An Anatomy of the 2022 Gilt Market Crisis

Gabor Pinter*
Bank of England

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COMMENTS WELCOME

Abstract

We use transaction-level data on the UK government bond, repo and interest-rate swap markets to analyse market liquidity, investor behaviour and price dynamics during the market disruptions in September-October 2022. We provide a detailed account of how selling pressure in gilt markets – due to deteriorating derivative and repo positions of liability-driven investors (LDI) – led to evaporating market liquidity, especially in long-dated conventional gilts and index-linked gilts. We find that firms in the LDI-pension-insurance (LDI-PI) sector who had larger repo and swap exposure before the crisis sold more gilts during the crisis (while hedge funds were compensated for providing liquidity to the LDI-PI sector). Transaction costs in bond markets quickly soared, particularly for smaller trades, for trades at smaller dealers and for trades of non-LDI-PI investors too. The aggregate dispersion of transaction prices more than doubled in a matter of days, and price dispersion across primary dealers remained significant throughout the crisis, suggestive of tightened constraints on the intermediary sector. While the episode started with the forced selling by the LDI-PI sector, our results point to large costs on other market segments as well, consistent with the contagious nature of illiquidity.

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'It was not quite a Lehman moment. But it got close.'
(Sep 2022, Senior London-based banker)

1 Introduction

The UK government bond market experienced extreme stress during September-October 2022. Highly leveraged, liability-driven investment (LDI) strategies of certain pension funds and asset managers have been identified as an amplifier of the crisis: after an unexpected rise in yields, these firms experienced a sudden worsening of their repo and derivative positions and associated increases in collateral and margin requirements, which forced them to quickly liquidate gilts in exchange for cash. These selling pressures led to a rapid evaporation of gilt market liquidity: yields spiked further and market orderflows became so extreme that the Bank of England was required to intervene within days in order to restore market functioning (Breeden, 2022; Hauser, 2022).

In addition to presenting a detailed account of market dynamics and quantifying the extent of gilt market illiquidity during this crisis, this paper aims to deepen our general understanding of selling pressures and liquidity crises by focusing on the distribution of illiquidity in two ways. First, we study the distribution of forced sellers by quantifying how the swap and repo positions of firms in the LDI-pension-insurance (LDI-PI henceforth) sector determined the scale of their gilt liquidations.[1] Importantly, by inspecting the behaviour of individual firms, we also document how uniform these gilt liquidations were across LDI-PI firms. Second, we study which segment of the gilt market was the liquidity crisis concentrated in, i.e. which types of bonds, trades, clients and dealers were the most affected. Moreover, we also study the behaviour of hedge funds and other clients throughout the crisis and their liquidity provision (or lack thereof) for the LDI-PI sector.

Our empirical analysis yields six main results. First, we estimate that during the period between 23 September and 14 October the total net sales of gilts by the LDI-PI sector amounted to over £36 billion.[2] Gilt sales were larger in index-linked gilts (that make up only about quarter of the market) and more uniform across the maturity spectrum, whereas selling pressures in conventional gilts were smaller and were only present in long-maturity (>10 years) bonds.

Second, a few firms were responsible for the majority of gilt liquidations in the LDI-PI sector. For example, three firms account for over 70% of total gilt sales of the LDI-PI sector to primary dealers during the crisis. This is consistent with the LDI-PI sector being highly concentrated, with a few firms generating most of the LDI-PI activity in the UK market. Regression analysis shows that gilt sales by these firms had a significant price impact in gilt markets in our sample.

[1] Note that our definition of the LDI-PI sector is based on a broad category which includes both LDI funds as well as pension schemes and insurance companies. See section 2.1 for further details.

[2] This is consistent with the estimate reported in Section 5 of FSR (2022).

Third, LDI-PI firms[3] with larger interest rate exposures in repo and swap markets before the crisis experienced more severe selling pressures during the crisis, consistent with the importance of funding conditions for market liquidity (Brunnermeier and Pedersen, 2009). Regression results show that a 1% increase in interest rate exposure in the overnight index swap (OIS) market before the crisis (on 22 September) is associated with a 0.52% increase in gilt liquidations by LDI-PI firms who faced selling pressures during the crisis (between 23 September and 14 October). Interestingly, this effect becomes insignificant once we include in the regression firms' exposure in the secured repo market. The most conservative specification suggests that the pre-crisis repo market exposure, where index-linked gilts are used as collateral, is the most significant driver of subsequent gilt market sales, with a 1% increase in linker-repo exposure before the crisis (on 22 September) associated with a 0.49% increase in subsequent gilt liquidations (between 23 September and 14 October) by the average LDI-PI firm in our sample. This is consistent with the narrative that the large leveraged positions of LDI-PI firms played a major role in the crisis (Breeden, 2022; Cunliffe, 2022b).

Fourth, transaction costs – a measure of market illiquidity – soared rapidly from 23 September, with nominal gilt trades being more affected in the first few days followed by large increases in the costs of trading linkers. While the outbreak of the crisis coincided with selling pressures in long-dated linkers by the LDI-PI sector, transaction costs quickly rose among other non-LDI-PI clients as well as short-dated nominal bond trades, suggestive of illiquidity spillovers across clients and assets as well as general liquidity problems in gilt markets. This interpretation of illiquidity spillovers is further supported by our results on transaction cost changes across the trade size distribution: while costs for larger trades increased (mainly driven by forced sellers who traded larger amounts) we also find that trading smaller amounts (e.g. by retail clients) became persistently more expensive too. We also find evidence that a stronger trading relationship between a client and a primary dealer – measured by the pre-crisis trading volume between the two parties – mitigated some of the cost hikes that the given client experienced during the crisis.

Fifth, the increase in transaction costs during the crisis was larger among smaller dealers than among larger dealers, pointing to tightened constraints on bond market intermediation. To analyse this issue further, we study the dynamics of aggregate price dispersion – an alternative measure of market illiquidity – and decompose this measure into within-dealer and cross-dealer components. We find that total price dispersion more than doubled within days after the outbreak of the crisis, and the cross-dealer component remained significant throughout the crisis. Overall, these results

[3] Firms in our analysis are defined at the group level. (Also, see section 2.1 for further details). To illustrate our consolidated approach to defining a 'firm', take the following example: an asset manager with many index-tracker funds (with each fund having a distinct Legal Entity Identifier (LEI)) also manages a few LDI funds (with each fund having a distinct LEI). In this case, we define the 'firm' as the sum of LEIs of the asset manager. In our empirical analysis, we analyse the total gilt, swap and repo activity of this consolidated entity – the 'firm'. Future research could take a more granular approach to classification and explore the heterogeneity in behaviour across the LEIs of the given asset manager.

echo recent concerns regarding the functionality of government bond markets in face of increasing amounts of bonds issued and constraints on dealers' intermediation capacity (Duffie, 2020).

Sixth, hedge funds provided liquidity for the LDI-PI sector during the crisis, but their liquidity provision in gilt and repo markets remained modest. Our evidence suggests that this is not because of deteriorating financing conditions facing hedge funds (similar to the LDI-PI sector). If anything, hedge funds experienced gains during the crisis from acting as counterparties (receiving the floating-rate leg) for the LDI-PI sector in the OIS market. The more likely explanation for the overall limited provision by hedge funds is that these investors timed their liquidity provision so as to maximise the return from such an activity. This is supported by our empirical evidence showing that hedge fund returns from liquidity provision were positive throughout the crisis.

To arrive at these answers, we use a granular transaction-level dataset merged across the UK government bond markets, the sterling interest-rate swap markets and the secured repo market, covering close to the universe of market participants over the period from 30 August to 28 October of 2022. Importantly, the identities of the clients and dealers are observable, which allows us to provide a detailed anatomy of investor behaviour during the different phases of the liquidity crisis. This enables us to zoom in on individual clients and dealers (acting across multiple fixed-income markets) and to explore the importance of client- and dealer-heterogeneity in this liquidity crisis. The previous empirical evidence on these issues – at such a granular level – has been rather scant due to data limitations.

Related Literature Our paper relates to several strands of the literature. First, the empirical analysis echoes recent papers that studied the liquidity crisis in government bond markets which was triggered by the COVID-19 pandemic (Barth and Kahn, 2020; Fleming and Ruela, 2020; Duffie, 2020; He, Nagel, and Song, 2022a; Schrimpf, Shim, and Shin, 2021).[4] Second, the focus of our analysis on the LDI-PI sector relates to the expanding finance literature on insurance companies (Ellul, Jotikasthira, and Lundblad, 2011; O'Hara, Wang, and Zhou, 2018; Hendershott, Li, Livdan, and Schürhoff, 2020; Koijen and Yogo, 2022) and pension funds (Greenwood and Vayanos, 2010; Blake, Sarno, and Zinna, 2017; Douglas and Roberts-Sklar, 2018; Klingler and Sundaresan, 2019). Our contribution to these literatures is twofold. First, observing the identities of almost all government bond, repo and interest rate swap traders provides us with an unprecedentedly detailed picture of investor behaviour during a liquidity crisis. Second, our detailed analysis of LDI-PI firms is done jointly with analysing other client types as well as the dealer sector, thereby giving a more complete picture of investor behaviour, market liquidity and price dynamics.

Our empirical results on the forced selling by the LDI-PI sector and associated bond price

[4]Related research that studied the liquidity crisis in corporate bond markets includes Falato, Goldstein, and Hortacsu (2021); O'Hara and Zhou (2021); Kargar, Lester, Lindsay, Liu, Weill, and Zuniga (2021); Haddad, Moreira, and Muir (2021); Ma, Xiao, and Zeng (2022) amongst others.

movements contribute to the large literature on asset fire sales (Coval and Stafford, 2007; Jotikasthira, Lundblad, and Ramadorai, 2012; Shleifer and Vishny, 2011; Khan, Kogan, and Serafeim, 2012; Choi, Hoseinzade, Shin, and Tehranian, 2020; Falato, Hortacsu, Li, and Shin, 2021). The spillover of illiquidity from the LDI-PI sector to other segments of the gilt market echoes previous results from the empirical literature on liquidity spillovers and contagion (Chordia, Sarkar, and Subrahmanyam, 2005; Goyenko and Ukhov, 2009; Longstaff, 2010; Karolyi, Lee, and van Dijk, 2012).[5] Our finding of pre-crisis derivative positions affecting the magnitude of selling pressures during the crisis is connected to the literature on funding and market liquidity (Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009; Kahraman and Tookes, 2017; Bian, He, Shue, and Zhou, 2018; Kahraman and Tookes, 2020).

Moreover, our empirical analysis of aggregate price dispersion and our novel decomposition of dispersion into within-dealer and cross-dealer components add to the empirical literature that studies trading frictions in OTC markets (Jankowitsch, Nashikkar, and Subrahmanyam, 2011; Friewald, Jankowitsch, and Subrahmanyam, 2012; Uslu and Velioglu, 2019).

The remainder of the paper is organised as follows. Section 2 provides some institution background and describes the sources for our aggregate and transaction-level data; Section 3 presents stylised facts from the gilt market; Section 4 presents stylised facts from the sterling interest-rate swap and repo markets; Section 5 presents an empirical analysis of transaction costs; Section 6 describes the behaviour of price dispersion over the crisis; Section 7 analyses the liquidity provision of hedge funds; and Section 8 concludes.

2 Data and Institutional Background

2.1 Data

2.1.1 Data Sources

Aggregate daily data on zero coupon bond yields on UK government bonds are obtained from the Bank of England.[6] The dataset includes nominal and real yield curves and the implied inflation term structure for the UK, that are derived using spline-based techniques (Anderson and Sleath, 2001).

To study the microstructure of UK bond markets during the recent crisis, we use the MIFID II database. This is a detailed transaction-level dataset, sourced by the UK Financial Conduct Authority, which contains information on the identity of both sides of a trade. This information is summarised by the Legal Entity Identifier (LEI), which allows us to categorise clients into

[5]For the related theoretical literature on liquidity-induced financial contagion, see Allen and Gale (2000); Kodres and Pritsker (2002); Brunnermeier and Pedersen (2005) among many others.

[6]The data can be downloaded from the Bank of England's website.

different types such as LDI-PI firms, hedge funds, asset managers and others. The dataset also contains information on the transaction time, the transaction price and quantity, the International Securities Identification Number, the account number, and buyer-seller flags.[7] To study the recent crisis episode, we process the data covering the period 30 August – 28 October of 2022. We merge our transaction-level data with price quotes (at hourly frequency) from Thomson Reuters Eikon.

To study the derivatives exposures of bond market participants, we use contract level data on overnight index swaps (OIS) with the floating legs linked to the Sterling Overnight Index Average (SONIA)[8] as well as on inflation swaps with the floating legs linked to the retail price index (RPI).[9] The primary source is the EMIR TR dataset. Similar to MIFID II, each transaction report contains multiple fields that include information on trade characteristics (e.g., LEI codes, price, notional amount, maturity date, execution time, reference rate). Given the availability of LEI codes in the EMIR TR data, we are able to merge our gilt-market dataset with the swap-market dataset, and we can also apply consistent client classification across these markets. To align the sample period in the swap market sample, we download five snapshots of the EMIR TR data: 30 August, 22 September, 27 September, 14 October and 28 October.

For repos secured by UK government bonds, we use the Sterling Money Market Data (SMMD), a proprietary dataset of the Bank of England, which is a daily, transaction-level collection that covers the most significant segments of the sterling money markets.[10] The dataset includes, for each transaction, information on trade volume, pricing and collateral. In addition, the LEI codes of both counterparties are provided, which allows us to have a consistent merge across the gilt and swap market datasets.

2.1.2 Client Classification

Our definition of gilt market sectors builds on the Bank of England's internal classification system, which allocates each LEI code to a sector. We then try to consolidate all LEI codes at the firm-level, and assign a sectoral definition to the firm based on its main business profile. The task of consolidating LEI codes at the firm-level is challenging, as clients – especially large ones – tend to have multiple accounts across different sectors (possibly under different names and subsidiaries). We use a combination of manual checking of LEI codes and searching through account names to consolidate accounts – on a best-endeavours basis – at the level of the parent organisation. To illustrate our consolidated approach to defining a 'firm', take the following example: an asset

[7]For further details on the MIFID II dataset, see the Reporting Guidelines: https://www.esma.europa.eu/sites/default/files/library/2016-1452_guidelines_mifid_ii_transaction_reporting.pdf. Recent applications of the datasets can be found in Czech and Pinter (2020); Pinter, Wang, and Zou (2022) among others.

[8]Further information on Sonia can be found on the Bank of England's website.

[9]The majority of inflation swap contracts in the UK are still linked to the RPI.

[10]See Van Horen and Kotidis (2018); Gerba and Katsoulis (2021) for recent applications of the dataset.

manager with many index-tracker funds (with each fund having a distinct Legal Entity Identifier (LEI)) also manages a few LDI funds (with each fund having a distinct LEI). In this case, we define the 'firm' as the sum of LEIs of the asset manager. In our empirical analysis, we analyse the total gilt, swap and repo activity of this consolidated entity – the 'firm'. Future research could take a more granular approach to classification and explore the heterogeneity in behaviour across the LEIs of the given asset manager in this example.

Our baseline sample includes around 1500 firms. Our definition of the LDI-pension-insurance (LDI-PI) sector is a broad category that incorporates asset managers with an LDI remit as well as pension funds and insurance companies. A similarly broad sectoral definition was adopted in, for example, the FSR (2022). (See p. 95 of FSR (2022) for further details on sectoral definitions and estimated net purchases of gilts by the sector.) Using such an aggregated sectoral definition also serves the purpose of mitigating issues of identifiability of individual firms in our analysis.[11] Our definition of asset managers include both wealth and asset managers as well as other mutual funds. Our definition of hedge funds include both discretionary and systemic funds featuring both macroeconomic and relative value strategies. The 'others' category includes all remaining client types including commercial banks, foreign central banks, trading platforms, non-financial companies among others. The dealer sector comprises all active gilt-edge market makers (GEMMs).[12]

Note that the LDI-PI sector in our dataset encompasses agent- as well as principal-type firms. For example, LDI managers can be thought of as "agents" in so far as they manage LDI funds (by directly conducting gilt, repo and swap transactions) that pension funds – the" principals" – invest in. Alternatively, principals themselves could manage liabilities by engaging in gilt, repo and swap transactions. Our sample of LDI-PI firms include both "agent" and "principal" type firms. Analysing how the pre-crisis repo and swap positions of both types of firms affected their gilt trading behaviour during the crisis seems inconsistent at first sight, as agent-type firms are acting on behalf of other investors. That is, any losses that the agent realises (and associated margin calls) would ultimately have to be covered by the capital of the principal, i.e. the principal has the ultimate exposure to the risks associated with the LDI fund. However, in practice, capital of the principal was slow-moving during this crisis, which meant that losses (and associated margin calls) of the LDI fund had to be managed by the agent in the short-term. In this sense, the agent's own derivatives positions had a direct effect on their gilt market behaviour. For this reason, we argue that it is consistent to jointly analyse the (short-term) behaviour of "agent" and "principal" type firms in our LDI-PI sample, and how this behaviour was impacted by their derivatives positions.

[11] Note that a difference between the classification scheme used in this paper and that used in the FSR (2022) is that the sectoral classification in our paper is applied at the consolidated, 'firm'-level, whereas the classification in the FSR (2022) is applied at the LEI-level. The approach adopted in this paper is motivated, for example, by our focus on the variation in trading relationships and transaction costs (Section 5) that are more likely to vary across firms than across LEIs within the same firm.

[12] For further details on the identities of GEMMs, see https://www.dmo.gov.uk/responsibilities/gilt-market/market-participants/.

2.2 Liability-Driven Investment (LDI)

As a useful preliminary, we provide a short description of the market of liability-driven investment (LDI) and related strategies of liability hedging, given that firms applying these trategies were at the heart of the 2022 gilt market crisis (Hauser, 2022; Breeden, 2022).

2.2.1 Market Structure

According to recent estimates, more than £1 trillion is invested in LDI products in the UK. Pension schemes apply these strategies either directly (for example, via segregated accounts or on-balance sheet management) or via pooled vehicles.[13] These 'pooled' LDI funds, that a number of smaller pension funds may invest in, are typically managed by an asset manager (FSR, 2022). The market of these LDI funds is highly concentrated with a few asset managers providing most LDI services (Elder, 2022).

In addition, pooled LDI funds have concentrated and correlated exposures in derivatives and gilt markets, which could amplify the effect of deleveraging and the associated forced selling on yields and market liquidity in the face of a shock. Indeed, following the sudden rise in yields following the government's announcement of its 'Growth Plan' on 23 September, the selling pressure from these highly leveraged pooled LDI funds (with a size of around £200 billion) began to pose a severe threat to the gilt market (Breeden, 2022). The selling pressure of LDI funds originated from mark-to-market losses on their leveraged position (as discussed below). To cover these losses, LDI firms needed cash injections, which in the case of 'pooled' LDI funds, the participating pension funds were more reluctant to provide or they were not operationally ready to inject capital so quickly. There was also an additional, incentive problem associated with limited liability: the benefits from capital injections would have been shared by all pension schemes but the costs would have been borne by the contributing pension fund(s) (p. 7-8 of BIS, 2022).[14]

2.2.2 Liability Hedging

LDI strategies were originally employed in the context of hedging liabilities of defined benefit pension schemes. For the sake of illustration, consider the following example: a pension scheme is liable to deliver £100 in 40 years time in real terms; expected inflation over this period is 2% and the discount rate – the current riskfree rate – is 3%. Applying the simple present value formula, the current value of this liability amounts to approximately £67.6, that is, the pension fund needs to hold this amount today to deliver the required cashflow at end of the contract term. Note that there are two main risks that could increase the current value of this liability: a fall in the discount

[13] Pooled vehicles make up about 15% of the LDI market (Breeden, 2022).

[14] A noted by Breeden (2022), LDI funds with segregated mandates found it easier to raise funds from their individual pension scheme clients. But given their size (85-90% of the market) these funds also contributed to selling pressure, making the task at hand for pooled LDI funds even more difficult.

rate and an increase in inflation. For example, if inflation increased from 2% to 2.5%, then the present value of the pension liability would increase from £67.6 to £82.3; if the discount rate fell from 3% to 2.5%, then present value would increase from £67.6 to £82.2. (Note that these large effects are due to the long (40-year) horizon of the pension plan.)

To hedge both these risks, pension funds in practice invest significant amounts in long-dated inflation-linked bonds, as the nominal value of these assets would increase in a fall in the discount rate or an increase in inflation. However, compared to outright bond purchases, there are more efficient ways for a pension scheme to hedge against interest rate and inflation risks, such as using repo financing and swap contracts. Using these instruments would be more efficient because they would allow the fund to be fully invested in bonds to hedge their future liabilities while also accessing growth assets (e.g. equities) to close deficits. Using repos, the pension fund would finance bond purchases with borrowed money using the bond as collateral. This explains why the LDI-PI sector is such a significant player in the linkers market, as shown in Section 3, as well as in the repo market with linkers (and to a lesser extent nominal bonds) used as collateral, as shown in Section 4 below.

As an alternative to repo, the pension scheme could use an interest rate swap, receiving the fixed-rate leg and paying the floating-rate leg of the contract. This would hedge against falls in the discount rate (that would increase the present value of the pension scheme's liabilities). Moreover, it can also enter into an inflation-swap contract, paying the fix-rate leg and receiving inflation (as the floating rate) in order to hedge against unexpected increases in liabilities because of shocks to inflation. These examples highlight why the LDI-PI sector is such a significant player in interest rate and inflation swap markets too, as shown in Section 4.[15]

2.2.3 Repos vs Swaps in Liability Hedging

This subsection briefly discusses the relative advantages of repo-financed bond purchases and swap contracts from the point of view of a pension fund. Given that both types of contracts can serve the purpose of hedging the fund's liabilities, a natural question is what the determines the choice of using one over the other. The question is particularly pertinent given that there is large variation in the relative use of repos and swaps across investors as well as over time. As an example for the cross-sectional variation, note that, in our sample of LDI-PI firms, two firms (call them 'A' and 'B' for illustration) that were amongst the largest sellers between period 23 September 2022

[15] An additional reason why pension funds are heavily reliant on derivatives is that pension schemes can be 'underfunded' (Greenwood and Vayanos, 2010). As noted in Cunliffe (2022b), 'more than 20% of UK DB pension funds were in deficit in August 2022 and more than 40% were a year earlier (p. 5).' Using the example above, this means that the pension fund would hold less than £67.6 on its balance sheet, thereby running an accounting deficit. This is because the pension scheme could generate £100 in 40 years time with less initial funding if it invested in riskier assets (e.g. equities) during the contract terms, as long as equities have higher average returns than the 3% riskfree rate. However, in practice, the liabilities of underfunded pension schemes would have increased exposure to interest rate and inflation risks, requiring the further use of derivatives to hedge these risks.

and 14 October 2022 had vastly different swap and repo exposure. Firm 'A' had twice as much repo exposure on 22 September as firm 'B' in our sample of contracts. In contrast, firm 'B' had an interest rate swap exposure that was more than three times that of firm 'A' in our sample of contracts. As an example for the time-series variation in the relative use of repo, note that swaps used to make up the majority of the hedging mix for the LDI-PI sector prior the Great Recession, whereas repos are now the dominant instrument for this sector to hedge liabilities (Rega-Jones, 2021).

Given such a heterogeneity in the relative use of repos and swaps, it is useful to briefly review the factors that can influence the use of the two types of instruments both at the firm- and the macro-level. There are at least five factors that influence the repo-swap margin, briefly discussed below: (i) costs, (ii) rollover risk, (iii) hedging precision, (iv) supply of derivatives and dealers' balance sheet constraints and (v) product complexity.

Costs The costs associated with margin requirements for swaps typically outweigh those related to repo financing, pointing to the relative cheapness of the latter hedging strategy.[16] Practitioners often cite stricter requirements to post initial margins as well as variation margins (to be exchanged daily in cash) as a reason why swap transactions are now perceived to be more capital-demanding compared to repo financing where haircuts and repo rates have remained compressed (Cameron, 2013; Rega-Jones, 2021). In addition, the relative cheapness of repo financing has also been driven by the increasing scarcity of safe collateral since the Great Recession (Arrata, Nguyen, Rahmouni-Rousseau, and Vari, 2020).

Importantly, the evolution of *future* financing conditions pose a risk to both types of hedging strategies. For example, if a pension scheme receives the fixed-rate leg on an interest rate swap, then an unexpected increase in market yields would generate a mark-to-market loss in the value of the contract, requiring the firm to use additional funds to cover increased variation margins (Duffie, Scheicher, and Vuillemey, 2015; FSB, 2022). Given that our dataset includes information on the mark-to-market value of the contracts, we are able to estimate the total losses that the LDI-PI sector suffered in its interest rate derivatives positions during the different stages of the crisis. Similarly, leveraged gilt positions using repos could quickly lead to capital losses as well (Cunliffe, 2022a,b).[17]

Rollover Risk The maturity of repo contracts tends to be much shorter than the maturity of swap contracts (as shown in Section 4 below). For example, the majority of repos in our sample of outstanding repo contracts on 22 September had maturity of less than six months. In contrast, the

[16]Note that pension funds in the UK are not legally required to centrally clear derivatives (unlike banks for example).

[17]It is important to note that repo is economically similar to swaps in this sense. Higher rates leads to collateral calls on repo and margin calls on swaps. Not meeting them would lead to capital losses in both cases.

distribution of maturity of interest rate and inflation swap contracts in our sample is more similar to the maturity distribution of gilt transactions. This implies that there is considerable rollover risk (He and Xiong, 2012) associated with repo-financed bond purchases to hedge long-term liabilities, compared to using swap contracts (Rega-Jones, 2021).[18]

Hedging Precision Swaps are considered by practitioners to be a more precise hedge for duration risk than repo-financed bond investments (Cameron, 2013; BMO, 2018). This is because swaps are available for almost any maturity, making them a more flexible hedging tool compared to repo-financed bond investments that are more restricted by the maturity structure of the government's bond portfolio. In addition to flexibility, swaps are not restricted by the physical bond supply, as is the case with repo financing.

Supply of Derivatives and Dealers' Balance Sheet Constraints Banking regulation and risk management after the Great Recession meant that dealer banks may now face tighter balance-sheet capacity, which could possibly impede intermediation services to clients both in bond and derivatives markets. These supply factors could have sizeable effects on derivatives prices. For example, tightened constraints on dealers' balance sheets have been cited among other things as a contributor to the inversion of swap spreads during the last decade (Boyarchenko, Gupta, Steele, and Yen, 2018; Jermann, 2020). In the context of the UK LDI-PI sector, as shown in section 4 below, dealers' play a dominant role in inflation swap markets (providing inflation protection to the LDI-PI sector) as well as in repos secured by linkers; whereas dealers play a relatively small role (compared to other client sectors) in providing LDI-PI clients with repo-funding secured by nominal gilts. This suggests that dealers' constraints should be less important in affecting the supply of nominal gilt repos (compared to swaps or linker repos), available to the LDI-PI sector (Baker, 2015).

