LASH risk and Interest Rates[☆]

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Abstract

We introduce a framework to understand and quantify a form of liquidity risk that we dub *Liquidity After Solvency Hedging* or "LASH" risk. Financial institutions take LASH risk when they hedge against losses, using strategies that lead to liquidity needs when the value of the hedge falls, even as solvency improves. We focus on LASH risk relating to interest rate movements. Our framework implies that institutions with longer duration liabilities than assets—e.g. pension funds and insurers—take more LASH risk as interest rates fall, because solvency concerns rise in a low rate environment. Using UK regulatory data from 2019-22 on the universe of sterling repo and swap transactions, we measure, in real time and at the institution level, LASH risk for the non-bank sector. We find that at peak LASH risk, a 100bps increase in interest rates would have led to liquidity needs close to the cash holdings of the pension fund and insurance sector. Using a cross-sectional identification strategy, we find that low interest rates caused increases in LASH risk. We then find that the pre-crisis LASH risk of non-banks predicts their bond sales during the September 2022 LDI crisis, contributing to the yield spike in the bond market.

Keywords: Liquidity, Monetary policy, Non-Bank Financial Intermediaries, Hedging

JEL Codes: E44, G10, G22, G23

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1 Introduction

Liquidity crises have become increasingly common in the non-bank financial sector. Recent examples include the pandemic-era "Dash for Cash" in Spring 2020, the 2022 commodity market turmoil following Russia's invasion of Ukraine, and the UK LDI crisis in September 2022.[1] and These liquidity crises are linked to the surge in the use of hedging instruments in the past decade — by pension funds, insurance companies, and alternative investment funds employing tools like interest rate swaps and repos.[2] These crises have also been accompanied by distinctive trends in interest rates. While government bond yields have been low and falling in recent decades, they have often risen sharply around these crises.

This paper argues that falling interest rates lead to a less examined form of liquidity risk, which relates to the recent rise in hedging instruments, and applies to non-banks and banks alike. We label this risk *Liquidity After Solvency Hedging* or "LASH" risk. Institutions take LASH risk when they hedge against losses, using strategies that lead to liquidity needs when the value of the hedge falls and the solvency of the institution improves. As such, LASH is different from other forms of liquidity risk that materialize when solvency deteriorates. We argue that lower interest rates lead non-bank financial institutions, with longer term liabilities than assets, to increase LASH risk, which then materializes when rates rise sharply.

We start with a simple framework to define LASH risk, differentiate it from other forms of liquidity risk, and link LASH risk to falling interest rates. As an example, consider a fund, best thought of as a life insurer or a pension fund, with long-duration liabilities, arising from its commitments to its members. These commitments stretch beyond the duration of most bonds and so the fund has a portfolio of shorter-duration assets. A fall in interest rates lowers solvency, since the value of its liabilities rises more than the value of its assets. The fund has different strategies to hedge this solvency risk. In particular, the fund can use an interest rate swap, which pays out when rates fall. However, this hedging strategy exposes the fund to liquidity risk when rates rise, because the value of the swap falls and the fund must pay margin to their counterparty (Froot, Scharfstein and Stein, 1993). That is, the fund must pay liquid assets equal to the fall in the value of the swap. This requirement to pay margin is LASH risk materializing.

[1]The disruption in global sovereign bond markets during the Dash for Cash has inspired a volume of academic research, see e.g. Duffie (2022); He, Nagel and Song (2022) or Czech, Huang, Lou and Wang (2023). Other recent studies examine the dynamics during the 2022 commodity market turmoil (Avalos and Huang, 2022) or the UK LDI crisis in the same year (Pinter, 2023).

[2]For example, the outstanding gross notional in interest rate derivatives has increased from \$426 trillion in 2017 to \$574 trillion in 2023. Similarly, FX gross notionals have risen by 38% to \$120 trillion over the same period (BIS, 2023).

We formalize these ideas using a simple model of a fund with short duration assets and long duration liabilities. The fund hedges the duration mismatch using interest rates derivatives to avoid the costs of insolvency. The derivative in our model is best interpreted as a swap, but we also discuss how LASH risk applies to other hedging strategies for financial institutions, such as repo (i.e. short term collateralized debt). A loss on the swap generates the need for liquidity, which can be costly because holding liquid assets requires paying a convenience premium, and selling longer term assets requires paying liquidation costs. The optimal hedging strategy trades off the loss of solvency when rates fall with illiquidity when rates rise.

LASH risk is different from some other common forms of liquidity risk. In our example, the fund is exposed to LASH risk precisely when their solvency improves, due to rising rates. Therefore, LASH risk differs from the feedback between funding and market liquidity (Brunnermeier and Pedersen, 2009), which arises when solvency deteriorates. In the example LASH risk applies to institutions who borrow long duration and invest in short duration assets, the opposite of the maturity mismatch of a typical bank.[3] As such, LASH risk is associated neither with maturity transformation and callable claims (Diamond and Dybvig, 1983), nor with rollover risk (Calvo, 1988).

We show that incentives to take on LASH risk increase in a low interest rate environment. Unless the fund is fully hedged against interest rate risk, falling rates reduce net worth and bring the fund closer to costly insolvency. Funds can avoid insolvency by further hedging—at the expense of further LASH risk. This idea is again formalized using the trade off in our simple model.

With our conceptual framework in hand, we make three contributions. First, we measure LASH risk for pound sterling interest rate contracts held by UK non-banks, and find that LASH risk is large. In this context, LASH risk measures how many liquid assets an institution needs to provide as margin when interest rates change. For instance, suppose a pension fund holds an interest rate swap to hedge against falling rates. We measure how many liquid assets the fund must pay to its counterparty when the value of the swap falls because rates have risen. We also discuss how to apply our methods to measuring LASH risk for other markets and hedging strategies, such as foreign exchange (FX) risk and FX swaps. We apply the measure to regulatory data from the Bank of England on the universe of sterling repo transactions, the universe of pound sterling interest rate swap positions and the universe of UK government bond transactions. Our measure is available at the institution level and in

[3]Nevertheless LASH risk can also apply to banks, when they use derivatives or other funding strategies to hedge their solvency risk.

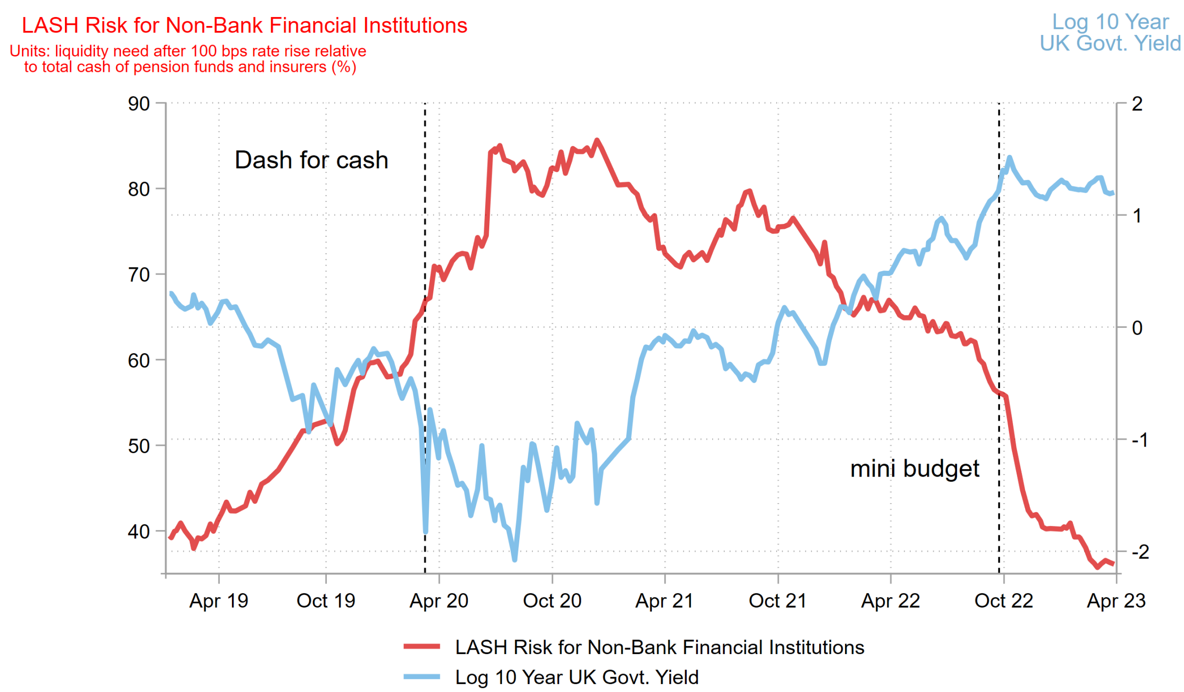
real time, starting from 2019. We find that LASH risk is large: at the peak level of risk, a 100bps rise in interest rates would have generated liquidity needs close to the cash balances of the entire UK pension fund and insurance sector.

Our second contribution is to argue that low interest rates cause LASH risk. To start, we find that in the aggregate time series, low interest rates associate with high LASH risk. LASH risk increases from 2019 through 2022 as interest rates fall; and then falls as interest rates rise. This association remains when we remove mechanical effects of interest rates on LASH risk due to the convexity of the hedging strategy. However, other factors could have caused these patterns. For instance, macroeconomic conditions could have affected both rates and LASH risk. Therefore, to identify the causal effect of interest rates on LASH risk, we pursue a cross-sectional identification strategy. We identify non-banks that are particularly exposed to a decline in interest rates, as they hold relatively short-duration assets. These investors experience declining solvency as interest rates fall. Our framework predicts these investors should hedge more against interest rate risk, in order to avoid costly insolvency, and in doing so raise LASH risk. Consistent with our framework, the exposed institutions raise their LASH risk as interest rates fall, relative to investors with higher-duration assets.

Our final contribution is to show that when rates rise sharply, the LASH risk caused by the previous decline in rates leads to liquidity crises. We study the liquidity crisis in the UK pension fund sector in October 2022. That period was characterized by sharply rising interest rates, and margin calls and gilt sales by UK pension funds. We find that investors with larger LASH exposures sold substantially higher quantities of gilts during the LDI crisis: a one standard deviation increase in pre-crisis LASH risk is associated with 15% higher daily sell volumes during the crisis. The effect is particularly pronounced for index-linked gilts, high-duration gilts, and gilts that are frequently used as repo collateral by these hedging entities. Gilt sales due to LASH risk exacerbated the crisis further. High LASH risk investors significantly contributed to the yield spike in the gilt market: a one standard deviation increase in LASH-induced trading is associated with a 4.1bps daily increase in gilt yields (or 66bps over the entire 16-day crisis period).

Figure 1 summarizes the main empirical results of the paper. The figure reports our measure of LASH risk for non-bank sterling rates instruments, at weekly frequency, alongside the ten-year government bond rate. There are several findings. First, LASH risk is large. A 100bps point rise in interest rates exhausts almost the entire cash holdings of the pension fund and insurance sector at several points in our sample. Second, the figure captures an evident "inverse U" shape, meaning low rates associate with high LASH risk. As a result, LASH risk is high on the eve of the September 2022 LDI crisis, which we have argued contributed to the ensuing market turmoil.

Figure 1 LASH RISK: NON-BANK FINANCIAL INTERMEDIARIES



NOTE. Estimated liquidity needs after 100bps rise in interest rates relative to total cash holdings of UK pension funds and insurers (%). The measure corresponds to $LASH^A_{i,t}$ as defined in equation 4 in Section 3.

Our paper suggests that LASH risk is different from other forms of liquidity risk, with implications for policy. With other forms of liquidity risk, policymakers tend to worry about providing liquidity support during crises. The reason is that institutions often require liquidity support when their solvency deteriorates. Providing liquidity support ex post encourages solvency risk and moral hazard ex ante (Farhi and Tirole, 2012). LASH risk is different. Institutions increase LASH risk precisely when they hedge against solvency risk. Therefore mitigating LASH risk ex post—for instance, by providing liquidity support during crises—may *reduce* solvency risk by encouraging hedging ex ante. As such the policy trade-offs from intervening against LASH risk may be quite different from other liquidity crises. A full exploration is beyond the scope of the paper, but policymakers are actively debating these questions (e.g. Hauser, 2023a).

Related literature

We contribute to several strands of the literature. First, we contribute to the literature on liquidity risk, which has traditionally centered on banks and liquidity risk stemming from maturity transformation or coordination failures (Diamond and Dybvig, 1983; Diamond and Rajan, 2001; Rochet and Vives, 2004; Morris and Shin, 2004). In the context of reducing banks' interest rate risk, the literature explores the use of financial instruments (McPhail, Schnabl and Tuckman, 2023), the role of maturity transformation as a hedge (Drechsler, Savov and Schnabl, 2021) and the trade-off between interest risk and liquidity risk (Drechsler et al., 2023). A related research strand focuses on the interactions between liquidity risk and claims arising from mark-to-market valuations (Brunnermeier and Pedersen, 2009; Adrian and Shin, 2010). Our paper, focusing on how non-banks hedge solvency risks in the context of interest rates, adds a new dimension complementing these papers.

Second, our work adds to general theories of investment incentives by examining how non-banks respond to monetary policy in their pursuit of solvency (Campbell and Sigalov, 2022).[4] Bertaut, Bruno and Shin (2023) highlight the significant influence of non-banks on global capital markets through their long term borrowing strategies. In their analysis, duration risk interacts and is amplified by FX risk via valuation changes, affecting sovereign bonds. Our paper focuses on the interaction of duration with solvency and liquidity risks. In a similar vein, contemporaneous work studies the Dutch pension fund sector (Jansen, Klingler, Ranaldo and Duijm, 2023), financial and non-financial sectors (Khetan, Li, Neamțu and Sen, 2023), and non-bank entities in the UK (Pinter and Walker, 2023). We contribute to this literature by quantifying the liquidity implications associated with non-banks' efforts to maintain solvency by exploiting high-frequency data across various instruments and different interest rate regimes.

Third, our paper links to the vast literature on the role of monetary policy, interest rates, and financial stability. Stein (2012) develops a framework that explains the nexus between financial stability, monetary policy, and the real economy. Theoretical and empirical studies study and document the risk-taking channel of monetary policy (Adrian and Shin, 2010; Jiménez, Ongena, Peydró and Saurina, 2014) or the importance of credit creation in times of loose monetary policy on subsequent financial fragility (Grimm, Jordà, Schularick and Taylor, 2023). Moreover, Greenwood, Hanson, Shleifer and Sørensen (2022) show how rapid credit and asset price growth predict financial crises.[5] We expand this literature by documenting how solvency hedging in low-interest rate environments has "sowed the seeds"

[4] The relationship between interest rates and 'reach for yield' has been documented for insurers, pension funds, mutual funds, and banks (Becker and Ivashina, 2015; Martinez-Miera and Repullo, 2017; Lu, Pritsker, Zlate, Anadu and Bohn, 2023; Aramonte, Lee and Stebunovs, 2022).

[5] Adrian and Liang (2018) and Boyarchenko, Favara and Schularick (2022) provide comprehensive reviews of the research at the intersection of monetary policy and financial stability.

of future liquidity crises.

Fourth, we contribute to the literature on the regulation of pension funds and related sectors, which considers various reforms to promote financial stability.[6] Lucas and Zeldes (2009) and Lucas (2017) investigate how reforms to the discount rates applied to pension funds' liabilities affect the asset allocation of pension funds. Jansen et al. (2023) study how regulatory constraints affect pension funds' swap usage, and the resulting implications for pension funds' exposure to liquidity risks. Furthermore, Koijen and Yogo (2022) ask how risk-based capital regulation affects the portfolio choice of life insurers. We argue that LASH risk presents different challenges to regulators relative to other forms of liquidity risk, because LASH risk rises when solvency improves.

Lastly, we contribute to the liquidity and financial crisis literature. Brunnermeier (2009); Adrian, Kiff and Shin (2018); Bernanke (2018) document mechanisms, causes, and effects of the liquidity dry-ups during the Great Financial Crisis. Furthermore, Borio, Claessens, Schrimpf and Tarashev (2023) document the increased use of collateral to mitigate risk. Recent studies analyze the market liquidity shocks during the onset of the Covid-19 pandemic ("Dash for Cash") in the US (Haddad, Moreira and Muir, 2021), the role of mutual funds' liquidity transformation (Ma, Xiao and Zeng, 2022; Huang, Jiang, Liu and Liu, 2021), and the role of holding dollar assets for UK investors (Czech, Huang, Lou and Wang, 2023; Cesa-Bianchi, Czech and Eguren-Martin, 2023). Pinter (2023) and Chen and Kemp (2023) dissect the market dynamics and policy responses during the UK LDI crisis in Autumn 2022. This paper sheds light on non-banks' role in the run-up to and during the LDI crisis. More broadly, our paper is connected to the literature on the role of liquidity providers (Holmström and Tirole, 1998; Farhi and Tirole, 2012) with a more recent focus on monetary policy (Acharya and Rajan, 2023).

The paper is organized as follows. Section 2 advances the framework and the definition of LASH risk. Section 3 describes the measurement of LASH risk for sterling rate exposures of non-banks. Section 4 presents the institutional background of non banks' hedging strategies and describes our data in more detail. Section 5 shows stylized facts on LASH risk in the context of sterling rates. Section 6 analyzes the causal effect of interest rates on our behavioral LASH risk measure. Section 7 analyzes the consequences and the whiplash during the recent LDI crisis episode. Section 8 concludes.

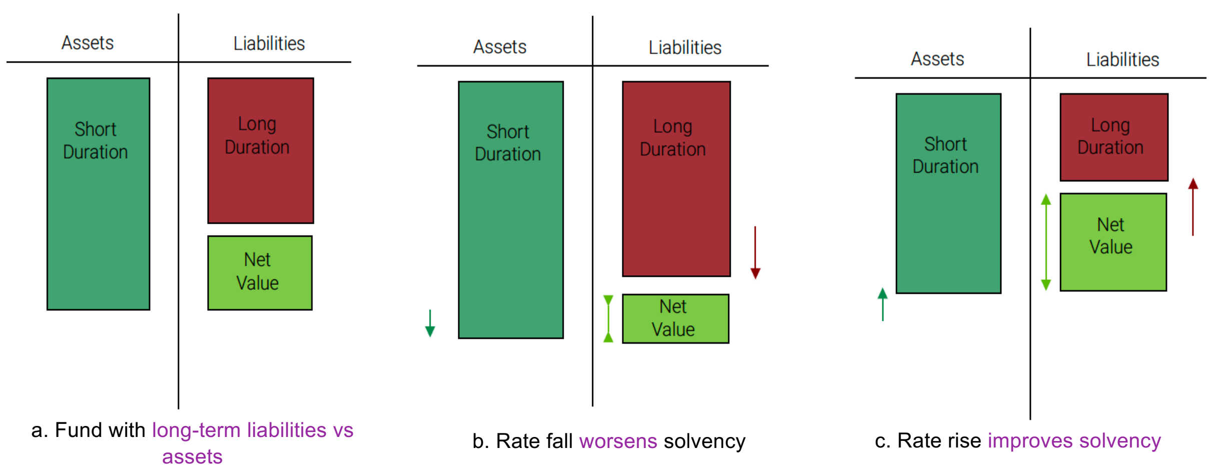
[6] See Scharfstein (2018) for an overview.

