When Dealers Are the Gatekeepers: Non-Bank Transmission of Central-Bank Interventions

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Abstract

This paper examines how balance-sheet-constrained non-bank investors influence sovereign bond pricing during market stress. Using the 2022 U.K. gilt crisis as a quasi-natural experiment, we show that when margin constraints bind, sovereign bond prices become demand-driven, and safe asset markets fragment. Central bank interventions stabilize prices not only through direct purchases of eligible securities, but also indirectly, via portfolio rebalancing by pension funds—generating spillovers to ineligible assets and mutual funds.

Exploiting cross-sectional variation in pre-crisis gilt exposure across pension funds and in the intensity and timing of Bank of England purchases, we identify exogenous shifts in effective demand. Combining high-frequency gilt transaction data with fund-level holdings and intervention records, we document that more-exposed funds rebalance more aggressively into ineligible securities, raising their prices. These price changes propagate to mutual fund performance. A simple model formalizes this mechanism.

Our findings challenge the conventional view of government bonds as frictionless benchmarks and reveal a new asset-pricing channel: under stress, constrained non-bank demand governs the pricing of safe assets.

JEL: E58,G01, G23, G38.

Keywords: Pension funds, Asset Purchase Programs, Non-Banks.

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1 Introduction

An important question in asset pricing is how institutional investors' demand shapes the level and slope of government bond yields, especially during periods of large, exogenous portfolio adjustments. This paper uses the 2022 UK gilt crisis to study how exogenous shifts in institutional demand affect gilt prices, and portfolio rebalancing across asset classes. We focus on some of the most important investors in government bond market: pension and mutual funds.

Over the past decade, non-bank financial institutions (NBFIs) have become dominant holders of sovereign securities. Episodes of market stress — most notably the 2022 U.K. gilt crisis — have showed that shocks originating in the non-bank sector can rapidly destabilise even the safest government bond markets. Pinter et al. (2024). These events challenge the conventional view of sovereign bonds market as frictionless benchmarks whose prices primarily reflect macroeconomic fundamentals and monetary policy expectations.

This paper provides new evidence that sovereign bond prices become strongly demand-driven when the marginal holders are balance-sheet-constrained non-bank investors. We show that under binding margin constraints, safe asset markets become segmented and prices reflect shifts in constrained investor demand rather than only fundamental valuation. In this case, central-bank interventions affect prices not only via direct purchases of eligible securities but, crucially, also via portfolio rebalancing by pension funds, as this generates spillovers to ineligible assets holdings of other institutional investors (in our case mutual funds). This identifies a new asset-pricing channel through which constrained non-banks demand shapes price formation in sovereign bond markets during negative shocks.

The paper makes four main contributions. First, it provides direct empirical evidence that sovereign bond demand curves become steeper when marginal investors are constrained, and that investor balance-sheet conditions play a first-order role in determining prices even in markets traditionally viewed as deep and liquid. By exploiting heterogeneity in pre-crisis gilt exposure and the intensity of Bank of England purchases, we identify exogenous variations in effective demand and trace their impact on both eligible and ineligible asset prices. We document that funds with higher exposure to the Asset Purchase Programs (APPs) rebalance more aggressively into ineligible securities, increasing their prices, and that this repricing affect the performance of mutual funds holding these assets.

Second, the paper identifies a non-bank transmission mechanism of central-bank interventions. Whereas much of the existing literature emphasises dealer balance-sheet capacity and bank intermediation as the primary channel through which asset purchases affect prices (e.g. Krishnamurthy and Vissing-Jorgensen, 2011; D'Amico and King, 2013; Falato, Goldstein and Hortaçsu, 2021), the 2022 U.K. episode allows us to isolate a distinct setting in which stress originates within NBFIs and interventions operate through intermediated access. Unlike studies of COVID-19-era facilities, which alleviate dealer constraints and restore bank intermediation, our evidence shows that portfolio rebalancing by constrained pension funds is the central mechanism through which price stabilisation occurs.

Third, the paper contributes to the literature on market functioning and portfolio-balance effects by clarifying how investor heterogeneity and balance-sheet constraints govern price dynamics in safe asset markets. Prior work documents portfolio-balance effects of central-bank purchases in conventional APP environments (e.g. Breckenfelder and De Falco, 2024; Greenwood and Vayanos, 2014; Vayanos and Vila, 2021), but focuses on periods characterised by accommodative policy and relatively stable market functioning. In contrast, the 2022 U.K. gilt crisis represents a severe non-bank stress episode in which liability-driven investment (LDI) funds were forced into fire sales under binding margin constraints. This setting allows us to isolate how safe asset prices respond when demand collapses due to funding frictions rather than shifts in macro fundamentals.

