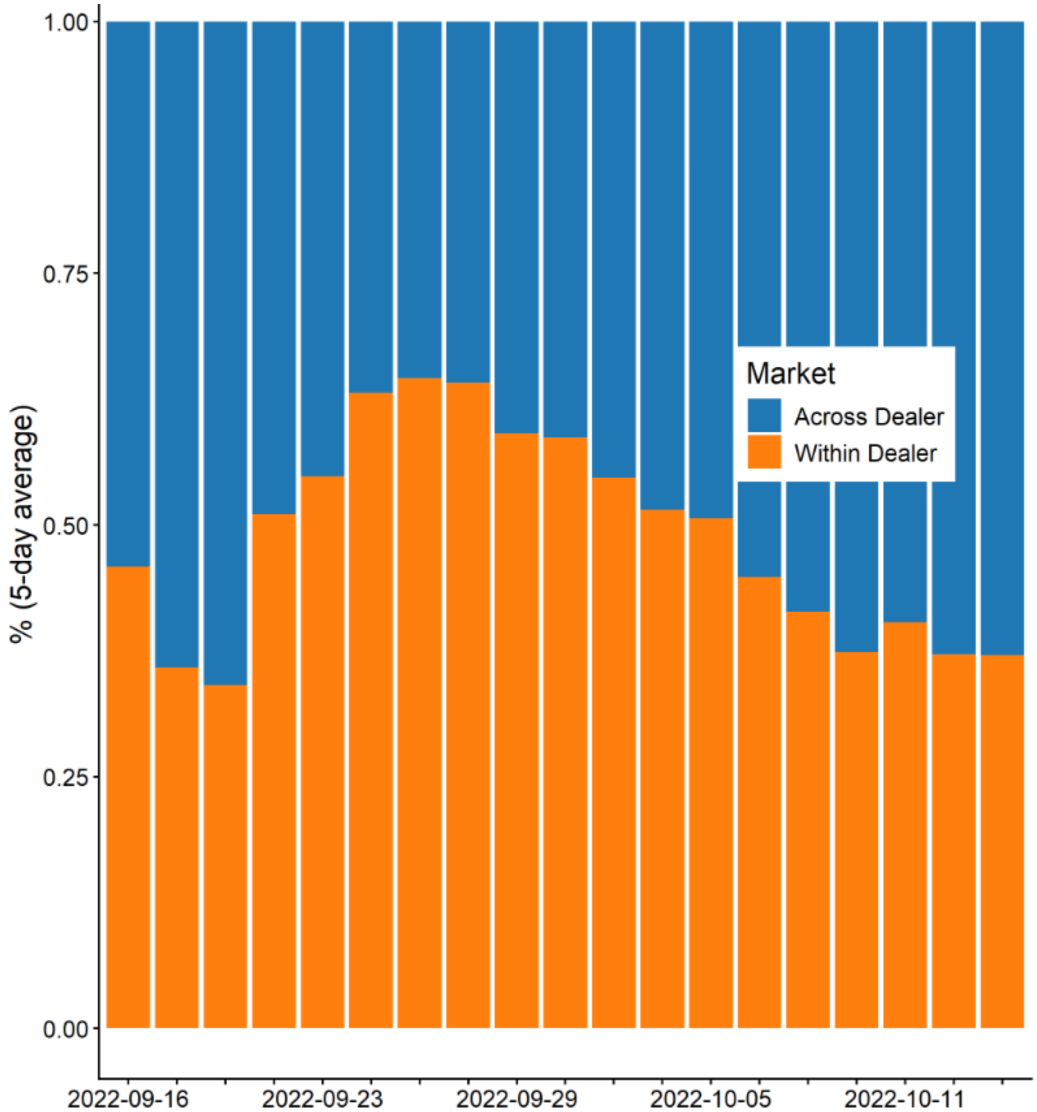
Note: The figure plots the volume-weighted average trade costs across the entire gilt market. The black line indicates the mini-budget announcement on September 23, the red line indicates the start of the BoE asset purchases on September 28. The green line indicates the expansion of the asset purchases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

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



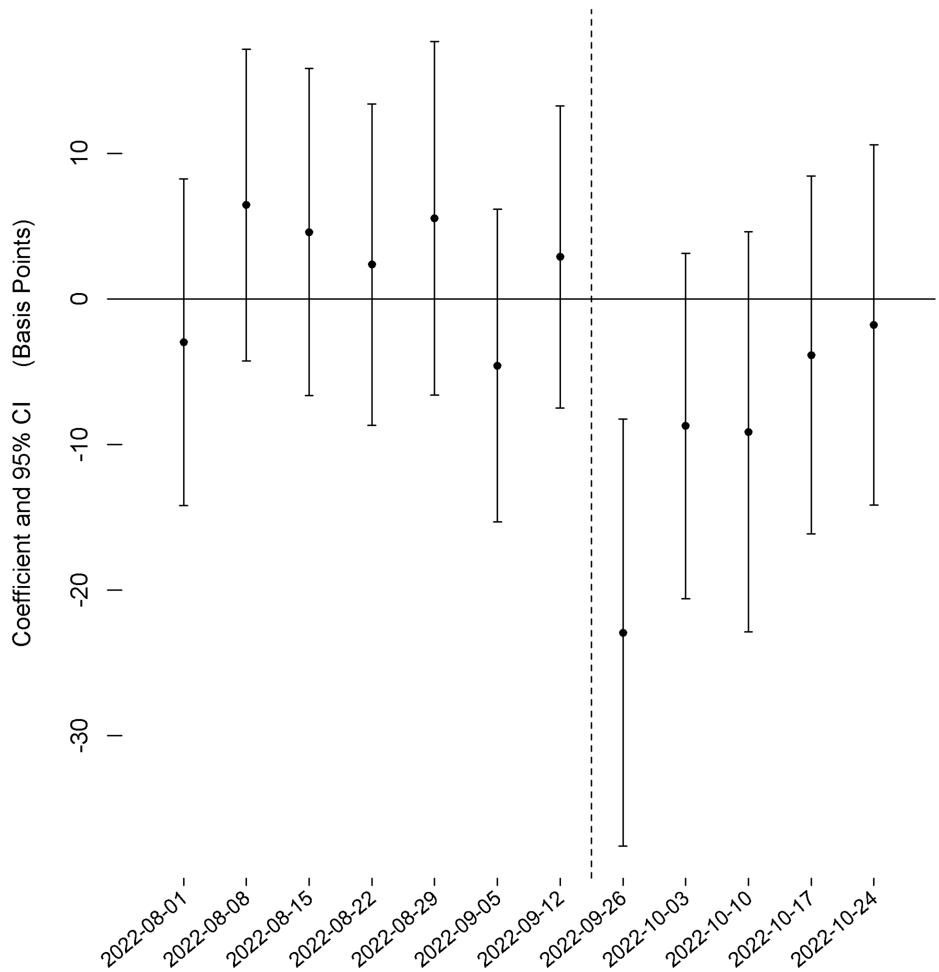
Note: The figure plots the total price dispersion in the dealer-to-client and interdealer markets, as described in equation (2). The deviations are summed up across bonds and dealers and then plotted as a five-day rolling average. The black line indicates the mini-budget announcement on September 23. The red line indicates the start of the BoE asset purchases on September 28. The green line indicates the expansion of the asset purchases on October 11. The blue line indicates the conclusion of the BoE market intervention on October 14.