Product Complexity The use of swaps in liability hedging is typically regarded by practitioners as more complex compared to the use of repo-financed purchases of long-dated gilts (BMO, 2018).[19] The relative complexity of swap instruments compared to repo, coupled with dealers' dominant role as suppliers (e.g. in RPI swap markets as shown in section 4), could give rise to dealers' extracting more rents from clients in swap markets compared to repo markets. This cream-skimming mechanism is formalised by Bolton, Santos, and Scheinkman (2016), and empirical

[18] As one market strategist put it: "If you did a new repo transaction today, in a year's time you don't know what rate you'll be rolling the repo at, and you don't know if there'll be enough banks with enough balance sheet to offer you the repo. So that's an extra risk that you have in repo that you don't have with a swap, which is why I always encourage clients to find a balance between gilt repo and swaps." (Rega-Jones, 2021).

[19] As a practitioner put it "Using gilt repos is a good alternative to swaps [...] In a lot of ways repos are simpler [than swaps] and they are proving a popular approach."

evidence in the UK swap markets indeed shows large heterogeneity in contract-level swap rates, consistent with dealers' bargaining power (Cenedese, Ranaldo, and Vasios, 2020).

2.2.4 Illustrative Theory

To formalise how some of the factors, discussed above, would influence the repo-swap hedging mix of LDI-PI investors, we write down a simple equilibrium model in the spirit of Sharpe and Tint (1990) and Klingler and Sundaresan (2019). We focus on underfunded pension plans for which the amount of underfunding (F) is defined as:

$$F = L - A, \tag{2.1}$$

where liabilities, L, are random, $L \sim N\left(\mu_L, \sigma_L^2\right)$; and assets, A, consist of (leveraged) bond and swap positions:

$$A = A_0 + x_S\left(D_S - P_S\right) + x_B\left(D_B - P_B\right), \tag{2.2}$$

where A_0 is initial wealth, x_S and x_B are positions in swaps and (repo-financed) bonds, respectively, that are to be determined as part of the optimisation. The payoffs from these assets are normally distributed random variables, $D_S \sim N\left(0, \sigma_S^2\right)$ and $D_B \sim N\left(\mu_B, \sigma_B^2\right)$. The mean, μ_B, captures the average difference in the payoffs across the two assets. For example, a positive mean, $\mu_B > 0$, could be a reduced-form way of modelling the drivers of negative swap spreads, documented in various developed markets after the Great Recession, or could be due to the product complexity associated with swaps (BMO, 2018).

Further, we assume that the variance of bond payoffs is larger than that of swap payoffs, $\sigma_B^2 > \sigma_S^2$. Specifically, the difference in variances is driven by the risk associated with rolling over repos to finance bond positions. That is, $\sigma_B^2 = \sigma_S^2 + \sigma_R^2$ where σ_R^2 denotes rollover risk associated with the short maturities of repo contracts compared to the maturity of the underlying collateral, as mentioned above.

Regarding the hedging properties of the assets, we assume that both swaps and bonds hedge against uncertain movements in liabilities, $cov\left(L, D_S\right) \equiv \sigma_{L,S} < 0$ and $cov\left(L, D_B\right) \equiv \sigma_{L,B} < 0$. However, given that long-dated bonds tend to be less precise hedge for duration risk than swaps (Cameron, 2013), we set $\sigma_{L,S} < \sigma_{L,B}$.[20]

The objective of the pension fund is to minimise funding costs, defined as:

$$\min_{x_S, x_B} \left\{ \mathbb{E}\left[F\right] + \frac{\gamma}{2} Var\left(F\right) + \Phi\left(x_S\right) \right\}, \tag{2.3}$$

where γ is the fund's coefficient of risk aversion and $\Phi\left(x_S\right) = \frac{\kappa}{2}\left(x_S\right)^2$ is a quadratic cost function

[20] For simplicity, we assume that swap and bond returns are uncorrelated, $\sigma_{S,B} = 0$.

(Antill and Duffie, 2021; Garriott, van Kervel, and Zoican, 2022; Lou, Pinter, and Uslu, 2022) related to holding swaps. This is a reduced-form way of capturing increased margin requirements that are often cited as a main contributor to the increased use of repo-financing in place of swaps during the last decade of LDI-PI hedging practice (Rega-Jones, 2021).

The supply of assets (s_S and s_B) is modelled in a reduced-form way:

$$s_S = \beta_S P_S \tag{2.4}$$

$$s_B = \beta_B P_B, \tag{2.5}$$

where β_S and β_B are the slopes of the supply curve in the swap and bond markets, respectively. While in practice the bond supply is fixed (and is determined by the government's fiscal needs), the price-elastic bond supply (2.5) is a reduced-form way of capturing the short-run behaviour of (balance sheet-constrained) dealers. The lower the value of β_S (β_B), the more inelastic the supply of swaps (repos) is, reflecting tighter constraints on dealers' ability to intermediate in the given market.

In equilibrium, both the repo and swap markets clear:

$$x_S = s_S \tag{2.6}$$

$$x_B = s_B. \tag{2.7}$$

The following proposition summarises how the various factors influence the equilibrium mix of swap and repo use in the model.

Proposition 1. *The equilibrium repo-swap ratio increases in the repo payoff (μ_B), in the margin requirements associated with swaps (κ) and in the elasticity of repo supply (β_B); the ratio decreases in the hedging benefit of swaps ($\sigma_{L,S}$), in the rollover risk of repo (σ_R^2) and in the elasticity of swap supply (β_S).*

Proof. The solution to 2.1–2.7 determines the equilibrium ratio of repo-financed bonds and swaps, $\phi \equiv s_B/s_S$, written as (see Appendix A.2 for further details):

$$\phi = \frac{\beta_B}{\beta_S} \times \left[\frac{\mu_B}{-\gamma\sigma_{L,S}} + \frac{\sigma_{L,B}}{\sigma_{L,S}}\right] \times \frac{1 + \beta_S\gamma\left(\sigma_S^2 + \kappa/\gamma\right)}{1 + \beta_B\gamma\left[\sigma_S^2 + \sigma_R^2\right]}. \tag{2.8}$$

Taking partial derivatives of 2.8 with respect to μ_B, κ, β_B, σ_R^2, $\sigma_{L,S}$ and β_S completes the proof. $\square$

Proposition 1 shows that our simple equilibrium model can formalise many of the factors that are regarded to have influenced LDI-PI firms' hedging decisions. An interesting econometric exercise, outside the scope of the present paper, would be to estimate these effects in the data and to identify which factors have influenced the most the changing repo-swap mix in the LDI-PI sector during the last decade.

After reviewing the market and providing some institutional background on the LDI-PI market, we turn to presenting the empirical results in the next sections.

3 Gilt Market Dynamics

3.1 Trade Volume

We begin the empirical analysis by documenting the behaviour of bond market participants before, during and after the gilt market crisis. Table 1 provides a timeline of the events. We primarily focus on the behaviour of LDI-PI firms – the group of clients that encompass pension funds, insurance companies and asset managers with an LDI remit. Figure 1 plots the 3-day moving average daily trade volume of the LDI-PI sector against primary dealers (magenta line) and against all firms (black line) including both dealers and other clients.

[Figure 1]

Total trade volume (including both nominal and inflation-linked bond markets) averaged around £4-5 billion before the announcement of the mini budget on 23 September, and almost all of it was intermediated by the dealer sector. Trade volume doubled by the time the Bank of England (BoE) made the announcement on 28 September to launch a market intervention, and it further increased, peaking the day before the BoE intervention ended. Notice that the peak in trade volume which includes client-to-client trades (£19 billion) was much larger than volume against dealers (£12 billion), which implies that client-to-client trading became more significant during the crisis compared to pre-crisis. In the following two weeks, trade volume gradually declined to the pre-crisis levels with client-to-dealer trades becoming dominant again.

[Figure 2]

Decomposing the time-series of total LDI-PI trade volume into nominal bonds and inflation-linked bonds (linkers) is illustrated by Figure 2. Linkers typically make up about 20-30% of UK government bond markets, depending on whether one measures the size of the market based on number of transactions, trade volume or total debt outstanding. However, as shown by Figure 2, LDI-PI trade volume in linkers increased sharply during the crisis and, on certain days of early October 2022, it even overtook LDI-PI trade volume in nominal bonds. This is consistent with the linkers market playing a prominent role in this crisis, and it helps explain the central bank's announcement on 11 October (marked by the black vertical line in the figures) to buy linkers for the first time as part of its gilt market intervention.

[Figure 3]

Figure 3 shows that other sectors too experienced an increase in trade volume, though this increased activity was more muted compared to that of the LDI-PI sector. During the week before the announcement of the mini budget on 23 September, daily trade volume of hedge funds and asset managers was around £5 billion, which is similar in magnitude to the LDI-PI sector during this time. Trade volume of these sectors quickly grew as the crisis unfolded. Note that while LDI-PI trade volume continued to increase until 14 October, trade volume of hedge funds and asset managers peaked (at around £11 billion) before the BoE announcement on 28 September. A similar pattern is exhibited by other clients (including foreign central banks, commercial banks, retail clients among others), though their activity remained negligible compared to the other three client sectors in our analysis.

[Figures 4–5]

Figures 4–5 employ other measures of trading activity to paint a similar picture of the four client sectors. Figure 4 shows the evolution of the 3-day moving average of the number of transactions for each sector. LDI-PI firms had about 1000 daily transactions before the crisis, which surged to 2000 daily transactions by 28 September and returned to this level once again before the BoE operation ended on 14 October. Transactions by hedge funds and asset managers increased from pre-crisis levels of 400 and 1800, respectively, and peaked at 1000 and 5000 transactions by 28 September. Consistent with these findings, Figure 5 shows that evolution of the daily number of firms who traded in gilt markets, indicating a rapid increase in market participation by firms in all four sectors.

3.2 Orderflow

We now turn to analysing signed trade volume initiated by clients (i.e. orderflow) in order to study the market segment from which the selling pressured originated. Figure 6 plots the evolution of the total bond market orderflow of the LDI-PI sector, providing a visual illustration of the major factor in the gilt market upheaval. We find that the cumulative LDI-PI outflows between 23 September and 14 October amounted to the liquidation of more than £36 billion worth of nominal and inflation-linked bonds.[21] Note that there are no signs of the LDI-PI sector anticipating these outflows given that the sector had a positive cumulative orderflow of around £4 billion between 29 August and 22 September.

[Figures 6–7]

[21] To obtain these estimates, we aggregate across trades using the net amount of each transaction. For details regarding the computation of the net amount, see p. 181-182 of the MIFID II reporting guidelines.

Figure 7 decomposes the cumulative orderflow of the LDI-PI sector into nominal bonds and linkers, yielding three main takeaways. First, during the the pre-crisis period, LDI-PI orderflow in nominal bonds was larger than in linkers, and the sector's holding of linkers started to decline a few days before 23 September. Second, the outbreak of the crisis (23-27 September) saw a larger and more rapid liquidation of linkers than nominal bonds. Third, the LDI-PI sector's total bond liquidation was larger in linkers than in nominal bonds: the cumulative orderflow by the end of our sample (28 October) is -£6 billion and -£18 billion, respectively, in nominal bonds and linkers.

To draw comparisons with the LDI-PI sector's behaviour during the COVID-19 crisis, Figures A.1–A.3 in the Appendix show the orderflow dynamics from above along the orderflow dynamics of the same LDI-PI firms during March 2020. There are two main differences between the two periods. First, the total LDI-PI gilt sales were around 2-3 times as big this time around as during COVID-19. Second, the selling pressure during March 2020 concentrated in nominal bonds, and the LDI-PI sector actually increased its position in linkers then.

[Figures 8–9]

To understand which maturity segments the selling pressure was concentrated in, Figures 8–9 decompose the cumulative orderflow in nominal bonds and linkers to three maturity buckets: less than 10 years, 10-25 years and above 25 years of maturity. The figures highlight some differences between the two gilt markets: LDI-PI liquidation in linkers was uniform during the outbreak across the three maturity segments compared to LDI-PI orderflow in nominal bonds. The BoE announcement then triggered some reversal in longer maturity linkers, which persisted in very long-dated (>25 years) linkers. Long-dated (10-25 years) linkers soon came under renewed pressure, and followed short-term linkers in being heavily sold by the LDI-PI sector. Overall, LDI-PI outflow in linkers troughed at around -£2 billion, -£9 billion and -£10 billion across the three maturity segments by the end of BoE operation on 14 October. In contrast, the LDI-PI sector had a persistently positive orderflow in short-date nominal bonds, and the outflow in nominal bonds concentrated mainly in the middle maturity segment (10-25 years), corresponding to bond liquidations worth £10 billion over the 9/23-10/14 period. The dynamics in very long-dated (>25 years) bonds are similar, albeit quantitatively more muted, with the cumulative orderflow being close to zero over our sample period.

[Figures 10–12]

While the BoE gilt market operation was a major source of liquidity for the LDI-PI sector (Hauser, 2022; FSR, 2022), a natural question is whether other clients too might have stepped in to provide liquidity. To investigate this, we plot the cumulative orderflow of LDI-PI firms along other client sectors in all bonds (Figure 10), in nominal bonds (11) and in linkers (Figure 12). Figure 11 shows that both asset managers and hedge funds increased their holding of nominal bonds by about £4 billion and £6 billion, respectively, between 23 September and 14 October. This complemented the liquidity provision of the BoE operation during this period.[22]

Note that hedge fund orderflow seems quite erratic, suggestive of speculative trading (which will be investigated in Section 7 below). Other clients kept their nominal orderflow fairly constant during this period. Figure 12 shows that the cumulative sales of linkers by the LDI-PI sector was much larger compared to the cumulative purchases of linkers by other clients, suggestive of the sector's larger liquidity needs in linkers compared to nominal bonds. With the exception of hedge fund purchases of about £5 billion (before the BoE announcement and towards the end of the BoE operation around 10-14 October) other clients refrained from purchasing linkers during the crisis.

Regarding changes in dealers' inventories, we find that nominal bond inventories of dealers were fairly balanced throughout the crisis, whereas dealers' inventories in linkers increased by more than £10 billion. This implies that in addition to the BoE operation, primary dealers' increased inventories played an important additional source of liquidity for the LDI-PI sector during the crisis. After 14 October, dealers began to gradually unwind these accumulated linker positions.

[Figure 13]

So far, we have focused on flows between clients and dealers, as GEMMs continue to be a dominant source of intermediation in the gilt market. However, in recent years certain large clients started acting as effective markers (Aldasoro, Huang, and Tarashev 2021; Saar, Sun, Yang, and Zhu 2022), and the COVID-19 crisis also saw an increase in liquidity provisions in electronic client-to-client trading (O'Hara and Zhou, 2021). This naturally begs the question whether client-to-client trades during the gilt market crisis may have eased some of the liquidity needs of the LDI-PI sector. To address this, Figure 13 shows the cumulative orderflow of our four client sectors against non-dealers. We find that client-to-client signed trades remained modest in our sample and the LDI-PI sector conducted little of its gilt liquidations directly with other clients (if anything, LDI-PI firms were buying gilts from other clients), and instead continued to use primary dealers to off-load unwanted gilt positions.

3.3 Selling Heterogeneity in the LDI-PI Sector

We now take a closer look at the LDI-PI sector and explore how heterogeneous the selling pressure was across clients within the sector. To that end, we identify those LDI-PI firms that were overall net sellers of gilts to the dealer sector during the period 23 September 2022 – 14 October 2022. We then compute the fraction of these clients' individual contribution to the total selling

[22] For further information on the BoE operation, which amounted to a total gilt purchase of around £20 billion, see the FSR (2022).

pressure of the LDI-PI sector against dealers, and find substantial heterogeneity in selling activity across LDI-PI activity, consistent with the concentrated nature of the LDI-PI market (Breeden, 2022). Specifically, the top three sellers were responsible for over 70% of the LDI-PI sector's gilt liquidation to the dealer sector. When calculating this share for the nominal bond market and the linker market separately, the results are qualitatively similar. Though we find the seller concentration to be quantitatively more extreme in linkers: the top three sellers were responsible for more than 75% of linker sales of the sector, whereas the three largest sellers in nominal bonds account for less 60% of the sector's bond sales during this 3-week period.

[Figures 14–16]

To further illustrate client heterogeneity in the LDI-PI sector, we decompose the sectoral orderflow (Figure 7) into a component that is driven by the three largest sellers in the sector and another component driven by all other LDI-PI firms in our sample. Figures 14–16 present the results, confirming that the majority of the orderflow dynamics (depicted by the magenta lines) in both gilt markets is generated by three LDI-PI firms. Their combined selling amounted to about £30 billion of the total LDI-PI sector sales by 14 October, with the effect more dominant in linkers compared to nominal bonds. Note that the dynamic patterns of the orderflow suggest that during the outbreak of the crisis (23-27 September), the larger part of nominal gilt sales was conducted by other LDI-PI firms, and the three largest sellers conducted most of gilt sales during the last week of the crisis.

3.4 Price Dynamics

3.4.1 Time-series Patterns

To complement our analysis of trade flows, we now document how bond yields behaved during the crisis period. Figure 17 presents the evolution of yields on nominal bonds of 5-year, 20-year and 40-year maturity.

[Figure 17]

There was a gradual increase in yields leading up to the announcement of the mini budget on 23 September, after which yields spiked dramatically. In a matter of days, nominal yields across the medium and long maturity spectrum rose by more than 100 bps, which had been unprecedented in recent economic history of the UK. The BoE announcement on 28 September then led to a sharp fall. As the LDI-PI sector accelerated selling its gilt holdings, yields quickly went up again with 20-year yields rising above 5% on 12 October. As the BoE Intervention came to an end and the LDI-PI sector off-loaded its gilt holdings (Figure 7), yields started declining towards pre-crisis levels.

[Figure 18]

Note that the variation in nominal yields during the crisis was larger in longer maturities (>20 years) than in shorter maturities (5 years). To illustrate this point, Figure 18 plots the time-series of the term spreads corresponding to the three maturities (using the 1-year yield as the short leg). There is virtually no variation in the 5y-1y spread during the crisis, whereas the 20y-1y and 40y-1y spreads exhibit large fluctuations. The yield dynamics seem to mirror the orderflow pattern of the LDI-PI sector (Figure 8), whereby nominal bond sales concentrated in longer maturities (10-25 years and >20 years) and were absent in short (<10 years) maturities. To illustrate these points, Figure 19 shows nominal term spreads along with LDI-PI orderflow in nominal bonds of short (upper panel) and long maturities (lower panel). As shown by the lower panel, the huge selling pressure in long-dated nominal bonds during the crisis is mirrored by an increase in the long-maturity term-spread during the same period, with both variables starting to revert after the BoE intervention ended. In contrast, as shown by the upper panel of Figure 19, we do not observe such price variation in short-term nominal bonds, where LDI-PI selling pressure was absent.

[Figure 19]

This is consistent with previous theories on the relevance of orderflow in driving price dynamics due to price pressures caused by temporary illiquidity in the market (Coval and Stafford, 2007; Lou, 2012) or by market segmentation due to preferred habitat investors (Vayanos and Vila, 2021).[23]

Compared to nominal yields, real yields exhibited a more uniform behaviour across the different maturities during the crisis, as shown by Figure 20. Real yields spiked in tandem after 22 September and increased again in parallel during the BoE intervention. Inspecting breakeven inflation across difference maturities (Figure 21) reveals some heterogeneity, with 40-year rates remaining relatively stable across the different periods compared short-dated breakeven inflation rates.

[Figures 20–21]

To link this difference in the dynamics of breakeven inflation rates to the heterogeneity in LDI-PI orderflows, recall that the overall selling pressure in very long-dated linkers remained muted compared to linkers with shorter maturity (Figure 9). These differential trade flows might have impacted breakevens differently across the maturity spectrum. To make the argument more incisive, Figure 22 shows breakeven inflation rates along with LDI-PI orderflows in linkers of short (upper panel) and very long maturities (lower panel). As shown by the upper panel, the huge selling pressure in short-dated linkers during the crisis tracks the decline in the short-maturity breakeven inflation rate (i.e. the fall in the relative price of linkers to nominals). In contrast, as

[23] In addition, orderflow could also have price impact because of informational reasons as in Brandt and Kavajecz (2004); Pasquariello and Vega (2007) among others.

shown by the lower panel of Figure 19, we do not observe such variation in long-term breakevens, where LDI-PI selling pressure was muted.

[Figure 22]

Overall, these results corroborate the importance of trade flows in affecting prices in government bond markets, reminiscent of the findings of Greenwood and Vayanos (2010). Though we acknowledge the suggestive nature of our findings given the limited time-series variation in our sample period. To undertake a more rigorous analysis of price pressures, we turn to regression analysis which exploits the cross-sectional variation in gilts during the crisis.

3.4.2 Cross-sectional Variation

To quantify price pressures in our sample, we estimate the following panel-regression for gilt j and day t:

$$r_{j,t} = \beta \times Flow_{j,t} + \delta_t + \alpha_j + \varepsilon_{j,t}, \tag{3.1}$$

where $r_{j,t}$ is the natural logarithm of daily change in the price of gilt j, where we measure price as the end-of-day price quote; $Flow_{j,t}$ is the orderflow of the LDI-PI sector (or the three largest sellers in the sector as in section 3.3) in gilt j on day t against primary dealers (i.e. GEMMs); the terms δ_t and α_j are day and bond fixed effects. To compute standard errors, we use two-way clustering at the bond- and day-level.

Table 2 presents the results from six separate panel regressions. We experiment with three different ways of measuring $Flow_{j,t}$ in order to check whether the results are robust to controlling for variation in orderflow volatility across gilts (due to, for example, differences in liquidity). In columns (1) and (4), we measure the orderflow in £ billions; in columns (2) and (5) we standardise the gilt-specific time-series of orderflow; in column (3) and (6), we scale the orderflow by the average daily (gilt-specific) market volume using the sample before 23 September (i.e. pre-crisis).

[Table 2]

Inspecting columns (1) and (4) of Table 2, we find that a £1 billion increase in the orderflow of the LDI-PI sector and the three largest sellers in the sector (see section 3.3) increase the price of the given bond by around 2.8% and 6%, respectively. Note that the inclusion of day fixed effects in regression 3.1 controls for the average, market-wide effect of selling pressures. That is, we identify the estimated effects primarily by exploiting the cross-bond variation in returns and orderflow. The results are qualitatively similar when we look at the remaining columns of Table 2, corresponding to alternative measures of the orderflow.

Note that the various measures of orderflow in this analysis are computed against primary dealers, as these entities play a primary role in the pricing of gilts.[24] Given that client-to-client

[24] See the literature on intermediary asset pricing such as He and Krishnamurthy (2013) and many others.

trades increased during this crisis (Figure 1), we recompute the three orderflow measures of the LDI-PI sector against all other firms (including GEMMs and other clients). Table A.1 of the Appendix confirms that the estimated price impacts in this case are weaker compared to when we compute orderflows against GEMMs only (Table 2).

An interesting direction for future research would be to estimate the sensitivity of gilt yields to institutional orderflow over a longer sample (possibly using more sophisticated empirical models such as Hendershott and Menkveld (2014)) and to estimate how this sensitivity may be changing as we have been moving away from a period of very low interest rates. Moreover, one could further investigate the determinants behind the relatively large price impact of the large LDI-PI sellers in our sample, and check whether their price impact may be large outside crisis periods as well.

4 Results from the UK Swap and Repo Markets

4.1 Swap Market Positioning

We now turn to documenting how the gilt market participants analysed above positioned themselves on the interest rate swap market during the crisis. Figure 23 shows the net positions of the four client types as well as the dealer sector in the overnight index swap (OIS) market on 22 September. The largest (fixed-rate) receiver in the market is the LDI-PI sector with an interest rate exposure of £185 billion. Most of the counterparties in these contracts are hedge funds (with a net position of £155 billion) and other clients (with a net position of £120 billion). We find that dealers and asset managers are net receivers with a total exposure of £95 billion and £5 billion, respectively.

[Figure 23]

We then decompose the sectoral net positions into four groups depending on the maturity of the swap contracts. The five sectors have the largest net positions (in absolute value) in the short-maturity (0-5 years) segment. Dealers, LDI-PI firms and asset managers are net payers of the floating leg with net positions of around £140 billion, £80 billion and £5 billion, respectively. Hedge funds and other clients are net receivers of the floating leg of short-maturity swaps, with net positions around £125 billion and £100 billion, respectively. The large net positions of other clients are driven by certain deposit-taking institutions such as commercial banks and building societies, that could reflect their desire to hedge interest rate exposures (Hoffmann, Langfield, Pierobon, and Vuillemey, 2019).

[Figure 24]

When we look at positioning in OIS contracts with longer (above 5 years) maturity in Figure 24, the LDI-PI sector is virtually the only net payer of the floating leg with dealers, hedge funds and other clients standing on the other side of these contracts. This is consistent with LDI-PI firms' desire to hedge (in a capital efficient way) against possible falls in interest rates and associated risks of increased liabilities, as explained in Section 2. However, the spikes in interest rates during the outbreak of the crisis led to a quick deterioration of the sector's swap positions. Mark-to-market values of these contracts dropped sharply, putting pressure on the sector's funding capacity. To estimate these losses in contract values, we use the different snapshots of our swap-market data to compute changes in the mark-to-market values of the LDI-PI sector's swap contracts.

[Figure 25]

Figure 25 shows that the drop in the contract values during 23-27 September amounted to about £8 billion, which meant significant increases in required variation margins by counterparties. The increase in losses continued until 14 October. Moreover, the LDI-PI sector made adjustments in positioning by reducing its exposure throughout the crisis. As shown by Figure 26, the sector consistently reduced its net position in absolute value by around £23 billion by 14 October.

[Figure 26]

In addition to OIS contracts, (RPI) inflation-swaps are the other major hedging instrument that LDI-PI investors in the UK have employed. To get sense of the client composition in this market, Figure 23 shows the net positions of the four client types as well as the dealer sector on 22 September. As documented in Barria and Pinter (2022), the UK inflation swap market is almost entirely dominated by the LDI-PI sector buying inflation protection (i.e. receiving inflation and paying the fixed-rate) and the dealer sector acting as the provider of this insurance.

[Figure 27]

Specifically, the LDI-PI sector had a net position of about £62 billion. The main counterparties were dealers that had a negative net position of about £72 billion. The difference in net positions is accounted for by the remaining market participants.