Fourth, it provides security-level evidence that directly links institutional investor heterogeneity to cross-sectional gilt pricing during the stress episode. It shows that securities more heavily held by institutions facing greater selling pressure experience significantly larger yield dislocations in the event window and stronger subsequent reversals. This security-level analysis offers a clean asset-pricing test of the demand-curve mechanism: it isolates price impacts arising from exogenous shifts in investor demand. These result strengthens our fund-level results and provides micro-founded evidence on how institutional demand shapes government bond prices under stress.

Empirically, the paper exploits an identification strategy which combines heterogeneity in pre-crisis gilt exposure across pension funds with variation in the intensity and timing of central-bank purchases to construct exogenous shifts in effective demand. This approach allows us to isolate the causal impact of constrained non-bank behaviour on price formation using a difference-in-differences and instrumental-variable framework. By linking gilt transaction data with fund-level holdings and intervention records, the paper traces how balance-sheet constraints translate into portfolio rebalancing and spillover price effects across eligible and ineligible securities.

The paper studies the effects of the shock at both the fund level and the security level. These two levels of observation capture complementary but distinct dimensions of the underlying economic mechanism in our model. Fund-level variation allows us to identify how the liquidity shock affect institutional investors through their portfolios, balance-sheet constraints, and net asset values. However, fund-level alone cannot reveal how these institutional constraints mapped into the pricing of the underlying assets. Therefore, the security-level analysis provides the second, essential component: it traces how predicted selling pressure, as constructed from ex-ante exposure, affect the cross-section of gilt returns and the price of ineligible assets. Together, the two layers of analysis allow us to move from an institutional perspective (which investors were affected and by how much) to an asset-pricing perspective (how demand shocks reach prices).

The paper speaks directly to asset-pricing questions concerning the elasticity of demand for safe assets and the role of investor constraints in price formation. The model formalises a downward-sloping demand curve for sovereign bonds, in which prices react to shifts in private supply and margin constraints amplify price sensitivity when funding limits bind. The model generates testable hypothesis in which prices respond to shifts in private supply through a downward-sloping demand curve (Equation (3)) and balance-sheet constraints amplify price sensitivity when margins bind. Hypothesis I: Pension funds with higher exposure to APP rebalance more assets to ineligible securities during the mini-budget crisis. This increased the price of ineligible securities. Thereafter, we formulate and test the second hypothesis: an increase in the share of ineligible securities held by pension funds can lead to an increase in their prices.The final step tests hypothesis III: an increase in the price of ineligible securities has a positive impact on the cumulative performance of mutual funds. In sum, our framework and mechanism offer a departure from standard asset-pricing frameworks that treat government bond markets as frictionless and investor demand as infinitely elastic.

The paper further distinguishes itself from studies of the COVID-19 shock and euro-area interventions. For instance, Breckenfelder and De Falco (2024) and Breckenfelder and Hoerova (2023) examine ECB asset purchase programmes during COVID-19 and find evidence consistent with portfolio-balance channels, but do not study a setting in which stress originates from leveraged non-bank investors forced into fire sales. Similarly, Falato, Goldstein and Hortaçsu (2021) and Eren, Schrimpf and Sushko (2020) focus on dealer-centric liquidity support. Our paper instead examines a crisis in which the marginal sellers are non-bank pension funds, allowing us to isolate a non-bank demand channel of price formation.

These results show that when marginal investors are leveraged non-banks subject to funding constraints, sovereign bond prices become governed by constrained demand dynamics and spillovers across segmented asset classes. The findings imply that price deviations during stress episodes reflect not only changes in expected fundamentals but also shifts in the balance-sheet capacity and portfolio constraints of key institutional investors.This is very relevant and has important policy implications.

The empirical strategy combines high-frequency gilt transaction data with participant-level holdings and detailed Bank of England intervention records. The identification strategy leverages quasi-experimental variation in gilt exposure and employs an instrumental-variable design to isolate exogenous shifts in portfolio composition. This combination of setting, data and method allows us to trace how central-bank purchases affect prices and portfolio allocation across segmented investor groups in a way not previously documented in the literature.