Figure 4 Share of Total Price Dispersion



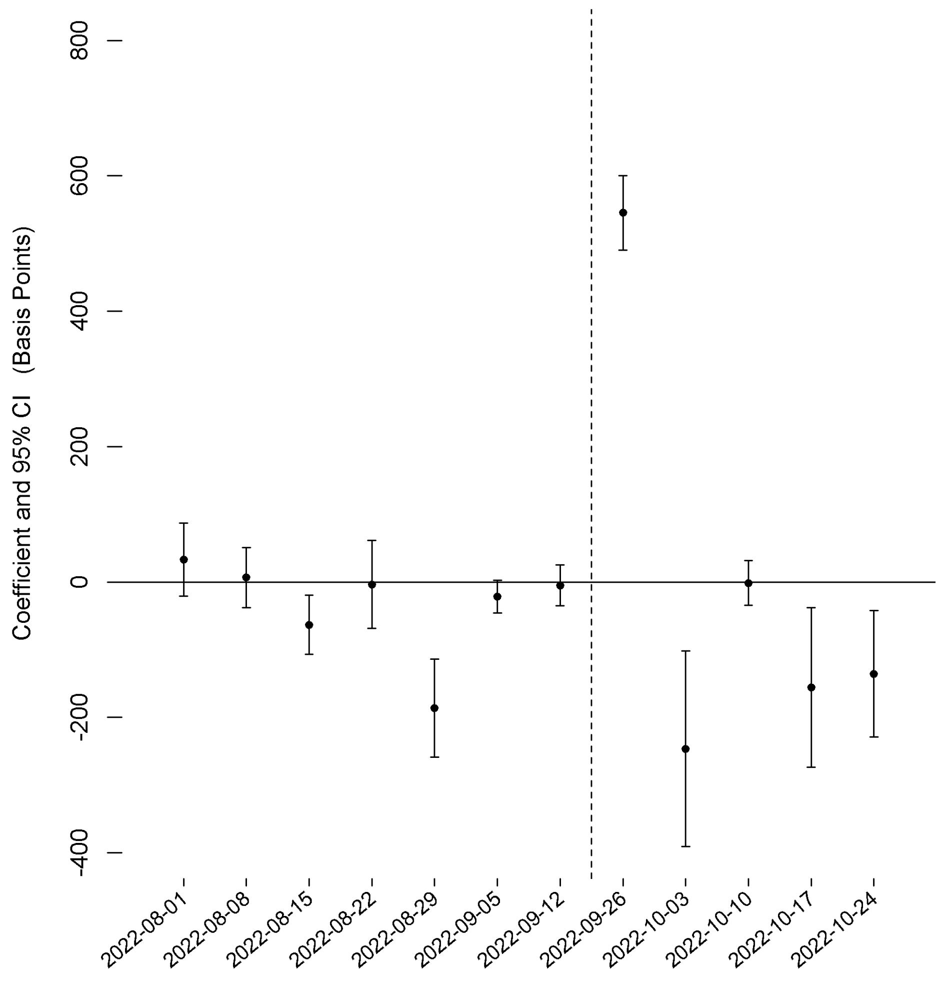
Note: The figure plots the shares of total price dispersion in the dealer-to-client market attributable to across-dealer and within-dealer components, as defined in equation (3). For each component, deviations are aggregated across bonds and dealers, normalized by total price dispersion, and reported as a five-day rolling average.