2 LASH risk: A Framework

This section provides an overview of our conceptual framework, which introduces "LASH risk" — the liquidity risk following hedging against solvency risk. To start, we focus on changes in interest rates as the underlying threat to solvency but we will argue that LASH risk can extend to other classes of risk. In Appendix A, we express the framework in a model of the portfolio choice problem of a fund exposed to both interest rate and liquidity risk; this model formalizes the discussion below.

Consider a financial institution with a portfolio characterized by short-duration assets and long-duration liabilities, as illustrated in Figure 2. This could represent a pension fund or insurer with liabilities to its members that will realise after much of the existing stock of bonds matures. An asset or liability with a relatively longer duration will experience a greater decline in its value when interest rates rise and a greater increase when rates fall. Due to the duration mismatch, a decline in interest rates increases the value of the institution's liabilities more than the value of its assets, as illustrated in 2.b, and its solvency worsens. In contrast, when rates increase, the depreciation in the value of the institution's liabilities is greater than that of its short-duration assets, as depicted in 2.c, and its solvency improves.

Figure 2 Non-Bank Financial Intermediaries and Interest Rates

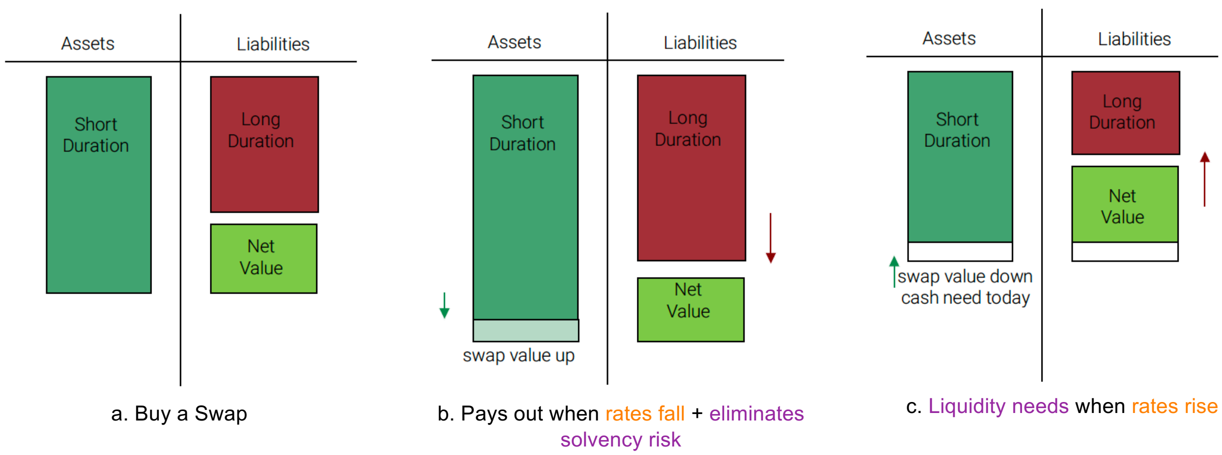


How can the institution in Figure 2 institutions hedge its duration mismatch? The obvious approach is to lengthen the duration of its assets. However, the liabilities of a life insurer, for example, can extend well beyond three decades, exceeding the maturity of most outstanding bonds. The funds needs a hedge. One option is to write a derivative contract—such as an interest rate swap—where the institution pays a floating rate in exchange for a fixed rate (as in Figure 3). Such a contract will appreciate in value when rates fall, offsetting the loss on the rest of the institution's portfolio. The swap partially neutralises the sensitivity of the institution's solvency to interest rate risk (Figure 3.b). However, such a strategy generates liquidity risk, given that derivative contracts such as swaps are constantly revalued. The contract requires the frequent transfer of liquid assets or cash between counterparties to keep the contract net present value at zero based on prevailing market prices (a practice known as variation margining). Hence, when interest rates increase, the institution may become more solvent, but there is simultaneously a decline in the value of the hedge. Consequently, the institution must make payments today to its derivatives counterparty (Figure 3.c). In such a case, the hedging strategy generates an immediate demand for liquidity even if the underlying improvement in the institutions' solvency position has yet to be realized (Froot et al., 1993).

The institution faces a trade-off that we formalize in our model. Hedging transfers resources to states of the world where the institution is facing a loss from states of the world where it has potentially costly liquidity needs. Hence, despite having access to the necessary instruments, the institution does not perfectly hedge the risks to its solvency. This result relies on several ingredients. First, the institution cannot simply invest in longer term assets to close its duration mismatch; this reflects a relative scarcity of very long duration debt, and we take this inability to match duration precisely as a premise given the observed hedging behaviour documented in Section 5. Second, the institution needs to be adverse to insolvency, this generates effective risk aversion and a motive to hedge. Third, liquidity must be costly to obtain, because: (i) holding liquid assets is expensive due to, for example, a convenience premia on money-like assets; (ii) liquidating longer-term assets comes at a cost or (iii) obtaining finance, even as solvency improves, is costly. The latter reflects the transactional, arms-length nature of financial market transactions compared to relationship-based finance where a verifiably more solvent, less liquid position could be handled with the extension of unsecured credit.

Importantly, this trade-off depends on the underlying solvency position of the financial institution. A fund with a large net value is less concerned about insolvency and hence the trade-off swings towards not bearing liquidity risk. In contrast, an institution with limited net worth cannot afford further shocks to its solvency and so hedges more. However, the solvency of a fund with the duration mismatch in Figure 2 depends intrinsically on the level of the interest rate. Given imperfect hedging, a rise in rates raises net worth, which in turn lowers hedging demand and LASH risk. With low rates, the opposite is true and so a low interest rate environment leads to more LASH risk. In the Appendix, we demonstrate this rise in liquidity risks following a decline in the long term average rate.

Figure 3 Non-Bank Financial Intermediaries and Hedging



Derivatives are not the only means to hedge. The institution could also manage interest rate risk by shortening the duration of its liabilities by borrowing short term. Specifically, the institution could use a repurchase agreement (repo) to borrow short and use the proceeds to invest in longer-duration assets.[7] This effectively replicates an interest rate swap as the institution pays a short term rate on its borrowing and receives the fixed, long term rate on the assets it purchases. However, repurchase agreements are also subject to margin requirements. A fall in the value of the underlying collateral needed to secure the borrowing either requires further assets (or cash) to be pledged or the borrowing to be repaid. Again, interest rate rises, and the subsequent fall in bond prices generates immediate liquidity needs. The financial institution does not even have to engage in the borrowing itself. It could instead take an equity stake in a fund that uses the equivalent repo contracts to leverage up and buy longer-dated assets. The payoff from the stake in the fund replicates the hedging strategy. Still, lower interest rates increase the solvency risk for the institution, while liquidity needs rise with higher interest rates.

In the case of minor market fluctuations, this adjustment in liquidity needs is unlikely to cause significant disturbances. Financial institutions maintain liquidity buffers, therefore small shocks need not precipitate fire sales. However, significant asset price movements can potentially disrupt financial stability. This leads to a semi-paradoxical situation when it is

[7]A repo is a form of short term borrowing where the borrower sells a financial security to a lender with the contractual agreement to buy it back at a later date at a specified price. In our setting, we focus on the liquidity demands—rather than the rollover risks—connected with these contracts.

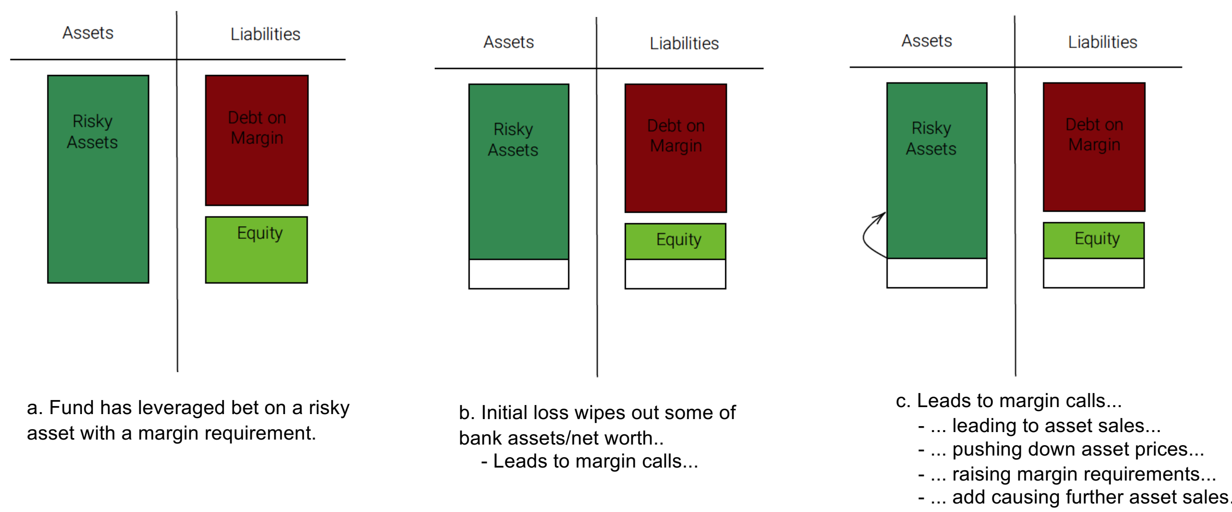
the asset price movements that, in the absence of hedging, are associated with large gains in solvency that generate liquidity crises.

Interest rate risk is one sizeable application of LASH risk, but the concept is generalizable to other financial instruments and hedging strategies. An institution that has an FX mismatch on its balance sheet can make use of FX derivatives (e.g., swaps or forwards) to hedge movements in exchange rates. Again this reduces solvency risk, but at the expense of increasing liquidity risks as these derivatives are also margined. Large swings in exchange rates can then lead to costly fire sales (e.g., the "Dash for Cash" in Spring 2020, see Czech et al. 2023) which share the same features. Similarly, the Ukraine-Russia war led to large margin calls in commodities markets, and the funding costs of commodity traders facing these liquidity demands spiraled (Avalos and Huang, 2022).

The discussion—and the link between risk in financial institutions and crises—reveals distinct mechanisms. LASH risk differs from traditional notions of maturity transformation and run-risk (Diamond and Dybvig, 1983). In this case, the risk of a bank run is linked to the mismatch between financial intermediaries' engagement in illiquid, long-duration projects and the provision for savers to withdraw funds on demand. However, illiquidity in our framework is independent of callable claims or short term debt liabilities. Indeed, our example considers institutions with illiquid longer-duration liabilities actively trying to hedge solvency risk. Our model stands apart from those studies that feature multiple equilibria and self-fulfilling crises, such as Calvo (1988), where a cycle of high interest rates that increase the likelihood of default, which then perpetuates higher interest rates, is observed. Our mechanism also differs from scenarios where rollover risks are spawned by 'sunspots' that exacerbate underlying bad fundamentals (Cole and Kehoe, 2000). Furthermore, our mechanism is separate from rollover crises stemming from creditors' coordination failures (Morris and Shin, 2004). In contrast to the prior literature, we highlight a mechanism where solvency and liquidity risks are negatively correlated. Lastly, the change in asset values stems predominantly from changes in the value of fundamentals and external shocks, and not necessarily from trading frictions that lead to fire sales.

Our perspective is also distinct from the framework proposed by Brunnermeier and Pedersen (2009), which stresses the feedback between funding and market liquidity. In particular, their model delineates the interplay between an asset's market liquidity and a trader's funding liquidity, with traders' provision of market liquidity contingent on their funding conditions. The authors elaborate on the dependency of traders' funding requirements—such as capital and margin calls—on the liquidity of assets in the market. In their analysis, margin requirements can, under specific circumstances, contribute to financial instability, and a symbiotic reinforcement exists between market liquidity and funding liquidity that can incite liquidity spirals. To further illustrate the difference, consider a fund that has entered a leveraged bet on a risky asset with a margin requirement as in Figure 4. A shock leads to an initial loss, which wipes out some of the bank assets/net worth, which leads to margin calls (Figure 4.b). The financial institution sells assets to meet margin calls, which pushes down asset prices, further raising margin requirements and causing further asset sales (Figure 4.c), leading to a "liquidity spiral" as explained by the authors (see Figure 2 in their paper). A fundamental difference is that in our case, there are no losses; instead, as explained, solvency improves as liquidity risks materialize.

Figure 4 COMPARISON: FUNDING LIQUIDITY (BRUNNERMEIER AND PEDERSEN, 2009)



3 Measurement: Interest rate LASH risk for Non-Banks

In its most general form, LASH risk measures the liquidity needs derived from the sensitivity of the net present value of a financial hedging contract with respect to changes in the value of the hedged instrument—for example, FX, inflation, or interest rates. In this section, we focus on LASH risk arising from interest rate hedging and consider the two most common hedging strategies: the use of repo and the use of interest rate swaps.

3.1 Measurement: General Concept

LASH risk from interest rate risk for hedging contract i at time t can be conceptualised in the following manner:

$$LASH_{i,t} \approx \Lambda_i \times \frac{\partial NPV_{i,t}}{\partial R_t}, \tag{1}$$

where $NPV_{i,t}$ is the relevant net present value of the hedging contract (this could be either the discounted value of a swap or repo collateral), and R_t is the underlying interest rate. One can interpret $\frac{\partial NPV_{i,t}}{\partial R_t}$ as the effect of a uniform shift in the yield curve. Λ_i captures liquidity needs per unit of NPV change, which may differ based on the contract type. We assume Λ_i to be a constant $\left(\frac{\partial \Lambda_i}{\partial R_t} = 0\right)$, and hence we abstract from second-order effects from R to liquidity needs, which may for instance arise from margin spirals or an increase in repo haircuts.

For a given institution j that holds $Q_{i,j,t}$ of a given hedging contract, its aggregate LASH risk is given by

$$LASH_{j,t} = \sum_i Q_{i,j,t} \mathrm{LASH}_{i,t}. \tag{2}$$

Letting $Q_{i,t}$ denote the aggregation of contracts across institutions, aggregate LASH risk is given by

$$LASH_t^A = \sum_i Q_{i,t} \mathrm{LASH}_{i,t} = \sum_j LASH_{j,t}^A. \tag{3}$$

Note that liquidity claims, and LASH risk, are not unidirectional - firms can be either net liquidity receivers or payers at any moment in time, depending on both the direction of their exposure and the price moves of the underlying instrument. If the contract value $Q_{i,t}$ decreases (increases) from the perspective of institution j, then the firm is obliged to post (receive) margin. For example, pension funds are exposed to liquidity demands when yields rise, whereas their counterparties (mainly dealer banks) have to post margin when rates fall.

Therefore, given that each contract involves two counterparties, the aggregate measure of $LASH_t^A$ for all institutions in the economy is close to zero. When we document positive LASH risk for the non-bank financial sector, it implies that another set of agents in the economy has negative LASH risk exposures (in the UK, for example, that would be the banking sector—see, e.g., Khetan et al., 2023).

3.2 Measurement: Mechanical versus Behavioral LASH risk

The term $\frac{\partial NPV_{i,t}}{\partial R_t}$ in equation (1) is not constant at the contract level, as it depends on the level of interest rates. For example, the value of a bond or the fixed leg of a long-dated swap both become more sensitive to interest rate movements when rates are lower; this is reflected by the convexity of the hedging contract. Since a goal of the paper is to explore how LASH risk varies with interest rates we need to account for this automatic link. We introduce a simple decomposition of LASH risk into two separate parts, which we label its "mechanical" and "behavioral" components. The mechanical component captures convexity. The behavioral factor captures how the financial institutions have shifted their allocation of hedging, $Q_{i,j,t}$, towards contracts i with ex-ante higher or lower LASH risk.

Consider the definition of aggregate LASH risk in equation (3). We can separate the behavioral and mechanical components via a standard first-order decomposition. In particular, we can write the change in aggregate LASH risk as

$$\overbrace{\Delta \sum_i Q_{it}\mathrm{LASH}_{i,t}}^{\text{aggregate change}} = \underbrace{\sum_i Q_{i,t}\Delta\mathrm{LASH}_{i,t}}_{\text{mechanical change}} + \overbrace{\sum_i \mathrm{LASH}_{i,t-1}\Delta Q_{i,t}}^{\text{behavioral change}}. \tag{4}$$

As can be seen, the behavioral component measures how LASH risk changes as firms' holdings of different hedging contracts change, holding fixed the duration and convexity of the hedging contracts themselves. Equation (2) can be likewise decomposed the obtain a measure of behavioral LASH risk at the institution level.

Both the mechanical and the behavioral components of LASH risk are relevant for liquidity needs. However, the behavioral component is of particular interest. The response of the behavioral component to interest rate changes will measure "reach for illiquidity" behavior; that is, whether firms reallocate towards hedging strategies with greater LASH risk in a low-rate environment.

We measure LASH risk arising from interest rates for repos and interest rate swaps, with the methodology described in Appendix C.

4 Institutional Background and Data Sources

Next, before discussing our data sources, we give a birds-eye overview of the non-bank financial institutions for whom our measure of interest rate-based LASH risk will be particularly relevant.

4.1 Non-bank financial institutions

Among non-bank financial institutions, pension funds and insurers traditionally have the largest duration gap between their assets and liabilities. Their liabilities consist of long term payment promises to pensioners or contingent insurance beneficiaries. And they typically invest in a mix of shorter duration assets, including stocks, government and corporate bonds, or real estate. Insurance companies traditionally have a smaller duration gap than pension funds and, as we will see, tend to exhibit lower interest rate hedging positions compared to the pension fund sector.[8] Other non-banks include, inter alia, asset managers, hedge funds, and money market funds. Hedge funds and money market funds have a very small duration gap, and are hence unlikely to build up substantial exposures to hedge solvency risks (in the context of interest rate risk).

By way of example, Figure 5 presents the aggregate balance sheet of UK defined benefit private pension funds at the end of 2022.[9] The balance sheet includes repo and investments in funds that engage in a liability hedging which we will elaborate on in a moment. However, the assets and liabilities exclude swap positions, which are off-balance sheet and noted separately. We provide a longer discussion of the institutional details behind the UK pension fund sector in Appendix B, but three points stand out from the figure. First, combining derivatives, short term borrowing and investments in specialised funds, the UK pension fund sector has interest rate hedging exposures with a notional value the equivalent of 50% of the liabilities to fund members. This figure is also equivalent to three times the aggregate cash holdings of the funds, which can limit the ability of the sector to meet margin calls.