Finally, the paper sheds light on the broader implications of central-bank interventions in an NBFI-dominated financial system. While purchases can stabilise prices during acute stress, they may also compress yields and incentivise reach-for-yield behaviour, potentially inflating prices beyond fundamentals, De Santis and Holm-Hadulla, (2020). When interventions are unwound, these positions may reverse abruptly, amplifying volatility. By documenting how safe asset prices become demand-driven under constrained non-bank participation, the paper contributes to a deeper understanding of importance and limits of dealer-based interventions in modern sovereign bond markets.

There are important similarities between the COVID-19 shock and the 2022 budget shock in UK. For example both caused severe dysfunctions in the core market for safe assets and central banks had to intervene to restore market functioning,(Breeden 2022). Therefore, our paper directly speaks to recent papers studying the effect of APPs in Europe during the COVID-19 shock. For example,Breckenfelder and Hoerova (2023) study investment grade funds in the US and European markets during the COVID-19 shock and find that the performance of funds with higher ex-ante shares of assets eligible for European central bank purchases improved. They present evidence that asset purchase programs are key tools to mitigate "runs" on funds by investors. Their results also suggest that, liquidity tools in place at the European Central Banks, were not as effective as asset purchase program, because these do not remove the leverage in place in the financial system.

Although the empirical setting of this paper is the UK gilt market during the 2022 crisis, the mechanism documented by our model is structurally general. It applies whenever asset markets are dominated by leveraged non-bank investors subject to binding margin constraints and where interventions operate through intermediated demand channels. Under these conditions, price formation reflects constrained investor demand rather than purely fundamental valuation, generating spillovers across segmented asset classes.

2 What happened in 2022?

2.1 The September 2022 Shock

The September 2022 UK Government's growth plan led to large volatility in gilt market, across all the maturities. Pension funds, particularly funds with liability-driven investment (LDI) strategies, were at the core of the crisis (Breeden 2022). See Appendix A for further information on the pension industry and the UK budget shock.

Many UK funds were in deficit, that is, their liabilities (i.e. the promise of future payments to pensioners) exceeded the assets held on their balance sheets. To meet their future obligations, they invested in long-term gilts, and in 'growth assets' such as equities to generate additional returns. The LDI strategy was instrumental to achieve that goal. But that strategy rests on higher leverage via large purchases of gilts as repo collateral (see online Appendix 1 for detailed explanations).

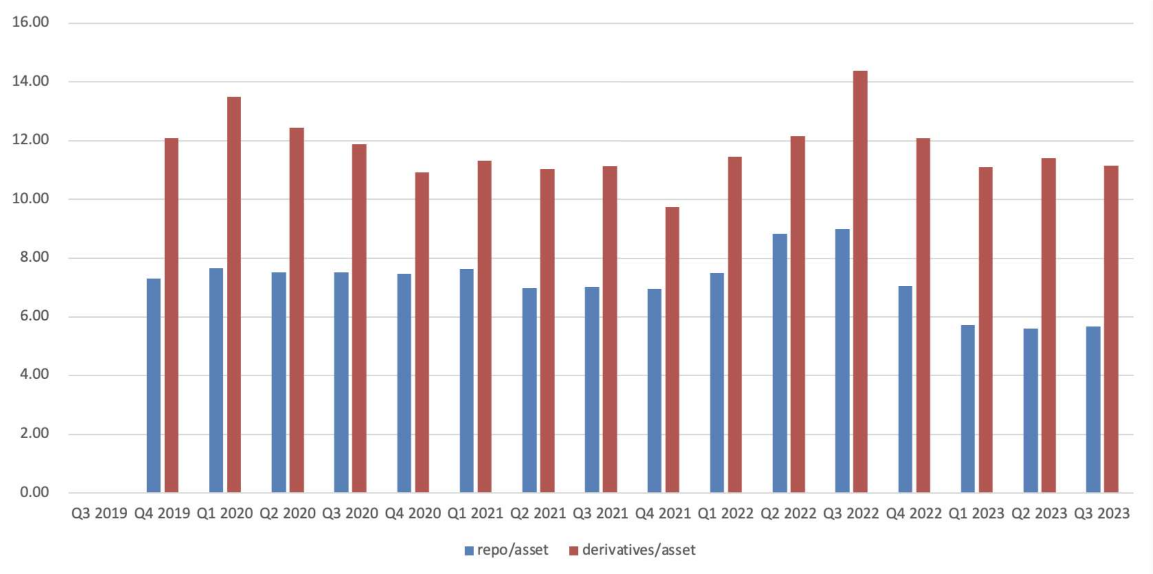
Following the news about mini-budget in September 2022, gilt yields rose sharply, leading to a drop in bond prices. For LDI funds, highly exposed to repo leverage, the significant and rapid fall in gilt prices (a large rise in yields), meant that the asset value decreased significantly.