Figure 5 Time-varying Trade Costs for Informed Investors



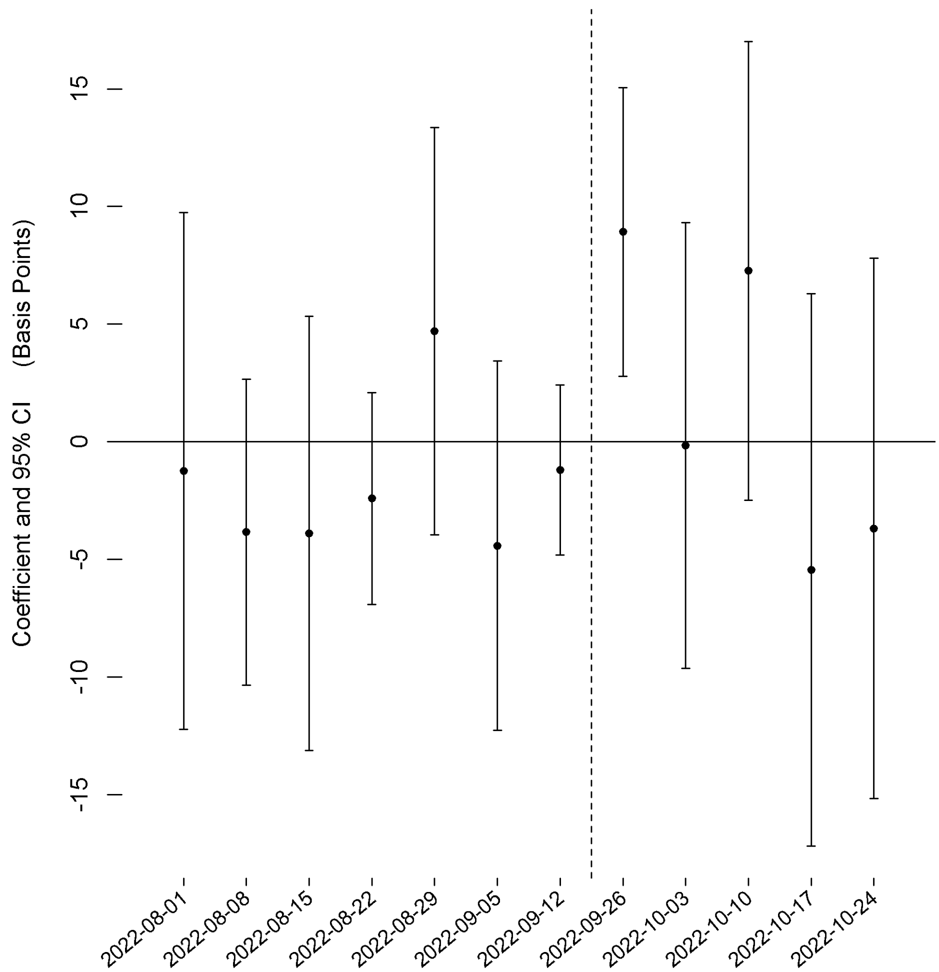
Note: The figure depicts time-varying estimates of the transaction costs for informed investors relative to uninformed investors in the same bond, expressed in basis points. The black dashed line indicates the mini-budget announcement on September 23, which triggered the crisis. The omitted baseline time period is the week before the crisis. The coefficients are estimated using equation (7), using volume-weighted trade costs, and controlling for the number of clients' dealer connections as well as dealer-time, investor-dealer and transaction size-day fixed effects. Standard errors are clustered at the investor-day level, and 95% confidence intervals are shown.

Figure 6 TRADE INFORMATIVENESS



Note: The figure depicts time-varying estimates of the returns to informed investors' trades which received trade cost discounts from dealers, using equation (8). Trades are evaluated over a 3-day horizon. Low trade costs are defined as being in the lowest tercile of daily trade costs. The regression controls for dealer-day, dealer-client, and size-day fixed effects, as well as clients' daily number of connections. Standard errors are clustered at the investor and dealer level, and 95% confidence intervals are shown. The black dashed line indicates the mini-budget announcement on September 23, which triggered the crisis. The omitted baseline time period is the week before the crisis.

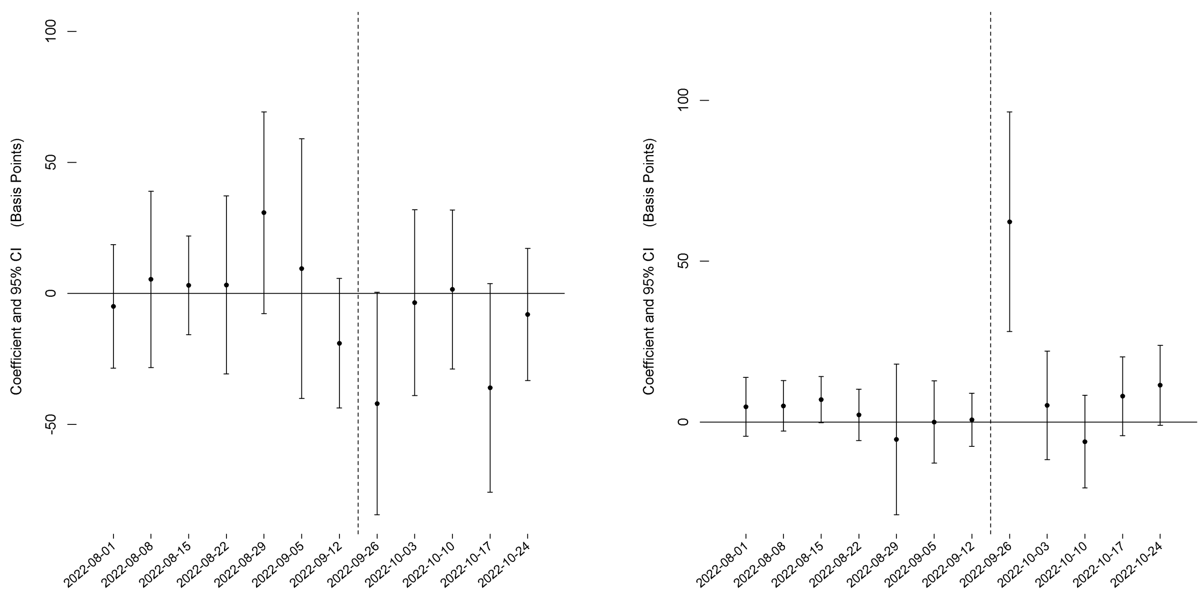
Figure 7 Informed Dealers—Trade Costs of Uninformed Clients



Note: The figure shows time-varying estimates of the effect of dealers' informed order flow on trade costs of uninformed clients, following equation (10). Dealers' share of informed order flow is lagged one day and instrumented as in equation (11). The estimates control for dealer, investor-day and transaction size-day fixed effects. Standard errors are clustered at the dealer-day level, and 95% confidence intervals are shown. The black dashed line indicates the mini-budget announcement on September 23, which triggered the crisis. The omitted baseline time period is the week before the crisis.