[Figure 28]

We then decompose the sectoral net positions into four groups depending on the maturity of the inflation swap contracts. Figure 28 shows that dealers and LDI-PI firms have the largest net positions (in absolute value) across all maturities, with net positions peaking in the 11-25 year maturity segment. The hedge fund sector is an inflation receiver in the 0-5 year tenor, and it is an inflation payer in the 5-11 year tenor. A closer inspection of the data reveals that it is driven by the same hedge funds who use steepener strategies to speculate on future inflation dynamics.

[Figures 29–30]

Similar to the OIS market, the LDI-PI sector experienced mark-to-market losses in its inflation swap positions during the crisis (Figure 29), and consistently reduced its net position, which amounted to a fall of around £2 billion by 14 October (Figure 30).

4.2 Repo Market Positioning

As discussed in section 2.2.3, repo-financed gilt purchases have emerged as a dominant strategy of the LDI-PI sector to hedge liability risks, mainly because of the simplicity and cost advantages of repo compared to swaps. To get a sense of the LDI-PI sector's repo exposure along with the positioning of other sectors, Figure 31 shows the net positions of the four client types as well as the dealer sector in the gilt repo market on 22 September. We find that, among the five sectors, the LDI-PI sector is by far the largest net borrower in the gilt repo market with a net position of around £135 billion, consistent with the role of repo exposure in the LDI-PI crisis (Cunliffe, 2022a,b). The largest lenders are primary dealers with a negative net position of over £80 billion, followed by hedge funds with a negative net position of over £60 billion.

[Figures 31–32]

Figure 32 decomposes the total gilt repo positions on 22 September into net positions in repos secured by nominal gilts (upper panel) and linkers (lower panel). We find that the majority of LDI-PI exposure concentrates in linkers with total borrowing amounting to around £95 billion, whereas total LDI-PI borrowing in repos secured by nominal bonds amounted to more than £40 billion. Interestingly, the major cash lenders are different across the two repo markets. In repos secured by nominal gilts, hedge funds are the largest lenders with a negative net position of almost £65 billion, suggestive of the hedge fund sector taking large short positions in the gilt market prior to the outbreak of the crisis. In repos secured by linkers, primary dealers are the largest lenders with a negative net position of around £100 billion.

[Figures 33–34]

Figure 33 decomposes the sectoral net positions in gilt repos into four groups depending on the maturity of the repo contracts. We find that the LDI-PI sector borrows the most in the 1-9 month tenor (almost £100 billion), and the sector's overall exposure in repos with less than one month maturity (including overnight repos) is negligible. Figure 34 shows this maturity decomposition for nominal gilt repos and linker repos separately. Panel A shows that, on 22 September, hedge funds were significant cash-lenders in nominal repos of 0-1 month maturity (with dealers being on the other side of most of these contracts), which may reflect the sector's speculative (short) positions in nominal gilts. While hedge funds continue to be cash lenders in nominal gilt repos with maturity longer than one month, LDI-PI firms are the primary borrower at such long maturities. Panel B of Figure 34 shows that net positions in linker repos concentrate in longer (>1month) maturities and the market is dominated by LDI-PI firms borrowing from dealers.

[Figure 35]

As the events unfolded, the LDI-PI sector substantially reduced its repo exposure (which accompanied the sector's liquidation of its gilt positions). To document this, Figure 35 shows the net positions of the five sectors after the crisis (17 October) along with the pre-crisis positions (22 September). We find that the LDI-PI sector reduced its repo exposure by around £33 billion by the end (consistent with the sales of gilts worth over £36 billion as shown in section 3.2), which coincided with a reduction in cash lending by the dealer and hedge fund sectors.

4.3 The Role of Pre-crisis Repo and Swap Exposures in Gilt Sales

To investigate the role of funding positions of LDI-PI firms in driving their subsequent gilt liquidations, we test whether LDI-PI firms with larger interest rate swap or repo exposures before the crisis ended up selling more gilts during the crisis. We also decompose repo positions into borrowing backed by nominal bonds as collateral and borrowing backed by linkers, so we get a better understanding of the type of repo positions most relevant to understanding forced selling during this episode.

Such an analysis requires us to match at the firm-level our gilt market dataset with the repo and swap datasets. In our baseline sample of LDI-PI firms, we managed to find 58 firms who were net sellers of gilts during the crisis period and who had positive repo and OIS exposures, i.e. they were borrowing in the repo market and paying the floating rate in interest rate swaps.[25]

[Figure 36]

The scatter plots in Figure 36 illustrate the relationships between gilt sales and the initial gilt-repo and OIS positions, respectively, in our matched sample of LDI-PI firms. We find that both types of funding positions are predictive of subsequent gilt sales during the crisis, i.e. LDI-PI firms with larger linker-repo or OIS exposures on 22 September ended up selling more gilts during 9/23-10/14 compared to firms with lower exposures. However, the histograms differ in two aspects: the marginal effect of gilt-repo positions on subsequent gilt sales is more than twice as big as the effect of OIS exposures (the slope coefficients are around -1.17 and -0.52, respectively, for the two instruments), and the explanatory power of initial gilt-repo positions is more than three times as large as that of OIS exposures (with the corresponding R^2-statistics being 0.56 and 0.17, respectively, for the two instruments). This is suggestive of repo exposures being more important than OIS exposures in explaining subsequent gilt market sales.

To undertake a more rigorous analysis, we turn to multivariate regression analysis. This allows us to run a horse race among the various exposures in determining subsequent gilt sales as well as to control for size effects (as larger firms may have larger funding exposures, and they may

[25] While this subsample of firms is substantially smaller than the sample of LDI-PI firms used for the analysis in section 3, it is important to note that the subset of LDI-PI firms used in this section were responsible for the majority (over 80%) of the sector's orderflow during this crisis.

systematically sell more in a crisis as well). The most conservative specification of our cross-sectional regression is written as follows:

$$\begin{aligned} BondSales_i^{9/23-10/14} =& \beta_1 \times OISExposure_i^{9/22} + \beta_2 \times RepoLinkerExposure_i^{9/22} \\ &+ \beta_3 \times RepoConventionalExposure_i^{9/22} + \beta_4 \times Size_i \\ &+ \beta_5 \times RPI_i^{9/22} + c + \varepsilon_i, \end{aligned} \tag{4.1}$$

where $BondSales_i^{9/23-10/14}$ is the cumulative orderflow of net gilt seller i in the LDI-PI sector during the period 23 September – 14 October; $OISExposure_i^{9/22}$ is the net position of seller i in the OIS market at the end of 22 September; the terms $RepoLinkerExposure_i^{9/22}$ and $RepoConventionalExposure_i^{9/22}$ capture total net borrowing of LDI-PI seller i in collateralised repos backed by linkers and nominal bonds, respectively; the term $Size_i$ controls for the size of the firm measured by the median daily turnover of seller i in our sample; the term $RPI_i^{9/22}$ is a dummy variable indicating whether seller i has a positive exposure in the RPI market (i.e. receiving inflation); the term c is a regression intercept. We winsorise the sample at the 1-99% level, and we take the natural logarithm of the continuous variables in regression 4.1 so that our estimated coefficients have an approximate percentage interpretation.

[Table 3]

Table 3 shows the results for various combinations of regressors. Columns (1)-(2) correspond to the scatter plots above (Figure 36), confirming that pre-crisis gilt-repo and OIS exposures have a statistically significant relationship with gilt sales during the crisis, with the corresponding coefficients estimated to be -0.52 and -1.17, respectively. Inspecting column (3) reveals that the effect of gilt-repo exposures dominates that of OIS exposures once we include both variables in the regression (the effect of OIS exposures are now economically and statistically insignificant, whereas the effect of gilt-repo exposures hardly changes compared to column (2)).

Column (4) shows the results when we control for firm size. While the estimated effect of gilt-repo exposures is somewhat weakened (-0.79), it remains statistically significant. Column (5) decomposes gilt-repo exposures into secured borrowing backed by linkers as collateral and nominal bonds. We find that pre-crisis linker-repo exposures have an economically and statistically stronger effect on gilt sales during the crisis compared to repos secured by nominal gilts. The point estimates suggest that a 1% increase in pre-crisis exposures in linker-repos and conventional-gilt-repos are associated with a 0.47% and 0.3% increase in net gilt sales during 9/23-10/14. These results are robust to controlling for pre-crisis inflation swap exposures, as shown by column (6). Overall, the findings of this section are consistent with the narrative that the large leveraged positions of LDI-PI firms were a major force behind the sector's subsequent gilt liquidations (Breeden, 2022; Cunliffe, 2022b; Baranova and Valentini, 2023).

5 Transaction Costs During the Crisis

5.1 Summary Statistics and Measurement

To analyse the dynamics of government bond illiquidity during the crisis, we study how transaction costs changed during the crisis and in which segment of the market these cost changes concentrated the most. In particular, we explore whether transaction cost changes were heterogeneous across the different client sectors, across the trade size distribution and across dealers. To provide a description of our sample at the sector-day level, Table 4 provides summary statistics of trade size, turnover and the number of firms trading in the market.

[Table 4]

The table presents the mean values across the four client sectors and the three sub-periods. Daily turnover in the LDI-PI sector was about £3.4 billion before the crisis, which more than doubled and averaged around £7.2 billion during the crisis. This is partly because the average trade size of LDI-PI firms increased (from £5 million to £7.5 million) and partly because the number of transactions and number of LDI-PI firms in the market increased. In terms of relative share, the LDI-PI sector accounted for 27.8% of client turnover before the crisis, with hedge funds accounting for the largest share (42.6%). While hedge funds also increased their turnover (from 5.1 billion to 6.6 billion) during the crisis, the rise in client activity was dominated by intensified trading of LDI-PI firms, As a result, hedge fund turnover accounted for 33% of client turnover during the crisis, with LDI-PI firms have the largest turnover share (36%). During the post-post crisis period, most of these values returned to their pre-crisis levels.

To measure trading costs, we follow O'Hara and Zhou (2021) and Pinter, Wang, and Zou (2022). Specifically, for each trade v we compute the following measure:

$$Cost_v = \left[\ln\left(P_v^{\star}\right) - \ln\left(\overline{P}\right)\right] \times \mathbf{1}_{B,S}, \tag{5.1}$$

where $P_v^{\star}$ is the transaction price, $\mathbf{1}_{B,S}$ is an indicator function equal to 1 when the transaction is a buy trade, and equal to -1 when it is a sell trade, and $\overline{P}$ is a benchmark price. As benchmark price, we use the quoted price from Datastream at hourly frequency. We multiply $Cost_v$ by 10,000 to compute costs in basis points of value.

5.2 Baseline Results

Our baseline specification is the following trade-level regression:

$$\begin{aligned} Cost_v = &\beta_1 \times D_t^{9/23-9/27} + \beta_2 \times D_t^{9/28-10/14} \\ &+ \beta_3 \times D_t^{10/17-10/28} + Size_v + \lambda_b + \delta_{i,j} + \varepsilon_v, \end{aligned} \tag{5.2}$$

where $Cost_v$ is the trading cost as computed in 5.1; the terms $D_t^{9/23-9/27}$, $D_t^{9/28-10/14}$ and $D_t^{10/17-10/28}$ are dummy variables indicating the outbreak, crisis and post-crisis periods, respectively. The term $Size_v$ is an indicator variable based on three size categories: small (<£100,000), medium (£100,000-£1,000,000) and large (>£1,000,000) trades. The terms λ_b and $\delta_{i,j}$ are, respectively, bond and client-dealer fixed effects. The objects of interest are the three estimated β coefficients, which capture how much transaction costs changed compared to the pre-crisis period (8/29-09/22).

[Table 5]

Table 5 shows the results for our baseline regression 5.2, using all client sectors. Panel A presents the results for all bonds, whereas Panel B and Panel C show the results after re-estimating model 5.2 on the subsample of nominal and inflation-linked bonds, respectively. We find that trading costs increased immediately during the outbreak of the crisis, and this increase concentrated entirely in nominal bonds. Trading costs in nominal bonds increased by about 6-7 bps during 23-27 September, whereas there was no significant change in the cost of trading linkers.

Transaction costs in the whole sample rose further during crisis period (09/28-10/14), however, this is mainly driven by the subsample of linkers where costs increased by 14-16 bps depending on the fixed-effect specification. This is consistent with deteriorating market liquidity in linkers, consistent with the BoE's decision to widen the scope of its gilt purchase operations to include purchases of linkers during the last four days of this period, 11-14 October (BoE, 2022). In the post-crisis period, transaction costs dropped but continued to be higher than pre-crisis period.

5.3 Client Heterogeneity

To explore the heterogeneity in the dynamics of transaction costs across client types, Tables 6–9 re-estimate regression 5.2 on four subsamples that only include trades by the LDI-PI sector, other clients, hedge funds and asset managers, respectively. Table 6 shows that most of the rise in transaction costs that LDI-PI firms faced concentrated in the crisis period (09/28-10/14) and was wholly driven by trades in the linkers market where LDI-PI firms faced the more severe selling pressure: costs increased by 17-19 bps depending on fixed-effect specification. Column (4) is the most conservative specification with client-dealer fixed effects included, which allows an interpretation of how costs within the same client-dealer relationship varied across the different phases of the crisis. Interestingly, including these controls results in the largest cost increase (19 bps) in linkers, faced by LDI-PI firms during the crisis.

[Tables 6–9]

Table 7 highlights that clients other than LDI-PI firms faced elevated transaction costs throughout the crisis, which indicates that the liquidity crisis which originated in the LDI-PI sector quickly spilled over to other sectors such as commercial banks, building societies, retail traders and others. Comparing Table 7 to Table 6 shows that almost all estimated cost increases are larger for other clients than for LDI-PI firms. We interpret this evidence as consistent with the notion of illiquidity spillovers from the LDI-PI sector (where selling pressure and the crisis originated) to other sectors. Note that, to a lesser extent, we also find a similarly pervasive increase in transaction costs among asset managers, as shown by Table 8. Moreover, both asset managers and other clients experience a persistent increase in illiquidity, indicated by continued high levels of trading costs in the post-crisis period (10/17-10/28).

In contrast, hedge funds experienced a rather different dynamic of transaction costs. As shown in Table 9, costs increased during the outbreak of the crisis which is entirely driven by linkers. (Recall that the selling pressure started in the linker market.) One explanation is that adverse selection risk, faced by dealers, on hedge fund trades in the linker market was the highest during the outbreak when yield movements were the most extreme (Glosten and Milgrom, 1985; Easley and O'Hara, 1987). Subsequently, transaction costs on hedge fund trades normalised with the exception of a small increase in nominal bonds during the post-crisis period.

5.4 Dealer Heterogeneity

To explore the heterogeneity in the dynamics of transaction costs across dealer types, Tables 10–11 re-estimate regression 5.2 on two subsamples that only include trades with small and large dealers, respectively. We label a dealer large (small) if the given dealer's total turnover during the pre-crisis period (8/29-9/22) was above (below) the median value.

[Tables 10–11]

The results show that almost all estimated coefficients are larger for smaller dealers than for larger dealers. For example, column (4) of Panel A shows that it costs almost twice as much (12 bps vs 7 bps) to trade an average bond at a smaller dealers compared to a larger dealer. This suggests that smaller dealers experienced worse liquidity conditions during the crisis than larger dealers.[26] The fact that smaller dealers (having lower balance sheet capacity) have an enhanced sensitivity to liquidity crises is consistent with the expanding literature on frictional intermediation in financial markets.[27] Section 6 below will provide further evidence in support of this.

[26] Note that the results are not driven by smaller dealers facing larger selling pressures from LDI-PI firms than larger dealers. The correlation between dealer size and the cumulative orderflow during the crisis is about 17%, i.e. large dealers tend to buy more gilts from clients than smaller dealers.

[27] Specifically, our results relate to the literature that highlights the role of dealers' balance sheet constraints in liquidity provision, and analyses changes in the tightness of these constraints since the Great Recession (Duffie, 2020; Augustin, Chernov, Schmid, and Song, 2021; He, Nagel, and Song, 2022b; Du, Hebert, and Li, 2022). For related analysis on corporate bond markets, see Adrian, Boyarchenko, and Shachar (2017); Bao, O'Hara, and Zhou (2018); Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018); Goldberg and Nozawa (2021) and references herein.

5.5 Heterogeneity in Client-Dealer Relationships

While the results so far point to a significant increase in transaction costs for the average client, a stronger trading client-dealer relationship might have mitigated these cost hikes to some extent. The literature found empirical evidence in support of this hypothesis from other markets and time periods (Maggio, Kermani, and Song, 2017; Hendershott, Li, Livdan, and Schürhoff, 2020; Jurkatis, Schrimpf, Todorov, and Vause, 2022). We test this hypothesis in the context of the recent episode, by estimating whether cost increases during the crisis were different in trades where counterparties had a stronger trading relationship with one another (compared to trades between counterparties with weaker relationships).

As a small contribution to the literature, we distinguish between client-dealer relationships that are important to the dealer and relationships that are important to the client. Specifically, we define a favourite dealer as the one with whom a client traded the most in terms of total trade volume (before the crisis period). Similarly, we define a favourite client with whom a dealer traded the most in terms of total trade volume (before the crisis period). Given that we have less than 20 dealers (and hundreds of clients), we pick the three most favourite clients for each dealer so that we have enough observations in the subsample to estimate our baseline regression 5.2. Altogether we end up with four subsamples, on which we-estimate regression 5.2.

[Tables 12–13]

As shown by Table 12, the average client did not experience an increase in trading costs at its favourite dealer during the outbreak of the crisis, with all coefficients across bonds types being statistically insignificant. In contrast, non-favourite dealers were responsible for the cost hikes at the outbreak. However, during the crisis, favourite dealers did not insulate clients from cost hikes.

To analyse the role of relationship strength from the dealer's point of view, Table 13 shows the results for favourite and non-favourite clients. In this case, the results are more clear-cut: dealers provided more favourable transactions costs for their more regular clients, and most cost hikes were concentrated at their less favourite clients.

Related to counterparty relationships, future work could analyse (in the spirit of Hollifield, Neklyudov, and Spatt, 2017; Di Maggio, Franzoni, Kermani, and Sommavilla, 2019; Li and Schürhoff, 2019) how the trading network in the gilt market changed throughout the crisis. To motivate such an analysis, Figures A.4–A.5 visualise the gilt market trading network during the pre-crisis (09/01 – 09/22) and crisis periods (09/23 – 10/14), respectively. The nodes represent clients and dealers participating in the market. To illustrate the importance of firms, the size of nodes captures the natural logarithm of first-order connections of the given firm, and the edges are determined by transactions. We find that the network becomes denser during the crisis (with more connections being established) as well as local hubs appear to be formed among clients, consistent with client-to-client trades complementing client-to-dealer trades during the crisis.

5.6 Bond Heterogeneity

To explore the heterogeneity in the dynamics of transaction costs across different maturity segments of the yield curve, Tables 14–16 re-estimate regression 5.2 on three subsamples that only include trades with less than 10 years, 10-25 years and above 25 years of maturity, respectively. We find that transaction costs in short maturity bonds were elevated throughout the crisis, and these effects are stronger in linkers than in nominal bonds (Table 14). Transaction costs in nominal bonds of longer (>10years) maturities were the highest at the outbreak (9/23-9/27), while traders in linkers during this period did not yet experience significant changes in transaction costs.

[Tables 14–16]

For example, column (4) of Table 15 shows that trading nominal bonds (10-25 years of maturity) was about 9 bps more expensive during the outbreak than pre-crisis, whereas the change in transaction costs for linkers is not significantly different from zero. This suggests that liquidity in long-dated linkers during the first phase of the crisis was still at normal levels, while liquidity in long-dated nominal bonds began to dry up. However, during the deepening of the crisis (09/28-10/14), selling pressures in long-dated linkers began to intensify and transaction costs quickly spiked (while transaction costs in nominal bonds somewhat normalised).

5.7 Trade Size Heterogeneity

To explore the heterogeneity in the dynamics of transaction costs across different trade sizes, Tables 17–19 re-estimate regression 5.2 on three subsamples that only include trades with small (<£100,000), medium (£100,000-£1,000,000) and large (>£1,000,000) nominal values. There are two main messages revealed by this analysis. First, the largest increase in transaction costs is concentrated in large linker trades during the crisis period (Panel C of Table 19), consistent with LDI-PI firms using large trades (Table 4) to liquidate linker positions which the dealer sector found too difficult to absorb. Second, small trades too experienced persistent increases in transaction costs throughout the crisis (Table 17). This suggests that deteriorating market liquidity, triggered by the selling pressures from the LDI-PI sector, spilled over into straining liquidity among smaller trades, e.g. transactions of retail traders, categorised as other clients in the analysis above (Table 7). One explanation why this spillover effect pertains to small (rather than medium-sized) trades could be that small trades tend to be initiated by smaller traders who also have lower bargaining power when negotiating the terms of trade with primary dealers. Dealers would then find it easier to increase spreads against these smaller clients (Harris and Piwowar, 2006).

[Tables 17–19]

To further investigate the relationship between trading costs and trade size (and how this relationship changed during the crisis), we now apply the recent analysis by Pinter, Wang, and Zou

(2022). The idea is to decompose the cost-size relation into a cross-client variation (i.e. comparing costs for smaller and larger clients), and within-client variations (i.e. comparing costs for smaller and larger trades of the same client). Their evidence shows a negative cost-size relation using the cross-client variation ('size discount'), and a positive cost-size relation using the within-client variation ('size penalty'). The size discount is consistent with theories of bargaining and trading frictions (Bernhardt, Dvoracek, Hughson, and Werner, 2005; Green, Hollifield, and Schurhoff, 2007) and the size penalty is consistent with models of inventory (Ho and Stoll, 1981) and informational frictions (Kyle, 1985; Easley and O'Hara, 1987). To get a sense of how trading frictions as well as inventory and informational frictions may have changed during the recent crisis, we estimate the size discount and size penalty during the pre-crisis (08/30-09/22) as well as the whole crisis (09/23-10/14) periods.

[Figures 37–38]

Figure 37 shows a drastic change in the size discount: the negative cross-client relation between transaction costs and trade size becomes about 5.5 times steeper during the crisis period compared to pre-crisis. This is in line with the results in Tables 17–19 and indicates a severe worsening of trading frictions. These results are also consistent with the findings of Pinter and Uslu (2022), underlining the important role of trading frictions and the fragility of government bond markets in the face of large shocks. Moreover, Figure 38 shows that the size penalty also doubled during the crisis period, suggestive of an increase in informational frictions as well.

6 Aggregate Price Dispersion

This section analyses the aggregate dispersion of market transaction prices and its dynamics throughout the crisis. Since Jankowitsch, Nashikkar, and Subrahmanyam (2011), aggregate price dispersion has often been used as an alternative measure of market liquidity.[28] As a small contribution to this literature, we decompose total dispersion into within-dealer and cross-dealer components, as explained below. Our measure of total price dispersion, D_T, is as follows:

$$D_T = \sqrt{\frac{1}{N}\sum_{v}^{N}\left(\ln\left(P_v^{\star}\right) - \ln\left(\overline{P}\right)\right)^2}, \tag{6.1}$$

[28]See Friewald, Jankowitsch, and Subrahmanyam (2012); Uslu (2019); Uslu and Velioglu (2019); Coen and Coen (2022); Wang (2022) among many others.

where $P_v^\star$ is the transaction price corresponding to trade v, and $\overline{P}$ is the average hourly transaction price in a given bond. The decomposition of total dispersion 6.1 is then written as:

$$D_T^2 = \underbrace{\frac{1}{N}\sum_v^N \left(\ln\left(P_v^\star\right) - \ln\left(\ddot{P}\right)\right)^2}_{within-dealer} + \underbrace{\frac{1}{N}\sum_v^N \left(\ln\left(\ddot{P}\right) - \ln\left(\overline{P}\right)\right)^2}_{cross-dealer}, \tag{6.2}$$

where $\ddot{P}$ is the average hourly transaction price at the dealer where trade v is executed.[29]

[Figure 39]

Figure 39 shows the time-series of total price dispersion, measured by standard deviation (6.1), in all bonds (Panel A) and for the nominal and linker markets separately (Panel B). We find that around 23 September total price dispersion jumped from 0.1-0.2% to around 0.7% (peaking on 29 September), consistent with rapidly deteriorating liquidity conditions. Price dispersion started to gradually decline, but it remained at elevated levels compared to the pre-crisis period. Panel B of the Figure shows that even before the crisis, price dispersion in linkers was higher than that in nominal bonds, consistent with the relative illiquidity of the linker market during normal times (Campbell, Shiller, and Viceira, 2009). The Figure also reveals that linkers experienced a larger jump in price dispersion during the crisis than nominal bonds.

[Table 20]

We now turn to the decomposition of total price dispersion following formula 6.2.[30] Table 20 presents total dispersion, measured in variance, along with the within-dealer and cross-dealer components across the different time-periods, separately for linkers and nominal bonds. We find that before the crisis the cross-dealer component was dominant, explaining around 60-70% of the total variance with the remaining variation explained by the within-dealer component. The level of both components jumped during the crisis, with each component explaining about half of total dispersion. The increase in the within-dealer component during the crisis suggests that dealers started to differentiate among their clients in terms of execution costs. (As shown by Section 5.5, the strength of trading relationships affect some of these cost differentials.) In a frictionless dealership market, the cross-dealer component of price dispersion should be zero. The increase in the cross-dealer component indicates a (possibly heterogeneous) tightening of intermediation and inventory constraints on primary dealers, consistent with our empirical results in the previous section (Tables 10–11) as well as consistent with recent research in the OTC literature (Bessembinder,

[29]For the implementation of the decomposition 6.2, we use a sample that includes at least two observations at the dealer-bond-hour level (so that we have non-trivial dispersion in the within-dealer dimension).

[30]As a robustness check, Table A.2 in the Appendix presents the decompositions using (as benchmark price $\overline{P}$) the average daily (instead of hourly) transaction price in a given bond. One can argue, however, that using daily average prices as benchmark price may lead to a less reliable decomposition during highly turbulent market dynamics.

Jacobsen, Maxwell, and Venkataraman, 2018; Dick-Nielsen and Rossi, 2018; Kargar, Lester, and Weill, 2022; Coen and Coen, 2022).

[Figure 40]

Moreover, we trace out the dynamics of aggregate dispersion and its components in Figure 40, with Panel A and B showing the time-series for nominal bonds and linkers, respectively. We find that both components spiked around 28 September. While quickly normalised in nominal bonds, they continued to be elevated in the linker market, pointing to persistent illiquidity in inflation-linked bonds. Note that the relative importance of the cross-dealer component in price dispersion remains high in both markets throughout our sample. This echoes recent concerns regarding the functionality of government bond markets in the face of increasing amounts of bonds issued and constraints on dealers' intermediation capacity (Duffie, 2020).