High leverage, especially via repo, was already apparent since 2021. Pension funds' leverage increased substantially Figure 1. This data is published by The Office for National Statistics (June 2024), and distinguish leverage into two sources: liabilities and derivatives. Liabilities include repurchase agreements held by the fund and derivatives including options, futures, and swaps. Figure 1 shows that both repo leverage (9.01%) and derivatives leverage (14.38%) reached three-year peaks in the third quarter of 2022. But following the mini-budget shock at the end of September 2022, leverage declined significantly. The repo-to-asset ratio was 7.07% in the fourth quarter of 2022, a reduction of 21.53% from the previous quarter. Pension funds were using the gilt's market to increase their leverage (Breeden 2022).

Probably due to the rapid (unexpected) raise in yields, and the slow movement of fresh capital injections into pension funds and mutual funds (Pinter et al. 2024), deleveraging took place primarily

Figure 1: Leverage of Funded Occupational Pension Schemes in the UK

This figure depicts the fund's leverage from Q4 2019 to Q3 2023, according to the 'Financial Survey of Pension Schemes' published by the Office for National Statistics. The fund's leverage is represented by quarterly data on the pension fund's repo-to-assets and derivatives-to-assets ratios.

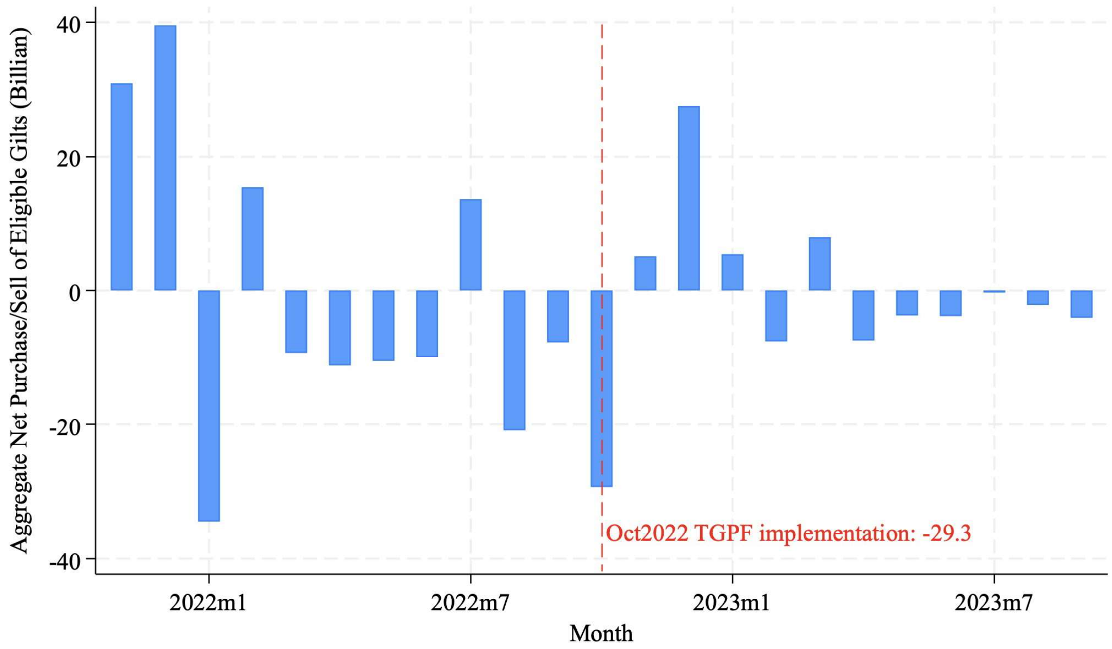


Source: Office for National Statistics. *Funded occupational pension schemes in the UK: July 2019 to September 2023: Reference table*. Published 21 March 2024.

through the sale of UK government bonds Figure 2.[1] During October 2022 there was a significant sale of eligible gilts by pension funds. The amount was significant and about £29.3 billion.

Figure 2: Aggregate gilt buy/sell for pension fund

This figure shows the aggregate amount of monthly buying and selling of targeted eligible gilts purchased by central bank during the minibudget crisis by pension funds from November 2021 to September 2023.