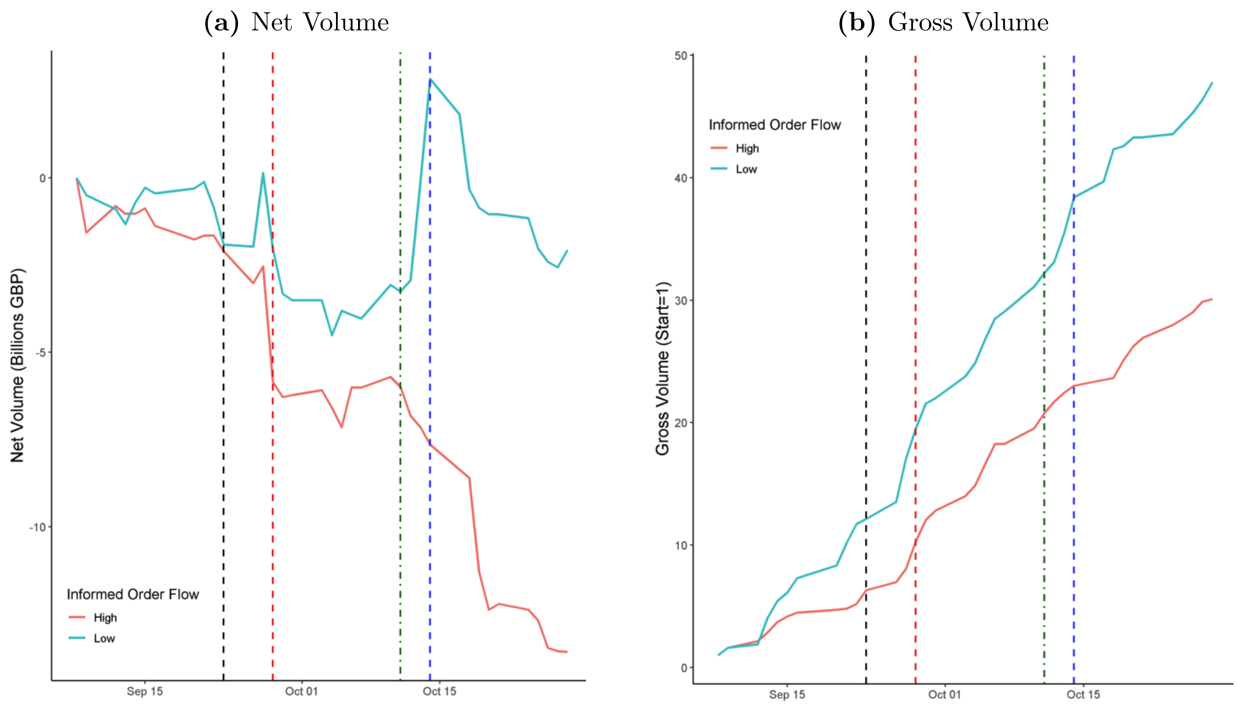
Figure 8 INFORMED DEALERS—TRADING PERFORMANCE

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



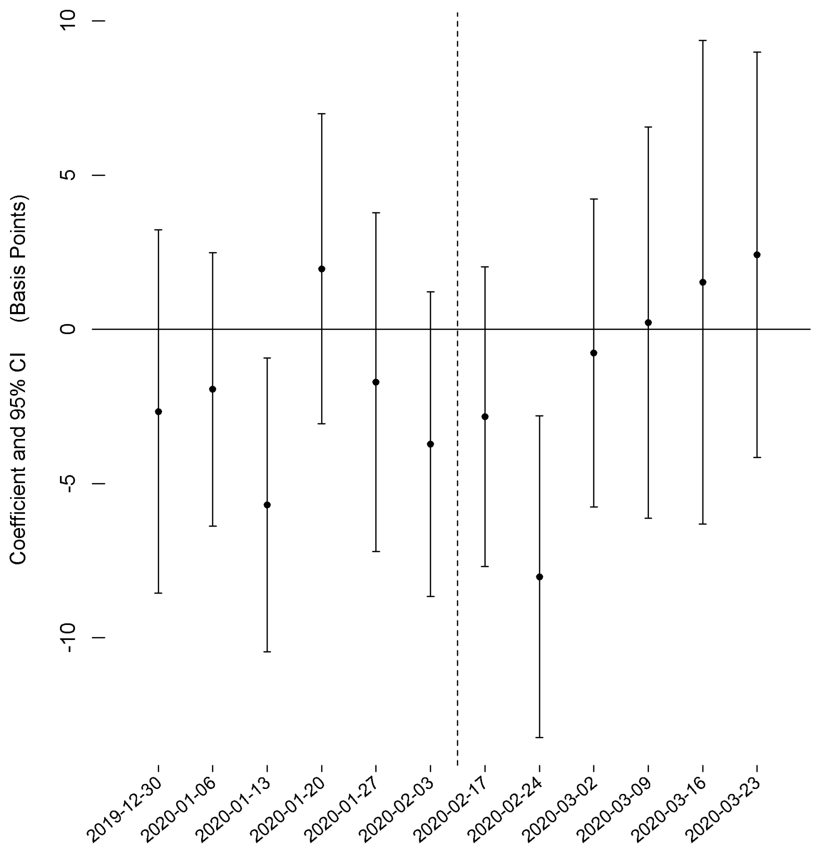
Note: The figure depicts time-varying estimates of the effect of dealers' informed order flow on dealers' trading returns, both in the dealer-to-client (left) and interdealer market (right), using equation (13). Returns are evaluated over a 3-day horizon. Dealers' share of informed order flow is lagged one day and instrumented as in equation (11). The regression controls for dealer and day fixed effects. Standard errors are clustered at the dealer-day level, and 95% confidence intervals are shown. The black dashed line indicates the mini-budget announcement on September 23, which triggered the crisis. The omitted baseline time period is the week before the crisis.

Figure 9 Informed Dealers—Trading Volumes



Note: The figures depict dealers' cumulative net and gross trading volumes, split into dealers with "high" and "low" informed order flow (defined as the top or bottom tercile) following equation (10). Net volumes are calculated as purchases less sales. Gross volumes are the sum of purchases and sales. The gross volumes are normalized to the start of the period. The black dashed line indicates the mini-budget announcement on September 23, which triggered the crisis. The red line indicates the start of the BoE asset purchases on September 28. The green line indicates the expansion of the asset purchases on October 11. The blue line indicates the conclusion of the BoE market intervention on October 14.

Figure 10 Dash for Cash: Trade Costs of Informed Investors



Note: The figure depicts time-varying estimates of trade costs of informed investors relative to uninformed investors for the same bond during the COVID-19 Dash for Cash, expressed in basis points. It is estimated using equation (7), using volume-weighted trade costs, and controlling for the number of clients' dealer connections as well as dealer-time, investor-dealer and transaction size-day fixed effects. Standard errors are clustered at the investor-day level, and 95% confidence intervals are shown. The dashed black line marks the emergence of the first signs of market stress in February 2020. The omitted baseline period is the week commencing 10 February, prior to the onset of market stress.