Second, at the end of 2022, the net asset position of the funds was positive and not insubstantial. The solvency of a pension fund is typically measured via its funding ratio, which is defined as the fraction of the market value of its assets to the discounted value of liabilities.[10] However, this snapshot masks time series variation that illustrates the duration gap that pension funds face. The aggregate funding ratio has swung from from approx. 90% in 2020 to around than 130% at the end of 2022 as interest rates have risen (see Figure 6).

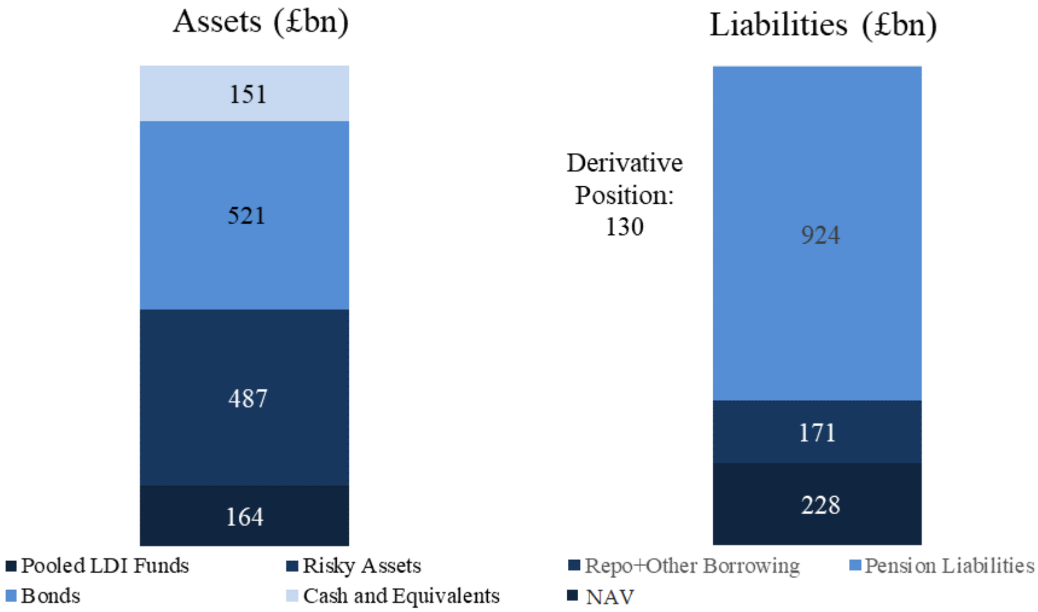
Third, around 10% of pension fund assets are invested in liability-driven investment (LDI)

[8] For instance, in the UK, insurers almost exclusively use interest rate swaps (and not repos) to hedge their interest rate risk.

[9] Calculations based on 2023 ONS data.

[10] As we discuss in Appendix B, the yield curve from UK government bonds is typically used to discount UK pension fund liabilities.

Figure 5 UK Pension Funds: Aggregate Balance Sheet

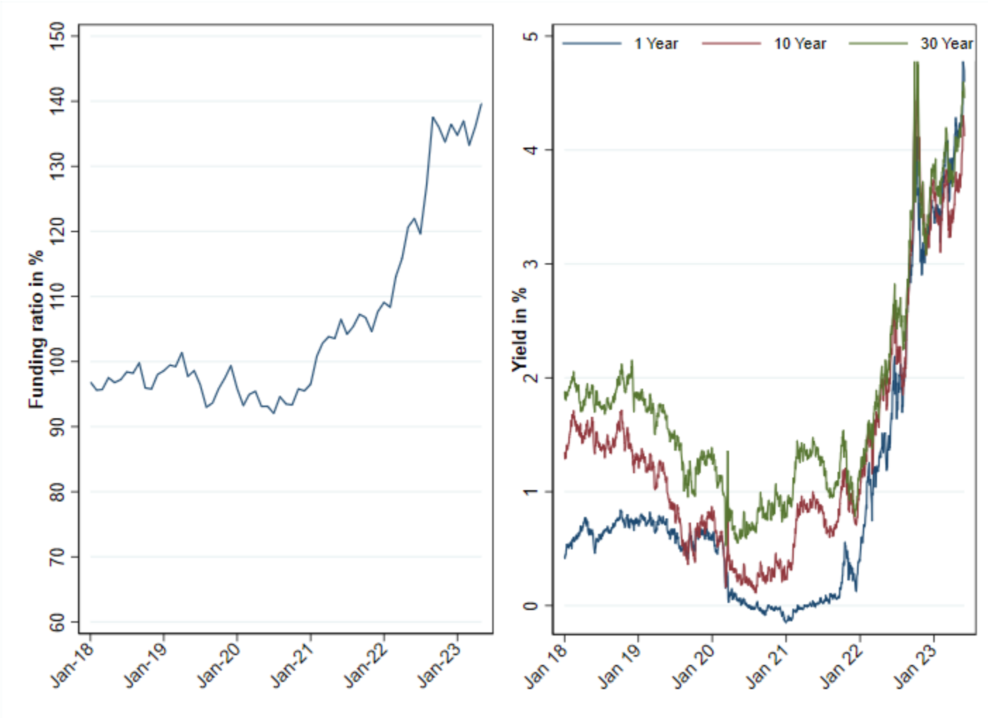


funds. As we describe in Section 2, an alternative to the fund purchasing hedging contracts itself is to invest in a separate fund whose equity generates the same payoffs. In practice, a pension fund will transfer a small portion of its assets to the LDI fund in the form of an equity stake, and the fund will then leverage those assets by engaging in repo borrowing to purchase long duration assets. The equity stake in an LDI fund has a payoff structure that looks like an interest rate swap: the LDI fund receives a fixed rate on its long duration assets and pays a floating rate on its repo borrowing. Such LDI funds are advantageous as they allow smaller pension funds to pool resources and outsource bargaining with repo counterparties. The flip-side is that liquidity risks are potentially even greater when the liquidity needs are concentrated in an arms-length fund due to the coordination problems that arise from the dispersion of fund investors. “Segregated” LDI funds are also available for larger individual pension funds, addressing coordination challenges while inhibiting potential benefits from economies of scale.

4.2 Data Sources and Coverage

To test our framework, we construct a database consisting of: i) the universe of UK government bond (gilts) transactions; ii) the universe of gilt repo transactions; iii) the universe of sterling interest rate swap positions and iv) hand-collected UK pension fund balance sheet data. The consolidated sample period across all datasets is January 2019 to March 2023.

Figure 6 Pension Funds' Funding Ratios and Bond Yields



NOTE. Left Panel: Aggregate funding ratio (defined as total assets divided by total liabilities) of UK pension funds in %. Source: Pension Protection Fund 7800 Data. Right Panel: Yields of UK government bonds (gilts) at different maturities in %.

Bond Market To analyze trading in the UK bond market, we use the transaction-level MiFID II database maintained by the UK's Financial Conduct Authority (FCA). The MiFID II data provide detailed reports of all secondary-market trades of UK-regulated firms or branches of UK firms regulated in the European Economic Area (EEA). Given that all bond dealers are UK-domiciled and hence FCA-regulated institutions, our data cover virtually all transactions in the market. Each transaction report contains information on the transaction date and time, ISIN, execution price, transaction size, and the legal identities of the buyer and seller. We will focus on the UK government, or gilt, segment of the wider bond market and from now on our usage of the term bond refers to those issued by the UK government (unless stated otherwise).[11]

Repo Market The Bank of England's Sterling Money Market data (SMMD) is a transaction-level dataset covering the sterling unsecured and secured (gilt repo) money markets. The data are obtained from dealers in the respective money markets and have been collected

[11] ISIN stands for International Securities Identification Number, and each bond issuance will have a unique ISIN.

since 2016. The data cover 95% of activity in which a bank or dealer is a counterparty, but the data do not capture the small segment of non-bank to non-bank repo transactions. We are again able to identify the identity of the counterparties, the collateral ISINs associated with each transaction, the transaction size, and the execution price.

Interest Rate Swap Market To analyse the interest rate swap positions, we use transaction-level data from two EMIR Trade Repositories, DTCC and LSEG Regulatory Reporting Limited (previously Unavista). We collect weekly positions on outstanding over-the-counter (OTC) GBP interest rate swap (IRS) and overnight index swap (OIS) trades where at least one of the counterparties is a UK entity.[12] The IRS dataset contains trade-level information on the counterparties' identities, notional, currency, floating rate, the direction of trade, maturity and execution date. The cleaning process of the database is largely based on Khetan et al. (2023), with several additions that allow us to better exploit and understand the outstanding positions of these entities.

In addition, to compute discount rates and construct our measure of LASH risk, we use Bank of England data on OIS and yield curves as well as daily data on modified duration of gilts from Bloomberg.

Pension Fund Balance Sheets We construct, to the best of our knowledge, the largest dataset with individual UK pension fund balance sheet details.[13] We hand-collect data from annual reports and newsletters for 100 individual pension funds from 2017 to 2022, covering more than 40% of the UK pension sector by asset size in 2020.[14] Our database includes information on net investments, cash, bond and derivative holdings. Tables D.3 and D.4 summarise the cross-section of actuarial assets and liabilities, and the evolution of funding ratios over time.

[12]We retrieve the data via the Bank of England's access to the mandatory reporting of the UK European Markets Infrastructure Regulation (UK EMIR). More details on the reporting obligation can be found here. For pre-2021 data (reported under EU EMIR), the Bank of England had access to (i) trades cleared by a CCP supervised by the Bank, (ii) trades where one of the counterparties is a UK entity, (iii) trades where the derivative contract is referencing an entity located in the UK or derivatives on UK sovereign debt, (iv) trades where the Prudential Regulation Authority (PRA) supervises one of the counterparties. For post-2020 data, the Bank of England has access to all data reported to trade repositories under UK EMIR.

[13]There is limited publicly available fund-level data on the composition of UK pension fund balance sheets. Aggregate values can be found on the Office of National Statistics and The Pension Regulator websites, but the breakdown at the pension scheme level is not publicly available. The closest exercise in collecting UK data is done by Konradt (2023), covering 12 UK pension funds worth $300bn in asset size.

[14]In 2020, we observe 65 pension funds worth £1046.9bn in actuarial assets, out of the total average of £2497bn in the UK pension fund sector that year. Our sample also includes 20 out of the largest 25 pension funds by asset size—see the list here.

5 LASH risk from Interest Rates: Descriptive Facts

This section presents four descriptive stylized facts about our measure of LASH risk, for non-bank financial institutions and sterling rates. In brief, we find that (i) LASH risk is large, and higher when interest rates are low; (ii) movements in LASH risk are largely due to behavioral rather than mechanical reasons; (iii) LASH risk is large for both interest rate swaps and repo contracts; and (iv) LASH risk is concentrated in the pension fund (including LDI funds) and insurance sector.

i. *LASH risk is large, and higher when interest rates are low.*

Figure 1 in the introduction demonstrates this fact, by reporting the aggregate LASH risk in the non-bank financial sector from 2019 to 2023. To give a sense of scale, we normalize LASH risk by the cash holdings of UK pension funds and insurers (who, as we will see, dominate the measure). The units indicate that at the peak, a 100bps increase in interest rates would have induced liquidity needs that would almost deplete the entire cash positions of both sectors—in other words, LASH risk is very large. Moreover, LASH risk moves inversely with interest rates. When long-dated government bond yields are relatively low, as in 2020, LASH risk is relatively high. This fits the predictions of our framework.

ii. *Movements in LASH risk are largely due to behavioral rather than mechanical reasons.*

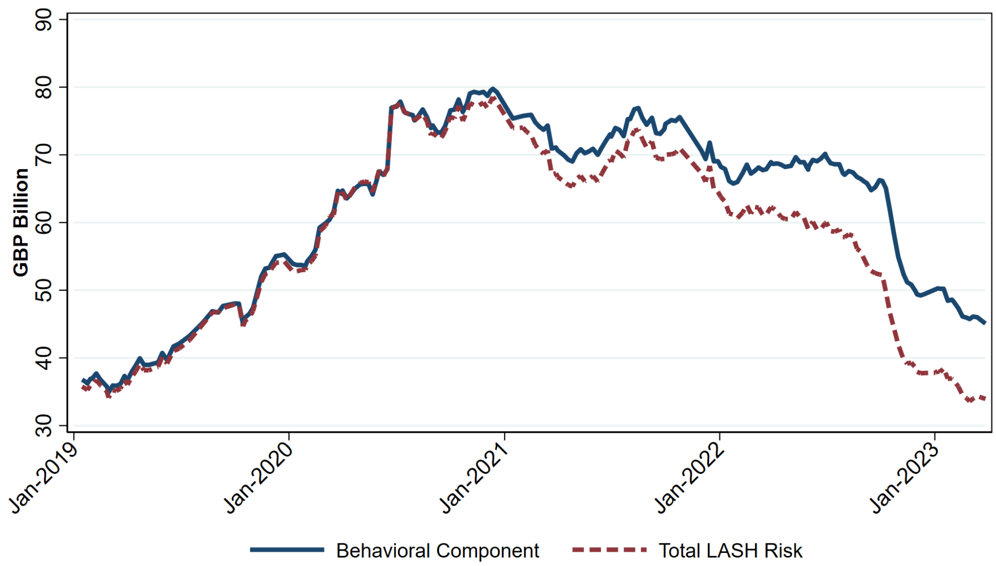
Recall that LASH risk can vary for two reasons: first, institutions might reallocate funds towards instruments with higher LASH risk; and second, the LASH risk of individual contracts mechanically rises as interest rates fall due to convexity. Figure 7 demonstrates that behavioral effects dominate—the total LASH risk is shown in blue, and the behavioral component in red. The two series co-move closely in the first three years of our sample. Therefore, movements in LASH risk over time primarily reflect how institutions reallocate funding and hedging towards instruments with greater LASH risk. The divergence in the last two years of the sample is due to mechanical effects—as interest rates rose over this period, the duration of hedging strategies fell.

The third and fourth descriptive facts are centered around the concentration of LASH risk within the financial system.

iii. *LASH risk is large for both interest rate swaps and repo contracts.*

These are the two primary hedging strategies that we consider, both prevalent throughout the non-bank financial system. In practice, both strategies generate significant LASH risk. Figure 8 reports this result. In the figure, the blue line captures LASH risk for repo contracts, whereas the red line is LASH risk for swaps. Both swap and repo exposures are large, and

Figure 7 LASH RISK: BEHAVIORAL COMPONENT



NOTE. This figure shows the evolution of the total LASH risk and the behavioral LASH risk component in £bn for all non-banks. The *Behavioral Component* is defined as $\sum_i \text{LASH}_{i,t-1}\Delta Q_{i,t}$ for interest rate swaps and repos, respectively, as shown in equation 4 in Section 3.

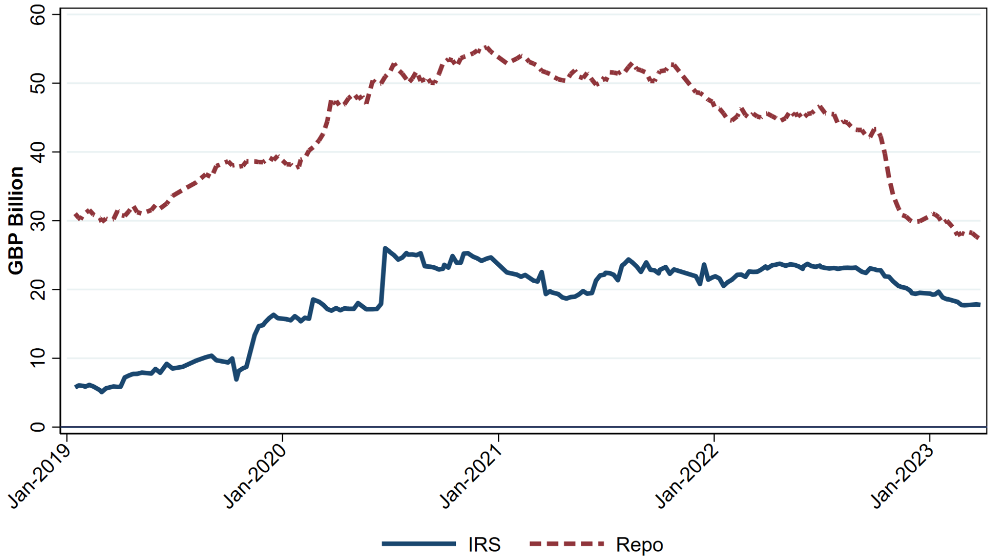
the LASH risk from repo tends to be £20-30bn higher than the LASH risk from swaps. However, towards the end of our sample, the LASH risk from swaps actually exceeds the one from repo as pension funds sought to de-lever in the aftermath of the LDI crisis.

iv. *LASH risk is concentrated in the pension fund sector.*

Figure 9 displays this result. In the figure, we disaggregate LASH risk across five sectors, namely regular pension funds, LDI funds, insurers, funds, and hedge funds. Broadly defined, LDI funds belong to the pension fund sector. Considering LDI funds and regular pension funds jointly, it is apparent that broad pension fund sector is the primary holder of LASH risk.

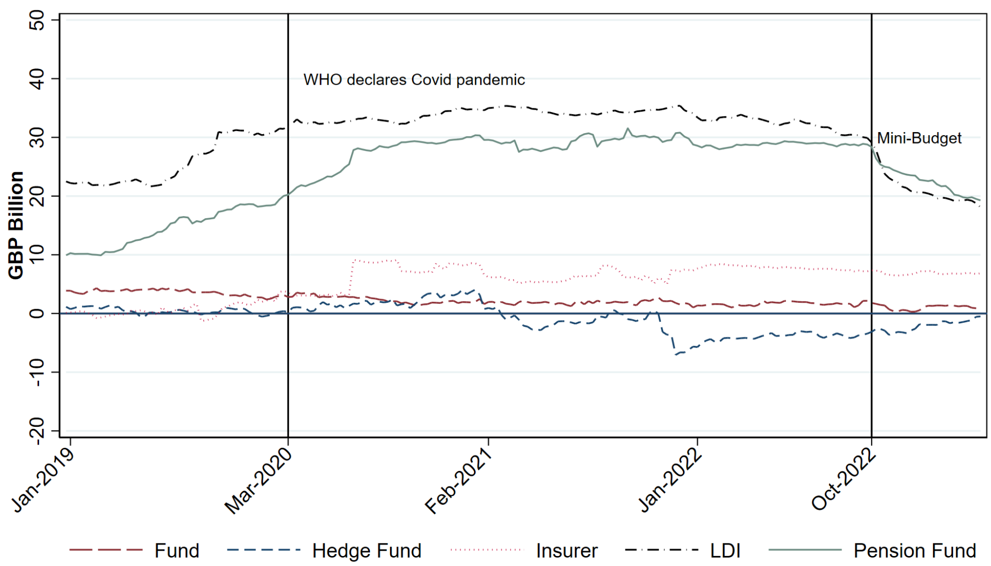
Overall, these descriptive facts invite two questions. First, based on the first two findings, what are the drivers of LASH risk—and do low interest rates induce investors to take on more LASH risk? Second, based on the third and fourth finding, can LASH risk lead to financial market turmoil, such as the distress in the pension fund sector after the announcement of the UK "Mini-Budget" in autumn 2022? We will tackle both questions next.