7 Liquidity Provision by Hedge Funds

Given the extreme gilt market volatility and forced selling by the LDI-PI sector, a natural question to ask is whether certain hedge funds may have benefited from liquidity provision during the crisis. To study this issue, we take a close look at hedge fund returns during the crisis period. Our focus on hedge funds is motivated by the empirical evidence on the ability of these clients to time macroeconomic changes and predict the orderflow in government bond markets (Bali, Brown, and Caglayan, 2014; Czech, Huang, Lou, and Wang, 2021; Kondor and Pinter, 2022). Moreover, Figures 11–12 show that while hedge funds provided liquidity to the LDI-PI sector, their liquidity provision was rather limited in scope. The existing literature offers at least two possibilities for this. First, it could be that hedge funds themselves became balance sheet constrained during the crisis, which impeded their ability to provide liquidity (Cotelioglu, Franzoni, and Plazzi, 2020).[31] Second, hedge funds may have chosen not to provide liquidity but they, instead, took advantage of the selling pressure of the LDI-PI sector (Barbon, Maggio, Franzoni, and Landier, 2019). Recent evidence shows that there indeed could be a tension between liquidity provision and speculative trading during informationally intensive periods (Lou, Pinter, and Uslu, 2022). Analysing hedge fund behaviour during the recent crisis can provide this literature with some answers.

As a useful preliminary, note that the hedge fund sector's positioning in the OIS market (Figure 23) meant that hedge funds realised large mark-to-market gains (while LDI-PI firms realising losses) on these derivative positions during the outbreak of the crisis. Ceteris paribus, this should have increased (rather than impeded) the ability of hedge funds to provide liquidity for the LDI-PI sector throughout the crisis. The hedge fund sector is also a major sector in terms of market

[31] Also see the earlier literature on the link between funding conditions and market liquidity, e.g. Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes (2010); Hameed, Kang, and Viswanathan (2010); Nagel (2012).

turnover (Table 4), making it a natural candidate for liquidity providers and absorbers of possible selling pressures from the LDI-PI sector.[32]

Moreover, we take a closer look at the performance of hedge funds trades: following Di Maggio, Franzoni, Kermani, and Sommavilla (2019), we compute the T-day-horizon return on each hedge fund trade on day t, measured as the percentage difference between the transaction price and a benchmark price T days after the transaction date.[33] Formally, for each trade j, we construct the measure $Performance_j^T$ as follows:

$$Performance_j^T = \left[\ln\left(P^T\right) - \ln\left(P_j^\star\right)\right] \times \mathbf{1}_{B,S}, \tag{7.1}$$

where $P_j^\star$ is the transaction price, P^T is the T-day ahead average transaction price of the corresponding bond, and $\mathbf{1}_{B,S}$ is an indicator function equal to 1 when the transaction is a buy trade, and equal to -1 when it is a sell trade. All transaction-specific returns are then averaged within day t for the hedge fund sector.

[Figures 41–43]

We compute both unweighted average as well as weighted average using the pound sterling volume of the trades as weights. In addition, we compute the average daily return as the median hedge fund return. We then compute cumulative returns for each of the three return definitions and plot the obtained time-series in Figures 41–43. We compute returns at the 3-day and 6-day horizons, as previous evidence (Czech, Huang, Lou, and Wang, 2021) suggests that hedge fund trades tend predict future price movements at such horizons (mainly due to their ability to predict short-horizon orderflow).

We find that cumulative hedge funds returns are sizeable across all our return definitions. For example, at the 6-day horizon, unweighted and size-weighted cumulative returns are around 80% and 30%, respectively, by the end of our sample. Importantly, the average hedge fund received significant compensation for liquidity during the crisis period, and we find that very little of this compensation is concentrated in the pre-crisis period.

Overall, one interpretation of these results is that the high hedge fund returns during the crisis were compensation for liquidity provision to the LDI-PI sector. Hedge funds as liquidity suppliers pursued contrarian strategies and increased their gilt purchases as yields were increasing.[34] The outperformance of liquidity-supplying hedge funds points to less-binding financing constraints in

[32] See Cunliffe (2020) for further details on the increasing role of hedge funds as liquidity providers.

[33] The T-day horizon starts at the start of each day and ends after T days. We use overlapping time windows. For example, to compute one-day performance measures ($T = 1$), we compare all trades on day 1 to the volume-weighted average price on day 2, and compare all trades on day 2 to the volume-weighted average price on day 3, and so on.

[34] Observe, for instance, the timing of linker purchases by hedge funds (Figure 12) and real yield dynamics (Figure 20).

this sector (consistent, for example, with the windfall gains hedge funds realised on their OIS positions against LDI-PI firms).[35]

8 Conclusion

This paper used transaction-level, granular datasets across the UK government bond, repo and interest-rate swap markets to document some of the facts from the 2022 gilt market crisis. To conclude, we summarise six of the main findings of our paper: (i) pre-crisis derivative positions of the LDI-PI sector were predictive of their gilt sales during the crisis; (ii) only three firms were responsible for over 70% of LDI-PI gilts sales to the dealer sector, consistent with the concentrated nature of the LDI-PI market; (iii) selling pressure started in linkers (across all maturities), followed by nominals, with evidence pointing to consistent price pressures on yields; (iv) transaction costs soared, especially in smaller trade sizes, at smaller dealers, and at clients other than LDI-PI firms too – indicative of illiquidity spillovers across assets, dealers and clients; (v) dispersion of transaction prices jumped, and the cross-dealer component remained high throughout the crisis, indicative of intermediation frictions; (vi) hedge funds were compensated for providing liquidity during the market turbulence.

Future research could address additional questions. For example, one could explore how new bond issuance might have interacted with the liquidity crisis, possibly putting further pressure on yields. For instance, as shown by Table A.3, there was a fresh supply of government bonds worth over £12 billion during the crisis. It would be interesting to estimate whether there were any differential yield movements that could be attributed to these issuances. Moreover, one could use structural equilibrium models to better understand the competing mechanisms during the different phases of the crisis and to provide useful counterfactuals. In ongoing work (Gavazza, Pinter, and Uslu, 2023), we are building on the framework of Pinter and Uslu (2022) to estimate a theoretical model with trading frictions to fit the data during the recent crisis episode. Such a structural econometric framework could also address normative implications regarding policy interventions.

[35]Similar results are presented by Jame (2018) in the context of equity markets.

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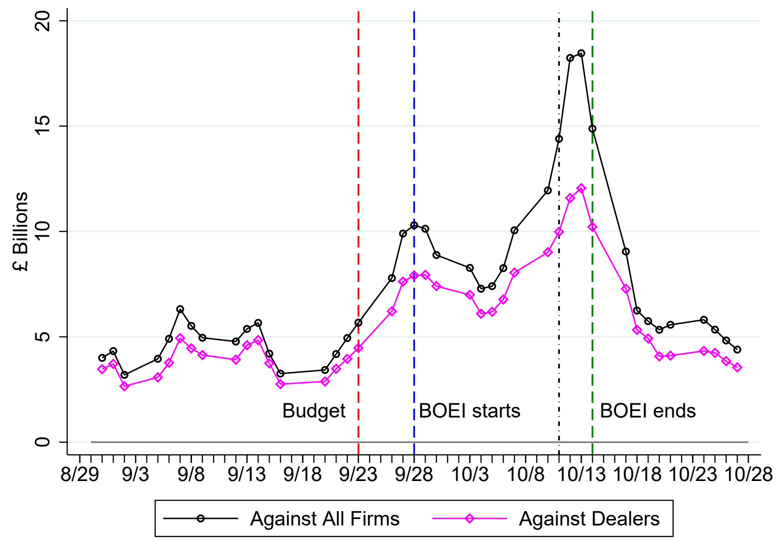
Figures and Tables

Table 1: Timeline of Events During the 2022 Gilt Market Crisis

Date	Events
23 September, 2022	The UK government announces its 'Growth Plan'.
28 September, 2022	The BoE announces that, in line with its financial stability objective, it would make temporary and targeted purchases of gilts to help restore market functioning and reduce any risks from contagion to credit conditions for UK households and businesses. It plans to end these operations and cease all gilt purchases on Friday 14 October.
10 October, 2022	The BoE announces additional measures to support market functioning and an orderly end to its gilt purchase scheme. These includes the launch of a Temporary Expanded Collateral Repo Facility (TECRF) through which banks would be able to help to ease liquidity pressures facing their client LDI funds through liquidity insurance operations, and the expansion of the scale of its remaining gilt purchase auctions.
11 October, 2022	The BoE announces that it will widen the scope of its daily gilt purchase operations also to include purchases of index-linked gilts. This enhancement to existing operations would be in effect until 14 October 2022 alongside the Bank's existing daily conventional gilt purchase auctions.
14 October, 2022	BoE gilt market operations end.

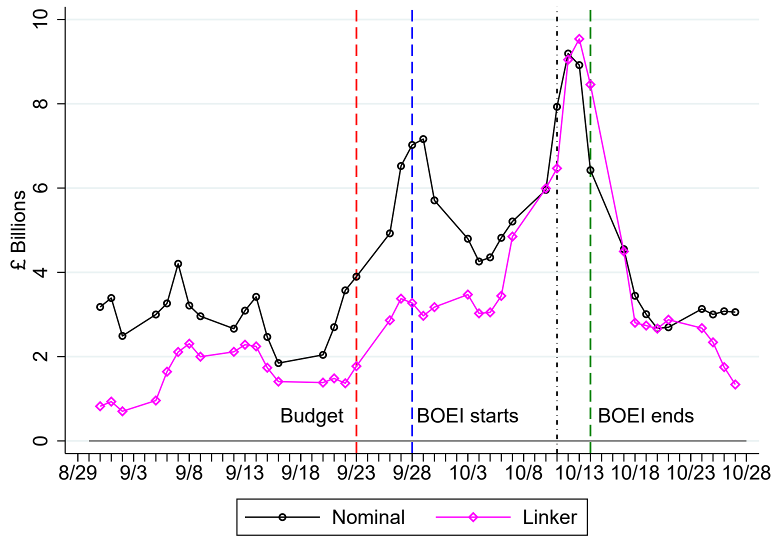
8.1 Stylised Facts from Gilt Markets

Figure 1: Trade Volume of the LDI-PI Sector



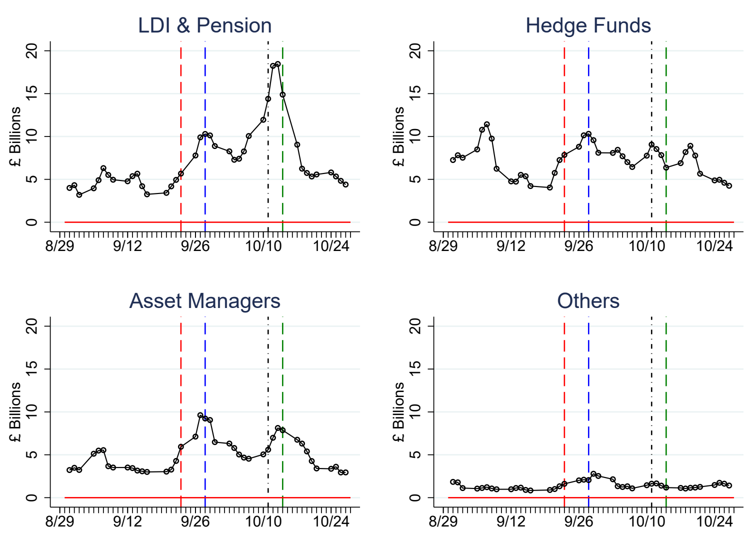
Notes: This figure shows the time-series of daily trade volume (in £ billions) of the LDI-PI sector, aggregated across the UK nominal and inflation-linked bond markets. The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep, 11 October and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention, the widening of the scope of the operations to purchase linkers and the end of the gilt market intervention.

Figure 2: Trade Volume of the LDI-PI Sector: Nominal vs Inflation-Linked Bonds



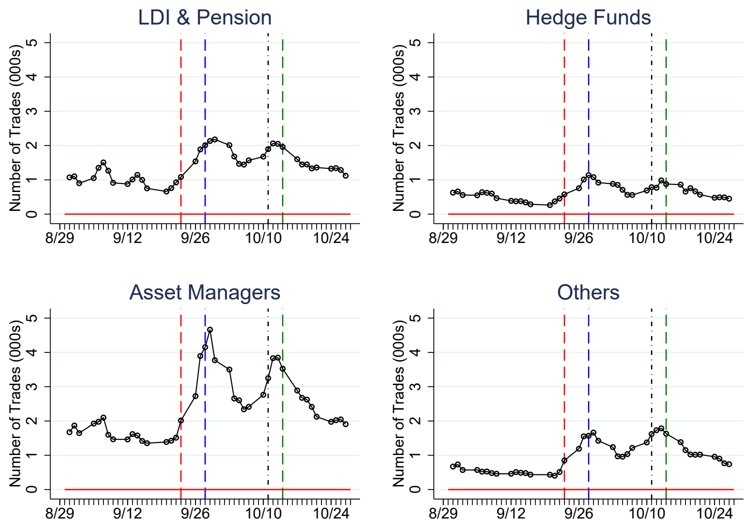
Notes: This figure shows the time-series of daily trade volume (in £ billions) of the LDI-PI sector, separately in the UK nominal (black line) and inflation-linked bond (magenta line) market. The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep, 11 October and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention, the widening of the scope of the operations to purchase linkers and the end of the gilt market intervention.

Figure 3: Trade Volume of Different Sectors



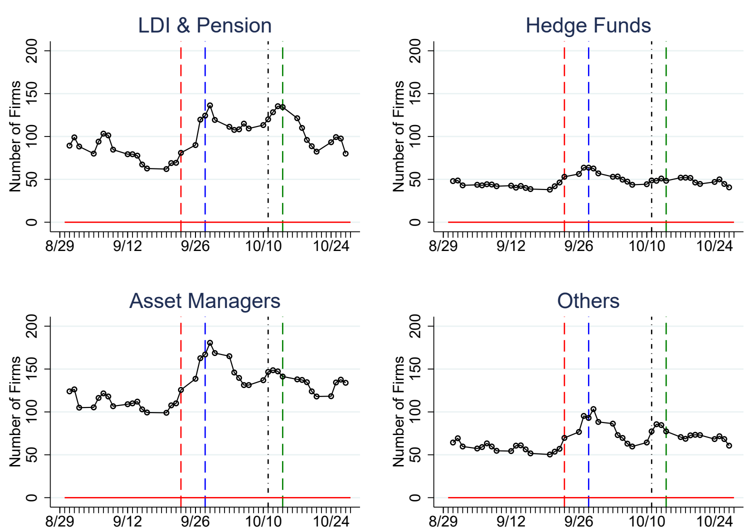
Notes: This figure shows the time-series of daily trade volume (in £ billions) of different client sectors, aggregated across the UK nominal and inflation-linked bond markets. The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep, 11 October and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention, the widening of the scope of the operations to purchase linkers and the end of the gilt market intervention.

Figure 4: Trade Intensity of Different Sectors



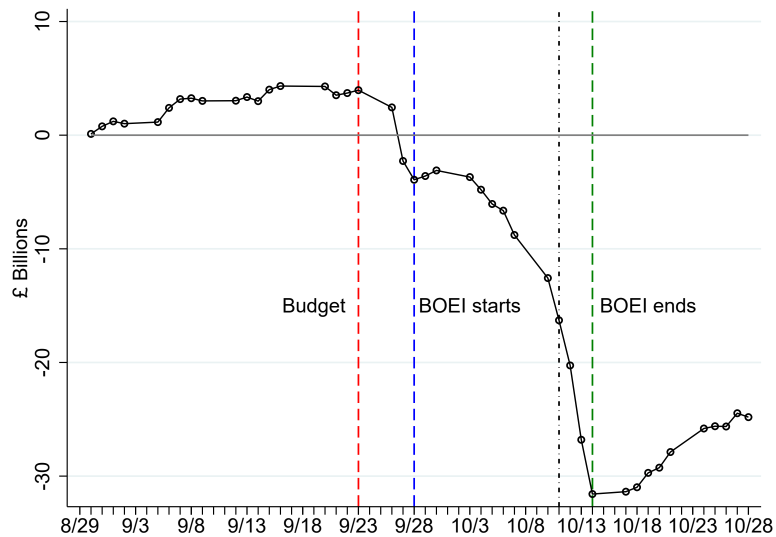
Notes: This figure shows the time-series of daily numer of transactions of different client sectors, aggregated across the UK nominal and inflation-linked bond markets. The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep, 11 October and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention, the widening of the scope of the operations to purchase linkers and the end of the gilt market intervention.

Figure 5: Number of Active Firms of Different Sectors



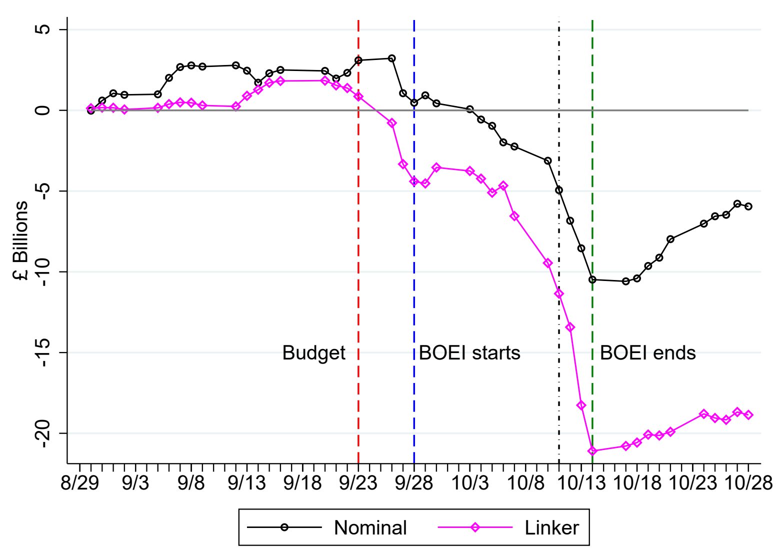
Notes: This figure shows the time-series of daily number of firms (of different client sectors) that are present in the UK bond market. The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep, 11 October and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention, the widening of the scope of the operations to purchase linkers and the end of the gilt market intervention.

Figure 6: Cumulative Orderflow of the LDI-PI Sector



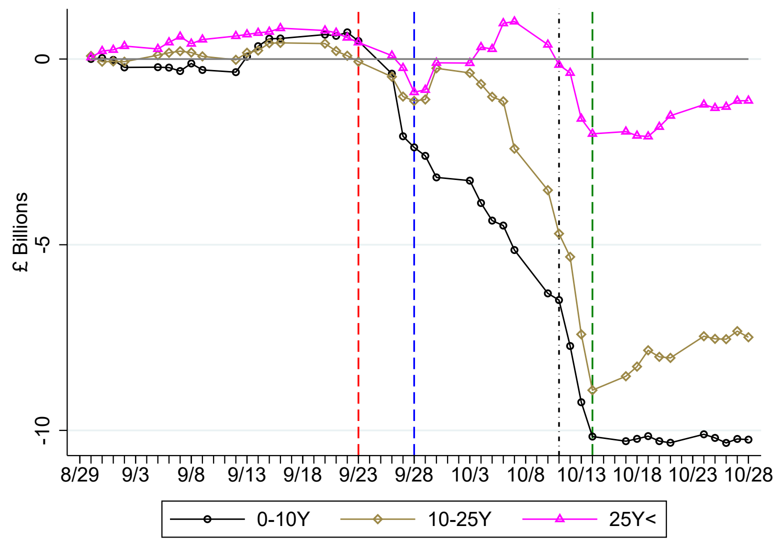
Notes: This figure shows the time-series of the cumulative orderflow (in £ billions) of the LDI-PI sector, aggregated across the UK nominal and inflation-linked bond markets. The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep, 11 October and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention, the widening of the scope of the operations to purchase linkers and the end of the gilt market intervention.

Figure 7: Cumulative Orderflow of the LDI-PI Sector: Nominal vs Inflation-Linked Bonds



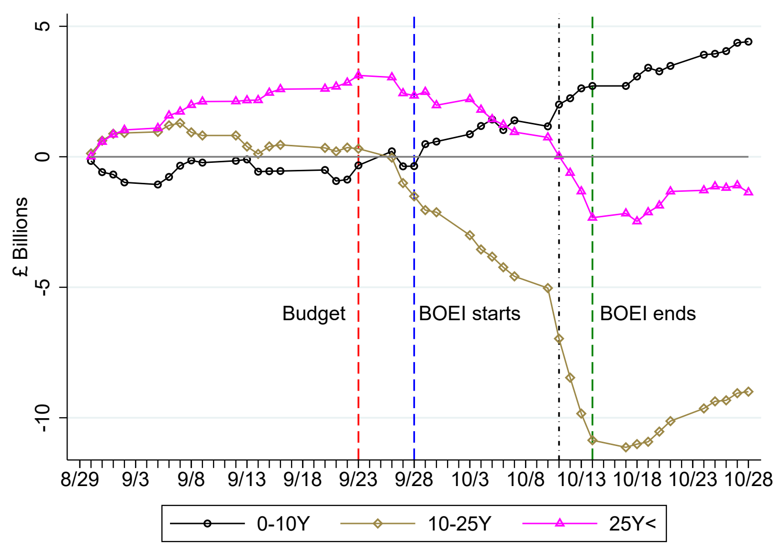
Notes: This figure shows the time-series of the cumulative orderflow (in £ billions) of the LDI-PI sector, separately in the UK nominal (black line) and inflation-linked bond (magenta line) market. The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep, 11 October and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention, the widening of the scope of the operations to purchase linkers and the end of the gilt market intervention.

Figure 8: Cumulative Orderflow of the LDI-PI Sector: Linkers of Different Maturities



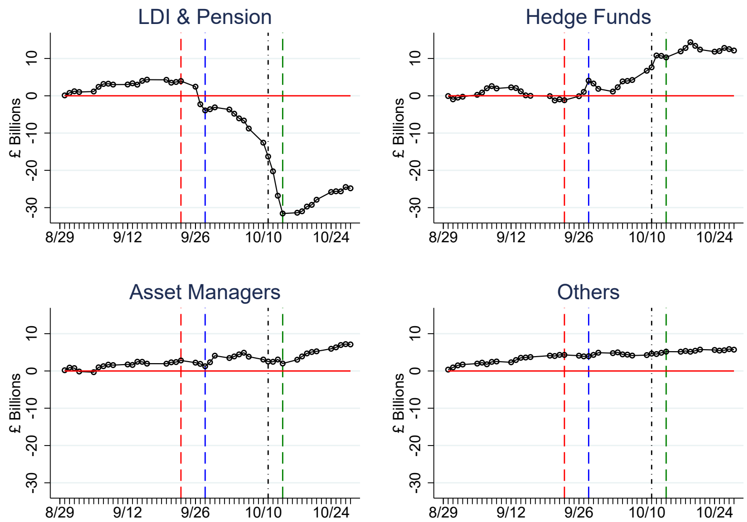
Notes: This figure shows the time-series of the cumulative orderflow (in £ billions) of the LDI-PI sector, across different maturities, in the UK inflation-linked bond market. The black, brown and magenta lines correspond to maturities 0-10 years, 10-25 years and above 25 years, respectively. The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep, 11 October and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention, the widening of the scope of the operations to purchase linkers and the end of the gilt market intervention.

Figure 9: Cumulative Orderflow of the LDI-PI Sector: Nominal Bonds of Different Maturities



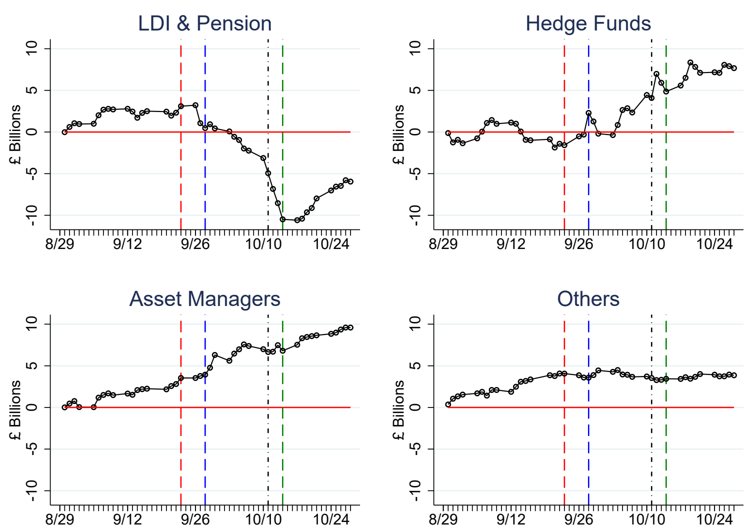
Notes: This figure shows the time-series of the cumulative orderflow (in £ billions) of the LDI-PI sector, across different maturities, in the UK nominal bond market. The black, brown and magenta lines correspond to maturities 0-10 years, 10-25 years and above 25 years, respectively. The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep, 11 October and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention, the widening of the scope of the operations to purchase linkers and the end of the gilt market intervention.

Figure 10: Cumulative Orderflow of Different Sectors



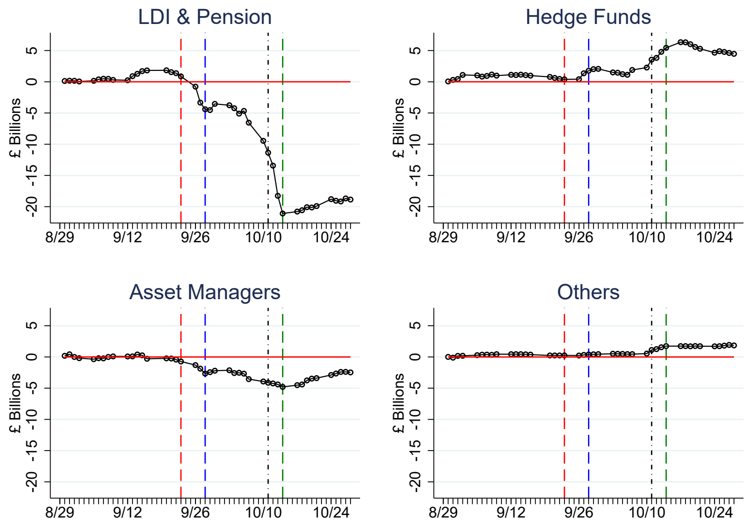
Notes: This figure shows the time-series of cumulative orderflow (in £ billions) of different client sectors, aggregated across the UK nominal and inflation-linked bond markets. The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep, 11 October and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention, the widening of the scope of the operations to purchase linkers and the end of the gilt market intervention.