Figure 11 Dash for Cash: Informed Dealers—Trading Volumes

Note: The figures depict dealers' cumulative net trading volumes, split into dealers with "high" and "low' informed order flow (defined as the top or bottom tercile) following equation (10). Net volumes are calculated as purchases less sales. The black dashed line indicates the announcement of the Bank of England's wide-ranging market intervention on March 19, 2020.

Table 1 Summary Statistics

Panel A: Trade Costs

Investor	Pre-Crisis	Crisis
Informed	3.8	-2.4
Uninformed	2.6	21.9

Panel B: Daily Average Trade Count and Volume

Investor	Variable	Mean	SD	p25	p75
Total	Trade Count	4446	1857	3048	5456
Informed	Trade Count	427	209	299	548
Total	Volume	37	16	25	48
Informed	Volume	5.5	2.5	3.8	6.9

Panel C: Trading Performance

Investor	Period	N	Mean	SD	p25	p50	p75
Uninformed	Pre-Crisis	53535	-0.34	5.02	-1.48	-0.13	0.85
Uninformed	Crisis	49907	0.43	12.63	-2.68	0.12	3.00
Informed	Pre-Crisis	12226	0.17	4.14	-1.08	0.12	1.50
Informed	Crisis	9991	1.26	12.01	-3.01	0.22	4.43

Panel D: Dealers

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
Informed Share	882	13%	11%	5%	12%	20%

Note: The table provides summary statistics for our gilt transaction sample. Panel A reports the volume-weighted average trade costs of informed and uninformed clients before and during the crisis, expressed in basis points. Trade costs are calculated following equation (1), using the prevailing interdealer prices as the benchmark. Informed investors are classified as described in Section 2.4. Panel B reports the daily average number and volume of trades for all market participants (incl. interdealer trades) and informed investors. Trading volume is expressed in £bn. Panel C reports statistics on clients' trading returns before and during the crisis, expressed in basis points. Returns are calculated using 3-day ahead trading returns, adjusted for execution costs following equation (6). Panel D provides statistics on the dealers, calculated at the dealer-day level.

Table 2 TRADE COSTS OF INFORMED INVESTORS

Dependent Variable:		Trade Cost		
Model:	(1)	(2)	(3)	(4)
Variables				
Post × Informed	-16.4***	-14.5***	-14.5**	
	(4.87)	(5.04)	(6.29)	
Value Info × Informed				-8.96**
				(3.64)
Check:			Clustering	Value of Info
Fixed-effects				
Investor	Yes			
Dealer-Time	Yes	Yes	Yes	Yes
Size-Day		Yes	Yes	Yes
Investor-Dealer		Yes	Yes	Yes
Connections Control		Yes	Yes	Yes
Fit statistics				
Observations	121,769	119,641	119,641	119,641
R^2	0.19	0.24	0.24	0.24

Clustered (Investor-Day) standard-errors in parentheses, except column (3)
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The table estimates the trade costs of an informed investor, relative to an uninformed investor, after the crisis begins. It is estimated using equation (7), clustering standard errors at the investor-day level, except for column (3). Column (1-2) provide different specifications for the main result, with the more demanding specification (2) being the baseline. Column (3) uses investor and day clustered standard errors. Column (4) replaces the Post date indicator with the time-varying estimate of the value of information as described in Appendix Section (A), standardized over the sample.

Table 3 Bond Heterogeneity

Dependent Variable:	Trade Cost					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Post × Informed	-2.62	-17.3**	-24.9	-0.460	-21.5**	-70.4**
	(3.22)	(7.47)	(19.3)	(4.77)	(9.30)	(30.9)
Bonds:	<10y	≥ 10y	Inflation	<10y	≥ 10y	Inflation
Weights:	Unw.	Unw.	Unw.	Volume	Volume	Volume
Fixed-effects						
Dealer-Time	Yes	Yes	Yes	Yes	Yes	Yes
Size-Day	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	41,011	42,844	27,191	41,011	42,844	27,191
R^2	0.36	0.35	0.42	0.58	0.49	0.56

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

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

Table 4 Competition for Trading Relationships

Dependent Variable:	Trade Cost			
Model:	(1)	(2)	(3)	(4)
Variables				
Post × Informed	-15.2***	-17.1***	-13.8***	-14.0***
	(5.22)	(5.17)	(5.01)	(5.35)
Post × Investor % Dealer	51.3			21.4
	(42.1)			(44.7)
Post × Size		3.20***		0.714
		(0.885)		(1.64)
Post × Trade Intensity			4.64***	3.56*
			(1.16)	(2.14)
Fixed-effects				
Dealer-Time	Yes	Yes	Yes	Yes
Size-Day	Yes	Yes	Yes	Yes
Investor-Dealer	Yes	Yes	Yes	Yes
Connections Control	Yes	Yes	Yes	Yes
Fit statistics				
Observations	107,139	115,418	115,418	107,139
R^2	0.22	0.23	0.23	0.22

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

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

Table 5 Ex Post Changes in Relationships

Dependent Variable:	Trade Cost		
Model:	(1)	(2)	(3)
Variables			
Post × Informed	-14.5***	-14.6***	-14.5***
	(5.04)	(5.05)	(5.04)
ΔQ		0.247	
		(0.161)	
Post × ΔQ		-0.098	
		(0.075)	
ΔTrades			0.154
			(0.203)
Post × ΔTrades			0.066
			(0.101)
Fixed-effects			
Dealer-Time	Yes	Yes	Yes
Size-Day	Yes	Yes	Yes
Investor-Dealer	Yes	Yes	Yes
Connections Control	Yes	Yes	Yes
Fit statistics			
Observations	119,641	119,641	119,641
R^2	0.24	0.24	0.24

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

Note: This table estimates the trade costs of informed investors relative to uninformed investors after the onset of the crisis, controlling for *ex post* dealer–client relationships as defined in equation (9). Column (1) reproduces the baseline specification. Column (2) additionally controls for changes in the share of trading volume allocated to each dealer, while column (3) controls for changes in the share of trades allocated to each dealer.