Source: Holding data from Morningstar Direct and calculated by authors.

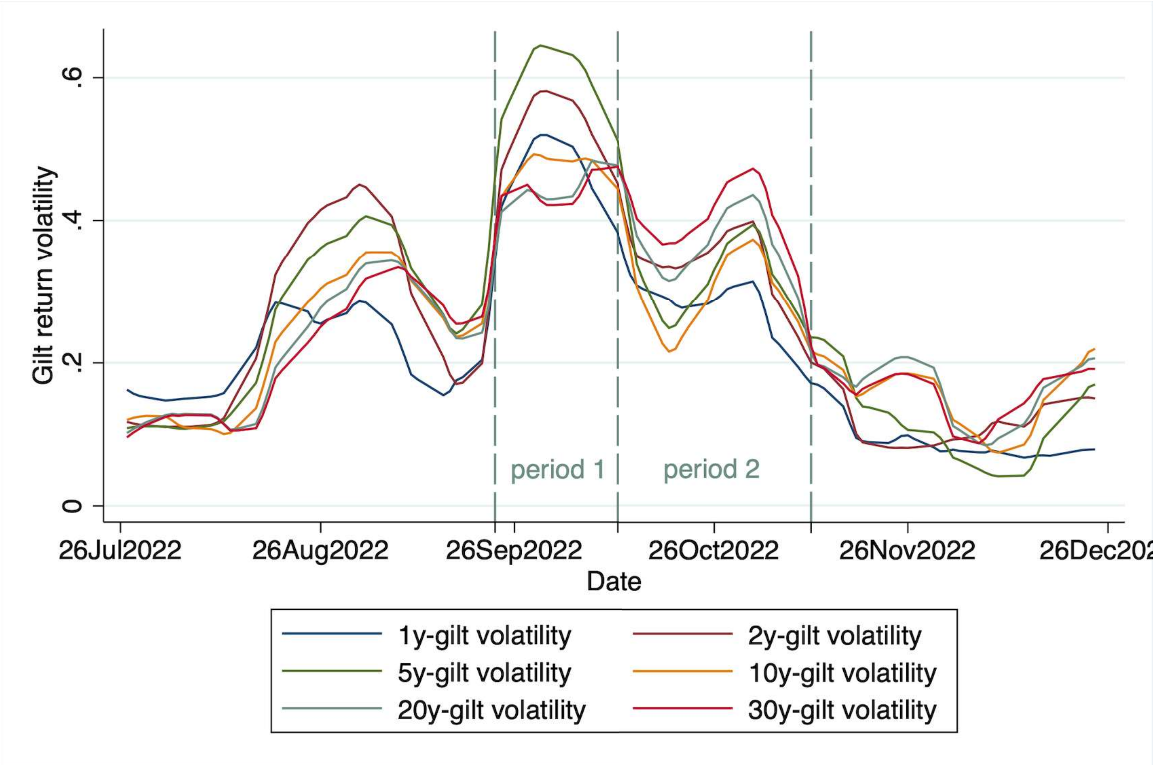
Figure 3 shows the gilts' yield volatility during and after the mini-budget. Period 1 is the date of the mini-budget 23Sep2022 announcement when gilts volatility increased significantly, and, crucially, sharply across all maturities. Volatility on short maturity was higher than long maturity during this period. In period 2, we note that volatility on short maturity gilts decreased significantly, but not the one on long-maturity gilt, especially 20-year and 30-year.

The cumulative performance of pension funds fell sharply from 23 September 2022, following

[1]The significant sale of UK government bonds (gilts) by UK pension funds in January 2022 came against the backdrop of a major shift in the Bank of England's monetary policy. Before that, following inflationary pressures, the BoE raised its benchmark interest rate twice, in December 2021 and February 2022, while ending its massive quantitative easing (QE) policy. This series of actions may have led to a rapid rise in market interest rates, resulting in a significant increase in UK government bond yields.

Figure 3: Volatility of gilts of different maturities, August-December 2022

This figure shows the 10-day moving average of return volatility of gilts on different maturities, including 1-year, 2-year, 5-year, 10-year, 20-year and 30-year gilts. To establish gilt return volatility, we calculate the rolling standard deviation to represent the volatility of gilts based on their daily returns. For each trading day of a gilt, take the yield data of the last 20 trading days, calculate their standard deviation within these 20 days, and record this result as the 'rolling standard deviation' or 'rolling volatility' of the gilt on that day. Second, we calculate the moving average of 'rolling volatility' over a 10-day time window. This makes the volatility trend of gilts more visible. The daily return data for gilts are downloaded from Bloomberg.