Figure 11: Cumulative Orderflow of Different Sectors: Nominal Bonds



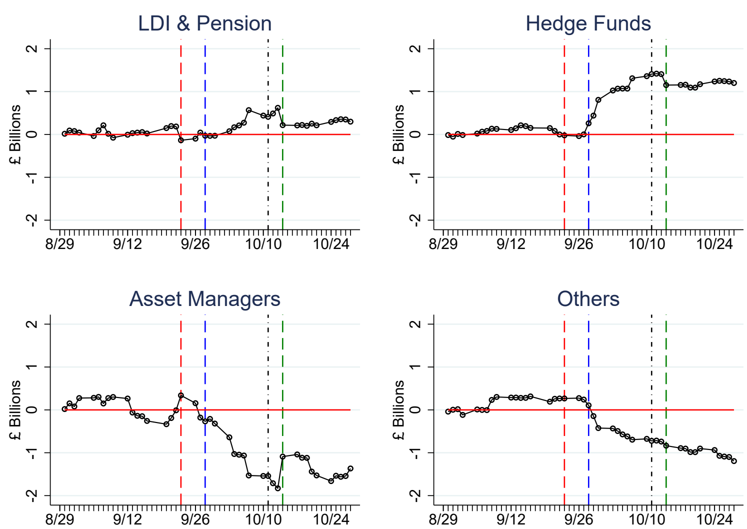
Notes: This figure shows the time-series of cumulative orderflow (in £ billions) of different client sectors, in the UK nominal bond market. The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep, 11 October and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention, the widening of the scope of the operations to purchase linkers and the end of the gilt market intervention.

Figure 12: Cumulative Orderflow of Different Sectors: Inflation-linked Bonds



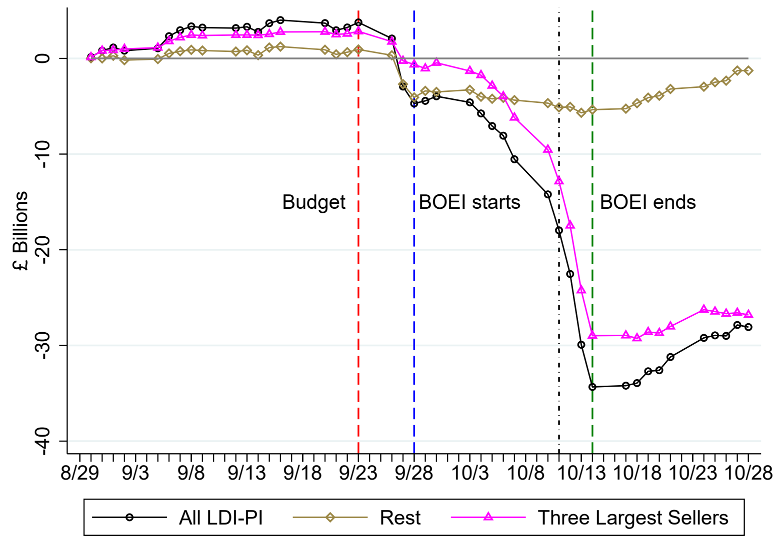
Notes: This figure shows the time-series of cumulative orderflow (in £ billions) of different client sectors, in the UK inflation-linked bond market. The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep, 11 October and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention, the widening of the scope of the operations to purchase linkers and the end of the gilt market intervention.

Figure 13: Cumulative Orderflow of Different Sectors: Client-to-Client Trades



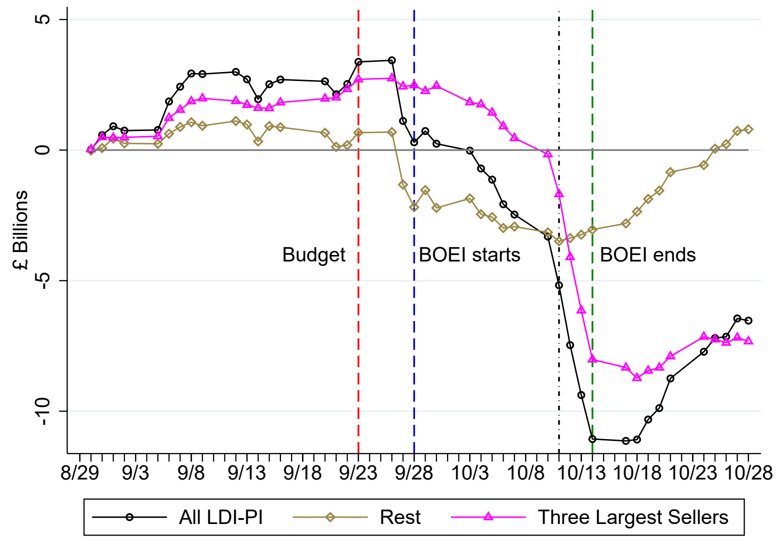
Notes: This figure shows the time-series of cumulative orderflow (in £ billions) of different client sectors, in the UK nominal and inflation-linked bond market. Only client-to-client trades are included in the calculations. The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep, 11 October and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention, the widening of the scope of the operations to purchase linkers and the end of the gilt market intervention.

Figure 14: Decomposing LDI-PI Orderflow: Three Largest Sellers vs the Rest



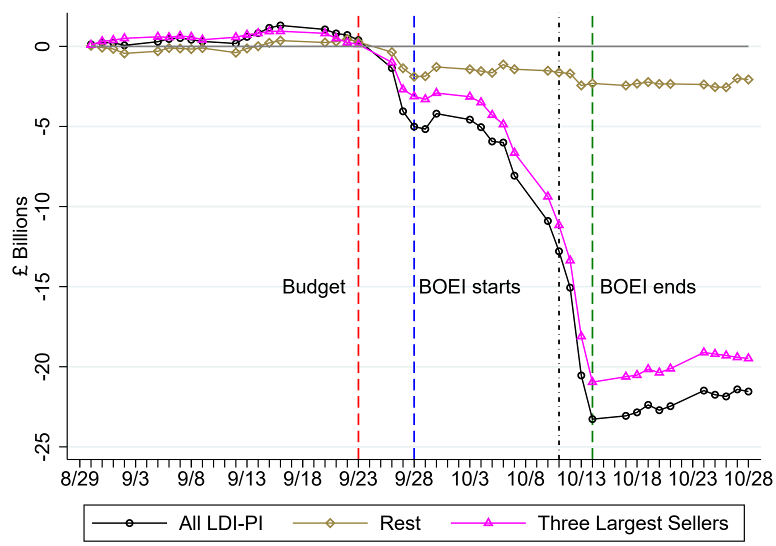
Notes: This figure decomposes the time-series of the cumulative orderflow (in £ billions) of the LDI-PI sector (aggregated across the UK nominal and inflation-linked bond markets) into the component that is driven by the trades of three of the largest sellers (magenta line) and the rest (brown line). The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep, 11 October and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention, the widening of the scope of the operations to purchase linkers and the end of the gilt market intervention.

Figure 15: Decomposing Nominal LDI-PI Orderflow: Three Largest Sellers vs the Rest



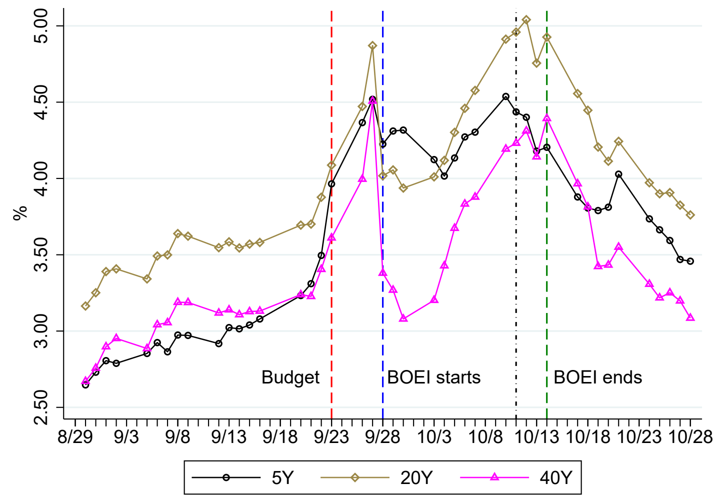
Notes: This figure decomposes the time-series of the cumulative nominal orderflow (in £ billions) of the LDI-PI sector into the component that is driven by the trades of three of the largest sellers (magenta line) and the rest (brown line). The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep, 11 October and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention, the widening of the scope of the operations to purchase linkers and the end of the gilt market intervention.

Figure 16: Decomposing Index-linked LDI-PI Orderflow: Three Largest Sellers vs the Rest



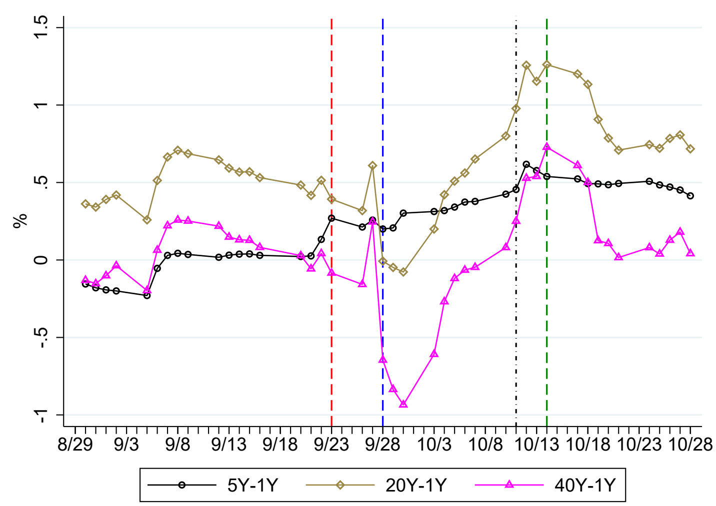
Notes: This figure decomposes the time-series of the cumulative index-linked orderflow (in £ billions) of the LDI-PI sector into the component that is driven by the trades of three of the largest sellers (magenta line) and the rest (brown line). The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep, 11 October and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention, the widening of the scope of the operations to purchase linkers and the end of the gilt market intervention.

Figure 17: Nominal Yields During the Crisis Across Different Maturities



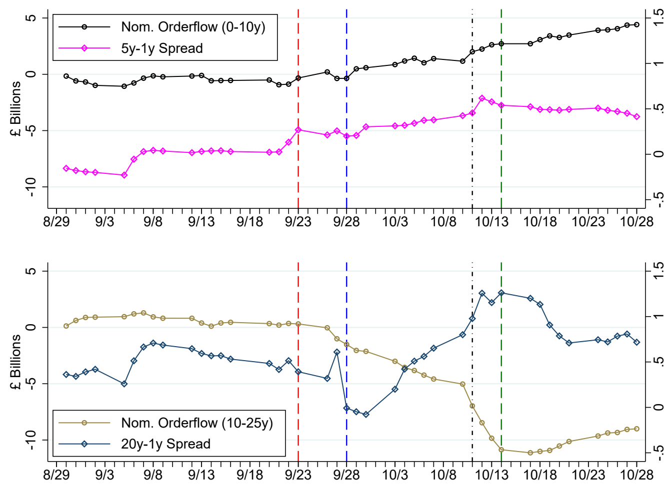
Notes: This figure shows the time-series of nominal yields of 5-year (magenta line), 20-year (brown line) and 40-year (magenta line) of maturities. The yields are from the from the Bank of England's website.

Figure 18: Nominal Term Spreads During the Crisis Across Different Maturities



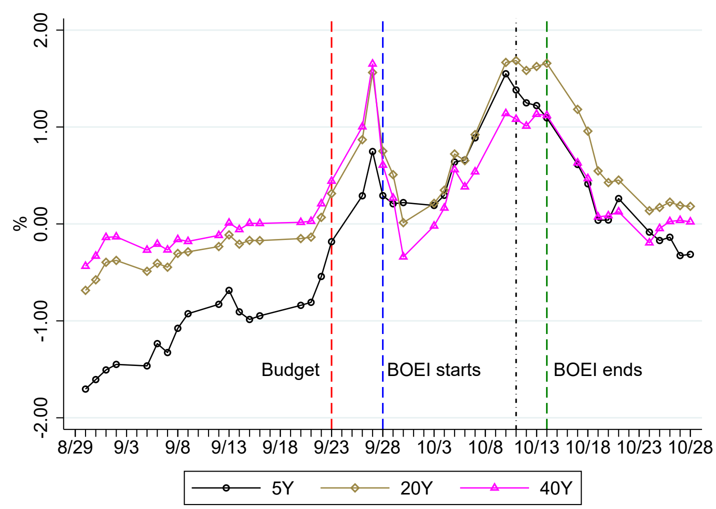
Notes: This figure shows the time-series of nominal term spreads, computed as the difference between the yields of 5-year (magenta line), 20-year (brown line) and 40-year (magenta line) of maturities and the 1-year yield. The yields are from the from the Bank of England's website.

Figure 19: Nominal Term Spreads and LDI-PI Orderflow During the Crisis



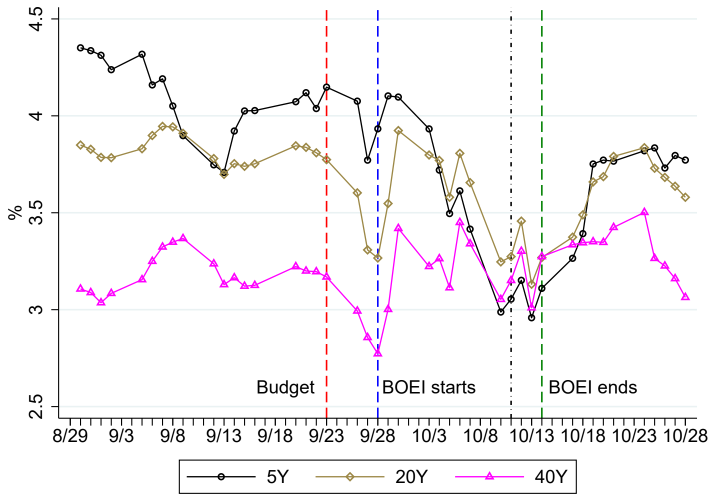
Notes: This figure shows the time-series of nominal term spreads along LDI-PI orderflow. The upper panel shows the 5y-1y term spread along with the orderflow in nominal gilts of 0-10y maturities. The lower panel shows the 20y-1y term spread along with the orderflow in nominal gilts of 10-25y maturities.

Figure 20: Real Yields During the Crisis Across Different Maturities



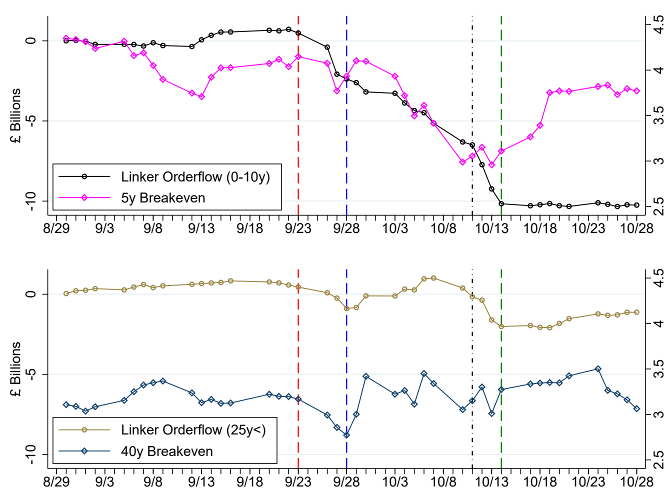
Notes: This figure shows the time-series of real yields of 5-year (magenta line), 20-year (brown line) and 40-year (magenta line) of maturities. The yields are from the from the Bank of England's website.

Figure 21: Breakeven Inflation During the Crisis Across Different Maturities



Notes: This figure shows the time-series of breakeven inflation of 5-year (magenta line), 20-year (brown line) and 40-year (magenta line) of maturities. The yields are from the from the Bank of England's website.

Figure 22: Breakeven Inflation and LDI-PI Orderflow During the Crisis



Notes: This figure shows the time-series of breakeven inflation along LDI-PI orderflow. The upper panel shows the 5-year breakeven along with the orderflow in linkers of 0-10y maturities. The lower panel shows the 40-year breakeven along with the orderflow in linkers of >25y maturities.

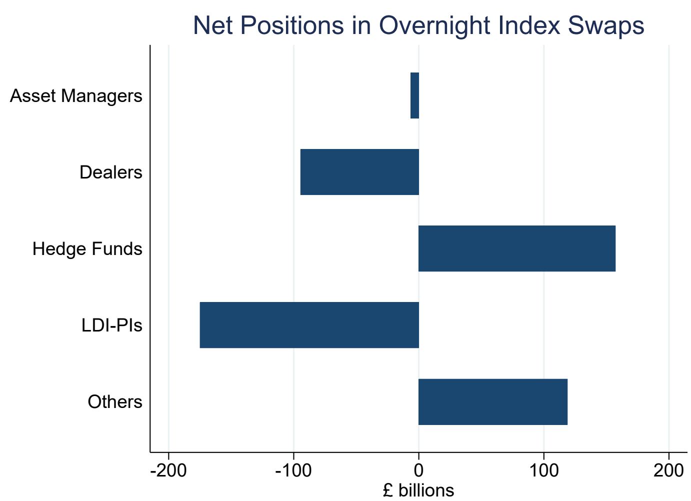
Table 2: Price Pressures from the LDI-PI Sector During the Crisis

	All LDI-PI Firms			Top 3 LDI-PI Sellers		
	OF in £ bn	OF stand.	OF scaled	OF in £ bn	OF stand.	OF scaled
	(1)	(2)	(3)	(4)	(5)	(5)
Flow	2.817*	0.190*	0.838**	6.013**	0.224**	1.336**
	(1.78)	(1.91)	(2.20)	(2.08)	(2.02)	(2.21)
N	3453	3453	3442	2977	2977	2966
R^2	0.586	0.587	0.582	0.632	0.632	0.628
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: this table regresses daily bond returns (measured in 100 times the natural logarithm of daily change in end-of-day price quotes) on the orderflow of the LDI-PI sector (columns 1-3) and of the top 3 sellers of the sector (columns 4-6) against primary dealers (i.e. GEMMs). Columns 1 and 4 measure the orderflow in £ billions, columns 2 and 5 standardise the gilt-specific orderflow and columns 3 and 6 scale the orderflow by the average daily (gilt-specific) market volume using the sample before 23 September (i.e. pre-crisis). To reduce noise, we winsorise the sample at the 1-99%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the gilt-day level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

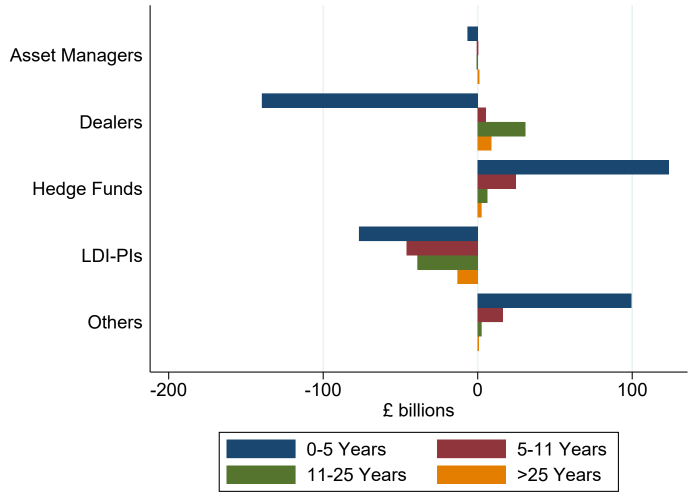
Stylised Facts from the UK Swap and Repo Markets

Figure 23: Net positions in the OIS Market



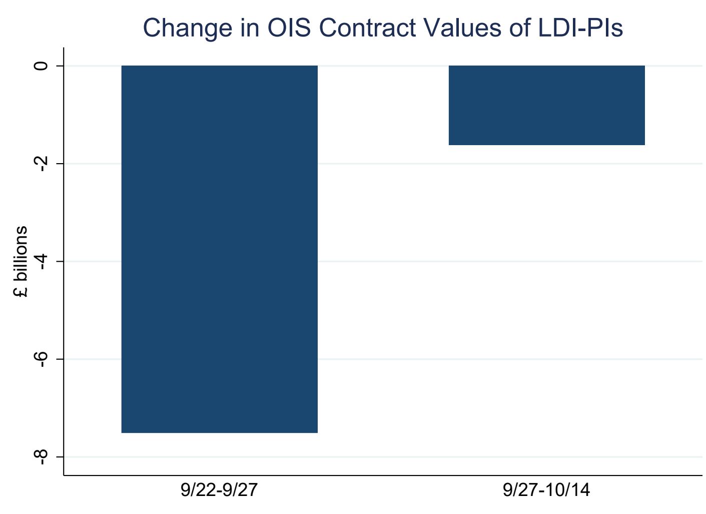
Notes: This figure shows the net positions – measured as the signed (net) notional – of different sectors on 22 September 2022 in the overnight index swap market. Positive (negative) values are associated with the sector being a net receiver (payer) of the floating leg. The sample includes all OIS contracts by clients and dealers that are active in our gilt market dataset. Positions against CCPs are excluded. The primary data source is the EMIR TR dataset.

Figure 24: Net positions in the OIS Market across Different Maturities



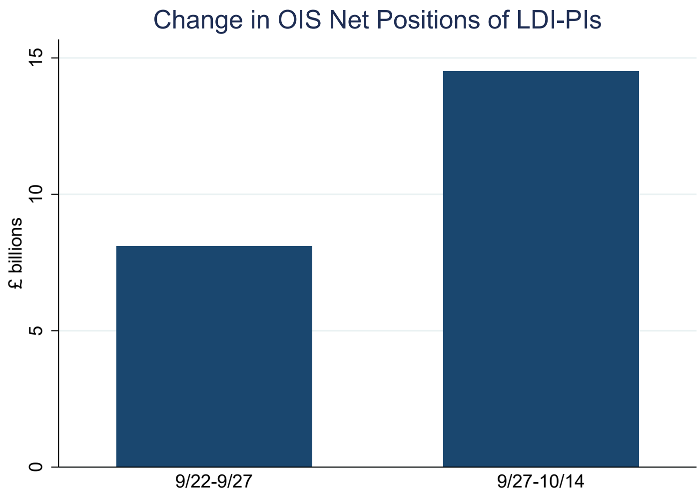
Notes: This figure shows the net positions – measured as the signed (net) notional – of different sectors on 22 September 2022 in the overnight index swap market in four different maturity segments. Positive (negative) values are associated with the sector being a net receiver (payer) of the floating leg. The sample includes all OIS contracts by clients and dealers that are active in our gilt market dataset. Positions against CCPs are excluded. The primary data source is the EMIR TR dataset.

Figure 25: Changes in Total (Mark-to-Market) OIS Contract Values of LDI-PI Firms



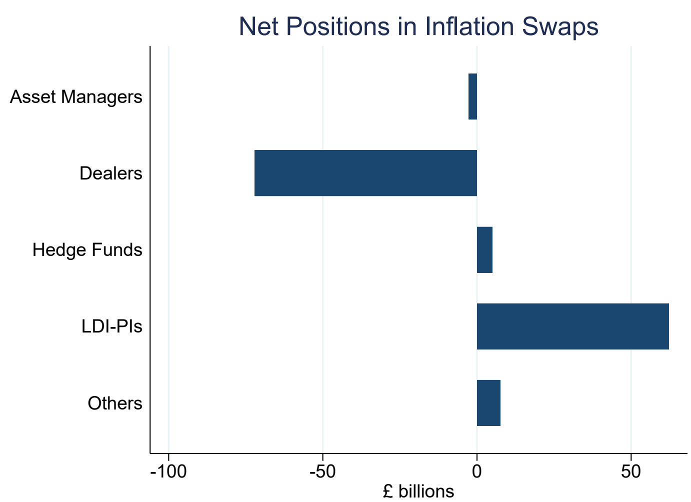
Notes: This figure shows the changes in outstanding mark-to-market OIS contract values of LDI-PI firms (in £ billions) over the period 9/22-9/27 (left bar) and 9/27-10/14 (right bar). The primary data source is the EMIR TR dataset.

Figure 26: Changes in the Net Positions of the LDI-PI Sector in the OIS Market Around the Crisis



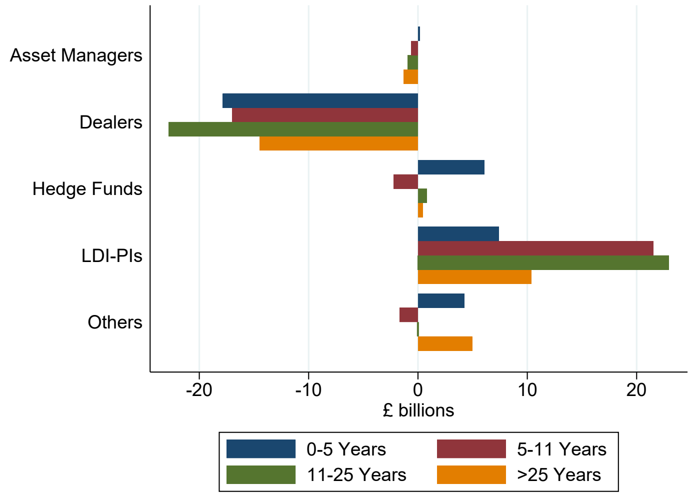
Notes: This figure shows changes in the net positions of the LDI-PI sectors in the overnight index swap market over the period 9/22-9/27 (left bar) and 9/27-10/14 (right bar). The primary data source is the EMIR TR dataset.

Figure 27: Net positions in the Inflation Swap Market



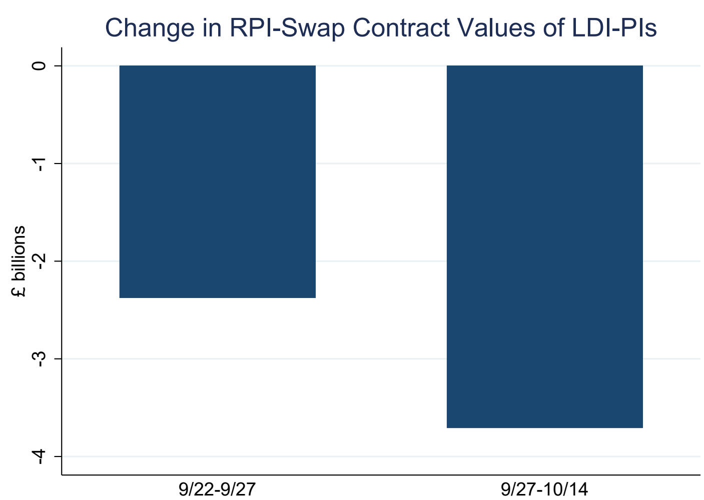
Notes: This figure shows the net positions – measured as the signed (net) notional – of different sectors on 22 September 2022 in the (RPI) inflation swap market. Positive (negative) values are associated with the sector being a net receiver (payer) of inflation. The sample includes all contracts by clients and dealers that are active in our gilt market dataset. Positions against CCPs are excluded. The primary data source is the EMIR TR dataset.