Figure 8 Behavioral LASH risk: Swaps vs. Repo



NOTE. This figure shows the evolution of the behavioral LASH risk by instrument in £bn for all non-banks. The *Behavioral Component* is defined as $\sum_i \text{LASH}_{i,t-1}\Delta Q_{i,t}$ for interest rate swaps and repos, respectively, as shown in equation 4 in Section 3.

Figure 9 Behavioral LASH risk: Sectoral Breakdown



NOTE. This figure shows the evolution of the behavioral LASH risk across different sectors in £bn. The *Behavioral Component* is defined as $\sum_i \text{LASH}_{i,t-1}\Delta Q_{i,t}$ for pension funds, insurers, LDI funds, hedge funds and funds, respectively, as shown in equation 4 in Section 3.

6 Low Interest Rates and High LASH risk

Our descriptive evidence shows a striking pattern: in aggregate, LASH risk is high when interest rates are low. This is line with our theoretical framework which finds that a decline in rates causes a loss of solvency for the relevant institution, which in turn raises hedging demand and LASH risk. This section tests and confirms that low interest rates cause an increase in LASH risk using a cross-sectional identification strategy.

To make causal claims, we exploit the cross-sectional variation from our rich regulatory data. Our identification strategy analyzes how the assets held at the beginning of the sample influence solvency afterwards. Specifically, investors holding relatively high duration assets experience lower capital losses as interest rates fall, relative to investors holding low duration assets. Therefore, as interest rates fall, solvency should deteriorate more for investors holding low duration assets.[15]

Since low duration investors face greater solvency risk following a decrease in interest rates, they require more hedging. As such, our simple framework predicts that low duration investors should disproportionately increase LASH risk after interest rate falls. Appealingly, the cross-sectional variation captures the same mechanism that we conjecture should operate at the aggregate level. That is, LASH risk increases because falling interest rates reduce solvency.

To implement our cross-sectional strategy, we assume that investors rebalance their portfolios each quarter, and hence estimate the following quarterly panel regression:

$$\Delta LASH_{j,t}^{Behavioral} = \alpha + \alpha_j + \alpha_t + \beta_1 \Delta Yield_t^{10Y} + \beta_2 (\Delta Yield_t^{10Y} (\sum_i^I \omega_{j,i,t=0} \times AD_{i,t})) + \epsilon_{j,t}, \quad (5)$$

where $\Delta LASH_{j,t}^{Behavioral}$ measures the quarterly change in the behavioral LASH risk of investor j at the end of quarter t. $\sum_i^I \omega_{j,i,t=0} \times AD_{i,t}$ is the weighted modified duration of investor j's assets, by calculating the investor-specific weights at the beginning of the sample for each gilt (as proxied by investor j's repo collateral portfolio) and multiplying these with the quarterly change in a given gilt's duration. $\Delta Yield_t^{10Y}$ is the quarterly change in the ten-year gilt yield. To facilitate the interpretation of the coefficients, the dependent variable is

[15] Technically, *net* asset duration is what matters for solvency, rather than our measure of *gross* asset duration. In Section E.1 of the Appendix, using our hand-collected balance sheet data, we explore the link between pension funds' gross asset duration and the sensitivity of their funding ratios to changes in interest rates (as a measure of funds' duration gap / net duration). The results confirm that there is a negative correlation between investors' gross asset duration and their net duration, i.e. the solvency of funds with a low gross asset duration is indeed more sensitive to a rate change.

transformed using the Inverse Hyperbolic Sine method. Therefore, the regression coefficients measure the percent change in LASH risk, even if LASH risk is negative (see, e.g., Czech et al. 2023). The yields are denoted in percentage points, and the weighted duration variable is standardized. We cluster standard errors at the quarterly level and include time fixed effects to control for all time-varying macroeconomic trends. We also include institution, institution-yield level (ten-year gilt yields) and institution-yield slope (ten-year minus two-year gilt yields) fixed effects. Our set of fixed effects therefore absorbs both macroeconomic and investor characteristics and hence most of the aggregate variation.

Our framework predicts that β_1 is negative and that β_2 is positive. That is, as bond prices rise and interest rates fall, investors with low duration assets suffer disproportionately. Therefore, the LASH Risk of these investors increases more relative to investors with high duration assets.

Our identification assumption is that investors with initial short asset duration would not have experienced capital losses relative to investors with initial long duration, for reason other than their initial asset holdings. Though this assumption is difficult to verify, it is certainly plausible. Investors hold long duration assets for many reasons that are orthogonal to the other determinants of solvency such as fund manager skill.

Table 1 presents the results. We find that the effect is statistically and economically significant and, as predicted, β_1 is negative and β_2 is positive. Column (1) shows that a 100bps quarterly decrease in the gilt yield index is associated with a 133% increase in the behavioral LASH Risk of investor j. Importantly, the coefficient of the interaction term reveals that this effect is reduced to a 44% increase (=-1.33+0.89) when the initial asset duration of investor j increases by one standard deviation. Therefore, when yields decrease, the LASH risk of low-duration investors increases more compared to the one their high-duration counterparts.[16]

Therefore, falling interest rates lead to an economically and statistically significantly greater LASH risk taken by low duration investors—consistent with our mechanism. Therefore our cross-sectional identification strategy suggests that low interest rates are associated with high LASH risk—reassuringly, using a different source of variation from the descriptive time series patterns of the previous section.

[16]In untabulated results, we find that the effects also remain robust when controlling for the share of index-linked gilts in investors' portfolios. We also obtain qualitatively similar results when using the the yields of the S&P gilt index instead of the 10-year gilt yields.

Table 1 Rates and Investor-level LASH risk

	(1)	(2)	(3)	(4)
	$\Delta LASH^{Behavioral}$			
$\Delta Yield^{10Y}$	-1.33***			
	(0.37)			
$\Delta Yield^{10Y}$ × Duration	0.89**	0.95**	1.08***	0.87**
	(0.37)	(0.35)	(0.35)	(0.37)
Observations	4657	4657	4657	4657
R squared	0.016	0.024	0.040	0.063
Time FE	no	yes	yes	yes
Institution FE	yes	yes	yes	yes
Institution-Yield Level FE	no	no	yes	no
Institution-Yield Slope FE	no	no	no	yes

Note. For each investor, we calculate the quarterly change in the behavioral LASH Risk. The independent variable is the quarterly change in the 10-year gilt yield, interacted with the modified duration of investor j's assets at the beginning of the sample. The dependent variable is transformed using the Inverse Hyperbolic Sine method; the yield change is denoted in percentage points; and the modified duration is standardized. Clustered standard errors on the quarter level are reported in parentheses. We include investor, quarter, institution-yield level (ten-year gilt yields) and institution-yield slope (ten-year minus two-year gilt yields) fixed effects. fixed effects. *** p<0.01, ** p<0.05, * p<0.1. Coefficients corresponding to the constant, control variables and fixed effects not reported.

7 Consequences: Backlash During Crises

Having established the pronounced build-up of LASH risk in recent years, we now examine the link between non-banks' pre-crisis liquidity risk exposures and their UK government bond trading activity, and the subsequent impact on yields during a recent stress episode. To do so, we examine the recent 2022 UK LDI crisis, when the yields of long-dated gilts spiked by more than 100bps.

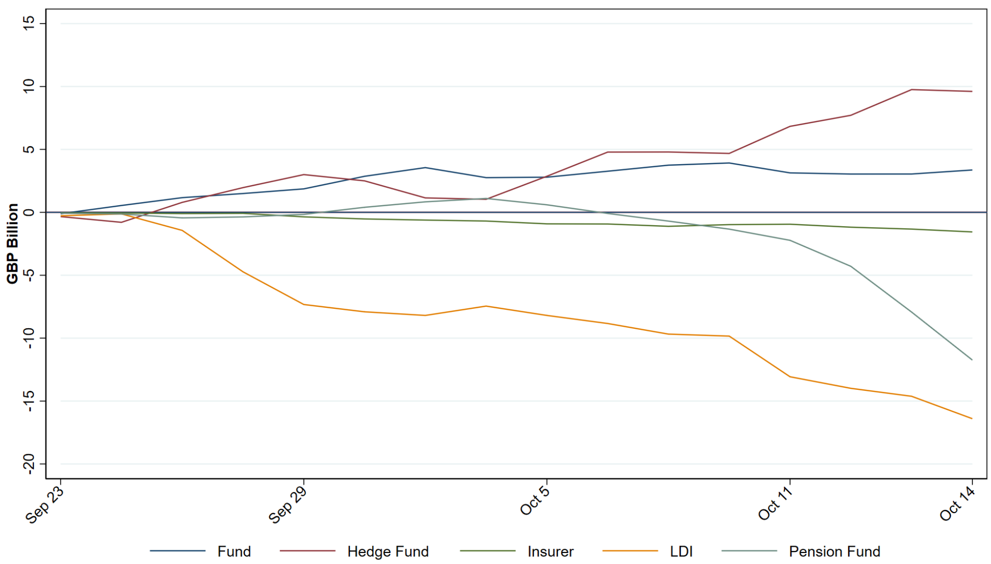
7.1 LASH risk and Investor Selling Pressure

On 23 September 2022, the then Chancellor, Kwasi Kwarteng, presented a "Mini-Budget" proposal to the UK Parliament. The abrupt change in the fiscal stance initiated a sharp downward adjustment in government bond prices, which was amplified by the vulnerabilities—LASH risk—in the pension fund and LDI sector (Figure 9). 30-year gilt yields rose by 130bps in a matter of days, as investors had to sell their holdings to obtain cash to meet margin calls on their term repo and IRS positions.[17] Importantly, these liquidity demands occurred

[17]During the 2020 "Dash for Cash", in contrast to the LDI crisis, the principal shock was a rapid depreciation of pound sterling against the dollar, triggering large margin calls on investors' FX hedging positions (Czech et al., 2023).

against the backdrop of pension funds' improving funding ratios, as the present value of their liabilities decreased due to higher discount rates (i.e. gilt yields, see Figure 6). As the liquidity crisis intensified, the Bank of England was required to intervene to safeguard financial stability. The Bank's temporary and targeted backstop, announced on September 28 and scheduled to end on October 14, proved effective in ending the fire-sale dynamic and helped pension funds to adjust their portfolios by reducing their repo leverage (Hauser, 2023b; Alexander et al., 2023). In total, pension and LDI funds sold nearly £30bn in the period between September 23 and October 14 (see Figure 10 and Pinter 2023).

Figure 10 LDI Crisis: Non-Banks' Bond Trading Volumes



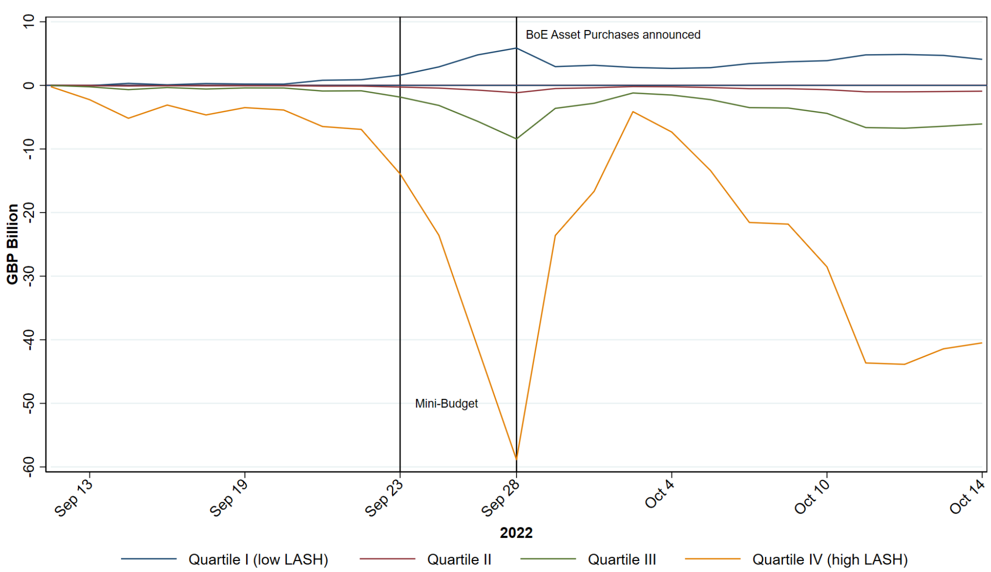
NOTE. Total net gilt trading volumes of UK non-bank financial institutions following the Mini-Budget announcement on September 23 up until the end of the BoE intervention on October 14.

Against this backdrop, we now analyze whether non-banks' pre-crisis LASH exposures can predict their gilt selling activities during the market turmoil. Our hypothesis is that institutions with larger pre-crisis LASH risk, and hence a more pronounced risk of facing large liquidity demands (i.e. margin calls) during the crisis, sold relatively higher quantities of gilts than investors with low pre-crisis LASH exposures.

To analyze the link between LASH risk, the liquidity demands and bond trading during the LDI crisis, we first divide the non-banks in our sample into four groups based on their pre-crisis LASH exposures, calculated from both their repo and IRS positions. We measure the investor-specific LASH exposure on August 30, hence well in advance of the onset of the crisis and before the election of Liz Truss as Prime Minister.

At the peak of the crisis, as shown in Figure 11, the estimated cumulative change in the value of repo collateral—an upper bound for repo variation margin calls (i.e. the crystallization of LASH risk for repo)— reached almost £60bn across non-bank financial institutions. Figure 11 also demonstrates how the group of non-banks with particularly large ex-ante LASH risk (Quartile 4) was most severely affected by the sharp drop in the value of the posted repo collateral. This group explains almost the entirety of the £60bn aggregate drop in value. Unsurprisingly, this group mainly consists of pension and LDI funds, who had large net exposures in term repo borrowing (see Figures D.3 & D.5). Consistent with this notion, we observe a similar pattern when plotting the same graph for pension funds only, as shown in Figure D.12 of the Appendix. Conversely, the group with the lowest LASH risk was likely a net *receiver* of repo variation margin during the crisis, with an estimated increase in the value of their repo collateral of around £6bn before the BoE intervention on September 28.

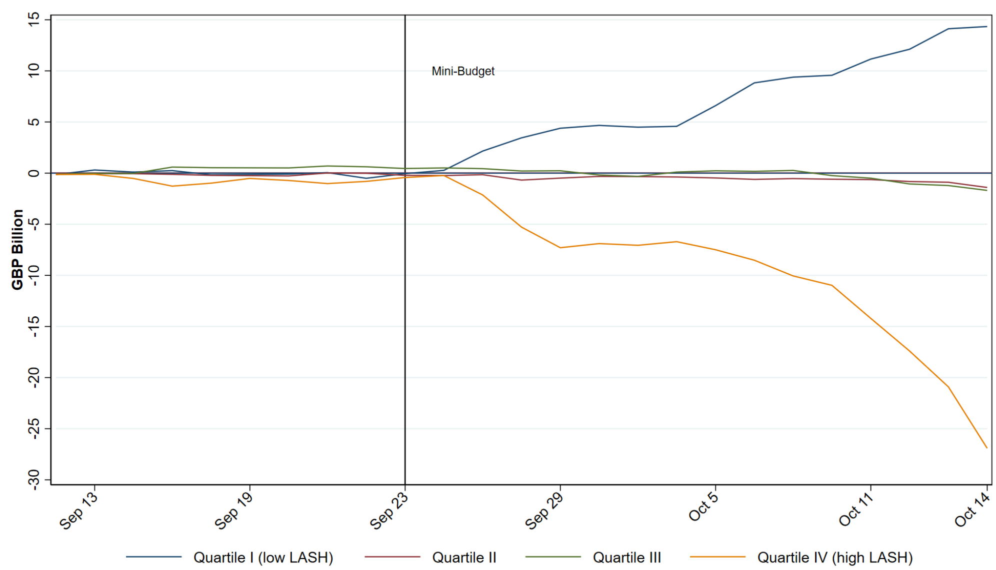
Figure 11 Estimated Cumulative Change in the Value of Repo Collateral by Pre-crisis LASH Exposure



NOTE. Aggregate estimated changes in the value of repo collateral posted by UK non-bank financial institutions in £bn during the 2022 LDI Crisis, by quartile of their pre-crisis LASH risk: Quartile I captures the non-banks with the lowest pre-crisis LASH exposures, while Quartile IV captures those with the highest pre-crisis LASH exposures. Source: Sterling Money Market data collection.

We now turn our attention to the impact of LASH risk on non-banks' bond trading behavior. As shown in Figure 12, the group of non-banks' with the highest pre-crisis LASH exposure (Quartile IV) sold substantially higher quantities of government bonds compared to the other three groups. In total, this group sold more than £25bn during the crisis, while the group with the lowest LASH risk (Quartile I) was in fact buying around £15bn worth of bonds. Before the crisis, the net volumes are very similar for all four groups. We again observe a similar pattern when plotting the same graph for pension and LDI funds only: as shown in Figure D.11 of the Appendix, the net sales of the pension fund sector were concentrated in the group of funds with the largest pre-crisis LASH exposures (Quartile IV). Again, we do not observe any differential pre-crisis trends.

Figure 12 Cumulative Gilt Trading Volumes by Pre-crisis LASH Exposure



NOTE. Total net bond trading volumes of UK non-banks, by quartile of their pre-crisis LASH risk: Quartile I captures the banks with the lowest pre-crisis LASH exposures, while Quartile IV captures those with the highest pre-crisis LASH exposures.

To test the link between LASH risk and gilt selling pressures more formally, we use the following regression specification :

$$Vol_{j,t} = \alpha + \alpha_{s,t} + \beta_1 LASH_{j,t=0} + \varepsilon_{j,t}, \tag{6}$$

where $Vol_{j,t}$ measures the net trading volume of institution j at time t, including all non-banks in our sample. We define the crisis period as the sixteen trading days between September 23 and October 14 (see Pinter 2023). We calculate a "combined" LASH measure, which captures the LASH risk from both repo and IRS exposures, but we also run separate regressions for these two individual LASH risk components. The LASH variable is standardized to facilitate the interpretation of the coefficients. Furthermore, we also run separate regressions for investors' sell volumes, which capture whether investor j was a net seller on a given day. Again, net and sell volumes are transformed using the inverse hyperbolic sine transformation to give the regression coefficient β_1 an approximate percent change interpretation even if volumes are negative. We include sector-day fixed effects and use standard errors clustered on the day and sector level.