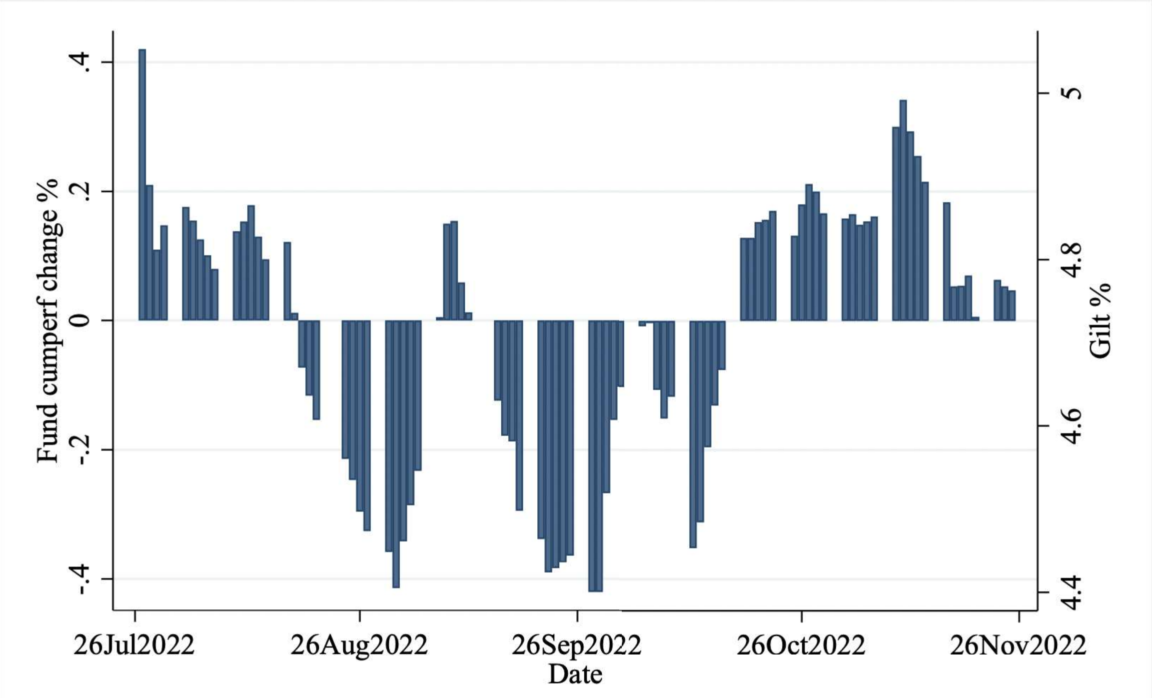


Source: Bloomberg and authors calculation.

the mini-budget announcement, and continued to do so for four weeks. The downward trend slowed at the beginning of October, when the Bank of England implemented a temporary gilt purchase facility.

Figure 4: Change in cumulative fund performance and long-term gilt yields

This figure shows the change in the cumulative performance of funds from August 2022 to December 2022. The cumulative performance of the fund is calculated based on the 4 January 2022 NAV. The change in cumulative performance is the cumulative performance on day-t minus the cumulative return on dayt-1. The change in cumulative performance is shown as moving averages over a 10-day window to smooth out fluctuations to make the trend more visible. The funds' NAV datas are downloaded from Bloomberg.



Source: Bloomberg and authors calculation.

3 The data

3.1 Sample construction

We use two main sources of data. Pension (mutual) funds' data is obtained from Morningstar. It is a leading rating agency with independent investment research on global capital markets and funds. Net asset value (NAV) is taken from Bloomberg by using the ISIN code of the fund and matching manually the sample funds with their ISIN codes. We also use Bloomberg to collect data for NAV and Morningstar for funds lists and funds holding information, and we manually match the information of these two data-sets to construct our sample. We restrict at the funds before 2020 ensuring that they already have a stable asset allocation at the time of the crisis. The sample period for which we obtain daily frequency data is from 2019 to 2023. We use daily frequency unless we do not specify it differently.