Figure 28: Net positions in the Inflation Swap Market across Different Maturities



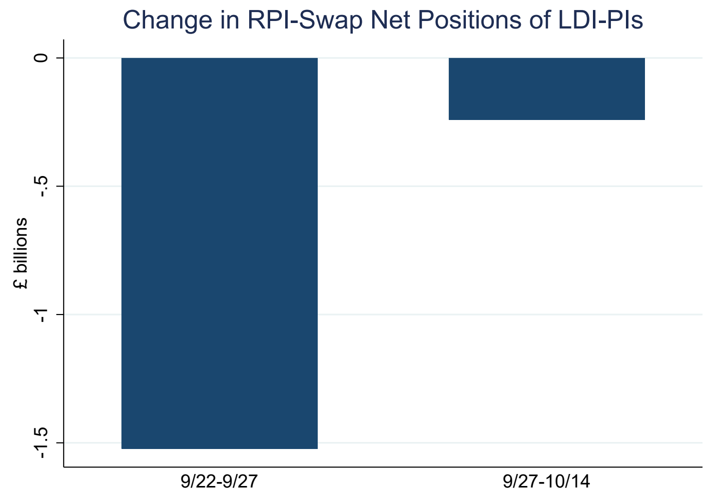
Notes: This figure shows the net positions – measured as the signed (net) notional – of different sectors on 22 September 2022 in the (RPI) inflation swap market in four different maturity segments. Positive (negative) values are associated with the sector being a net receiver (payer) of inflation. The sample includes all contracts by clients and dealers that are active in our gilt market dataset. Positions against CCPs are excluded. The primary data source is the EMIR TR dataset.

Figure 29: Changes in Total (Mark-to-Market) Inflation Swap Contract Values of LDI-PI Firms



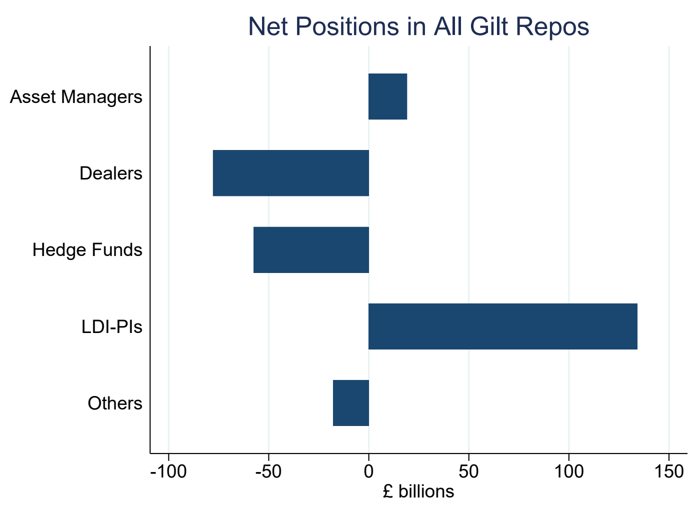
Notes: This figure shows the changes in outstanding mark-to-market inflation-swap (linked to RPI) contract values of LDI-PI firms (in £ billions) over the period 9/22-9/27 (left bar) and 9/27-10/14 (right bar). The primary data source is the EMIR TR dataset.

Figure 30: Changes in the Net Positions of the LDI-PI Sector in the Inflation Swap Market Around the Crisis



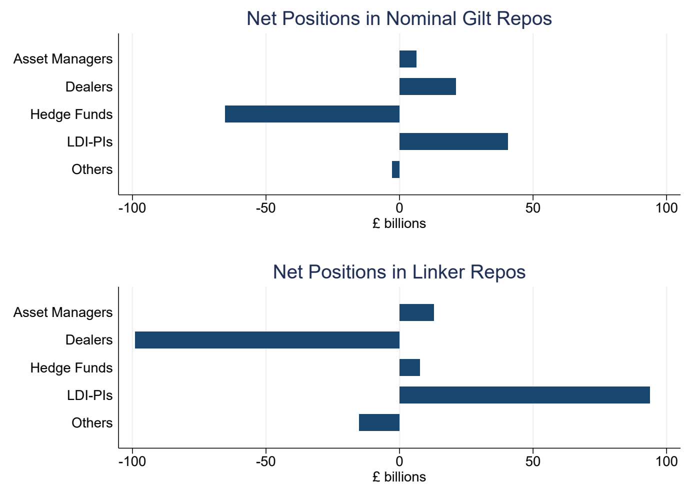
Notes: This figure shows changes in the net positions of the LDI-PI sectors in the (RPI) inflation swap market over the period 9/22-9/27 (left bar) and 9/27-10/14 (right bar). The primary data source is the EMIR TR dataset.

Figure 31: Net positions in the Gilt Repo Market



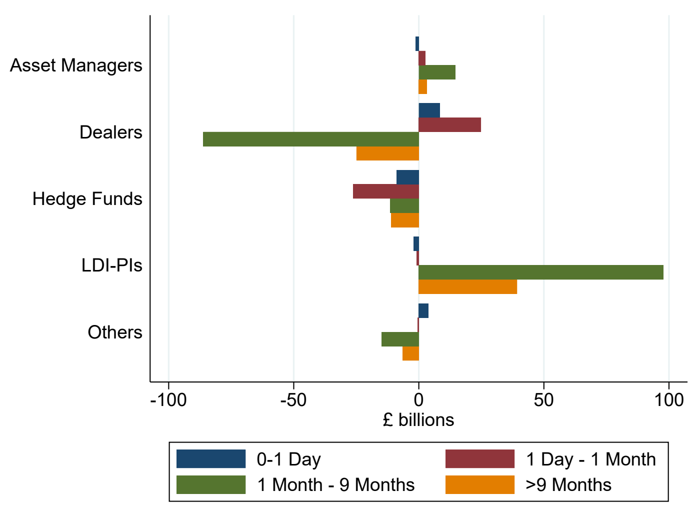
Notes: This figure shows the net positions of different sectors on 22 September 2022 in the repo market, using all outstanding repo contracts with UK gilts (either nominal or inflation-linked) used as the underlying collateral. Positive (negative) values are associated with the sector being a net borrower (lender). The sample includes all contracts by clients and dealers that are active in our gilt market dataset. Positions against CCPs are excluded. The primary data source is the SMMD dataset.

Figure 32: Net positions in the Gilt Repo Market: Nominal vs Linker Collaterals



Notes: The upper (lower) panel of the figure shows the net positions of different sectors on 22 September 2022 in the repo market, using all outstanding repo contracts with nominal (inflation-linked) gilts used as the underlying collateral.Positive (negative) values are associated with the sector being a net borrower (lender). The sample includes all contracts by clients and dealers that are active in our gilt market dataset. Positions against CCPs are excluded. The primary data source is the SMMD dataset.

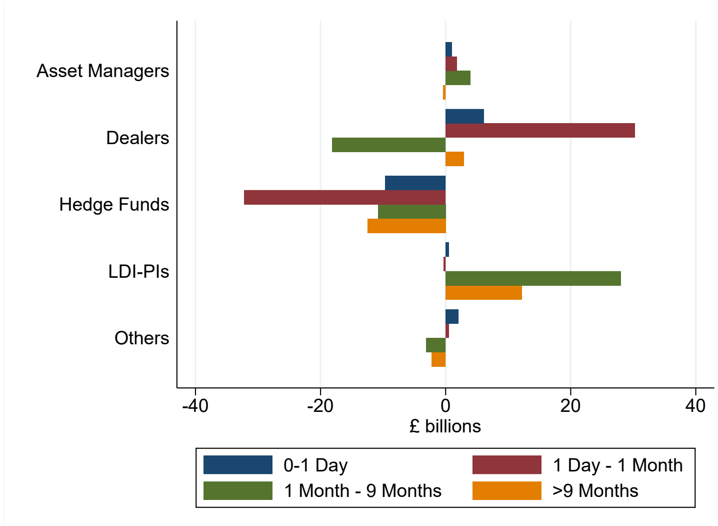
Figure 33: Net positions in the Gilt Repo Market Across Maturities



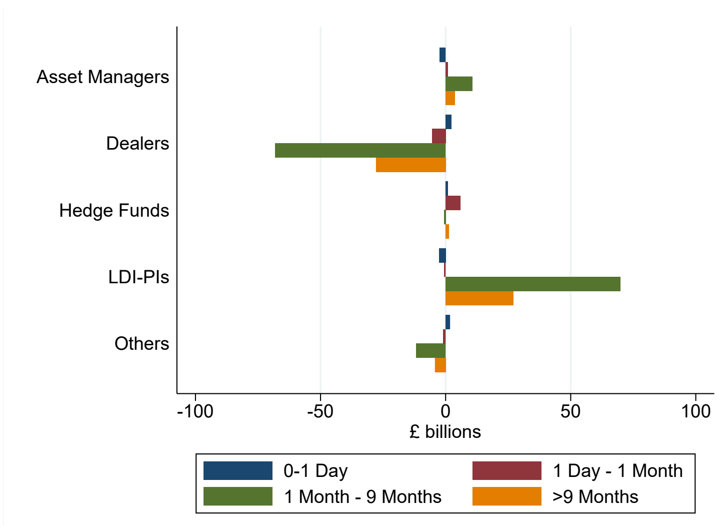
Notes: This figure shows the net positions of different sectors on 22 September 2022 in the repo market, using all outstanding repo contracts with UK gilts (either nominal or inflation-linked) used as the underlying collateral. Positive (negative) values are associated with the sector being a net borrower (lender). The sample includes all contracts by clients and dealers that are active in our gilt market dataset. Positions against CCPs are excluded. The primary data source is the SMMD dataset.

Figure 34: Net positions in the Gilt Repo Market: Nominal vs Linker Collaterals

(a) Nominal Gilt Repos

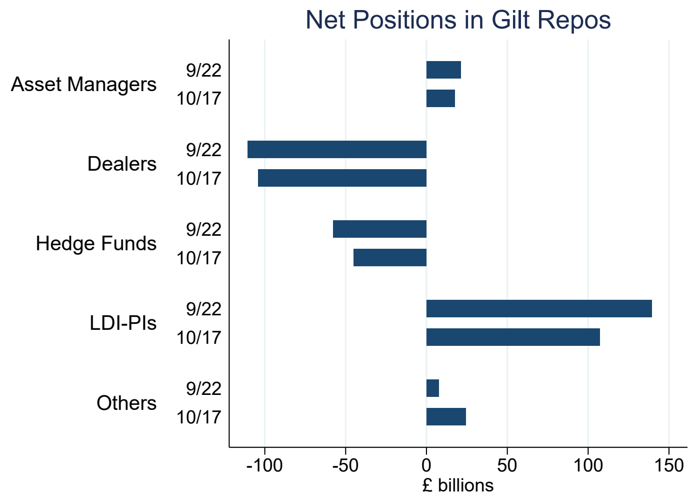


(b) Linker Gilt Repos



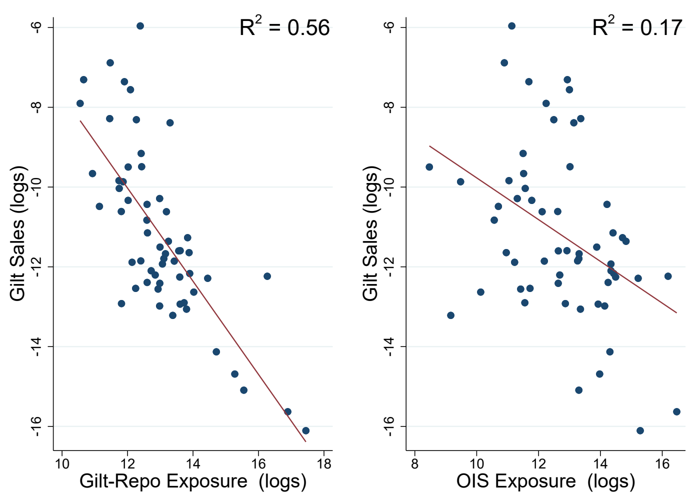
Notes: The upper (lower) panel of the figure shows the net positions of different sectors on 22 September 2022 in the repo market, using all outstanding repo contracts with nominal (inflation-linked) gilts used as the underlying collateral. Positive (negative) values are associated with the sector being a net borrower (lender). The sample includes all contracts by clients and dealers that are active in our gilt market dataset. Positions against CCPs are excluded. The primary data source is the SMMD dataset.

Figure 35: Net positions in the Gilt Repo Market: Before and After the Crisis



Notes: This figure shows the net positions of different sectors on 22 September 2022 and on 17 October 2022 in the repo market, using all outstanding repo contracts with UK gilts (either nominal or inflation-linked) used as the underlying collateral. Positive (negative) values are associated with the sector being a net borrower (lender). The sample includes all contracts by clients and dealers that are active in our gilt market dataset. Positions against CCPs are excluded.The primary data source is the SMMD dataset.

Figure 36: The Relation between Gilt Sales and Pre-crisis Repo and OIS Market Exposures



Notes: this scatter plot shows the relationship between the cumulative order flow of LDI-PI clients over the period 23 September – 14 October and the net positions in the secured gilt-repo and OIS markets on 22 September. The histograms are based on a matched sample of 58 LDI-PI firms for which we could merge our gilt, swap and repo datasets.

Table 3: The Relation between Gilt Sales and Pre-crisis Repo and OIS Market Exposures: Regression Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
$OISExposure_i^{9/22}$	-0.52***		-0.01	-0.03	-0.02	-0.01
	(-3.32)		(-0.06)	(-0.28)	(-0.21)	(-0.11)
$RepoALLExposure_i^{9/22}$		-1.17***	-1.16***	-0.79***		
		(-9.16)	(-8.53)	(-3.38)		
$RepoLinkerExposure_i^{9/22}$					-0.47**	-0.49***
					(-2.65)	(-2.75)
$RepoConventionalExposure_i^{9/22}$					-0.30	-0.29
					(-1.62)	(-1.51)
$Size_i$				-0.40**	-0.40**	-0.40**
				(-2.06)	(-2.07)	(-2.06)
$RPI_i^{9/22}$						-0.13
						(-0.32)
N	58	58	58	58	58	58
R^2_{Adj}	0.153	0.553	0.545	0.586	0.590	0.583

Notes: this table regresses the cumulative order flow of LDI-PI clients (that were net sellers during the period 23 September – 14 October) on the net positions in the secured gilt-repo, OIS and RPI-swap markets on 22 September. All regression variables are in natural logarithms (of £ millions) except $RPI_i^{9/22}$ which is an indicator variable taking value one if the firm has inflation exposure on the RPI swap market and zero otherwise. The variable $OISExposure_i^{9/22}$ is the net position in the OIS market. The variable $RepoALLExposure_i^{9/22}$ is total net borrowing in the repo market, whereas $RepoLinkerExposure_i^{9/22}$ and $RepoConventionalExposure_i^{9/22}$ are part of the borrowing which is backed by linkers and nominal bonds, respectively, as collateral. The regression is based on a matched sample of 58 LDI-PI firms for which we could merge our gilt, swap and repo datasets. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Trading Costs around the Crisis

Table 4: Summary Statistics Across Different Client Sectors

	Trade Size	Turnover		Number of Firms	
	(£m)	(£b)	%	N	%
	(1)	(2)	(3)	(4)	(5)
Panel A: Pre-crisis (8/29-9/22)					
LDI-PIs	5.01	3.35	27.8%	55.82	24.7%
Hedge Funds	16.45	5.13	42.6%	36.35	16.1%
Asset Managers	2.54	2.58	21.4%	87.12	38.5%
Others	3.42	1.00	8.2%	46.88	20.7%
Panel B: Crisis (9/23-10/14)					
LDI-PIs	7.51	7.16	35.9%	77.06	25.7%
Hedge Funds	14.43	6.61	33.2%	46.44	15.5%
Asset Managers	2.83	4.70	23.6%	112.44	37.5%
Others	2.10	1.46	7.3%	64.00	21.3%
Panel C: Post-Crisis (10/14-10/28)					
LDI-PIs	4.75	3.83	30.6%	67.10	25.1%
Hedge Funds	13.59	4.66	37.2%	42.50	15.9%
Asset Managers	2.10	2.82	22.5%	101.20	37.9%
Others	2.49	1.21	9.7%	56.40	21.1%

Notes: The tables present the means (across trading days) of trade size, turnover and number of firms present in the market.

Table 5: Trading Costs Around the Crisis: All Clients

	(1)	(2)	(3)	(4)
Panel A: All Bonds				
$D_t^{9/23-9/27}$	6.911***	6.890***	5.274***	5.409*
	(3.91)	(3.82)	(2.74)	(1.75)
$D_t^{9/28-10/14}$	10.325***	10.238***	9.391***	8.922***
	(3.61)	(3.64)	(3.61)	(4.11)
$D_t^{10/17-10/28}$	4.647*	4.204*	3.792	4.224*
	(1.85)	(1.72)	(1.53)	(1.71)
N	157747	157747	157747	154920
R^2	0.016	0.019	0.027	0.093
Panel B: Nominal Bonds				
$D_t^{9/23-9/27}$	7.289***	7.149***	5.388***	5.686***
	(5.73)	(5.45)	(3.66)	(3.51)
$D_t^{9/28-10/14}$	7.888***	7.636***	6.717***	6.647***
	(3.14)	(3.15)	(3.07)	(3.93)
$D_t^{10/17-10/28}$	5.222**	4.494**	4.094**	4.616***
	(2.63)	(2.33)	(2.05)	(2.71)
N	114658	114658	114658	111996
R^2	0.012	0.016	0.029	0.105
Panel C: Inflation-Linked Bonds				
$D_t^{9/23-9/27}$	3.917	4.317	3.417	1.623
	(0.82)	(0.88)	(0.77)	(0.27)
$D_t^{9/28-10/14}$	16.047***	16.086***	15.498***	14.221***
	(3.04)	(3.02)	(3.03)	(2.73)
$D_t^{10/17-10/28}$	3.380	3.431	3.037	3.512
	(0.68)	(0.70)	(0.63)	(0.59)
N	43089	43089	43089	42075
R^2	0.014	0.016	0.024	0.126
Bond FE	Yes	Yes	Yes	Yes
Size FE	No	Yes	Yes	Yes
Dealer FE	No	No	Yes	No
Client#Dealer FE	No	No	No	Yes

Notes: this table regresses trading costs on dummy variables (indicating different time periods around the crisis) and various fixed effects (5.2). The cost measure is in bp-points. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 6: Trading Costs Around the Crisis: LDI-PI Firms

	(1)	(2)	(3)	(4)
Panel A: All Bonds				
$D_t^{9/23-9/27}$	-5.626	-6.124	-6.711	-3.354
	(-0.44)	(-0.48)	(-0.50)	(-0.21)
$D_t^{9/28-10/14}$	9.394**	9.232**	8.385**	9.111**
	(2.31)	(2.36)	(2.04)	(2.27)
$D_t^{10/17-10/28}$	0.170	0.592	0.670	2.965
	(0.06)	(0.19)	(0.22)	(0.88)
N	42033	42033	42033	41041
R^2	0.007	0.009	0.012	0.075
Panel B: Nominal Bonds				
$D_t^{9/23-9/27}$	0.495	0.324	-1.050	2.588
	(0.11)	(0.07)	(-0.15)	(0.27)
$D_t^{9/28-10/14}$	4.262	4.222	3.070	4.359
	(1.03)	(1.02)	(0.81)	(1.35)
$D_t^{10/17-10/28}$	-0.750	-0.665	-0.810	1.963
	(-0.21)	(-0.19)	(-0.21)	(0.56)
N	26671	26671	26671	25704
R^2	0.003	0.004	0.008	0.081
Panel C: Inflation-Linked Bonds				
$D_t^{9/23-9/27}$	-17.464	-17.912	-16.026	-11.811
	(-0.73)	(-0.77)	(-0.73)	(-0.48)
$D_t^{9/28-10/14}$	18.368**	17.799**	18.400**	19.199**
	(2.25)	(2.44)	(2.49)	(2.21)
$D_t^{10/17-10/28}$	2.216	3.408	3.925	6.136
	(0.81)	(1.46)	(1.50)	(1.51)
N	15362	15362	15362	14882
R^2	0.013	0.017	0.022	0.110
Bond FE	Yes	Yes	Yes	Yes
Size FE	No	Yes	Yes	Yes
Dealer FE	No	No	Yes	No
Client#Dealer FE	No	No	No	Yes

Notes: this table regresses trading costs on dummy variables (indicating different time periods around the crisis) and various fixed effects (5.2). The cost measure is in bp-points. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 7: Trading Costs Around the Crisis: Other Clients

	(1)	(2)	(3)	(4)
Panel A: All Bonds				
$D_t^{9/23-9/27}$	11.667***	10.507***	7.738***	7.596***
	(4.46)	(6.87)	(13.08)	(4.18)
$D_t^{9/28-10/14}$	21.164***	19.738***	17.406***	17.599***
	(3.61)	(3.89)	(5.24)	(3.97)
$D_t^{10/17-10/28}$	13.119***	11.422***	10.446***	11.297***
	(3.61)	(3.72)	(5.22)	(4.63)
N	27364	27364	27364	26191
R^2	0.083	0.099	0.109	0.231
Panel B: Nominal Bonds				
$D_t^{9/23-9/27}$	9.761***	8.212***	5.214***	5.547***
	(7.29)	(5.18)	(5.73)	(4.87)
$D_t^{9/28-10/14}$	17.887***	16.178***	13.703***	14.112***
	(3.56)	(3.73)	(4.10)	(3.49)
$D_t^{10/17-10/28}$	11.282***	9.514***	8.441***	8.423***
	(3.85)	(3.91)	(4.37)	(3.44)
N	22514	22514	22514	21435
R^2	0.082	0.102	0.121	0.232
Panel C: Inflation-Linked Bonds				
$D_t^{9/23-9/27}$	14.809	17.548*	14.205**	4.071
	(1.53)	(1.85)	(2.52)	(0.35)
$D_t^{9/28-10/14}$	34.184***	35.313***	31.920***	24.613***
	(3.02)	(3.24)	(5.09)	(2.94)
$D_t^{10/17-10/28}$	20.912**	20.116***	16.616***	16.905***
	(2.62)	(2.81)	(5.17)	(3.63)
N	4850	4850	4850	4572
R^2	0.042	0.055	0.072	0.291
Bond FE	Yes	Yes	Yes	Yes
Size FE	No	Yes	Yes	Yes
Dealer FE	No	No	Yes	No
Client#Dealer FE	No	No	No	Yes

Notes: this table regresses trading costs on dummy variables (indicating different time periods around the crisis) and various fixed effects (5.2). The cost measure is in bp-points. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 8: Trading Costs Around the Crisis: Asset Managers

	(1)	(2)	(3)	(4)
Panel A: All Bonds				
$D_t^{9/23-9/27}$	10.092*	10.142*	10.184**	8.805**
	(1.93)	(1.92)	(2.10)	(2.28)
$D_t^{9/28-10/14}$	7.942**	8.173**	9.247***	8.667***
	(2.62)	(2.66)	(3.08)	(3.32)
$D_t^{10/17-10/28}$	5.269**	5.057**	6.152**	5.370*
	(2.21)	(2.11)	(2.31)	(2.00)
N	68330	68330	68330	67770
R^2	0.013	0.015	0.025	0.072
Panel B: Nominal Bonds				
$D_t^{9/23-9/27}$	10.846**	10.841**	10.152**	9.694***
	(2.28)	(2.28)	(2.33)	(2.94)
$D_t^{9/28-10/14}$	5.933**	6.041**	6.373**	6.117***
	(2.39)	(2.39)	(2.44)	(2.77)
$D_t^{10/17-10/28}$	4.561*	4.185*	4.710*	4.541*
	(2.01)	(1.83)	(1.81)	(1.71)
N	51823	51823	51823	51298
R^2	0.009	0.012	0.023	0.085
Panel C: Inflation-Linked Bonds				
$D_t^{9/23-9/27}$	4.352	4.548	5.580	-3.809
	(0.67)	(0.70)	(0.91)	(-0.51)
$D_t^{9/28-10/14}$	13.746**	14.051**	16.547***	14.855**
	(2.30)	(2.25)	(2.86)	(2.70)
$D_t^{10/17-10/28}$	7.457	7.665	10.402**	7.929
	(1.50)	(1.52)	(2.07)	(1.36)
N	16507	16507	16507	16318
R^2	0.012	0.017	0.035	0.103
Bond FE	Yes	Yes	Yes	Yes
Size FE	No	Yes	Yes	Yes
Dealer FE	No	No	Yes	No
Client#Dealer FE	No	No	No	Yes

Notes: this table regresses trading costs on dummy variables (indicating different time periods around the crisis) and various fixed effects (5.2). The cost measure is in bp-points. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 9: Trading Costs Around the Crisis: Hedge Funds

	(1)	(2)	(3)	(4)
Panel A: All Bonds				
$D_t^{9/23-9/27}$	11.848**	11.787**	12.041**	11.018**
	(2.48)	(2.54)	(2.65)	(2.13)
$D_t^{9/28-10/14}$	0.437	0.564	0.583	-0.417
	(0.18)	(0.24)	(0.28)	(-0.16)
$D_t^{10/17-10/28}$	-3.978	-4.003	-4.677	-5.056
	(-0.56)	(-0.55)	(-0.62)	(-0.58)
N	20020	20020	20020	19911
R^2	0.066	0.067	0.070	0.108
Panel B: Nominal Bonds				
$D_t^{9/23-9/27}$	-1.211	-0.945	-0.424	-0.755
	(-0.23)	(-0.19)	(-0.08)	(-0.20)
$D_t^{9/28-10/14}$	0.744	1.041	1.416	1.317
	(0.46)	(0.70)	(1.02)	(0.79)
$D_t^{10/17-10/28}$	5.009***	5.341***	5.103***	4.404**
	(2.95)	(3.09)	(2.96)	(2.57)
N	13650	13650	13650	13553
R^2	0.017	0.018	0.020	0.076
Panel C: Inflation-Linked Bonds				
$D_t^{9/23-9/27}$	55.585***	55.101***	54.754***	48.156***
	(7.43)	(7.68)	(8.07)	(5.45)
$D_t^{9/28-10/14}$	-3.051	-2.772	-4.072	-6.579
	(-0.40)	(-0.36)	(-0.57)	(-0.85)
$D_t^{10/17-10/28}$	-21.443	-22.001	-23.308	-27.618
	(-1.51)	(-1.49)	(-1.48)	(-1.60)
N	6370	6370	6370	6298
R^2	0.077	0.078	0.089	0.136
Bond FE	Yes	Yes	Yes	Yes
Size FE	No	Yes	Yes	Yes
Dealer FE	No	No	Yes	No
Client#Dealer FE	No	No	No	Yes