Table 2 LASH risk and Gilt Trading Volumes

	(1)	(2)	(3)	(4)
	Net Volume		Sell Volume	
LASH combined	-0.21***		0.15***	
	(0.04)		(0.02)	
LASH Repo		-0.16***		0.12***
		(0.04)		(0.02)
LASH IRS		-0.13*		0.08***
		(0.05)		(0.02)
Observations	8875	8875	8875	8875
R squared	0.035	0.035	0.046	0.046
Sector-Day FE	yes	yes	yes	yes

Note. For each investor, as defined in equation 3 in Section 3, "LASH" is measured as the potential liquidity needs following a 100bps shift in gilt yields, either for repo and IRS exposures combined, or separately for both instruments. The dependent variable is the investor's daily gilt net trading volume on day t in Columns (1) and (2), and the investor's sell volumes on day t in Columns (3) and (4). The dependent variables are transformed using the Inverse Hyperbolic Sine method. The LASH variable is standardized. Double-clustered standard errors on the day and sector level are reported in parentheses. We include sector-day fixed effects. *** p<0.01, ** p<0.05, * p<0.1. Coefficients corresponding to the constant, control variables and fixed effects not reported.

The results are shown in Table 2. Consistent with Figure 12, we find that investors with larger pre-crisis LASH exposures sold substantially higher quantities of gilts during the UK LDI crisis: a one standard deviation increase in pre-crisis LASH risk is associated with 15% higher daily sell volumes during the crisis period (Column 3). Importantly, this effect is robust to the inclusion of sector-day fixed effects, hence not driven by time-varying sector characteristics. Furthermore, the effect is economically and statistically more significant for the LASH risk from repo exposures, consistent with the larger magnitude of overall LASH risk in the repo market. As a robustness check, we also conduct our analysis exclusively for the pension and LDI fund sector in Table E.1 of the Appendix. Consistent with our baseline results, a one standard deviation increase in LASH risk is associated with a 10% increase in pension fund daily sell volumes.

An important feature of the LDI crisis was the pronounced selling by "pooled" LDI funds, in which multiple (often smaller) pension funds invest together—in contrast to segregated arrangements, where the assets of a single pension scheme are invested in a separate account.[18] The speed and scale of the moves in yields following the Mini-Budget announcement outpaced the ability of pooled funds' smaller clients—who typically rebalance their positions only on a weekly or monthly frequency—to provide new funds (Breeden, 2022). As a result, pooled funds became forced sellers and liquidated large quantities of gilts (see Figure D.10 in the Appendix). To test this more formally, we use the following specification:

$$Sell\ Vol_{j,t} = \alpha + \alpha_{s,t} + \beta_1 LASH_{j,0} + \beta_2 \left(LASH_{j,0} \times Type\ Fund_j\right) + \varepsilon_{j,t}, \tag{7}$$

where $Type\ Fund_j$ is an indicator variable for segregated and pooled LDI funds, respectively. The remaining variables are defined as in Equation (6). We again include sector-day fixed effects and use standard errors clustered on the day and sector level.

Table 3 LASH risk and Pooled LDI Funds

	(1)	(2)	(3)
		Sell Volume	
LASH	0.20***	0.14***	0.17***
	(0.05)	(0.02)	(0.03)
LASH × Segregated Fund	-0.08		-0.05
	(0.06)		(0.03)
LASH × Pooled Fund		0.93***	0.90***
		(0.02)	(0.01)
Observations	8875	8875	8875
R squared	0.047	0.050	0.050
Sector-Day FE	yes	yes	yes

Note. For each investor, as defined in equation 3 in Section 3, "LASH" is measured as the potential liquidity needs following a 100bps shift in gilt yields for repo and IRS exposures combined. The dependent variable is the investor's daily sell volume on day t. "Segregated Fund" and "Pooled Fund" indicate segregated and pooled LDI funds, respectively. The dependent variable is transformed using the Inverse Hyperbolic Sine method. The LASH variable is standardized. Double-clustered standard errors on the day and sector level are reported in parentheses. We include sector-day fixed effects. *** p<0.01, ** p<0.05, * p<0.1. Coefficients corresponding to the constant, control variables and fixed effects not reported.

The results are presented in Table 3. We find that the effect is indeed substantially more pronounced for pooled LDI funds: a one standard deviation increase in LASH risk is asso-

[18] At the end of 2021, approximately £200bn of the £1.4tn in UK LDI assets were in multi-investor pooled funds (Breeden, 2022).

ciated with 90% higher daily sell volumes for pooled LDI funds relative to other non-banks (Column 3). Intriguingly, the coefficient for segregated LDI funds is insignificant, emphasizing that the coordination frictions in pooled LDI funds—in combination with elevated LASH risk—was a particularly strong driver of gilt sales during the crisis.

7.2 Bond-level Liquidation Choices

An important question at this point is whether the selling pressure was concentrated in bonds with particular characteristics. As investors with pronounced LASH risk exposures frequently invest in high-duration assets, our hypothesis is that the selling pressure increases with the duration of a bond. Furthermore, we hypothesize that the selling pressure is also more pronounced for gilts that are frequently used as repo collateral as well as for inflation-linked gilts. To test these hypotheses, we exploit the granularity of our data and run the following regression on the investor-bond-day level:

$$Sell\ Vol_{j,b,t} = \alpha + \alpha_{s,t} + \alpha_{b,t} + \beta_1 LASH_{j,0} + \beta_2 \left(LASH_{j,0} \times Bond\ Characteristics_b\right) + \varepsilon_{j,b,t} \quad (8)$$

where $Vol_{j,t}$ measures the net trading volume of institution j in bond b at time t. *Bond Characteristics* includes: i) three duration buckets (low, medium, high), ii) two groups measuring the frequency of the gilt's usage as repo collateral (as measured by the total pre-crisis repo borrowing amount for each bond across all non-banks), and iii) index-linked gilts. $LASH_{j,0}$ is defined as in equation (6). We include both sector-day and bond-day fixed effects and use standard errors clustered on the day, sector and maturity-bucket level.

The results are presented in Table 4. Consistent with our baseline results, we find that higher pre-crisis LASH risk predicts bond sales pressure, even when controlling for sector-day and bond-day fixed effects. Importantly, confirming our hypotheses, we find that the effect is particularly pronounced for index-linked gilts. For example, a one standard deviation increase in LASH is associated with 6% higher daily sell volumes in index-linked gilts (relative to 4% higher sales in nominal bonds). Moreover, the effect is weakly statistically significant for high-duration gilts and gilts that are frequently used as repo collateral.

7.3 Impact of Selling on Yields

The previous analyses have shown that non-banks with higher pre-crisis LASH risk indeed sold significantly higher quantities of gilts during the LDI crisis, particularly in the case of longer-maturity bonds and bonds frequently used as repo collateral. An important question

Table 4 LASH RISK AND BOND-LEVEL LIQUIDATION CHOICES

	(1)	(2)	(3)	(4)
	Sell Volume			
LASH	0.05***	0.04***	0.04***	0.04***
	(0.00)	(0.00)	(0.00)	(0.00)
LASH × Frequent Collateral Use		0.01*		
		(0.00)		
LASH × Low Duration			0.01	
			(0.01)	
LASH × High Duration			0.01*	
			(0.00)	
LASH × Inflation-linked				0.02**
				(0.01)
Observations	42481	42382	41667	42481
R squared	0.115	0.115	0.114	0.115
Bond-Day FE	yes	yes	yes	yes
Sector-Day FE	yes	yes	yes	yes

NOTE. For each investor, as defined in equation 3 in Section 3, "LASH" is measured as the potential liquidity needs following a 100bps shift in gilt yields, for repo and IRS exposures combined. The dependent variable is the investor's daily gilt sell volume in bond b on day t. "Frequent Collateral Use" indicates the frequent use of bond b as repo collateral, i.e. the top 50% of bonds based on their use as repo collateral. "Duration" indicates the duration bucket of bond b (long, medium, short). "Inflation-linked" indicate index-linked gilts. The dependent variable is transformed using the Inverse Hyperbolic Sine method. The LASH variable is standardized. Clustered standard errors on the day, sector and maturity-bucket level are reported in parentheses. We include sector-day fixed effects. *** p<0.01, ** p<0.05, * p<0.1. Coefficients corresponding to the constant, control variables and fixed effects not reported.

at this point is whether and by how much this selling pressure contributed to the yield spike during the market turmoil in September and October 2022.

An obvious concern with this exercise is that non-banks' selling of bonds may be driven by many factors, including private information. To isolate the impact of LASH risk on non-bank trading and, in turn, on yield movements, we follow Czech et al. (2023) and construct a measure of *LASH-induced trading (LASH-IT)*. Specifically, we calculate each investor's LASH-induced trading in bond b assuming that each investor proportionally scales up or down its holdings in response to liquidity demands. Due to the lack of complete information on bond holdings of individual institutions, we approximate the weight of bond b in institution j's portfolio, $w_{j,b}$, by measuring the weight of the given bond in investor's j pre-crisis repo collateral portfolio. LASH-induced trading (LASH-IT) in bond b on day t is then defined as:

$$LASH\text{-}IT_b = \frac{\Sigma_j LASH_{j,t=0} \times w_{j,b,t=0}}{Amount\ Outstanding_{b,t=0}} \tag{9}$$

where $LASH_{j,t=0}$ is the estimated pre-crisis LASH exposure of institution j, and $w_{j,b}$ is the weight of bond b in investor's j pre-crisis repo collateral portfolio, and *Amount Outstanding*$_{b,t=0}$ is the bond's amount outstanding before the crisis. We then employ the following regression specification to measure the impact of LASH-induced trading on gilt yields during the LDI crisis:

$$\Delta Yield_{b,t} = \alpha + \alpha_{m,t} + \alpha_{g,t} + \beta_1 \times LASH\text{-}IT_b + \varepsilon_{b,t} \tag{10}$$

where $\Delta Yield_{b,t}$ is the daily change in yields. Again, we define the crisis period as the sixteen trading days between September 23 to October 14. We also include maturity bucket-day fixed effects ($\alpha_{m,t}$) as well as type gilt-day fixed effects ($\alpha_{g,t}$), which control for differential effects for nominal and index-linked gilts. Standard errors are clustered on the bond level.

Table 5 presents the results. The effect is statistically and economically highly significant. In most conservative specifications with maturity bucket-day and type gilt-day fixed effects (Column 4), a one standard deviation increase in LASH-IT is associated with a 4.1bps daily increase in gilt yields. Over the entire 16-day crisis period, this would attribute around 66bps of the yield spike to LASH-induced trading. For comparison, 30-year gilt yields spiked by 103bps over the same period—therefore, LASH-induced trading accounts for around two thirds of the yield spike during the LDI crisis.

Table 5 Impact of LASH-IT on Gilt Yields

	(1)	(2)	(3)	(4)
	$\Delta Yield_{t-1,t}$			
LASH-IT	9.29***	9.72***	3.21**	4.13**
	(0.91)	(1.06)	(1.49)	(1.60)
Observations	1253	1253	1253	1253
R squared	0.261	0.321	0.616	0.649
Day FE	yes	-	-	-
Day × Type Gilt FE	no	no	yes	yes
Day × Maturity Bucket FE	no	yes	no	yes

Note. As the dependent variable, we measure the daily change in yields for each bond. The independent variable is the bond's LASH-induced trading ("LASH-IT") in bond b on day t as defined in equation 9. The dependent variable is transformed using the Inverse Hyperbolic Sine method. The independent variable is standardized. Standard errors clustered on the bond level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Coefficients corresponding to the constant and fixed effects not reported.

8 Conclusion

In this paper, we introduce a framework to understand and measure the liquidity risk that arises from financial institutions' actions to mitigate solvency risk. *Liquidity After Solvency Hedging risk* or "LASH risk", arises when institutions use certain hedging strategies to reduce solvency risk, which leads to higher liquidity needs when the value of the hedge falls and solvency improves. We focus on LASH risk for non-banks such as pension funds, with long duration liabilities and shorter duration assets. For these non-banks, LASH risk ought to rise as rates fall, because solvency deteriorates which requires more solvency hedging.

We then make three empirical contributions. First, we measure LASH risk for the universe of non-banks' sterling interest rate exposures, from interest rate swaps and repo, in the UK from 2019 onwards. LASH risk is large—at peak, a 100bps increase in interest rates leads to liquidity needs that would nearly deplete the entire cash holdings of the combined pension fund and insurance sector. Second, we show that low rates increase LASH risk. In the time series, LASH risk is high when rates are low. We then exploit our granular data using a cross sectional identification strategy, comparing funds with different exposures to falling interest rates. Funds who are more exposed, due to having shorter duration assets, increase LASH risk by more. Third, we show that the LASH risk caused by low rates leads to liquidity crises. In particular, during the September 2022 LDI crisis in the UK, fund-level LASH risk is a strong predictor of bond sales by pension funds. As such, LASH risk contributed to the spike in yields during the crisis.

The implications of LASH risk are different from some other forms of liquidity risk. LASH arises from 'responsible' institutions trying to hedge solvency risks, and the risk materializes precisely when solvency improves. As such, LASH is different from other forms of liquidity risk that materialize when solvency deteriorates (Brunnermeier and Pedersen, 2009). Therefore mitigating LASH risk ex post—through measures such as liquidity support during a crisis—may not encourage solvency risk ex ante. As such, the policy tradeoffs from intervening during a crisis may be different from conventional liquidity crises. We leave a full investigation of these ideas to future work. Likewise, we leave the analysis of LASH risk and its implications in other market segments (e.g. foreign exchange or inflation) for future research.

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Appendix

A A Model: Net Asset Values and Hedging Demand

This appendix presents a concise model that forms the basis of the conceptual framework discussed in Section 2, mainly focusing on 'LASH Risk'—the liquidity risk that arises from hedging against solvency risk. The model considers the interest rate risk management problem of a non-bank financial institution, which we refer to as a fund and is best thought of as a pension fund or an insurer.

This fund has an exogenously given perpetual liability that it needs to cover with a portfolio of assets. It can use interest rate derivatives, effectively a swap contract, alongside manipulating the duration of it is portfolio to manage interest rate risk. The model has four important ingredients that makes the analysis interesting and serve to highlight the mechanisms we have in mind:

1. **Asymmetric payoffs.** For the fund (or more precisely its manager) reducing a deficit by $1 is more beneficial than increasing a surplus by $1. Practically, this asymmetry in payoffs might represent a regulatory penalty (e.g. in the UK, for example, pension funds are explicitly taxed via a risk-based levy if they fall into deficit, see here.), but broadly, it could encompass various reputational or behavioural explanations (see Lian et al. 2019).

2. **Duration mismatch.** The perpetual liability cannot be hedged by a perpetual bond, the fund only has access to financial assets of shorter duration. Swaps can be used to hedge (perfectly) but they generate the need for liquidity in the following period.

3. **Liquid assets are expensive.** The fund can self insure against liquidity needs by holding short duration assets but those assets require paying a convenience premium.

4. **Illiquidity of the long duration asset.** Holding only long term assets generates liquidity costs in the case where the swap contract is out of the money and short term debt holdings are insufficient, selling the long duration asset requires paying a proportional liquidation cost.

The net effect of the first ingredient is to introduce a kink in the objective of the fund. This generate effective risk aversion and that motivates the hedging of interest rate risk. The second ingredient guarantees that the fund will choose to the hedge interest rate risk partly through the use of derivatives. The third and fourth ingredients insure that liquidity needs generated by the hedge cannot be offset without a cost: either the fund must hold expensive liquid assets or run the risk of liquidating a portion of its long duration portfolio. Hence, there is an interior solution where the fund holds a combination of illiquid long duration assets, expensive liquid assets and a hedging strategy that generates liquidity risk.

This liquidity-solvency trade-off means that the fund is imperfectly hedged. Therefore, lower rates worsen the funds financial position. This pushes the fund closer to the kink in its objective function which in turn raises effective risk aversion. Higher risk aversion raises hedging demand and encourages the fund to take more liquidity risk.

A.1 Environment

We consider the investment problem of a non-bank financial institution ("the fund"). Time runs from $t = 0, 1, \ldots, \infty$. The fund has liabilities structured as a perpetuity that require paying a fixed l in every period. The pension fund can invest in (i) a one period bond, a_t, (ii) a geometrically decaying multi-period bond, b_t, with decay rate δ: i.e. the bond has a coupon b_t in $t+1$ with passive equation of motion $b_{t+1} = \delta b_t$ and (iii) an interest rate swap s_t. The fund cannot short bonds: $a_t \geq 0$ and $b_t \geq 0$, but the swap position, s_t, can be positive or negative.

All assets are priced by a deep pocketed marginal investor active in the bond and swap markets. The investor is competitive, risk neutral and discounts the future at rate R_t^{-1}. We assume R_t^{-1} evolves according to a first order Markov process, $F(R'|R)$. This discount factor is also used to value the fund's liabilities. For certain results we will treat R_t^{-1} as i.i.d with mean $\bar{R}^{-1}$. The marginal investor values the liquidity service from one period bond at rate η. This is non-pecuniary. The fund does not share this service, instead the fund will receive an endogenous liquidity benefit to one period debt.

Asset prices Let q_t^b denote the price of the geometric bond. The investor values the bond at $q_t^b = \mathbb{E}_t \left[\sum_{j=0} \delta^j \prod_{s=0}^{j} R_{t+s}^{-1} \right]$. In the i.i.d. case the price becomes $q_t^b = \left(1 - \delta \bar{R}^{-1}\right)^{-1} R_t^{-1}$. Let q_t^l denote the price of a perpetuity paying one every period: $q_t^l = \sum_{j=0}^{\infty} \prod_{s=0}^{j} \mathbb{E}_t \left[R_{t+s}^{-1} \right]$. In the i.i.d case, this price is $q_t^l = \left(1 - \bar{R}^{-1}\right)^{-1} R_t^{-1}$. Last, the liquidity service implies that the price of the short term bond is given by $q_t^a = R_t^{-1} (1 + \eta)$.

Interest rate swaps are priced fairly and have a fixed leg $\mathbb{E}_t \left[R_{t+1}^{-1} \right]$ and floating leg R_{t+1}^{-1}: buying the swap means paying fixed and receiving floating. So the cashflows from the realised swap position are given by $s_t \left(R_{t+1}^{-1} - \mathbb{E}_t \left[R_{t+1}^{-1} \right] \right)$.

We assume that the geometric bond is costly to sell. The fund bears a liquidation cost $q_t^b c$ per unit sold. The marginal investor does not discount the value of the bond due to the liquidation cost.