Table 1 summarizes our sample. We restrict the currency to GBP as well as the market to the UK, to ensure that funds were, to some extent, affected by the Mini-budget shock. For mutual funds, we used the fund category of 'GBP mixed assets funds' as defined in the Morningstar classification. In this way, we obtain 11810 pension funds and 794 mutual funds. Additionally to that, we select investment grade funds to control for credit risk. In this way we have 10563 pension funds and 254 mutual funds. After merging with ISIN code and NAV data, the final number for pension funds and mutual funds are 480 and 277 respectively.

3.2 Funds descriptive statistics

Table 2 shows the characteristics and asset allocation information for pension funds. In terms of return performance, pension funds holding higher proportion of government bonds have annually compounded returns of around -28.71%, indicating an overall underperformance of funds in 2022. The government asset allocation of pension funds is about 42.69% of their assets in UK, therefore they have a significant UK market exposure. Funds' information are based on 31 Aug 2022, and the annually compounded return is for 2022.

Table 1: Data Screening and Merging Process

	Pension funds	Mutual funds
1) Raw sample (before 2020, currency GBP). Market: United Kingdom; asset type: mixed asset; active; pricing frequency: daily[a]	11 810	3883
2) Average credit quality: above BBB–; fund-class family total market value: above 3000 million.	10 563	794
3) Merged with ISIN code[b]	9265	254
4) Merged with NAV data	2907	227
5) Merged with holding information[c]	480	227

[a] We restrict the market to the UK to ensure that the funds were to some extent exposed to the Mini-budget Crisis. We use bond asset funds for our empirical analyses as they are most affected by the Mini-budget Crisis. We only use funds where Bloomberg provides daily frequency for the NAVs.

[b] In Morningstar, not all funds have ISIN code. The key NAV data can only be downloaded from Bloomberg by searching for the ISIN code.

[c] Holding information including the share of asset category allocation, fixed income sector asset and asset regions.

Notes: This table describes how the data is screened and merged. The raw sample for pension funds is listed from Morningstar. The base date to all sample pension funds is before 2020. The sample is cleaned as well as screened and then merged with (i) ISIN code, (ii) net asset value-NAV data and (iii) asset holding information. The table shows the numbers of pension funds at each step.

Table 2: Pension Funds Summary statistics

	N	Mean	SD	p25	p50	p75	Min	Max
lower government bond holdings group								
Annually compounded return (%)	239	21.93	10.18	-25.75	-21.73	-19.41	-39.36	4.24
Government bond holdings (%)	239	2.08	1.49	0.82	1.52	3.66	0.0011	5.48
Total net asset (£ million)	239	2520.31	5997.71	2.32	13.75	165.41	0.0011	22182.02
Risk	239	42.48	14.44	32.02	43.89	50.73	1.30	78.32
higher government bond holdings group								
Annually compounded return (%)	241	-28.71	19.57	-37.05	-24.74	-20.83	-58.76	1.83
Government bond holdings (%)	241	42.69	34.99	8.46	37.50	85.02	6.01	85.98
Total net asset (£ million)	241	3177.71	6651.34	3.40	48.25	200.88	0.00	3990.11
Risk	241	44.05	18.13	32.55	36.56	59.87	3.29	126.04
total sample								
Annually compounded return (%)	480	-25.36	16.15	-26.59	-23.04	-20.90	-58.76	4.24
Government bond holdings (%)	480	22.47	32.06	1.52	6.71	37.50	0.02	85.98
Total net asset (£ million)	480	1426.37	4414.99	2.67	19.08	200.88	0.00	22182.02
Risk	480	43.29	16.44	32.41	38.68	51.88	3.13	126.04

Notes: This table provides descriptive information about sample funds that pass the screening process in Table 1. All fund information is based on 31 August 2022.Among other things, bond holdings will be the key measure by which we group our sample in the empirical section. The reason we choose 31 August 2022 as a cross-section time for descriptive statistics for the fund sample is because the Mini-budget occurred on 23 September 2022. We need to understand the characteristics of the fund sample in the face of the crisis.

Table 3 shows the characteristics and the asset allocation of mutual funds. We use mutual funds data in Section 6 to study spillover effects from pension funds to mutual funds during the crisis. In terms of return performance, mutual funds have similar annually compounded returns of around -13.05%, indicating an overall underperformance of funds in 2022. With regard to the asset allocation, firstly, the proportion of bond holdings in the asset class is at about 38%, suggesting that they have a significant exposure to this market. Secondly, mutual funds hold about 23.74% of their assets from UK, indicating that they also have a significant exposure to the UK. All funds information are based on 31 Aug 2022, and the annually compounded return is for 2022.