Notes: this table regresses trading costs on dummy variables (indicating different time periods around the crisis) and various fixed effects (5.2). The cost measure is in bp-points. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 10: Trading Costs Around the Crisis: Small Dealers

	(1)	(2)	(3)	(4)
Panel A: All Bonds				
$D_t^{9/23-9/27}$	10.076***	9.924***	7.806***	7.581***
	(3.92)	(3.91)	(4.40)	(3.27)
$D_t^{9/28-10/14}$	14.324***	14.258***	12.947***	12.118***
	(3.98)	(4.25)	(4.52)	(4.45)
$D_t^{10/17-10/28}$	7.660***	7.346***	6.731**	7.091***
	(2.76)	(2.77)	(2.54)	(2.84)
N	67128	67128	67128	65858
R^2	0.030	0.037	0.049	0.128
Panel B: Nominal Bonds				
$D_t^{9/23-9/27}$	8.924***	8.420***	6.588***	6.944***
	(6.17)	(4.88)	(3.69)	(3.24)
$D_t^{9/28-10/14}$	12.886***	12.542***	11.245***	11.696***
	(3.85)	(4.08)	(4.18)	(5.14)
$D_t^{10/17-10/28}$	7.334***	6.561***	5.866**	6.927***
	(3.06)	(2.77)	(2.34)	(3.41)
N	48509	48509	48509	47341
R^2	0.037	0.052	0.067	0.155
Panel C: Inflation-Linked Bonds				
$D_t^{9/23-9/27}$	11.113	11.991	9.462	8.142
	(1.24)	(1.35)	(1.38)	(1.03)
$D_t^{9/28-10/14}$	17.366***	17.882***	16.352***	14.916**
	(3.44)	(3.47)	(3.13)	(2.55)
$D_t^{10/17-10/28}$	8.561	9.246	8.293	9.006
	(1.56)	(1.67)	(1.60)	(1.42)
N	18619	18619	18619	18147
R^2	0.014	0.017	0.031	0.150
Bond FE	Yes	Yes	Yes	Yes
Size FE	No	Yes	Yes	Yes
Dealer FE	No	No	Yes	No
Client#Dealer FE	No	No	No	Yes

Notes: this table regresses trading costs on dummy variables (indicating different time periods around the crisis) and various fixed effects (5.2). The cost measure is in bp-points. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 11: Trading Costs Around the Crisis: Large Dealers

	(1)	(2)	(3)	(4)
Panel A: All Bonds				
$D_t^{9/23-9/27}$	3.821	3.827	3.689	4.276
	(1.32)	(1.30)	(1.00)	(0.75)
$D_t^{9/28-10/14}$	7.338***	7.367***	7.141**	7.075***
	(2.83)	(2.84)	(2.62)	(3.02)
$D_t^{10/17-10/28}$	1.818	1.870	1.768	2.451
	(0.65)	(0.67)	(0.62)	(0.79)
N	90619	90619	90619	89062
R^2	0.013	0.014	0.014	0.071
Panel B: Nominal Bonds				
$D_t^{9/23-9/27}$	5.233***	5.235***	4.787***	5.415**
	(4.52)	(4.54)	(2.79)	(2.05)
$D_t^{9/28-10/14}$	4.081**	4.092**	3.727*	3.400**
	(2.05)	(2.05)	(1.89)	(2.22)
$D_t^{10/17-10/28}$	3.157	3.162	3.019	3.376
	(1.51)	(1.51)	(1.46)	(1.56)
N	66149	66149	66149	64655
R^2	0.004	0.004	0.006	0.074
Panel C: Inflation-Linked Bonds				
$D_t^{9/23-9/27}$	-1.432	-1.328	-1.061	-3.365
	(-0.10)	(-0.09)	(-0.07)	(-0.23)
$D_t^{9/28-10/14}$	15.413**	14.948**	15.250**	14.037**
	(2.32)	(2.26)	(2.31)	(2.11)
$D_t^{10/17-10/28}$	-1.041	-1.243	-1.230	-1.012
	(-0.19)	(-0.23)	(-0.23)	(-0.15)
N	24470	24470	24470	23928
R^2	0.018	0.020	0.021	0.110
Bond FE	Yes	Yes	Yes	Yes
Size FE	No	Yes	Yes	Yes
Dealer FE	No	No	Yes	No
Client#Dealer FE	No	No	No	Yes

Notes: this table regresses trading costs on dummy variables (indicating different time periods around the crisis) and various fixed effects (5.2). The cost measure is in bp-points. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 12: Trading Costs Around the Crisis: The Role of Favourite Dealers

	(1)	(2)	(3)	(4)	(5)	(6)
	All Bonds		Nominal Bonds		Linkers	
Dealer type	Other	Favourite	Other	Favourite	Other	Favourite
$D_t^{9/23-9/27}$	9.758***	-3.867	9.473***	-1.848	9.264	-16.583
	(2.83)	(-0.58)	(3.41)	(-0.52)	(1.69)	(-1.47)
$D_t^{9/28-10/14}$	6.988***	13.933***	4.483***	10.830***	13.519***	21.348**
	(3.28)	(4.39)	(2.81)	(3.34)	(2.75)	(2.62)
N	89671	30045	63694	23465	25346	6471
R^2	0.099	0.147	0.094	0.168	0.143	0.196
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes
CL#DE FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: this table regresses trading costs on dummy variables (indicating different time periods around the crisis) and various fixed effects (5.2). The cost measure is in bp-points. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 13: Trading Costs Around the Crisis: The Role of Favourite Clients

	(1)	(2)	(3)	(4)	(5)	(6)
	All Bonds		Nominal Bonds		Linkers	
Client type	Other	Favourite	Other	Favourite	Other	Favourite
$D_t^{9/23-9/27}$	9.955**	-15.574	9.376***	-13.076	9.066	-18.489
	(2.56)	(-0.78)	(3.78)	(-1.11)	(1.02)	(-0.46)
$D_t^{9/28-10/14}$	9.812***	4.382	7.784***	-0.211	15.084***	15.778
	(4.95)	(0.84)	(4.70)	(-0.06)	(3.14)	(1.09)
N	99804	19912	73451	13708	25615	6202
R^2	0.124	0.043	0.128	0.054	0.173	0.060
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: this table regresses trading costs on dummy variables (indicating different time periods around the crisis) and various fixed effects (5.2). The cost measure is in bp-points. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 14: Trading Costs Around the Crisis: Short (<10Y) Maturity Bonds

	(1)	(2)	(3)	(4)
Panel A: All Bonds				
$D_t^{9/23-9/27}$	5.661***	5.445***	3.726***	3.944***
	(9.42)	(11.43)	(6.87)	(6.24)
$D_t^{9/28-10/14}$	8.214***	7.868***	7.503***	8.082***
	(5.04)	(5.38)	(5.92)	(6.08)
$D_t^{10/17-10/28}$	5.623***	4.854***	4.937***	5.614***
	(5.78)	(5.47)	(4.87)	(5.23)
N	67623	67623	67623	65347
R^2	0.060	0.100	0.182	0.296
Panel B: Nominal Bonds				
$D_t^{9/23-9/27}$	5.512***	5.241***	3.514***	3.566***
	(7.55)	(7.59)	(4.95)	(4.21)
$D_t^{9/28-10/14}$	7.762***	7.283***	6.802***	7.194***
	(4.67)	(4.92)	(5.21)	(5.27)
$D_t^{10/17-10/28}$	4.741***	3.915***	3.894***	4.376***
	(5.60)	(5.03)	(3.89)	(4.08)
N	56549	56549	56549	54488
R^2	0.067	0.107	0.192	0.318
Panel C: Inflation-Linked Bonds				
$D_t^{9/23-9/27}$	4.709***	5.056***	4.535**	4.815***
	(3.27)	(3.19)	(2.22)	(3.92)
$D_t^{9/28-10/14}$	10.616***	11.749***	12.466***	14.420***
	(5.53)	(5.47)	(5.94)	(5.45)
$D_t^{10/17-10/28}$	10.648***	10.737***	10.967***	13.710***
	(3.41)	(3.41)	(3.55)	(3.60)
N	11074	11074	11074	10477
R^2	0.038	0.090	0.191	0.341
Bond FE	Yes	Yes	Yes	Yes
Size FE	No	Yes	Yes	Yes
Dealer FE	No	No	Yes	No
Client#Dealer FE	No	No	No	Yes

Notes: this table regresses trading costs on dummy variables (indicating different time periods around the crisis) and various fixed effects (5.2). The cost measure is in bp-points. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 15: Trading Costs Around the Crisis: Long (10-25Y) Maturity Bonds

	(1)	(2)	(3)	(4)
Panel A: All Bonds				
$D_t^{9/23-9/27}$	4.696	4.806	3.520	4.413
	(1.14)	(1.17)	(0.82)	(0.94)
$D_t^{9/28-10/14}$	8.326***	8.461***	7.661**	7.362***
	(2.75)	(2.77)	(2.67)	(3.09)
$D_t^{10/17-10/28}$	4.364	3.910	3.667	4.241
	(1.47)	(1.36)	(1.30)	(1.66)
N	43987	43987	43987	42441
R^2	0.007	0.011	0.027	0.121
Panel B: Nominal Bonds				
$D_t^{9/23-9/27}$	8.267***	8.239***	7.409***	8.842***
	(3.70)	(3.68)	(2.97)	(2.81)
$D_t^{9/28-10/14}$	5.644*	5.676**	5.153*	5.392**
	(2.01)	(2.02)	(1.94)	(2.45)
$D_t^{10/17-10/28}$	5.551*	4.827*	4.863*	5.344**
	(2.01)	(1.82)	(1.76)	(2.15)
N	30712	30712	30712	29357
R^2	0.005	0.010	0.026	0.128
Panel C: Inflation-Linked Bonds				
$D_t^{9/23-9/27}$	-6.932	-6.234	-8.311	-9.925
	(-0.74)	(-0.66)	(-0.87)	(-1.32)
$D_t^{9/28-10/14}$	14.738***	14.996***	14.060***	12.428***
	(2.96)	(2.97)	(2.99)	(2.81)
$D_t^{10/17-10/28}$	1.818	1.848	1.450	2.968
	(0.46)	(0.47)	(0.42)	(0.87)
N	13275	13275	13275	12638
R^2	0.011	0.013	0.032	0.189
Bond FE	Yes	Yes	Yes	Yes
Size FE	No	Yes	Yes	Yes
Dealer FE	No	No	Yes	No
Client#Dealer FE	No	No	No	Yes

Notes: this table regresses trading costs on dummy variables (indicating different time periods around the crisis) and various fixed effects (5.2). The cost measure is in bp-points. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 16: Trading Costs Around the Crisis: Very Long (>25Y) Maturity Bonds

	(1)	(2)	(3)	(4)
Panel A: All Bonds				
$D_t^{9/23-9/27}$	11.025***	10.905***	9.293***	9.721
	(3.92)	(3.70)	(3.04)	(1.09)
$D_t^{9/28-10/14}$	14.304**	14.142**	11.620**	10.717**
	(2.52)	(2.50)	(2.19)	(2.23)
$D_t^{10/17-10/28}$	3.547	3.380	1.668	2.661
	(0.61)	(0.59)	(0.29)	(0.40)
N	46137	46137	46137	44758
R^2	0.013	0.014	0.021	0.121
Panel B: Nominal Bonds				
$D_t^{9/23-9/27}$	10.567***	10.577***	7.819**	10.374*
	(5.12)	(4.75)	(2.51)	(1.83)
$D_t^{9/28-10/14}$	10.496*	10.417*	7.064	7.594**
	(1.94)	(1.95)	(1.53)	(2.07)
$D_t^{10/17-10/28}$	5.999	5.387	3.362	5.126
	(1.27)	(1.16)	(0.71)	(1.25)
N	27397	27397	27397	26209
R^2	0.009	0.011	0.023	0.145
Panel C: Inflation-Linked Bonds				
$D_t^{9/23-9/27}$	12.007*	11.160*	10.297*	2.787
	(1.96)	(1.79)	(1.75)	(0.25)
$D_t^{9/28-10/14}$	19.970**	18.983**	16.616*	12.728
	(2.23)	(2.11)	(1.85)	(1.26)
$D_t^{10/17-10/28}$	0.654	0.271	-0.980	-3.526
	(0.07)	(0.03)	(-0.11)	(-0.27)
N	18740	18740	18740	18052
R^2	0.011	0.013	0.017	0.156
Bond FE	Yes	Yes	Yes	Yes
Size FE	No	Yes	Yes	Yes
Dealer FE	No	No	Yes	No
Client#Dealer FE	No	No	No	Yes

Notes: this table regresses trading costs on dummy variables (indicating different time periods around the crisis) and various fixed effects (5.2). The cost measure is in bp-points. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 17: Trading Costs Around the Crisis: Small Trades (<£100,000)

	(1)	(2)	(3)
Panel A: All Bonds			
$D_t^{9/23-9/27}$	18.827***	14.335***	14.720***
	(7.11)	(5.04)	(3.36)
$D_t^{9/28-10/14}$	16.864***	15.310***	14.407***
	(4.09)	(4.46)	(4.01)
$D_t^{10/17-10/28}$	12.107***	12.061***	11.988***
	(3.10)	(3.09)	(3.15)
N	53917	53917	52798
R^2	0.039	0.068	0.163
Panel B: Nominal Bonds			
$D_t^{9/23-9/27}$	17.365***	12.342**	11.422***
	(3.47)	(2.54)	(2.72)
$D_t^{9/28-10/14}$	15.719***	14.193***	12.760***
	(4.22)	(4.69)	(3.89)
$D_t^{10/17-10/28}$	11.862***	11.630***	10.410***
	(4.57)	(4.27)	(4.21)
N	38918	38918	38033
R^2	0.047	0.098	0.203
Panel C: Inflation-Linked Bonds			
$D_t^{9/23-9/27}$	15.230***	15.843***	24.983***
	(2.87)	(2.71)	(2.98)
$D_t^{9/28-10/14}$	17.774**	16.299**	16.619**
	(2.63)	(2.60)	(2.63)
$D_t^{10/17-10/28}$	12.009	10.585	11.575
	(1.17)	(1.05)	(1.04)
N	14999	14999	14527
R^2	0.024	0.053	0.196
Bond FE	Yes	Yes	Yes
Dealer FE	No	Yes	No
Client#Dealer FE	No	No	Yes

Notes: this table regresses trading costs on dummy variables (indicating different time periods around the crisis) and various fixed effects (5.2). The cost measure is in bp-points. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 18: Trading Costs Around the Crisis: Medium Trades (£100,000-£1,000,000)

	(1)	(2)	(3)
Panel A: All Bonds			
$D_t^{9/23-9/27}$	0.469	-0.648	0.354
	(0.06)	(-0.09)	(0.06)
$D_t^{9/28-10/14}$	5.672	5.057	4.043
	(1.54)	(1.40)	(1.35)
$D_t^{10/17-10/28}$	-0.010	-0.595	-0.291
	(-0.00)	(-0.19)	(-0.10)
N	43313	43313	41571
R^2	0.007	0.010	0.108
Panel B: Nominal Bonds			
$D_t^{9/23-9/27}$	4.792	3.593	5.565**
	(1.50)	(1.10)	(2.19)
$D_t^{9/28-10/14}$	4.759	3.966	4.592*
	(1.33)	(1.17)	(1.69)
$D_t^{10/17-10/28}$	-0.146	-0.546	-0.107
	(-0.04)	(-0.17)	(-0.04)
N	31256	31256	29767
R^2	0.005	0.011	0.122
Panel C: Inflation-Linked Bonds			
$D_t^{9/23-9/27}$	-10.778	-11.518	-16.533
	(-0.57)	(-0.63)	(-1.11)
$D_t^{9/28-10/14}$	8.114	7.768	-0.879
	(1.37)	(1.32)	(-0.17)
$D_t^{10/17-10/28}$	0.690	0.140	-0.122
	(0.17)	(0.03)	(-0.02)
N	12057	12057	11403
R^2	0.008	0.013	0.165
Bond FE	Yes	Yes	Yes
Dealer FE	No	Yes	No
Client#Dealer FE	No	No	Yes

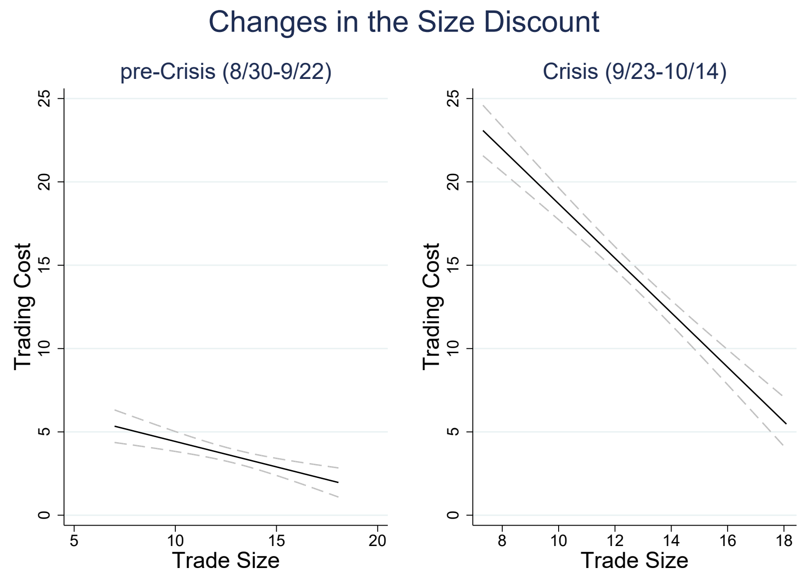
Notes: this table regresses trading costs on dummy variables (indicating different time periods around the crisis) and various fixed effects (5.2). The cost measure is in bp-points. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 19: Trading Costs Around the Crisis: Large Trades (>£1,000,000)

	(1)	(2)	(3)
Panel A: All Bonds			
$D_t^{9/23-9/27}$	1.166	1.870	1.932
	(0.30)	(0.46)	(0.30)
$D_t^{9/28-10/14}$	7.953***	8.054***	7.753***
	(3.21)	(3.23)	(4.22)
$D_t^{10/17-10/28}$	-0.231	-0.360	-0.077
	(-0.11)	(-0.16)	(-0.04)
N	60517	60517	58828
R^2	0.020	0.022	0.097
Panel B: Nominal Bonds			
$D_t^{9/23-9/27}$	0.304	0.606	2.024
	(0.11)	(0.21)	(0.52)
$D_t^{9/28-10/14}$	3.263	3.236	3.149**
	(1.52)	(1.51)	(2.16)
$D_t^{10/17-10/28}$	1.725	1.530	2.671*
	(0.96)	(0.83)	(1.84)
N	44484	44484	42834
R^2	0.006	0.008	0.097
Panel C: Inflation-Linked Bonds			
$D_t^{9/23-9/27}$	5.345	6.348	-5.157
	(0.45)	(0.54)	(-0.33)
$D_t^{9/28-10/14}$	20.809***	20.784***	20.531***
	(3.88)	(3.83)	(3.05)
$D_t^{10/17-10/28}$	-2.649	-2.583	-3.570
	(-0.63)	(-0.56)	(-0.56)
N	16033	16033	15440
R^2	0.028	0.032	0.144
Bond FE	Yes	Yes	Yes
Dealer FE	No	Yes	No
Client#Dealer FE	No	No	Yes

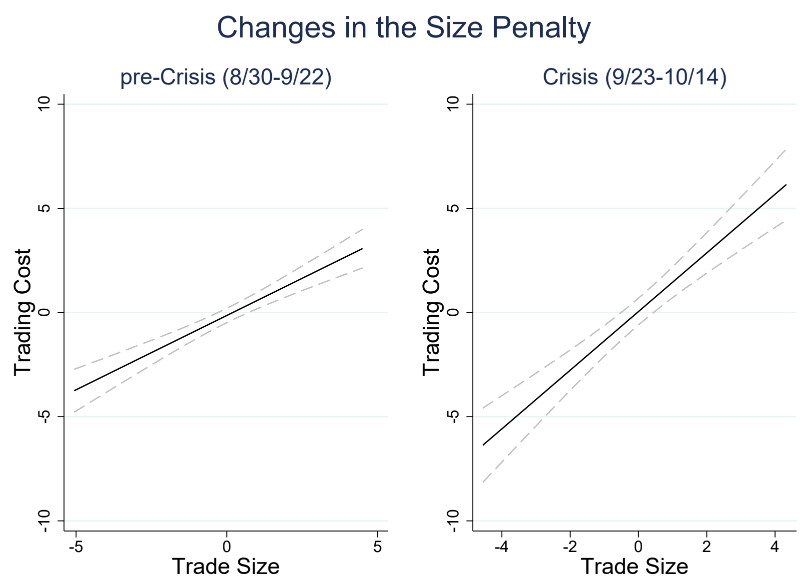
Notes: this table regresses trading costs on dummy variables (indicating different time periods around the crisis) and various fixed effects (5.2). The cost measure is in bp-points. To reduce noise, we winsorise the sample at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the day and client level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Figure 37: Size Discount: Cross-client relationship between trade size and trading costs



Notes: The figure illustrates how the cross-client relation between trade size and trading costs changed during the crisis. The figure shows a linear regression line on the pooled (transaction-level) data, thereby extending the analysis of Pinter, Wang, and Zou (2022) to the recent time period. Trading costs are measured by 5.1 (building on O'Hara and Zhou (2021)), and trade size is measured as the natural logarithm of the trade's notional. The confidence bands are based on 95% standard errors as in Gallup (2019).

Figure 38: Size Penalty: Within-client relationship between trade size and trading costs



Notes: The figure illustrates how the within-client relation between trade size and trading costs changed during the crisis. The figure shows a linear regression line after we removed client-specific averages from trading costs and trade sizes corresponding to each trade, thereby extending the analysis of Pinter, Wang, and Zou (2022) to the recent time period. Trading costs are measured by 5.1 (building on O'Hara and Zhou (2021)), and trade size is measured as the natural logarithm of the trade's notional. The estimated regression lines are based on around 1.2 million observations. The confidence bands are based on 95% standard errors as in Gallup (2019).

Changes in Aggregate Price Dispersion

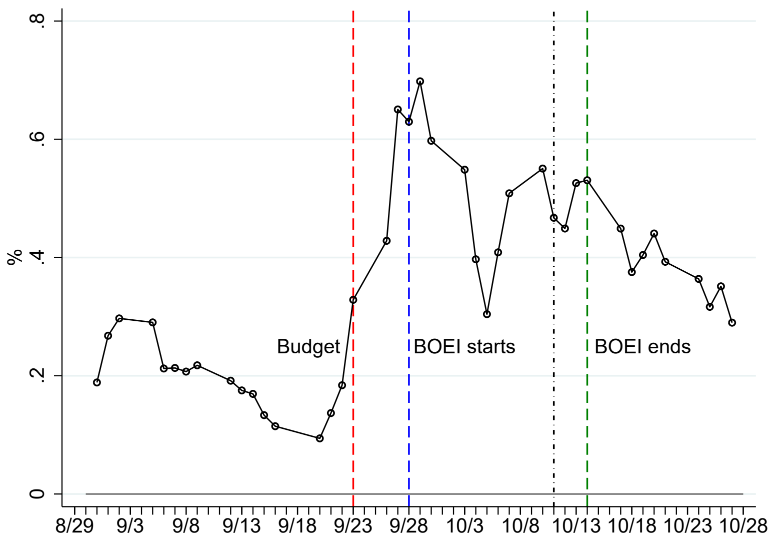
Table 20: Decomposing Price Dispersion During the Crisis

	Pre-crisis (8/30-9/22)		Crisis (9/23-10/14)		Post-Crisis (10/17-10/28)	
	Variance	%	Variance	%	Variance	%
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Bonds						
Cross-Dealer	0.02868	67.6%	0.15737	49.1%	0.07893	57.9%
Within-Dealer	0.01372	32.4%	0.16322	50.9%	0.05744	42.1%
Total Dispersion	0.04240	100.0%	0.32058	100.0%	0.13637	100.0%
Panel B: Nominal Bonds						
Cross-Dealer	0.00981	62.0%	0.07162	55.2%	0.02348	50.5%
Within-Dealer	0.00600	38.0%	0.05807	44.8%	0.023	49.5%
Total Dispersion	0.01581	100.0%	0.12969	100.0%	0.04647	100.0%
Panel C: Linkers						
Cross-Dealer	0.09851	70.0%	0.40218	46.5%	0.23191	60.3%
Within-Dealer	0.04229	30.0%	0.46342	53.5%	0.15246	39.7%
Total Dispersion	0.14080	100.0%	0.8656	100.0%	0.38437	100.0%

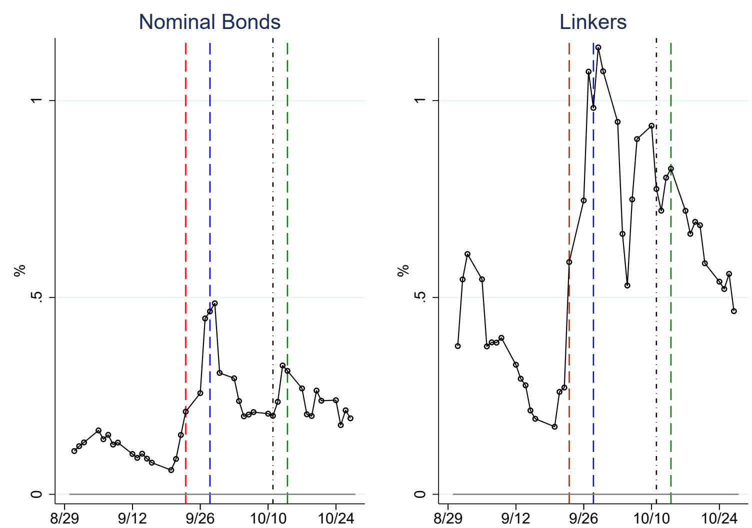
Notes: The tables present total, within-dealer and across-dealer price dispersions (measured by variance) during different periods of the crisis. Average prices are computed at the hourly level.