Table 6 Clients' Liquidity Provision

Dependent Variable:	Trade Cost			
Model:	(1)	(2)	(3)	(4)
Variables				
Post × Informed	-16.0***	-11.8**	-13.1***	-15.0***
	(4.97)	(5.92)	(5.02)	(5.57)
Client-Dealer Net Volume			-0.040***	
			(0.008)	
Post × Informed × Inventory				-2.92
				(12.2)
Sample:	No Fire Sales	Sales Only	All	All
Fixed-effects				
Dealer-Time	Yes	Yes	Yes	Yes
Size-Day	Yes	Yes	Yes	Yes
Investor-Dealer	Yes	Yes	Yes	Yes
Connections Control	Yes	Yes	Yes	Yes
Fit statistics				
Observations	89,726	46,649	119,641	119,641
R^2	0.27	0.46	0.24	0.24

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

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

Table 7 Informed Dealers and Net Trading Volumes

Dependent Variables:	Net Purchases	Net Risk	Asinh(Net)	Net Purchases	Net Risk	Asinh(Net)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Post $\times$ Info. Share$_{t-1}$	-0.098	-0.121*	-3.82*	-0.146**	-0.142**	-3.77*
	(0.081)	(0.068)	(2.05)	(0.061)	(0.058)	(2.06)
Sample:	All	All	All	Fire sale	Fire sale	Fire sale
Fixed-effects						
Dealer	Yes	Yes	Yes	Yes	Yes	Yes
Day	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	863	863	863	863	863	863
R^2	0.11	0.09	0.09	0.13	0.15	0.12

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

Note: This table estimates the effect of dealers' informed order flow on net trading volumes in the gilt market after the onset of the crisis. It estimates equation (14), using the instrument from equation (11). In column (1), the dependent variable *Net Purchases* captures the daily dealer net order flow (i.e., dealer purchases minus dealer sales). Both the dependent and independent variables are standardized. Column (2) re-estimates the model, but uses net risk-adjusted units as the dependent variable. Risk-adjusted volume is calculated by scaling nominal net order flow by DVO1 and implied rate volatility, normalized by monthly 95% Value-at-Risk. Column (3) re-estimates the model using the inverse hyperbolic sine of net purchases as the dependent variable. Columns (4)-(6) repeat these regressions, but for the subsample of bonds fire-sold by the PFLDI sector during the crisis. We classify a bond as being fire-sold by the PFLDI sector when it falls within the top tercile of net sales volume from this sector.

Table 8 Informed Dealers and Gross Trading Volumes

Dependent Variables:	Gross Volume	Gross Risk	Log(Gross)	Gross Volume	Gross Risk	Log(Gross)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Post × Info. Share$_{t-1}$	-0.074	-0.036	-0.079	-0.149***	-0.137***	-0.226**
	(0.079)	(0.079)	(0.095)	(0.057)	(0.050)	(0.107)
Sample:	All	All	All	Fire sale	Fire sale	Fire sale
Fixed-effects						
Dealer	Yes	Yes	Yes	Yes	Yes	Yes
Day	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	863	863	863	863	863	822
R^2	0.75	0.72	0.84	0.54	0.55	0.71

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

Note: This table estimates the effect of dealers' informed order flow on gross trading volumes in the gilt market after the onset of the crisis. It estimates equation (14), using the instrument from equation (11). In column (1), the dependent variable *Gross Volume* captures the daily dealer gross order flow (i.e., dealer purchases plus dealer sales). Both the dependent and independent variables are standardized. Column (2) re-estimates the model, but uses gross risk-adjusted units as the dependent variable. Risk-adjusted volume is calculated by scaling nominal order flow by DVO1 and implied rate volatility, normalized by monthly 95% Value-at-Risk. Column (3) re-estimates the model using the log of gross volume as the dependent variable. Columns (4)-(6) repeat these regressions, but for the subsample of bonds fire-sold by the PFLDI sector during the crisis. We classify a bond as being fire-sold by the PFLDI sector when it falls within the top tercile of net sales volume from this sector.

Table 9 PREDICTING ORDER FLOW

Dependent Variable:	PFLDI Order Flow$_{t+1:t+5,b}$			
Model:	(1)	(2)	(3)	(4)
Variables				
Order Flow$_{t-4:t,b,g}$	0.165**	0.035	0.092***	0.044
	(0.073)	(0.106)	(0.029)	(0.104)
Group:	Investors	Investors	Dealers	Dealers
Type:	Informed	Uninformed	Informed	Uninformed
Fixed-effects				
Bond	Yes	Yes	Yes	Yes
Day	Yes	Yes	Yes	Yes
Fit statistics				
Observations	4,763	4,763	4,763	4,763
R^2	0.16	0.16	0.17	0.16

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

Note: This table reports the results of group-bond-day level regressions of rolling weekly PFLDI order flow on lagged weekly order flow of informed and uninformed investors and dealers, following equation (15). Order flow for each group is the quantity of purchases less sales, scaled by the bond's pre-crisis average volume. The standard errors are double clustered at the bond and day level.

Appendix

A The Value of Information

Our hypothesis is that dealers strategically manage trade costs to gain insights from sophisticated investors, and their incentives to engage in such behavior increases during stress periods. However, *a priori* it is not obvious that the value of information increases in crises. While higher volatility increases the potential returns from informational advantages, liquidity generally decreases, increasing the average costs to trade. That is, the value of information is increasing in volatility and decreasing in illiquidity.

Starting from a Kyle (1985)-type model, generalized for multiple differentially informed investors, Kadan and Manela (2025) derive a sufficient statistic for the value of information as the ratio of the variance of returns over price impact, $\Omega_t = \sigma_t^2 / PI_t$. Price impact is a common measure of liquidity which aims to estimate the cost associated with trading a given quantity of a security (Foucault et al., 2013). Thus, this ratio captures the competing effects of volatility and illiquidity on the value of information.

We estimate the time-varying value of information in the UK gilt market by estimating the price impact and the average return variance across all gilts.[22] Specifically, we estimate daily bond-level price impact coefficients in a rolling two-week window based on the following model:

$$ret_{b,day} = \beta_{day}\ SOF_{b,day} + \theta_b + \theta_{day} + \epsilon_{b,day} \tag{A.1}$$

where $ret_{b,day}$ is the daily return in basis points for bond b, and $SOF_{b,day}$ is the daily signed order flow against dealers (investor buys minus sales) in billions GBP, while θ_b and θ_{day} are

[22]For their empirical estimation, Kadan and Manela (2025) calculate the variance and price impact of 7,400 US stocks over one-minute intervals, averaging across securities to estimate the market-level value of information. This approach is not feasible in our setting, as the UK gilt market contains only about 80 bonds and, although liquid, trades less frequently.