Fund value We can define the net asset value of the fund as $w_t = q_t^a a_t + q_t^b b_t - q_t^l l$. Accounting for liquidity costs, w_t evolves according to

$$w_t = a_{t-1} + b_{t-1} - l + q_t^b \delta b_{t-1} + s_{t-1} \left(R_t^{-1} - \mathbb{E}_{t-1} \left[R_t^{-1} \right] \right) - c q_t^b \underbrace{\max \left\{ 0, \delta b_{t-1} - b_t \right\}}_{\text{sales of geometric bond}} - q_t^l l.$$

In addition, the no shorting constraint implies that the fund must have sufficient cash on hand from the payments it receives on its assets and bond liquidations to cover its swap position. That is

$$a_{t-1} + b_{t-1} - l + (1 - c) q_t^b \max \left\{ 0, \delta b_{t-1} - b_t \right\} \geq s_{t-1} \left(\mathbb{E}_{t-1} \left[R_t^{-1} \right] - R_t^{-1} \right).$$

Fund manager's objective The fund manager is risk neutral, does not enjoy limited liability and receives period compensation (that is negligible compared to the value of the fund) proportional to

$$\pi_t = w_t + \kappa \mathbf{1} \left(w_t < 0 \right) w_t,$$

where, in line with the above, $\kappa > 0$ is a penalty term that incentivises the manager to avoid deficits. For simplicity, we assume the fund manager discounts the future at a fixed rate β rather than R_t^{-1}. How the manager discounts plays a limited role in the model and so the assumption of a fixed rate is innocuous.

A.2 The fund manager's problem

Let $\mathcal{S}_t = \{R_t, R_{t-1}\}$ denote the state of the world at time t. The fund manager's problem can be expressed recursively as

$$\max_{a_t, b_t, s_t} V(a_{t-1}, b_{t-1}, s_{t-1}; \mathcal{S}_t) = (1 + \kappa \mathbf{1}[w_t < 0]) w_t + \beta \mathbb{E}(V(a_t, b_t, s_t; \mathcal{S}_{t+1}))$$

subject to

$$w_t = q_t^a a_t + q_t^b b_t - q_t^l l,$$

$$q_t^a a_t + q_t^b b_t = a_{t-1} + b_{t-1} - l + q_t^b \delta b_{t-1} + s_{t-1}\left(R_t^{-1} - \mathbb{E}_{t-1}\left[R_t^{-1}\right]\right) - c q_t^b \max\{0, \delta b_{t-1} - b_t\}.$$

The no shorting condition on a_t also implies the following cash flow constraint

$$(1-c) q_t^b \max\{0, \delta b_{t-1} - b_t\} \geq \max\left\{s_{t-1}\left(\mathbb{E}_{t-1}\left[R_t^{-1}\right] - R_t^{-1}\right) - a_{t-1} - b_{t-1} + l, 0\right\}. \quad \text{(A.1)}$$

The right hand side is the loss on the swap contract net of the liquidity available to the fund. When this value is positive, the fund needs to liquidate long term assets. The left hand side is the proceeds from liquidations. When the left hand side of the above equation is positive, we have the model analogue to LASH risk materialising: the fund is forced to sell assets at a cost to cover losses on its hedges. Since the fund will only ever liquidate if it is forced to, equation (A.1) holds with equality.

The flow budget constraint therefore can be expressed entirely in terms of past choice variables and the interest rate:

$$\begin{aligned} q_t^a a_t + q_t^b b_t =& a_{t-1} + b_{t-1} - l + q_t^b \delta b_{t-1} + s_{t-1}\left(R_t^{-1} - \mathbb{E}_{t-1}\left[R_t^{-1}\right]\right) - \\ & - \frac{c}{1-c} \max\left\{s_{t-1}\left(\mathbb{E}_{t-1}\left[R_t^{-1}\right] - R_t^{-1}\right) - a_{t-1} - b_{t-1} + l, 0\right\}. \end{aligned}$$

A.3 Analysis

We start by illustrating the fund's exposure to interest rate risk, then discuss its optimal hedging strategy, before discussing how the level of rates affects the demand for hedging.

The fund's exposure to interest rate risk (excluding hedging). To start, imagine that the fund never hedges ($s_t = 0$), then

$$\frac{dw_t}{dR_t^{-1}} = b_{t-1}\frac{dq_t^b}{dR_t^{-1}} - l\frac{dq_t^l}{dR_t^{-1}}.$$

Assuming the discount factor is i.i.d. with unconditional mean $\bar{R}^{-1}$, then

$$\frac{dq_t^b}{dR_t^{-1}} = \frac{1}{1-\delta\bar{R}^{-1}}.$$

$$\frac{dq_t^l}{dR_t^{-1}} = \frac{1}{1-\bar{R}^{-1}} > \frac{dq_t^b}{dR_t^{-1}}.$$

So unless we have $w_t \gg 0$, we know $\frac{dw_t}{dR_t^{-1}} < 0$ (i.e. a fall in interest rates hurts the fund). The fund therefore should try to set $s_t > 0$.

Optimal hedging strategy. Consider the fund's first order condition with respect to s_t:

$$\beta\mathbb{E}_t\left[\frac{d}{ds_t}\left(1+\kappa\mathbf{1}\left[w_{t+1}<0\right]\right)w_{t+1}\right] = 0.$$

Define the following conditional expectations

$$\mathbb{E}_t^{\obar}\left[.\right] \equiv \mathbb{E}_t\left[.|w_{t+1}<0\right],$$

$$\mathbb{E}_t^{\circledcirc}\left[.\right] = \mathbb{E}_t\left[.|s_t\left(\mathbb{E}_t\left[R_{t+1}^{-1}\right]-R_{t+1}^{-1}\right)-a_t-b_t+l>0\right],$$

$$\mathbb{E}_t^{\ominus}\left[.|s_t\left(\mathbb{E}_t\left[R_{t+1}^{-1}\right]-R_{t+1}^{-1}\right)-a_t-b_t+l>0, w_{t+1}<0\right].$$

These correspond to the expectations conditional on the fund having a deficit, having to liquidate and being exposed to both (deficit and liquidation). Define $p_t^{\obar}$, $p_t^{\circledcirc}$ and $p_t^{\ominus}$ the corresponding probabilities. By Leibnitz's rule, we can ignore the effect of decisions on probabilities at the margin.

Splitting along the dimension of whether the fund pays liquidity costs allows us to rewrite the first order condition on s_t as

$$\frac{\beta c p_t^{\circledcirc}}{1-c}\left(\mathbb{E}_t^{\circledcirc}\left[R_{t+1}^{-1}\right]-\mathbb{E}_t\left[R_{t+1}^{-1}\right]\right)+p_t^{\obar}\beta\kappa\left(\mathbb{E}_t^{\obar}\left[R_{t+1}^{-1}\right]-\mathbb{E}_t\left[R_{t+1}^{-1}\right]\right)+$$
$$\frac{p_t^{\ominus}\beta\kappa c}{1-c}\left(\mathbb{E}_t^{\ominus}\left[R_{t+1}^{-1}\right]-\mathbb{E}_t\left[R_{t+1}^{-1}\right]\right)=0.$$

Now, note that absent liquidity costs, the fund would be perfectly hedged against interest rate risk and either set $p_t^{\obar}=0$ or $\mathbb{E}_t^{\obar}\left[R_{t+1}^{-1}\right]=\mathbb{E}_t\left[R_{t+1}^{-1}\right]$. But assuming $p_t^{\circledcirc}>0$, this is not optimal as insuring all interest rate risk ignores the costs of liquidity risk.

Since the fund is imperfectly hedged, we know that $\frac{dw_t}{dR_t^{-1}}<0$ and s_t. This means that

$$\left(\mathbb{E}_t^{\obar}\left[R_t^{-1}\right]-\mathbb{E}_t\left[R_t^{-1}\right]\right)>0,$$

the states of the world where the fund is in deficit are ones where the discount factor is higher than expected (rates lower than expected). In contrast, the fund will have a liquidity deficit if

$$s_t\left(\mathbb{E}_t\left[R_{t+1}^{-1}\right]-R_{t+1}^{-1}\right)-a_t-b_t+l>0.$$

So

$$\mathbb{E}_t^{\circledcirc}\left[R_{t+1}^{-1}\right]-\mathbb{E}_t\left[R_{t+1}^{-1}\right]<0,$$

the discount rate is low (interest rate high) when the fund faces a liquidity shortfall.

How about $p_t^{\ominus}$? This means that the fund faces a deficit and a liquidity shortfall at the same time. This is only possible if the fund's initial deficit (i.e. $w_t \ll 0$) is so big that even a positive interest rate surprise, which causes a liquidity shortfall, still has the fund in a deficit. So we still have

$$\mathbb{E}_t^{\ominus}\left[R_{t+1}^{-1}\right]-\mathbb{E}_t\left[R_{t+1}^{-1}\right]<0.$$

However, for simplicity, consider the case where $p_t^{\ominus}=0$ (i.e. $w_t\approx 0$). Then the optimal hedging strategy sets

$$p_t^{\obar} \kappa \left(\mathbb{E}_t^{\obar}\left[R_{t+1}^{-1}\right] - \mathbb{E}_t\left[R_{t+1}^{-1}\right]\right) = p_t^{\circledcirc} \frac{c}{1-c} \left(\mathbb{E}_t\left[R_{t+1}^{-1}\right] - \mathbb{E}_t^{\circledcirc}\left[R_{t+1}^{-1}\right]\right).$$

The fund trades off the fact that a swap transfers cashflows to states of the world where the fund is in deficit, against the fact that the swap transfers cashflows away from states of the world where the fund has a liquidity shortfall.

Low rates and LASH risk. The unhedged cashflows generated by the fund are given by

$$a_{t-1} + b_{t-1} - l,$$

these are independent of R_t, where as we have

$$w_t = q_t^a a_t + q_t^b b_t - q_t^l l,$$

which are linked to current and future interest rates.

It follows that $p_t^{\obar}$, the probability of a deficit, is more sensitive to rates than current cash flows. Holding s_t fixed, a fall in rates raises $p_t^{\obar}$, (via lower w_t) but it does not have much impact on $p_t^{\circledcirc}$. Hence, the left hand side of the hedging optimality condition rises more than the right hand side in response to a fall in rates. So a fall in rates raises hedging demand. To illustrate this, we solve the model numerically using value function iteration, assuming an i.i.d. interest rate and parameterizing the model as described in Table A.1:

Parameter	**Description**	**Value**
c	Cost of liquidation	0.015
δ	Decay rate of long term bond	0.91
l	Fund payment to its members at each period	0.04
η	Short term bond premium	0.014
κ	Penalty for fund's deficit	0.3
β	Discount factor	0.96

Table A.1 Summary of Parameters

We choose δ such that the duration of the long term bond is equal to 10 years. The values for c and η are from Harris and Piwowar (2006) and Nagel (2016), respectively. To show that funds are incentivized to increase their swap holdings after decreases in interest rates, we solve the model on 12 different grids for R^{-1}, in which average R^{-1} ranges from 0.8 to 0.95. This is equivalent to having average interest rates r_t, defined as $R_t = \dfrac{1}{1+r_t}$ ranging from 25% to 5%.

We then simulate the response of the model to a persistent decrease in interest rates. We start from the state $a = 1, b = 1, s = 0.2$ and R^{-1}=0.95 and then for the rest of the time, the interest rate falls so that R^{-1}=1.06 (this is equivalent to a fall in the interest rate from 5% to -6%). Figure A.1 displays the results.

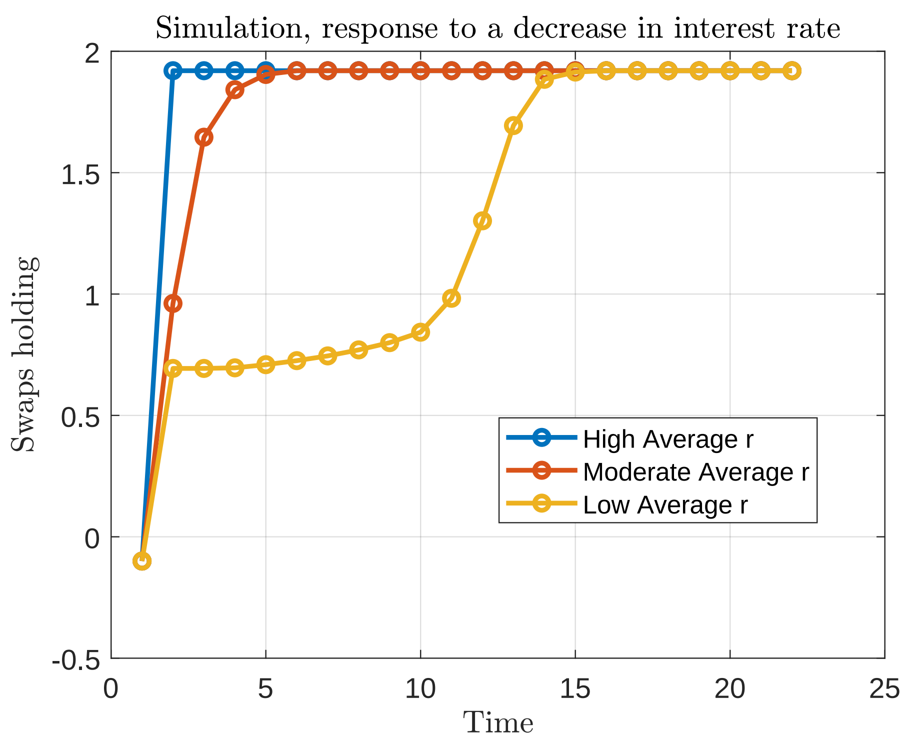


Figure A.1 Swaps holding response to a fall in interest rate across different average values for r

High, Moderate, and Low average interest rates in the figure correspond to 14%, 10%, and 7%, respectively.[19] The results are consistent with the intuition. When the interest rate goes down, funds hedge more by increasing their swap holdings.

[19]The result is qualitatively robust to the choice of higher/lower average interest rates.

B Institutional background on the UK pension fund sector

The pension fund sector, and specialized funds that service it, is a major source of LASH risk in the non-bank sector. Pension funds can be categorized as defined benefit (DB) or defined contribution (DC) funds. Defined benefit pension funds promise a guaranteed return to their beneficiaries upon retirement, while defined contribution funds have variable returns. By construction, defined benefit funds have higher hedging needs, as they need to meet certain guaranteed payments in the far future. For the UK pension fund system, out of the total £2.2tn of assets under management in Q1 2023, £1.8tn can be attributed to public and private defined benefit funds.[20]

Hedging strategies are not always the same—even for similar balance sheet structures—and depend not only on the duration gap and the pension fund type, but also on the way future liabilities are discounted. Differences in regulations and discounting practices across jurisdictions lead to diverging optimal hedging strategies. For instance, UK pension funds predominantly use gilt yields to discount their liabilities, while Dutch pension funds include the euro interest rate swap rate in their calculations, and US pension funds take a more bespoke approach and use a so-called asset-led discounting approach. As a consequence, Dutch pension funds almost exclusively hedge using interest rate swaps (Jansen et al., 2023), US pension funds have higher incentives to take on riskier assets as a hedging strategy (Andonov et al., 2017), and in our paper we find that UK pension funds more frequently use repos than swaps as part of their hedging strategy.

Pension fund market fragmentation also impacts the hedging landscape. In countries with a concentrated market, funds have sufficiently large balance sheets and in-house expertise to design and implement their individual hedging strategies. By contrast, in a fragmented pension fund system, small pension schemes would not have the size or capacity to make in-house hedging a viable solution, giving rise to alternative strategies. A solution is to delegate a part of the portfolio to alternative investment funds, which are designed to attract funds from one (segregated fund) or multiple pension funds (pooled fund). These funds then select

[20] See The Office for National Statistics (2023) dataset for details.

their assets, derivatives and repo leverage based on the desired duration profile of their clients.

The UK had over 5,300 defined benefit pension schemes in 2022, making it a very fragmented market.[21] It is therefore perhaps unsurprising that the UK saw a rapid rise in alternative investment funds in the recent decade, such as Liability Driven Investment funds (LDIs). In fact, we find that the LASH risk from repo exposures is mainly concentrated in the LDI sector, emphasizing the frequent use of repo leverage in this market segment.

C LASH risk from interest rates: Repo and interest rate swap measurement

We apply equation (1) to repos and interest rate swaps.

Repos As explained in the previous section, repos are short-dated collateralized borrowing arrangements that allow institutions to shorten the duration of their liabilities. The majority of repo transactions are overnight, but pension funds and other interest rate hedgers predominantly use term repos with a maturity of one month or more. LASH risk arises via price changes of the underlying collateral. As the collateral value decreases, ceteris paribus, a counterparty would need to pledge more collateral (or cash) to be able to borrow the same amount.

We approximate LASH risk for repos using the modified duration of the underlying collateral, which measures the impact of a 100bps change in interest rates on the value of the bond. Therefore, in the context of repo, LASH risk resembles the conventional DV01 (or "dollar duration"). For each contract i with bond collateral b of maturity m years and coupon payments c times a year, LASH risk for a 100bps increase in interest rates at time t reads:

$$LASH_{i,t}^{Repo} = \frac{Q_{i,t}}{100} \times \underbrace{\frac{\sum_{k=1}^{K}(1+r_t)^{-k_b} \cdot CF_{b,k} \cdot k_b}{P_{b,t}} \times \left(1 + \frac{YTM_{b,t}}{c_b}\right)^{-1}}_{\text{Modified duration of bond } b} \tag{C.1}$$

[21] See Pension Regulator Annual report.

where $Q_{i,t}$ is the borrowing amount of a given repo contract. $P_{b,t}$ is the market price of bond b, k_b is the time to each cash flow $CF_{b,k^{\cdot}}$ of bond b from time t perspective (in years), and $YTM_{b,t}$ is the bonds' yield to maturity. We assume zero haircuts as most of the LASH risk in our sample is due to longer-term repos, which are of course less frequently rolled over compared to overnight contracts (where haircuts play a bigger role, e.g., during the Great Financial Crisis). This implies a one-to-one liquidity need with respect to the cash flow sensitivity to interest rates, hence $\Lambda_i = 1$.

Interest Rate Swaps An interest rate swap is a contract where two counterparties agree to exchange a fixed interest rate with a variable one, e.g., LIBOR, SOFR, SONIA, c times a year, for a duration of m years. The interest is calculated on a notional amount, Q, but only the difference in interest payments is exchanged. The fixed interest rate is set so that the NPV of the contract is zero at initiation; that is, neither side needs to pay the other to enter the agreement. To guard against counterparty credit risk, entering a swap also requires a pledge of liquid collateral in the form of initial margin.