Figure 39: Price Dispersion Measured by Standard Deviation

(a) All Bonds



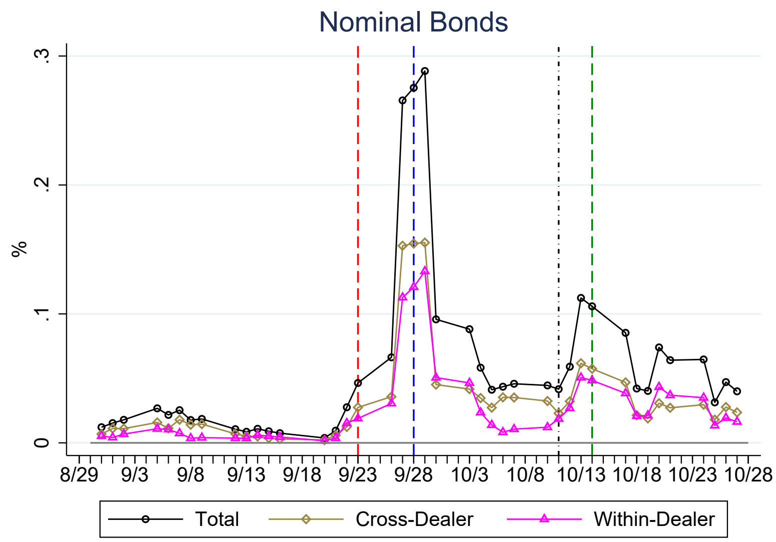
(b) Nominal Bonds vs Linkers



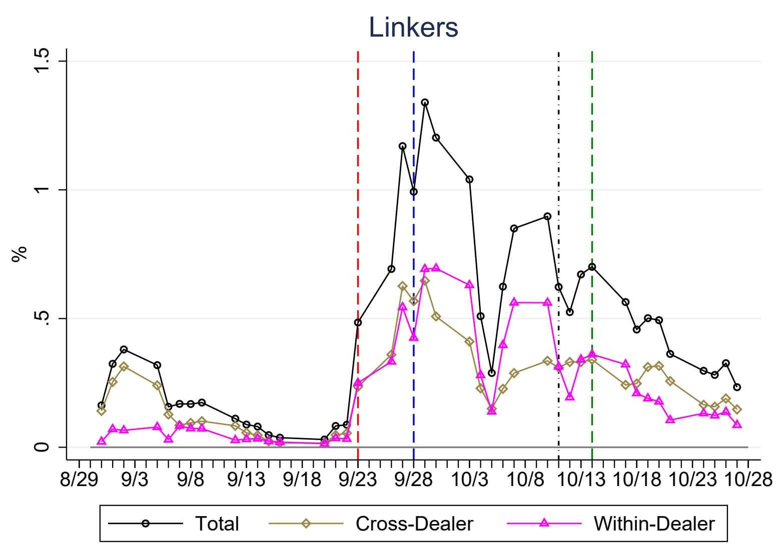
Notes: This figure shows the time-series of daily price dispersion (measured by standard deviation) aggregated across the UK nominal and inflation-linked bond markets (Panel A) and for each market separately (Panel B). The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep, 11 October and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention, the widening of the scope of the operations to purchase linkers and the end of the gilt market intervention.

Figure 40: Decomposing Price Dispersion into Within-Dealer and Cross-Dealer Components (Measured by Variance)

(a) Nominal Bonds



(b) Linkers

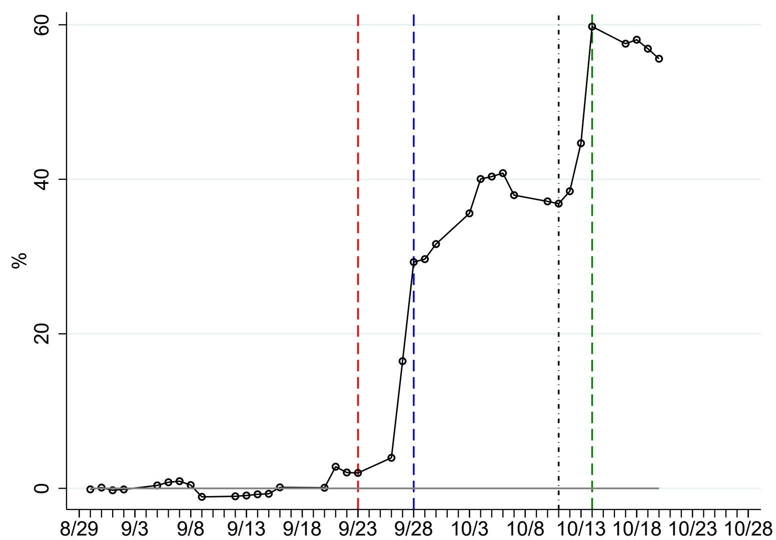


Notes: This figure shows the time-series of daily price dispersion (measured by variance) and its within-dealer and cross-dealer components in nominal (Panel A) and inflation-linked bond (Panel B) markets. The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep, 11 October and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention, the widening of the scope of the operations to purchase linkers and the end of the gilt market intervention.

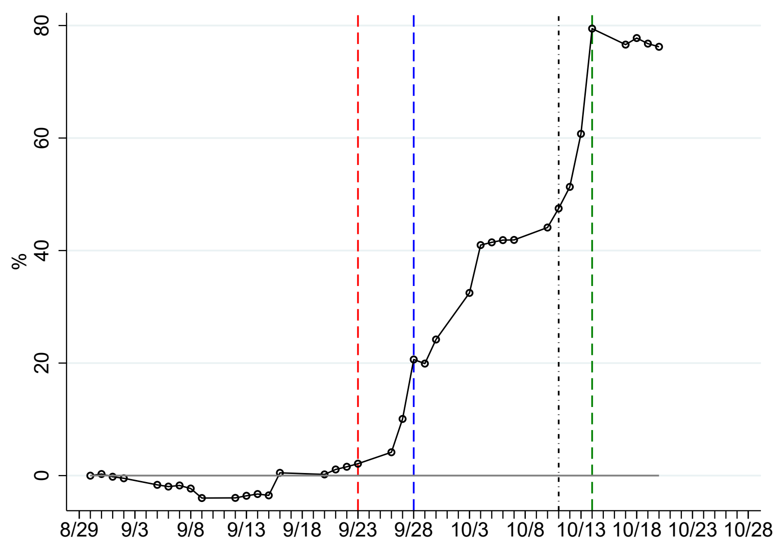
Results on Hedge Funds

Figure 41: Cumulative Hedge Fund Returns: Unweighted Mean

(a) 3-day Horizon



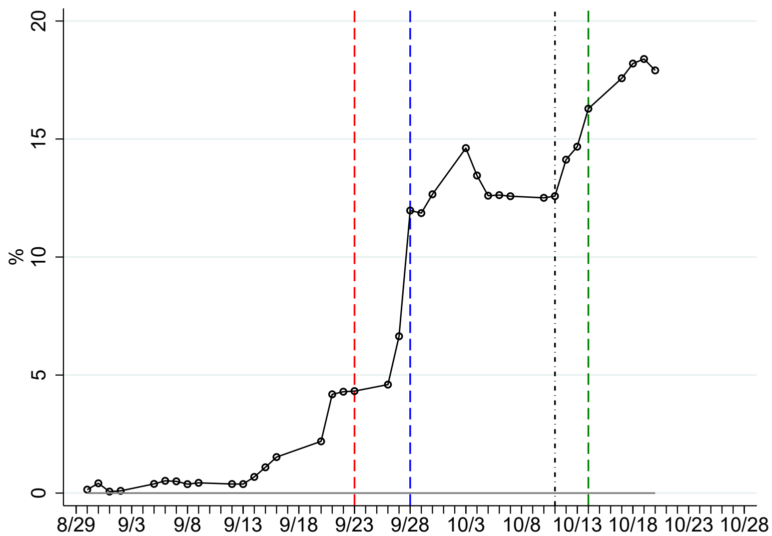
(b) 6-day Horizon



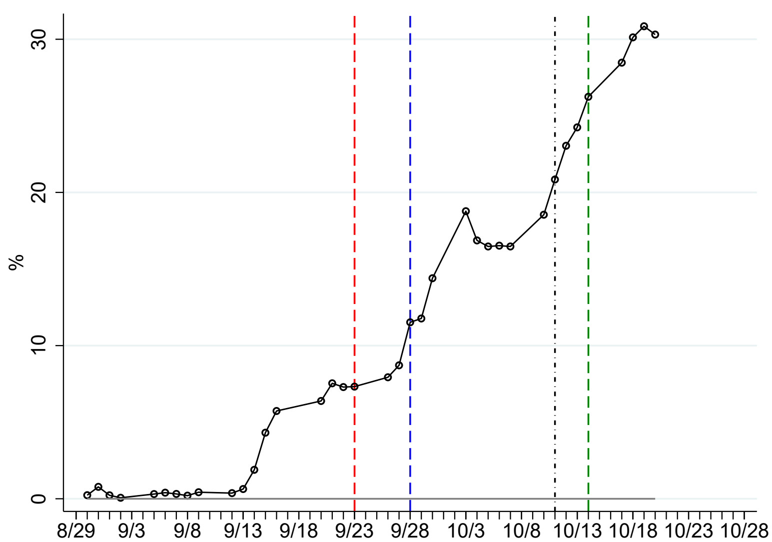
Notes: This figure shows the cumulative returns of the hedge fund sector around the crisis. The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep, 11 October and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention, the widening of the scope of the operations to purchase linkers and the end of the gilt market intervention.

Figure 42: Cumulative Hedge Fund Returns: Size-weighted Mean

(a) 3-day Horizon



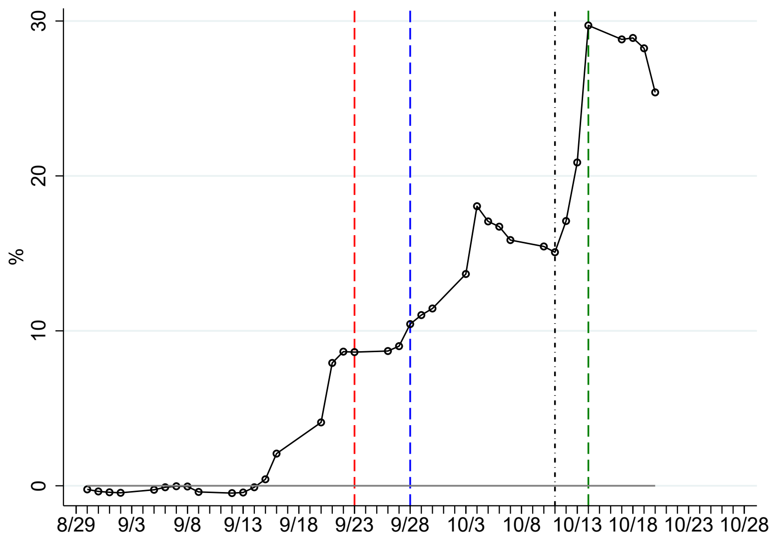
(b) 6-day Horizon



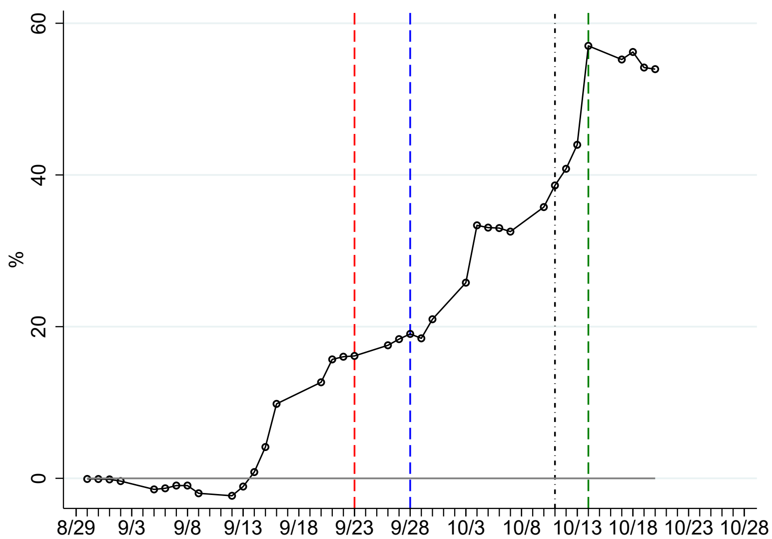
Notes: This figure shows the cumulative returns of the hedge fund sector around the crisis. The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep, 11 October and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention, the widening of the scope of the operations to purchase linkers and the end of the gilt market intervention.

Figure 43: Cumulative Hedge Funds Returns: Median

(a) 3-day Horizon



(b) 6-day Horizon



Notes: This figure shows the cumulative returns of the hedge fund sector around the crisis. The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep, 11 October and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention, the widening of the scope of the operations to purchase linkers and the end of the gilt market intervention.

A Online Appendix

"AN ANATOMY OF THE 2022 GILT MARKET CRISIS"

Gábor Pintér
Bank of England

31st March 2023

A.1 Additional Tables and Figures

Table A.1: Price Pressures from the LDI-PI Sector During the Crisis: Orderflow Against GEMMs and Other Clients

	All LDI-PI Firms			Top 3 LDI-PI Sellers		
	OF in £ bn	OF stand.	OF scaled	OF in £ bn	OF stand.	OF scaled
	(1)	(2)	(3)	(4)	(5)	(5)
Flow	2.322	0.171*	0.745*	3.336	0.099	0.857
	(1.48)	(1.71)	(1.96)	(0.90)	(0.82)	(1.15)
N	3465	3465	3453	2998	2998	2987
R^2	0.585	0.586	0.581	0.631	0.631	0.625
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes

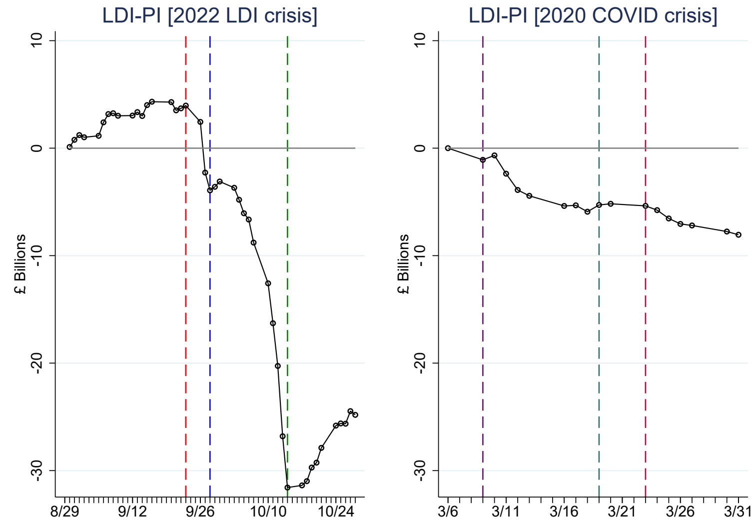
Notes: this table regresses daily bond returns (measured in 100 times the natural logarithm of daily change in end-of-day price quotes) on the orderflow of the LDI-PI sector (columns 1-3) and of the top 3 sellers of the sector (columns 4-6) against primary dealers (i.e. GEMMs) as well as other clients. Columns 1 and 4 measure the orderflow in £ billions, columns 2 and 5 standardise the gilt-specific orderflow and columns 3 and 6 scale the orderflow by the average daily (gilt-specific) market volume using the sample before 23 September (i.e. pre-crisis). To reduce noise, we winsorise the sample at the 1-99%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the gilt-day level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table A.2: Decomposing Price Dispersion During the Crisis

	Pre-crisis (8/30-9/22)		Crisis (9/23-10/14)		Post-Crisis (10/17-10/28)	
	Variance	%	Variance	%	Variance	%
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Bonds						
Cross-Dealer	0.19804	48.4%	2.2683	38.1%	0.54075	40.1%
Within-Dealer	0.21077	51.6%	3.69194	61.9%	0.80736	59.9%
Total Dispersion	0.40881	100.0%	5.96025	100.0%	1.34811	100.0%
Panel B: Nominal Bonds						
Cross-Dealer	0.07886	41.7%	0.52313	32.6%	0.11666	38.9%
Within-Dealer	0.11038	58.3%	1.08103	67.4%	0.18327	61.1%
Total Dispersion	0.18924	100.0%	1.60415	100.0%	0.29993	100.0%
Panel C: Linkers						
Cross-Dealer	0.57783	52.1%	6.8085	39.4%	1.58404	40.3%
Within-Dealer	0.53067	47.9%	10.48444	60.6%	2.34268	59.7%
Total Dispersion	1.10850	100.0%	17.29294	100.0%	3.92672	100.0%

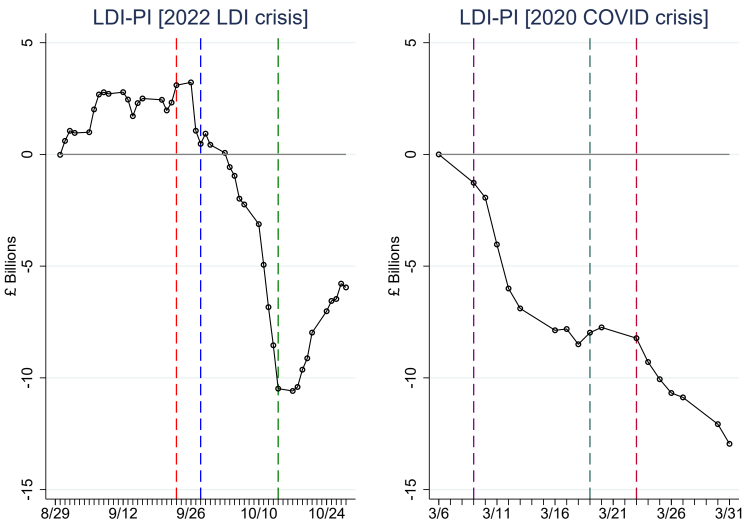
Notes: The table presents total, within-dealer and across-dealer price dispersions (measured by variance) during different periods of the crisis. Average prices are computed at the daily level.

Figure A.1: Cumulative Orderflow of the LDI-PI Sector: Sep-Oct 2022 vs March 2020



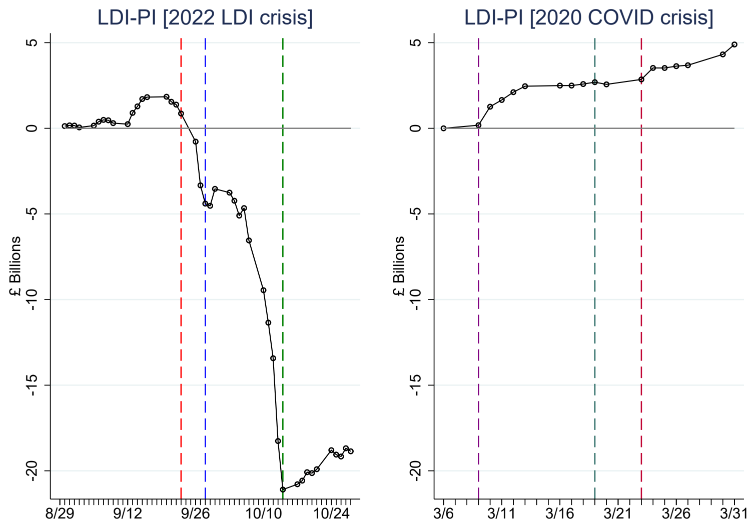
Notes: The left panel of this figure shows the time-series of the cumulative orderflow (in £ billions) of the LDI-PI sector, aggregated across the UK nominal and inflation-linked bond markets. The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention and the end of the gilt market intervention. The right panel of this figure shows the time-series of the cumulative orderflow (in £ billions) of the same LDI-PI firms during March 2020. The purple, green and dark red vertical lines mark 9 March (the start of the dash for cash (Hauser, 2020)), the BoE announcement of 19 March and the Fed announcement of 24 March.

Figure A.2: Cumulative Orderflow of the LDI-PI Sector in Nominal Bonds: Sep-Oct 2022 vs March 2020



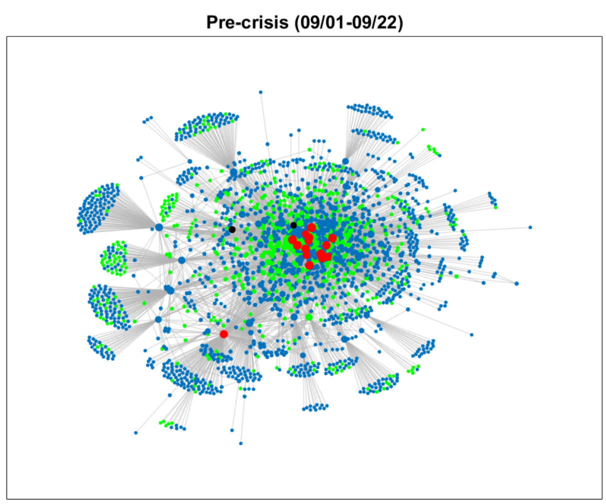
Notes: The left panel of this figure shows the time-series of the cumulative orderflow (in £ billions) of the LDI-PI sector in nominal bonds. The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention and the end of the gilt market intervention. The right panel of this figure shows the time-series of the cumulative orderflow (in £ billions) of the same LDI-PI firms during March 2020. The purple, green and dark red vertical lines mark 9 March (the start of the dash for cash (Hauser, 2020)), the BoE announcement of 19 March and the Fed announcement of 24 March.

Figure A.3: Cumulative Orderflow of the LDI-PI Sector in Linkers: Sep-Oct 2022 vs March 2020



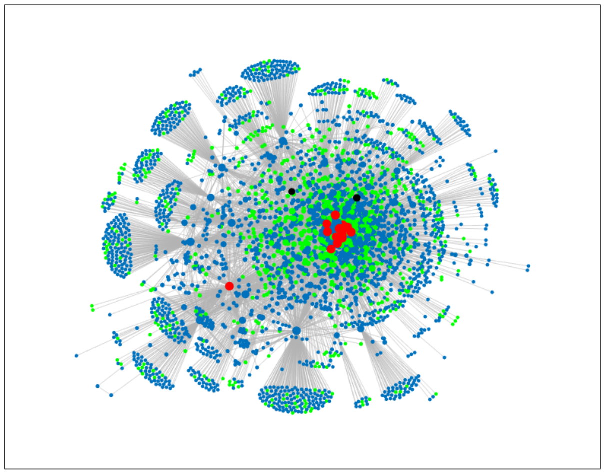
Notes: The left panel of this figure shows the time-series of the cumulative orderflow (in £ billions) of the LDI-PI sector in inflation-linked bonds. The sample covers 43 trading days from 30 Aug 2022 to 28 Oct 2022. The red, blue, black and green vertical lines mark the days of 23 Sep, 28 Sep and 14 October, respectively. These days correspond to the government's announcement of the mini budget, the BoE's announcement regarding the 13-day gilt market intervention and the end of the gilt market intervention. The right panel of this figure shows the time-series of the cumulative orderflow (in £ billions) of the same LDI-PI firms during March 2020. The purple, green and dark red vertical lines mark 9 March (the start of the dash for cash (Hauser, 2020)), the BoE announcement of 19 March and the Fed announcement of 24 March.

Figure A.4: Gilt Market Trade Network Before the Crisis



Notes: this figure illustrates the gilt market trading network during the pre-crisis (09/01 – 09/22) period. The nodes represent clients and dealers participating in the market. To illustrate the importance of firms, the size of nodes captures the natural logarithm of first-order connections of the given firm. The edges are determined by transactions. The colour scheme represents dealers (red), the two biggest LDI-PI sellers (black), all other LDI-PI firms (green) and all other clients (blue).

Figure A.5: Gilt Market Trade Network During the Crisis



Notes: this figure illustrates the gilt market trading network during the crisis (09/23 – 10/14) period. The nodes represent clients and dealers participating in the market. To illustrate the importance of firms, the size of nodes captures the natural logarithm of first-order connections of the given firm. The edges are determined by transactions. The colour scheme represents dealers (red), the two biggest LDI-PI sellers (black), all other LDI-PI firms (green) and all other clients (blue).

Table A.3: Issuance of Government Bonds during the 2022 LDI Crisis

Operation Date	Gilt Name	Nom. Amount	Cash Raised
27-Sep-2022	0 1/8% Index-linked Gilt 2031	1,200	1,383
28-Sep-2022	1½% Green Gilt 2053	4,500	2,352
4-Oct-2022	0½% Treasury Gilt 2061	2,500	948
5-Oct-2022	1% Treasury Gilt 2032	3,750	2,852
11-Oct-2022	0 1/8% Index-linked Gilt 2051	1,106	871
12-Oct-2022	4 1/8% Treasury Gilt 2027	4,365	4,252
		17,422	**12,658**

Notes: The table summarises the outcome of primary auctions during the LDI-PI crisis. The nominal amount and cash raised are in millions (source: Debt Management Office).

A.2 Theoretical Appendix

Proof. Proposition 1 is proved by first solving for the optimal portfolio problem of the pension fund. Given the variance of underfunding, $Var\left(F\right) = \sigma_L^2 + x_S^2\sigma_S^2 + x_B^2\sigma_B^2 + 2x_S\sigma_{L,S} + 2x_B\sigma_{L,B}$, the first-order conditions of the pension fund's optimisation problem 2.3 can be written as:

$$x_B = \frac{(\mu_B - P_B) - \gamma\sigma_{L,B}}{\gamma\left[\sigma_S^2 + \sigma_R^2\right]} \tag{A.1}$$

$$x_S = -\frac{P_S + \gamma\sigma_{L,S}}{\gamma\sigma_S^2 + \kappa} \tag{A.2}$$

Market clearing in the swap market, $s_S = x_S$, and the bond market, $s_B = x_B$, give the equilibrium prices:

$$P_S = \frac{-\gamma\sigma_{L,S}}{1 + \beta_S\left(\gamma\sigma_S^2 + \kappa\right)} \tag{A.3}$$

$$P_S = \frac{\mu_B - \gamma\sigma_{L,B}}{1 + \beta_B\gamma\left[\sigma_S^2 + \sigma_R^2\right]}. \tag{A.4}$$

Plugging A.3–A.4 into the supply curves (2.4–2.5) and taking ratios gives:

$$\phi \equiv \frac{s_B}{s_S} = \frac{\beta_B}{\beta_S} \times \left[\frac{\mu_B}{-\gamma\sigma_{L,S}} + \frac{\sigma_{L,B}}{\sigma_{L,S}}\right] \times \frac{1 + \beta_S\gamma\left(\sigma_S^2 + \kappa/\gamma\right)}{1 + \beta_B\gamma\left[\sigma_S^2 + \sigma_R^2\right]}.$$

□