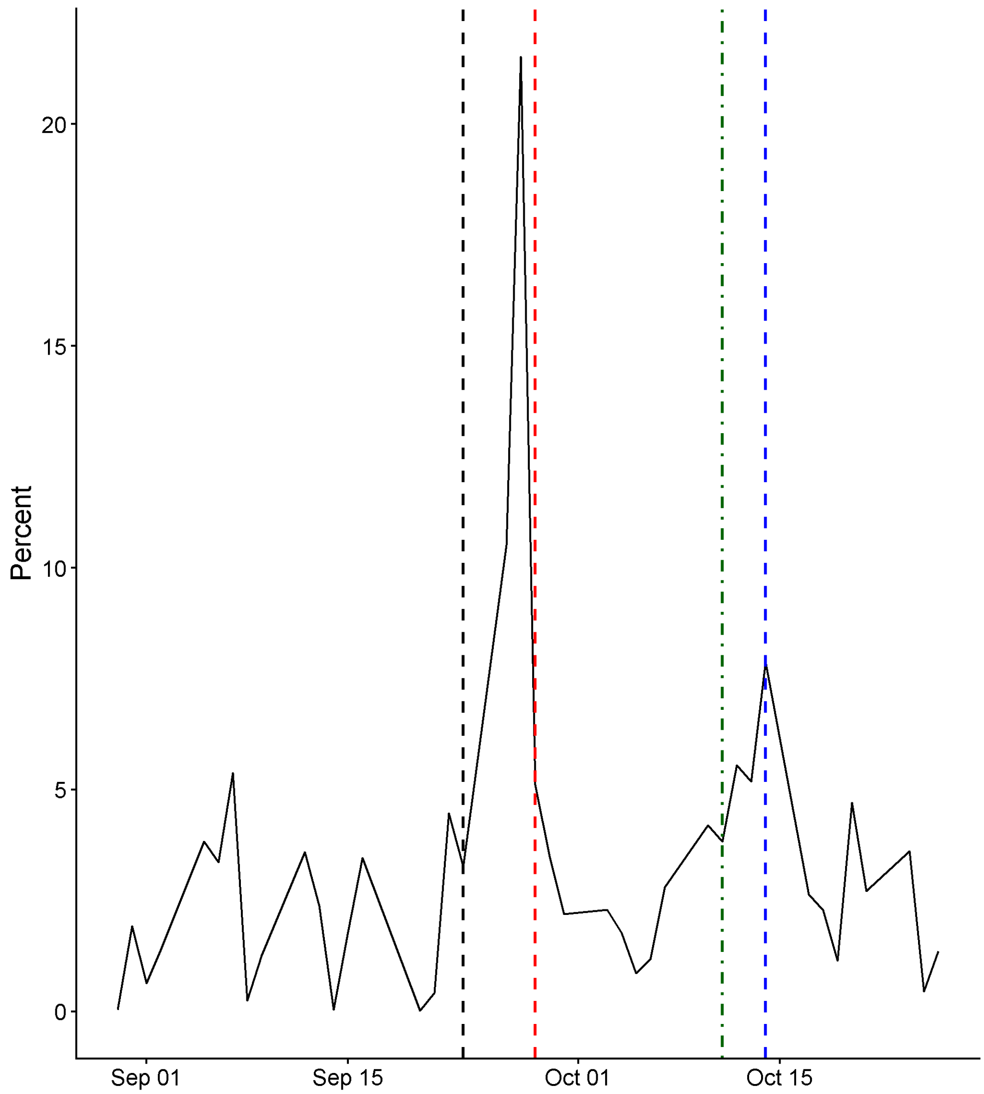
bond and day fixed effects, respectively.[23] The estimates of β_{day} provide a measure of how sensitive returns are to trading, and thus the price impact of a given net order flow on a given day. Next, we calculate the average return variance over rolling two-week windows.

Figure A.1 provides a graphical validation of our estimates, showing that the value of information increases significantly during the crisis and before policy announcements, consistent with the results in Kadan and Manela (2025). That is, although both volatility and illiquidity increased, the rise in volatility outpaced that of illiquidity, thereby creating greater opportunities for investors with an informational advantage. The increase in the value of information is economically large, exceeding its pre-crisis average by more than a factor of five. This result implies that market participants had strong incentives to gather information during this crisis.

[23]The results of this exercise are robust to a range of alternative specifications, including using volume-weighted variance and price impact estimates, using the inverse hyperbolic sine of signed order flow, or excluding the bond and day fixed effects.