LASH risk arises in swaps due to variation margin. The counterparties are required to exchange variation margin on a daily basis to maintain the zero net present value of the contract as interest rates change. The floating rate payer will post variation margin to the fixed rate payer when rates rise (and vice versa when rates fall). In practice, this is implemented through daily (cash) margin calls that reflect the change in the mark-to-market price of the contract.[22]

The size of the margin calls, and the demand for liquidity, depend on the sensitivity of the swap's fixed versus floating cash flows to changes in interest rates. We extend the methodology proposed by Bardoscia et al. (2021) to calculate the liquidity needs from a given interest rate move and hence to obtain an estimate of LASH risk. Imagine an interest rate swap of net notional value Q. We are at time zero and the swap matures at year T, and makes c coupon payments per year. Let k index coupon periods. There is a swap curve which defines the time zero sequence of annualised forward floating rates given by $r_{k,k-1}$,

[22] Variation margin is a regulatory requirement, and the requirements may differ between centrally-cleared and bilateral swaps. A centrally cleared swap requires daily cash pledges for variation margin, while bilateral swaps can have more bespoke conditions if permitted by regulation, e.g., the use non-cash collateral.

and a fixed rate $\bar{r}$ (for an at the money swap ($\bar{r} \equiv r_{T,0}$)). Cashflows are discounted at rate

$$d_k = (1 + \frac{r_{k,0}}{c})^{-k} \approx e^{-\frac{r_{k,0}}{c}k}$$

The present value of the floating and fixed leg of the swap is given by

$$PV_{floating} = Q \sum_{k=1}^{cT} d_k \frac{r_{k,k-1}}{c}$$

$$PV_{fixed} = Q \sum_{k=1}^{cT} d_k \frac{\bar{r}}{c}$$

Now the NPV of the contract for the floating rate payer is given by:

$$NPV = PV_{fixed} - PV_{floating} = \frac{Q}{c} \sum_{k=1}^{cT} d_k(\bar{r} - r_{k,k-1}).$$

For a ex-post shift upwards of the swap curve, the sensitivity reads:

$$\frac{\partial NPV}{\partial r} = -\frac{Q}{c} \sum_{k=1}^{cT} \left[\underbrace{d_k + \frac{\partial d_k}{\partial r} r_{k,k-1}}_{\text{change in value of floating leg}} - \underbrace{\frac{\partial d_k}{\partial r} \bar{r}}_{\text{change in value of fixed leg}} \right]. \tag{C.2}$$

Solving in continuous time yields:

$$\frac{\partial NPV}{\partial r} = -\frac{Q}{c} \sum_{k=1}^{cT} \left[d_k + \frac{k}{c} d_k(\bar{r}_i - r_{k,k-1}) \right].$$

Hence, LASH risk from a 100bps increase in interest rates for a swap contract i with maturity T based on notional Q and with c cash flow swaps a year reads:

$$LASH^{IRS}_{i,t} = \frac{Q_i}{100c} \sum_{k=1}^{cT} \left[d_k + \frac{k}{c} d_k(\bar{r}_i - r_{k,k-1}) \right]. \tag{C.3}$$

where the discount rate for cash flow k, $e^{-R_{k,t} \cdot (T_k - t)}$, is evaluated based on the daily Overnight Index Swap (OIS) yield curve for maturity $T_k - t$ from time t perspective. We derive the forward rates $r_{k,k-1}$ as implied by the OIS curve. We assume the fixed rate to be the prevailing OIS rate at the start of contract i corresponding to the trade maturity. Lastly, standard contracts have bi-annual coupons, so $c = 2$, without loss of generality. [23] The LASH risk for swaps via variation margin implies a one-to-one liquidity need with respect to the cash flow sensitivity to interest rates, hence $\Lambda = 1$.

D Data: Additional Information & Summary Statistics

This section of the Appendix provides additional information and summary statistics for the various data sources used in the empirical analysis.

Table D.1 SUMMARY STATISTICS: AVERAGE NET POSITIONS AND LASH RISK

	Repo net borrowing					**IRS net receive fixed**				
Sector	2019	’20	’21	’22	’23	2019	’20	’21	’22	’23
Pension fund	38	64	74	69	48	65	96	101	132	112
LDI	99	121	130	113	73	17	37	40	38	23
Insurer	0	0	0	0	0	10	23	27	72	60
Hedge Fund	-7	11	-3	-34	-15	59	82	-14	-108	-81
Fund	9	7	7	4	4	23	21	11	18	15
Other financial	7	20	18	10	5	-8	-11	-3	-9	-14
	Repo behavioral LASH					**IRS behavioral LASH**				
Sector	2019	’20	’21	’22	’23	2019	’20	’21	’22	’23
Pension fund	8	15	18	16	11	5	11	12	12	10
LDI	22	28	30	26	17	2	5	5	5	3
Insurer	0	0	0	0	0	0	6	6	8	7
Hedge Fund	0	1	-1	-3	-1	1	0	-1	-1	-1
Fund	2	1	1	1	1	2	1	1	0	0
Other financial	2	4	3	2	1	-2	-2	-1	-1	-1

NOTE. Sample: Summary statistics on repo and IRS positions from 2019 to 2023. Values reported in £bn. Repo net borrowing captures the daily average cash borrowing per sector in a given year. The IRS net position captures the average holding of net receive fixed positions (negative values read as net pay fixed) per sector in a given year. Behavioural LASH risk captures the average for each sector in a given year.

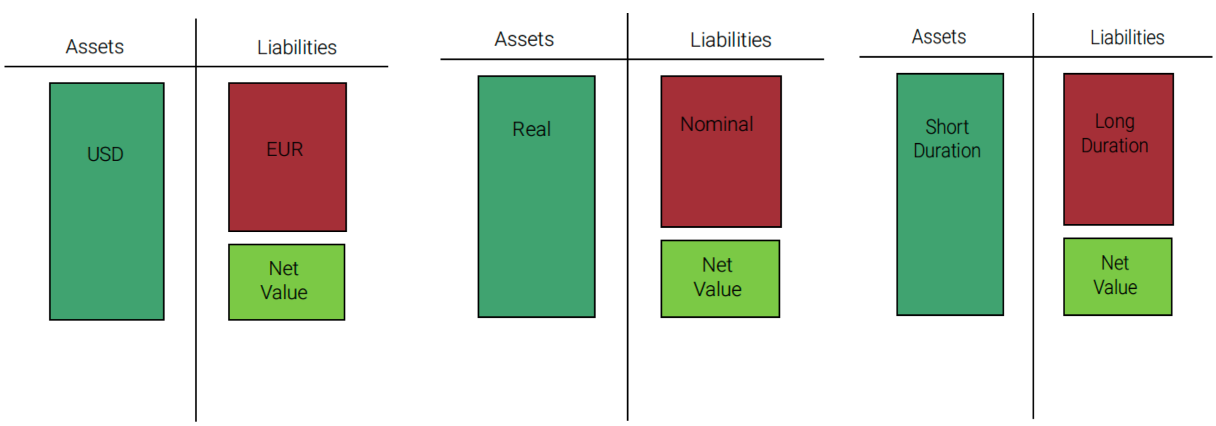
[23] In ongoing work, we incorporate second order effects coming from non-linearity of the yield curve.

Table D.2 SUMMARY STATISTICS: CROSS-SECTIONAL VARIATION OF NET POSITIONS AND LASH RISK

		Repo net borrowing			Repo behavioral LASH		
Sector	N	Mean	Median	Std dev	Mean	Median	Std dev
Pension fund	273	259.3	144.3	388.3	59.4	31.5	89.3
LDI	337	360.6	113.6	1275.5	82.6	25.5	300.6
Insurer	16	45.2	36.7	205.3	6.3	3.6	43.4
Hedge Fund	284	-59.7	-0.6	561.4	-4.0	0.0	65.6
Fund	203	117.6	3.7	626.6	22.9	0.6	143.7
Other financial	13	-10.5	0.0	116.7	-1.1	0.0	21.1
		IRS net receive positions			IRS behavioral LASH		
Sector	N	Mean	Median	Std dev	Mean	Median	Std dev
Pension fund	450	297.9	32.0	1372.2	29.9	2.6	183.9
LDI	231	199.3	48.2	477.1	24.9	3.0	72.6
Insurer	76	971.4	17.0	4034.6	139.2	0.2	691.3
Hedge Fund	149	-231.0	10.0	19493.3	-7.4	0.0	186.4
Fund	869	54.2	0.8	565.0	2.6	0.0	29.4
Other financial	217	-148.8	-6.5	1266.4	-14.1	-0.2	107.3

NOTE. Sample: Firm level summary statistics for repo (2017-2023) and IRS positions (2019-2023). Values are reported in £m, and N denotes the number of firms in each sector of our sample. The mean and median of repo net borrowing capture the total daily cash borrowing in the cross-section, and the IRS net position captures the outstanding net receive fixed positions (negative values read as net pay fixed). Behavioural LASH risk measures the outstanding LASH exposure at firm level in a given day.

Figure D.1 LASH RISK: ADDITIONAL EXAMPLES



a. FX Swaps

b. Infrastructure fund with indexed-linked assets

c. Reduce solvency risk but increase Liquidity Risk

Table D.3 Summary statistics: UK Pension fund balance sheets

	2017	2018	2019	2020	2021	2022	2023
N	10	22	50	65	68	69	10
Total assets (£bn)	115.0	553.7	801.3	1046.9	956.5	876.9	55.1
Total liabilities (£bn)	117.2	560.7	815.2	1099.9	900.0	807.9	50.8
Actuarial assets							
Min	907	933	179	62	145	177	916
Mean	11501	25170	15711	15863	14066	12709	5513
Median	3600	4360	3767	3676	3611	3029	2364
Max	60000	358175	395867	444167	463022	406597	23500
Std deviation	18973	75692	55560	55490	56579	49732	7605
Actuarial liabilities							
Min	1074	1044	193	95	125	162	835
Mean	11724	25485	15985	16665	13235	11709	5078
Median	3673	4501	3499	3642	3511	2960	2195
Max	67500	368981	404974	475130	418665	366574	20300
Std deviation	20615	78046	56894	59416	51396	45031	6659

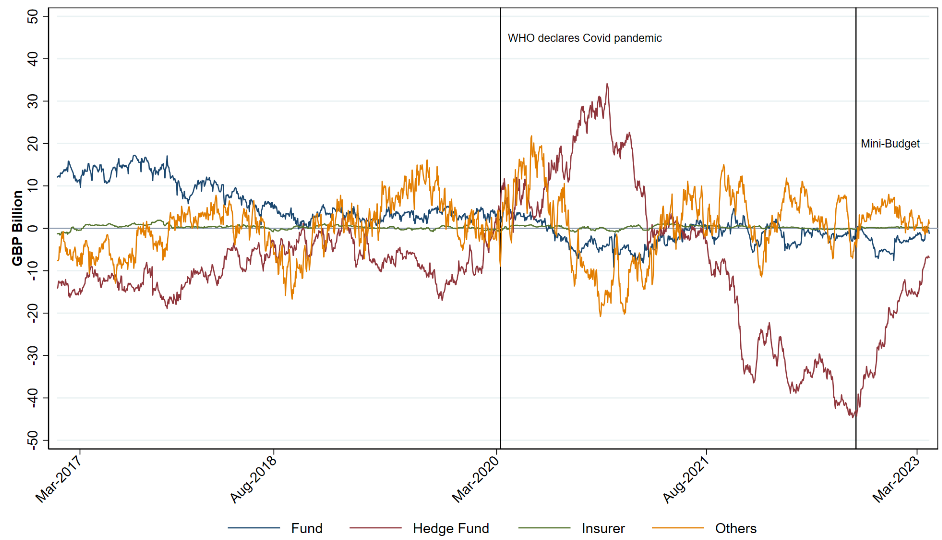
Note. Cross-sectional dispersion and total actuarial values and liabilities for the UK pension funds in our hand-collected sample. Values are reported in £m, unless otherwise stated, and N denotes the total number of pension funds in each year of our sample.

Table D.4 Summary statistics: UK Pension fund funding ratios

	2017	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**
N	13	23	52	70	76	74	11
Underfunded PFs	0.62	0.52	0.56	0.60	0.33	0.27	0.27
Pension fund funding ratios							
Min	0.81	0.78	0.81	0.65	0.80	0.91	0.91
Mean	0.98	1.02	1.00	0.98	1.04	1.06	1.07
Median	0.94	1.00	0.99	0.98	1.04	1.05	1.07
Max	1.31	1.39	1.40	1.49	1.54	1.42	1.23
Std deviation	0.13	0.12	0.11	0.12	0.10	0.10	0.09

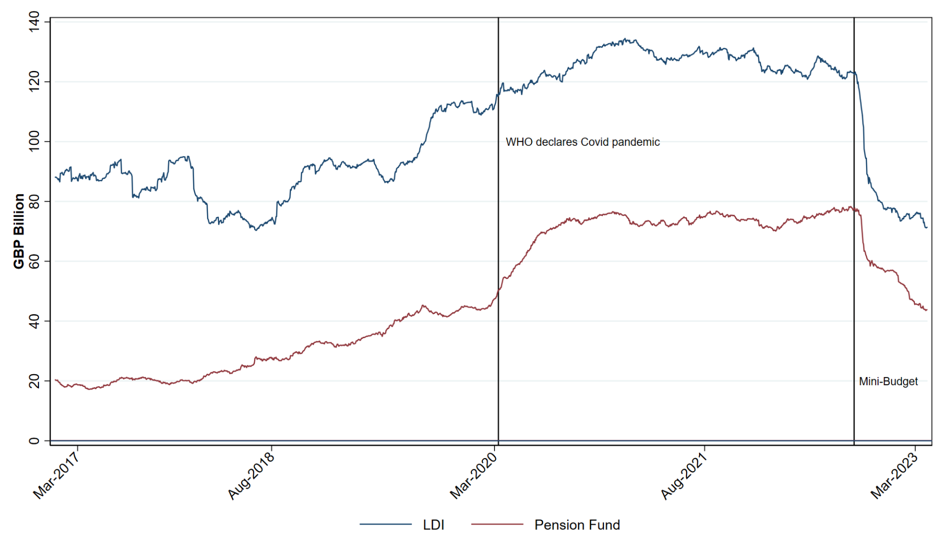
Note. Cross-sectional dispersion of funding ratios for the UK pension funds in our hand-collected sample. N denotes the total number of pension funds in each year of our sample, and the underfunded PFs denotes the share of pension funds with a negative funding ratio (so assets<liabilities) in the given year. A ratio of 1 indicates that the actuarial value of assets exactly matches the actuarial value of liabilities.

Figure D.2 Repo Net Borrowing Stocks Across Sectors



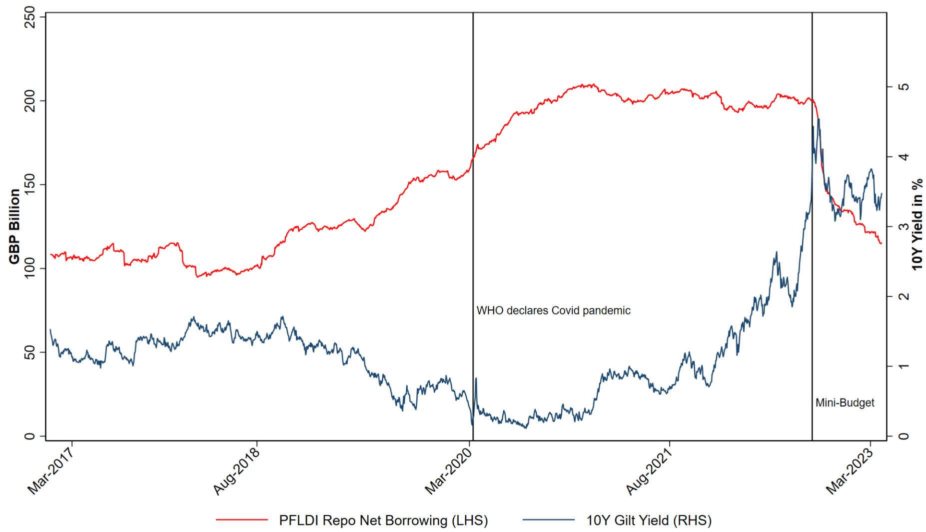
NOTE. Aggregate repo net borrowing across all sector types in £bn. "Others" include sovereign entities and other financials. Source: Sterling Money Market data collection.

Figure D.3 Pension & LDI Funds' Repo Net Borrowing Stocks



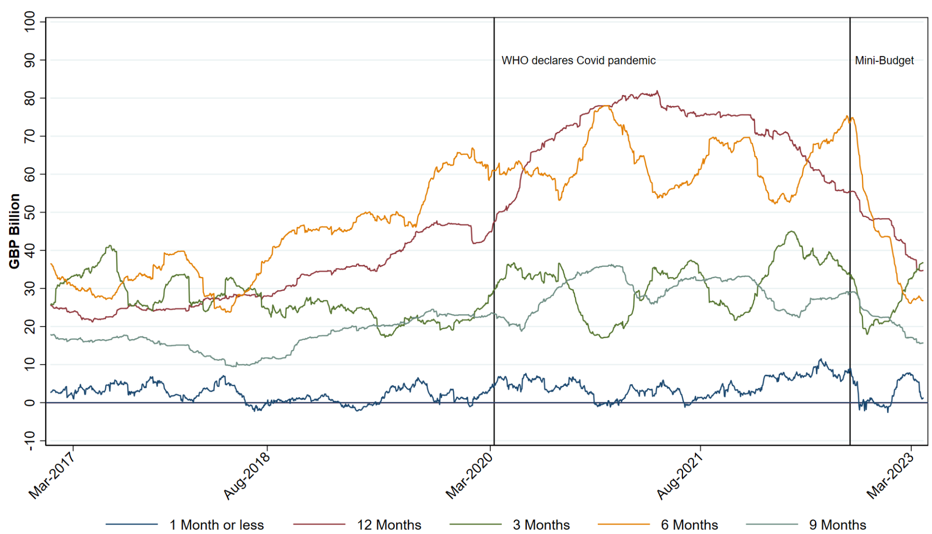
NOTE. Aggregate repo net borrowing stocks of UK pension and LDI funds in £bn. Source: Sterling Money Market data collection.

Figure D.4 PENSION & LDI FUNDS' REPO NET BORROWING STOCKS & 10Y GILT YIELDS



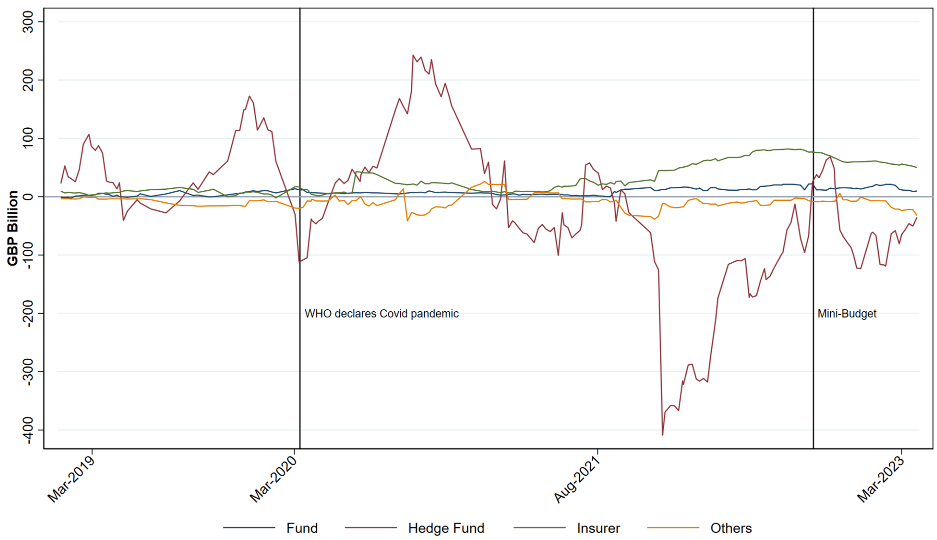
NOTE. Aggregate repo net borrowing stocks of UK pension and LDI funds in £bn and 10Y gilt yields in %. Source: Sterling Money Market data collection & Bank of England.

Figure D.5 PENSION & LDI FUNDS' REPO NET BORROWING STOCKS BY MATURITY



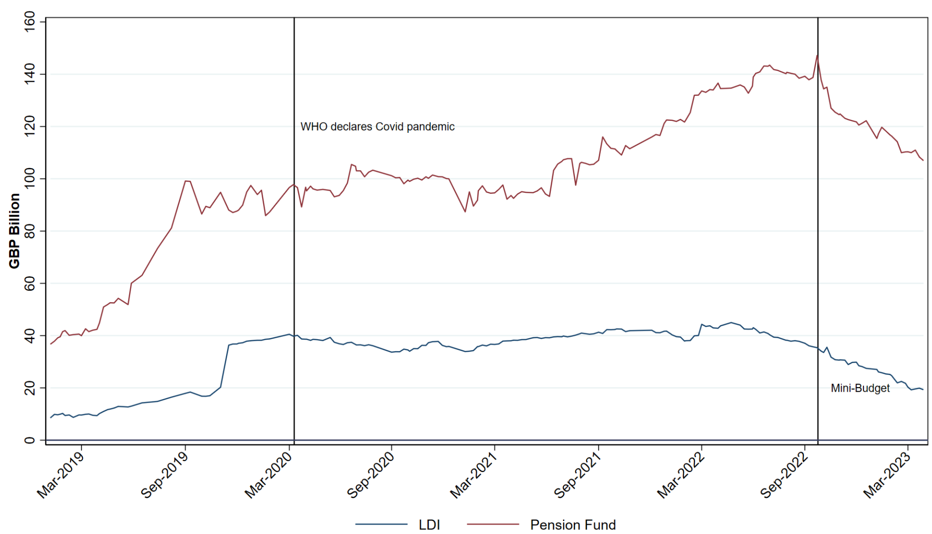
NOTE. Aggregate repo net borrowing stocks of UK pension and LDI funds by the maturity bucket at initiation in £bn. Source: Sterling Money Market data collection.

Figure D.6 IRS Net Notionals Across Sectors



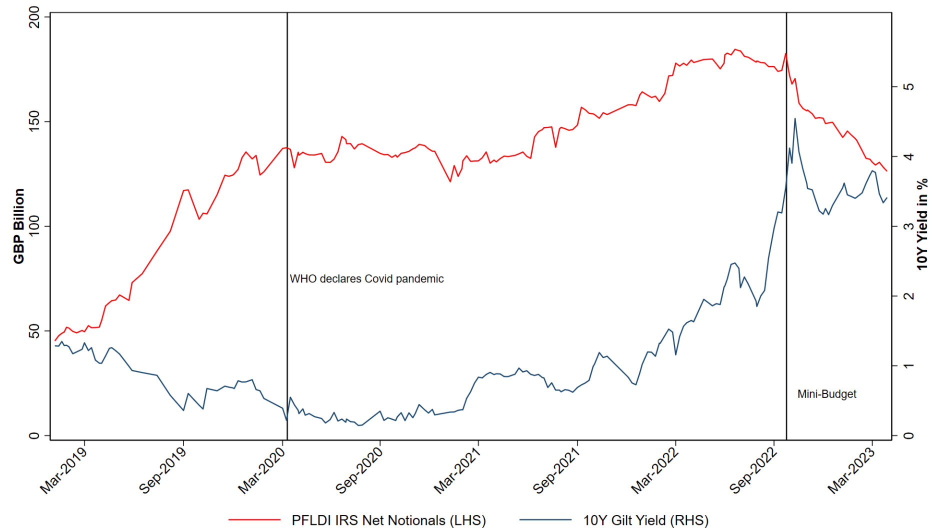
NOTE. Aggregate IRS net notionals across all sector types in £bn. "Others" include sovereign entities and other financials. Source: EMIR Trade Repository Data.

Figure D.7 Pension & LDI Funds' IRS Net Notionals by Sector



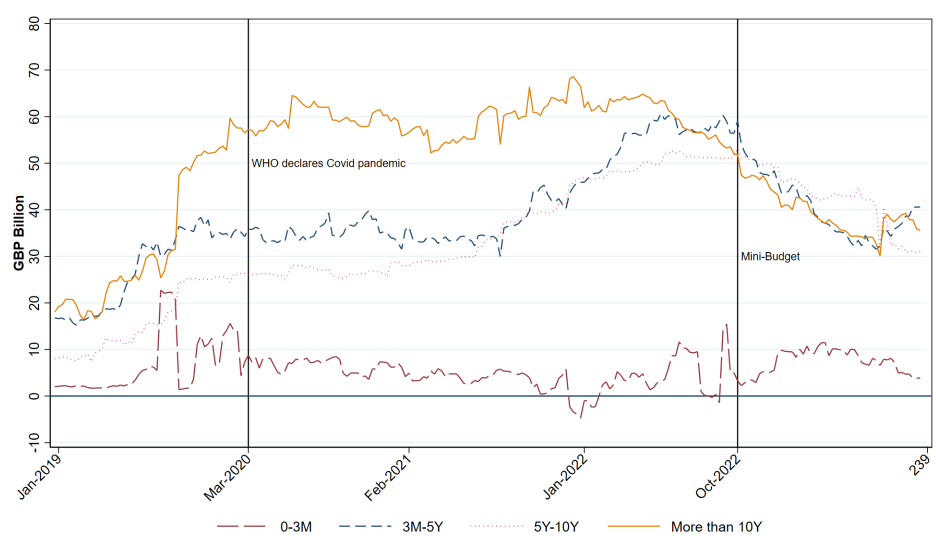
NOTE. Aggregate IRS net notionals of UK pension and LDI funds in £bn. Source: EMIR Trade Repository Data.

Figure D.8 PENSION & LDI FUNDS' IRS NET NOTIONALS & 10Y GILT YIELDS



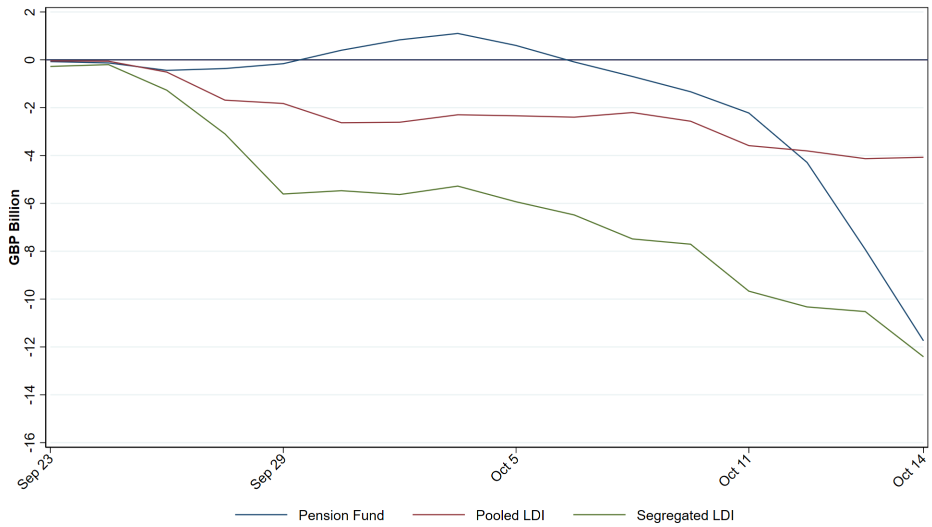
NOTE. Aggregate IRS net notionals of UK pension and LDI funds in £bn and 10Y gilt yields in %. Source: EMIR Trade Repository Data & Bank of England.

Figure D.9 PENSION & LDI FUNDS' IRS NET NOTIONALS BY MATURITY



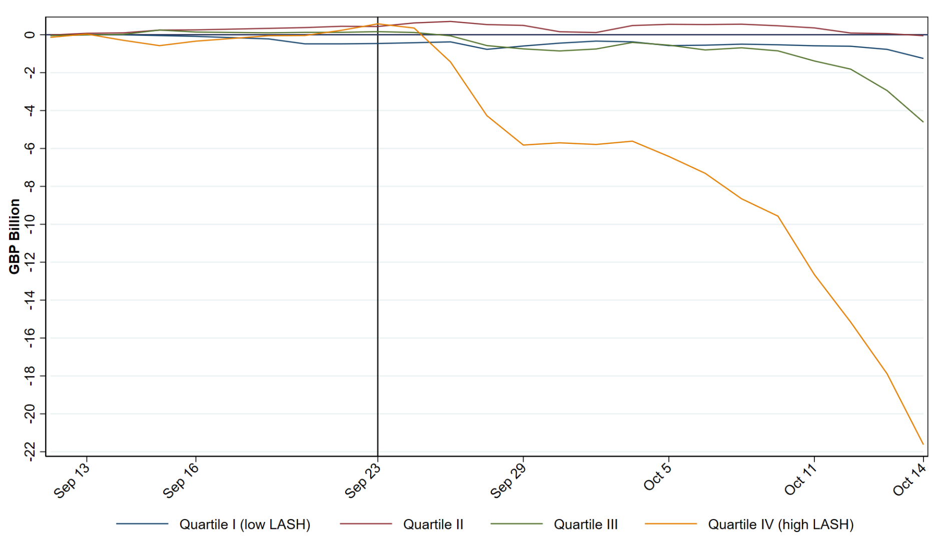
NOTE. Aggregate IRS net notionals of UK pension and LDI funds by maturity bucket in £bn. Source: EMIR Trade Repository Data.

Figure D.10 LDI CRISIS: PENSION & LDI FUNDS' GILT TRADING VOLUMES



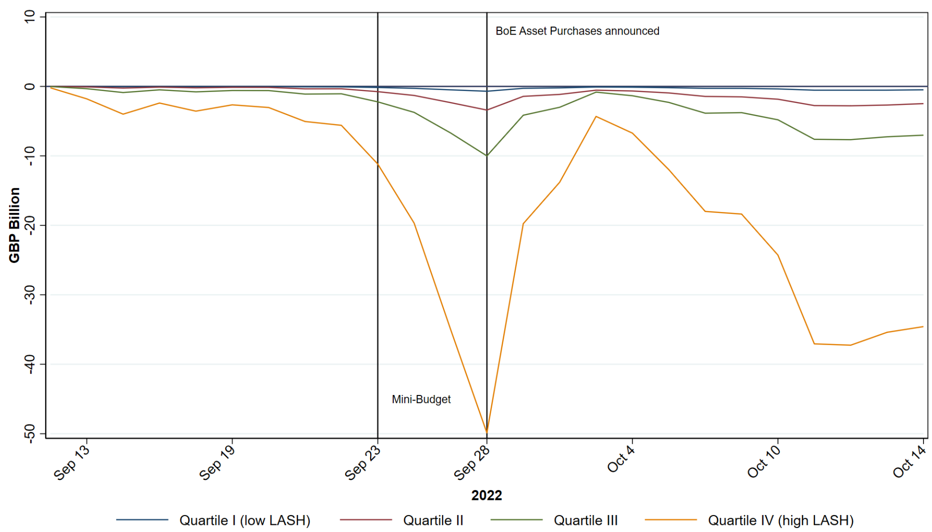
NOTE. Total net gilt trading volumes of UK pension & LDI funds' (split into pension funds, segregated LDI funds and pooled LDI funds) following the Mini-Budget announcement on September 23 up until the end of the BoE intervention on October 14.

Figure D.11 LDI CRISIS: PENSION & LDI FUNDS' CUMULATIVE GILT TRADING VOLUMES BASED ON PRE-CRISIS LASH EXPOSURE



NOTE. Total net gilt trading volumes of UK pension funds and LDI funds, by quartile of their pre-crisis LASH risk: Quartile I captures the non-banks with the lowest pre-crisis LASH exposures, while Quartile IV captures those with the highest pre-crisis LASH exposures.

Figure D.12 LDI Crisis: Estimated Cumulative Changes in the Value of Repo Collateral posted by Pension & LDI Funds



NOTE. Aggregate estimated changes in the value of repo collateral posted by UK pension and LDI funds in £bn during the 2022 LDI Crisis, by quartile of their pre-crisis LASH risk: Quartile I captures the non-banks with the lowest pre-crisis LASH exposures, while Quartile IV captures those with the highest pre-crisis LASH exposures. Source: Sterling Money Market data collection.

E Additional Results

This section of the Appendix provides additional results for the regression analyses in our empirical section.

E.1 Pension Funds' Gross Asset Duration and Solvency

In Section 6, we show that falling interest rates lead to an economically and statistically significantly greater LASH risk taken by investors with low asset duration. Technically, rather than gross asset duration, the duration gap between assets and liabilities (i.e. net duration) is what matters for solvency. In the absence of granular information on the duration of investors' liabilities, however, we use investors' initial gross asset duration (measured via the bonds in their repo collateral portfolio) as a proxy for their duration gap. To test the correlation between net and gross duration, we use our hand-collected balance sheet data for UK pension funds.

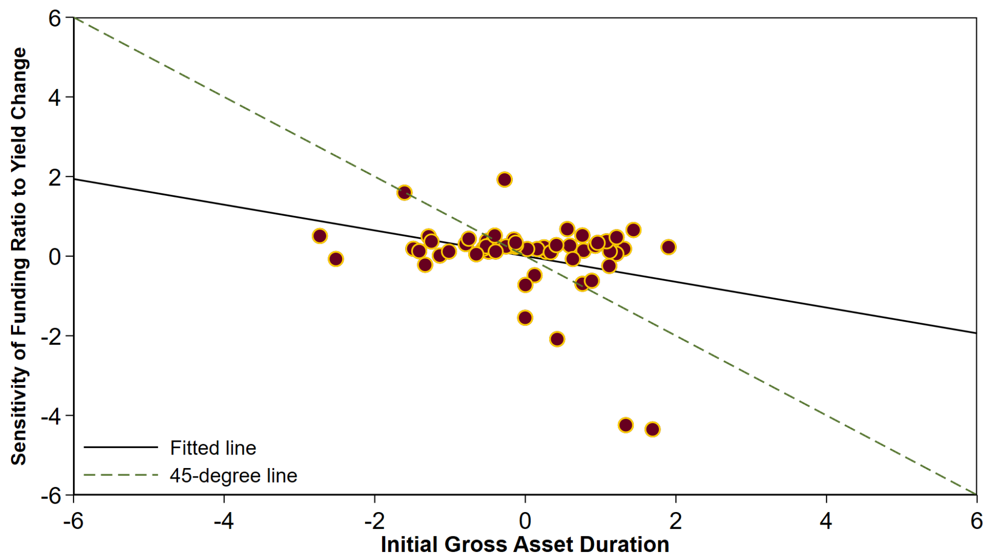
First, we measure the sensitivity of the funding ratios of individual pension funds to changes in the ten-year UK gilt yield using seemingly unrelated regressions:

$$\Delta FundingRatio_{j,t} = \alpha + \beta_1 \Delta Yield_t + +\varepsilon_{j,t}, \tag{E.1}$$

where $\Delta FundingRatio_{j,t}$ measures the annual change in the funding ratio—which is defined as the value of the fund's assets over liabilities—of pension fund j in year t. $\Delta Yield_t$ is the annual change in the ten-year UK gilt yield.

Figure E.1 shows a scatter plot of these estimates in comparison to the gross asset duration of these funds. Each are in standardized units, the funding ratio sensitivities on the vertical axis, and the gross asset duration on the horizontal axis. The association is clearly negative, even though the number of matched funds is relatively small. In other words, the funding ratio of funds with lower asset duration is more sensitive to a change in yields—and hence the solvency of these funds will decrease more sharply in response to lower interest rates relative to funds with higher asset duration. Therefore, the results emphasize the negative correlation between gross and net duration, and support our choice of gross asset duration as a viable proxy for investors' duration gap.

Figure E.1 SENSITIVITY OF PENSION FUNDS' FUNDING RATIOS TO YIELD CHANGES AND GROSS ASSET DURATION



NOTE.This figure shows a scatter plot of the sensitivity of individual pension funds' funding ratios to changes in the yield of the ten-year UK gilt yield, and the funds' gross asset duration. Each are in standardized units, the funding ratio sensitivities on the vertical axis, and the gross asset duration on the horizontal axis.

E.2 Pension & LDI Funds' LASH risk and Gilt Trading Volumes

Table E.1 LASH risk and Gilt Trading Volumes - Pension & LDI Funds only

	(1)	(2)	(3)	(4)
	Net Volume		Sell Volume	
LASH combined	-0.12**		0.10***	
	(0.05)		(0.02)	
LASH Repo		-0.10***		0.08***
		(0.03)		(0.02)
LASH IRS		-0.04		0.05
		(0.07)		(0.04)
Observations	2325	2325	2325	2325
R squared	0.036	0.036	0.044	0.044
Day FE	yes	yes	yes	yes

Note. For each investor, as defined in equation 3 in Section 3, "LASH" is measured as the potential liquidity needs following a 100bps shift in gilt yields, either for repo and IRS exposures combined, or separately for both instruments. The dependent variable is the investor's daily gilt net trading volume on day t in Columns (1) and (2), and the investor's sell volumes on day t in Columns (3) and (4). The dependent variables are transformed using the Inverse Hyperbolic Sine method. The LASH variable is standardized. Clustered standard errors on the day level are reported in parentheses. We include day fixed effects. *** p<0.01, ** p<0.05, * p<0.1. Coefficients corresponding to the constant, control variables and fixed effects not reported.