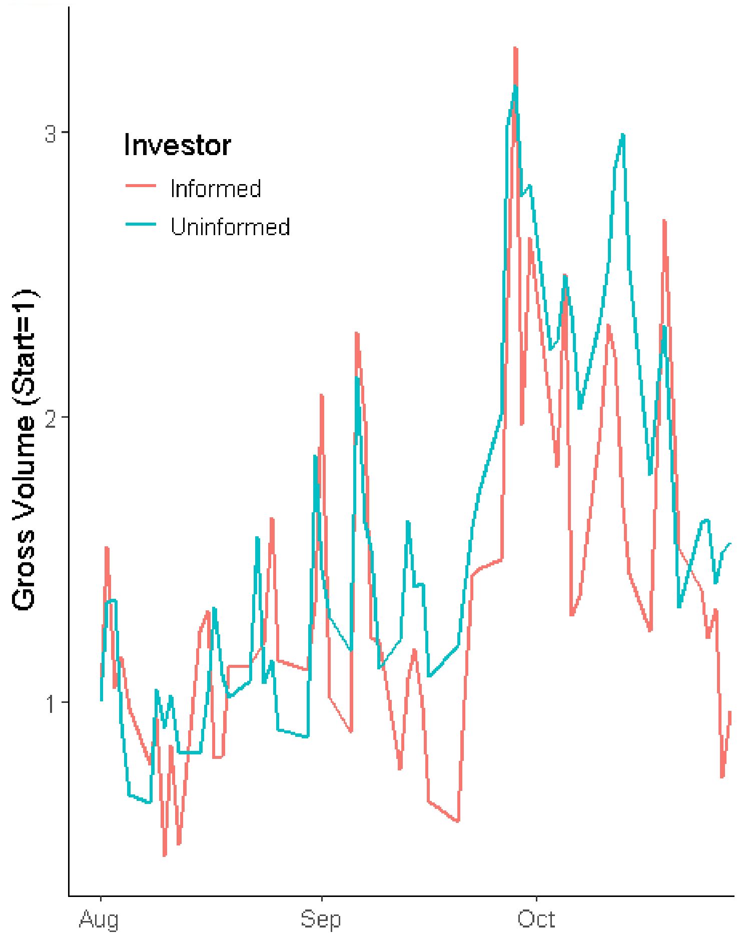
Figures and Tables

Figure A.1 THE VALUE OF INFORMATION IN THE GILT MARKET



Note: This chart plots the estimated value of information in the gilt market over our sample period. The black line indicates the mini-budget announcement on September 23, the red line indicates the start of the BoE asset purchases on September 28. The green line indicates the expansion of the asset purchases on October 11. The blue line indicates the conclusion of the BoE market intervention on October 14. The value of information is calculated as the ratio of the average variance of bond returns over the price impact, as described in equation (A.1).

Figure A.2 Trading Volume: Informed vs. Uninformed Clients



Note: The figure shows the daily gross volume of trading by informed and uninformed investors over the sample, normalized to the pre-crisis period. Informed investors are classified by their trading returns, as described in Section 2.4.

Table A.1 Persistence of Information Edge

Dependent Variables:	Informed(ExPost)		Informed
Model:	(1)	(2)	(3)
Variables			
Constant	0.237***	0.220***	0.195***
	(0.014)	(0.016)	(0.014)
Informed		0.084**	
		(0.035)	
Informed(COVID)			0.229***
			(0.071)
Fit statistics			
Observations	890	890	890
R^2		0.006	0.01

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This table studies the persistence of investors' information edge. The dependent variable *Informed Ex Post* in columns (1)-(2) is an indicator variable equal to one if an asset manager or hedge fund was in the top tercile of trading returns in the crisis period. The variable *Informed* indicates if an asset manager or hedge fund was in the top tercile of trading returns in the month prior to the crisis. Column (3) then uses *Informed* as the dependent variable, and *Informed(COVID)* is an indicator variable equal to one if an asset manager or hedge fund was in the top tercile of trading returns in the COVID-19 Dash for Cash episode.

Table A.2 Different Trade Cost Measures

Dependent Variables:	Baseline TC	Bloomberg TC	Market TC	Trade Cost	
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Post × Informed	-14.5***	-14.2***	-2.05***	-14.5***	-14.5***
	(5.04)	(4.43)	(0.731)	(5.04)	(5.04)
Time Since Trade				-0.002***	
				(0.0007)	
Time Since Window					-0.029
					(0.100)
Fixed-effects					
Dealer-Time	Yes	Yes	Yes	Yes	Yes
Size-Day	Yes	Yes	Yes	Yes	Yes
Investor-Dealer	Yes	Yes	Yes	Yes	Yes
Connections Control	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	119,641	114,950	95,769	119,641	119,641
R^2	0.24	0.34	0.24	0.24	0.24

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

Note: The table estimates the trade costs of an informed investor, relative to an uninformed investor, after the crisis begins. It is estimated using equation (7), but using alternative measures for the dependent variable, *Trade Cost*. Column (1) reproduces the baseline for comparison. Column (2) uses the hourly Bloomberg price as the benchmark for calculating trade costs. Column (3) uses the average bond-time price in the entire market (incl. dealer-client trades), excluding the given transaction. Columns (4) and (5) control for the time in minutes since the last interdealer trade and since the 30-minute time window began, respectively.

Table A.3 Clients Trade Cost - Full Market Benchmark

	Pre-Crisis	**Crisis**
Informed	0.9	0.2
Uninformed	1.2	4.7

Note: The table provides statistics on average trade costs of informed and uninformed clients before and during the crisis, expressed in basis points. Trade costs are calculated comparing the log transaction price with the average log price across all transactions in the interdealer market in a 30-minute window.

Table A.4 NON-LINEARITY OF INFORMED INVESTORS' TRADE COSTS

Dependent Variables:	Low(Trade Cost)	Med(Trade Cost)	High(Trade Cost)
Model:	(1)	(2)	(3)
Variables			
Post × Informed	2.78**	1.16	-3.95***
	(1.20)	(1.14)	(1.22)
Fixed-effects			
Dealer-Time	Yes	Yes	Yes
Size-Day	Yes	Yes	Yes
Investor-Dealer	Yes	Yes	Yes
Connections Control	Yes	Yes	Yes
Fit statistics			
Observations	119,641	119,641	119,641
R^2	0.24	0.27	0.24

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

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

Table A.5 Alternative Measures for Informed Investors

Dependent Variable:	Trade Cost						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Post × Informed	-17.5***	-14.5***	-16.4***	-21.2***	-17.2***	-29.3**	-22.2***
	(4.84)	(5.04)	(5.02)	(4.74)	(4.26)	(13.4)	(6.43)
Measure:	1 day	3 day	5 day	Risk-Weighted	P&L	Ex Post	Top COVID
Fixed-effects							
Dealer-Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size-Day	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor-Dealer	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Connections Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	119,641	119,641	119,641	119,641	119,641	119,641	119,641
R^2	0.24	0.24	0.24	0.24	0.24	0.24	0.24

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

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

Table A.6 INFORMED DEALERS—FIRST STAGE

Dependent Variable:	*InformedShare*	
Model:	(1)	(2)
Variables		
$\widehat{InformedShare}$	1.37***	1.15***
	(0.236)	(0.159)
Fixed-effects		
Dealer		Yes
Day		Yes
Fit statistics		
Observations	1,049	1,049
R^2	0.32	0.56
F-statistic	488.9	16.9

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

Note: This table estimates the relationship between dealers' share of informed order flow shown in equation (10) and the instrument described in equation (11). Columns (1) and (2) estimate the relationship at the dealer-day level, excluding and including fixed effects, respectively.