Table 3: Mutual Funds Descriptive Information

	Pension fund			
	Mean	25th Pct	50th Pct	75th Pct
Fund characteristics				
Bond holdings (% of total asset)	38.02	22.69	36.60	52.96
Annually compounded return (%)	-13.05	-8.74	-12.95	-15.24
Fund asset allocation (% of total)				
Stocks	53.03	38.86	54.97	68.30
Bonds	38.02	22.69	36.60	52.96
Cash	3.48	0.85	2.20	5.64
Other	5.06	1.31	3.09	5.46
Fund portfolio region (% of total)				
United Kingdom issuers	23.74	13.67	23.86	30.19
Eurozone issuers	8.04	6.10	7.43	9.70
United States issuers	42.50	34.59	40.44	51.91

Notes: This table provides descriptive information about sample funds that pass the screening process in Table 1 up to step (6). All fund information is based on September 2022, where the annually compounded return is for 2022. Among other things, bond holdings will be the key measure by which we group our sample in the empirical section. The reason we choose 1 September 2022 as a cross-section time for descriptive statistics for the fund sample is because the Mini-budget occurred on 23 September 2022. We need to understand the characteristics of the fund sample in the face of the crisis.

We obtain fund-level holdings from Morningstar Direct, which reports security-level positions (ISIN, weight held by fund relative to its total assets and maturity date). Each gilt is assigned to one of seven maturity buckets — 0-5 years, 6-10 years, 11-15 years, 16-20 years, 21-25 years, 26-30 years, and 30+ years — matching the BoE's gilt purchase groups. For each pension fund p, we compute pre-event weights w_{ig} by summing up the weight for all the bonds that assigned in bucket g on 31 August 2022. These weights are merged with BoE purchase amounts s_{gt} by bucket to form the predicted exposure instrument $Z_{pt} = \sum_g w_{pg} s_{gt}$. The resulting matched sample covers 391 pension funds ($\approx 81\%$ of total DB assets) and 39 mutual funds, spanning 2 months and representing £103.38 billion AUM. Funds with missing or zero gilt holdings are retained with w_{ig}=0.

3.3 Some other sources of data

We use the Financial Survey of Pension Schemes, which provides references table for Funded Occupational Pension Schemes in the UK from July 2019 to September 2023. The Financial Survey of Pension Schemes (FSPS) is a quarterly survey conducted by the Office for National Statistics (ONS) in the UK. This survey collects detailed information about the income, expenditure, transactions, assets, and liabilities of UK-funded occupational pension schemes.

We also use the PPF 7800 Index which is a key statistical indicator published by the UK's Pension Protection Fund (PPF) to measure the latest estimated funded status of all qualifying defined benefit pension schemes, based on a Section 179 basis[2]. The index is published on a monthly basis and follows the standards of the UK Statistics Authority. It includes the size of the pension scheme's assets and liabilities, surplus and deficit, from March 2006 to May 2024.

We download 1-year, 2-year, 5-year, 10-year, 20-year and 30-year gilts daily returns since 01Jan 2019 to 31Dec 2023 from Bloomberg.

From Morningstar direct, we obtain data on the long-term & short-term debt capitalisation ratios of selected pension funds called debt-to-cap(long) & debt-to-cap(short), which can be used as the measure of a pension fund's financial leverage. The data is daily frequency, and we download it for the period from 1 January 2022 to 31 May 2023, a total of one year and a half.

[2]Section 179 refers to section 179 of the UK Pensions Act 2004. This provision sets out a standardised methodology for assessing the funded status of pension schemes. The PPF uses Section 179 assessments to determine whether to take over a scheme and to set the premiums that companies pay to the PPF.

About Bank of England asset purchase facility - financial stability gilt portfolio purchases, we obtained facility information from Bank of England offcial website[3]. Long-dated Gilt purchase operational results and Index-linked gilt purchase[4] operational results can be download from it, which offer detailed list of gilts purchased by BoE during Mini-budget with the magnitude data.

4 Can Central Bank APP reach NonBanks during times of stress?

An important question is whether central-bank asset-purchase programmes reach beyond the securities they directly target and reach nonbank investors during periods of market stress. In stressed markets, nonbank institutions such as pension funds and mutual funds often face sharp balance-sheet constraints that affect their trading capacity and valuations. If central-bank purchases alleviate these constraints or reshape expected demand curves, their effects may propagate to nonbanks even without direct transactions. IN what follows, we focus on the APP implementation, but we also focus on the announcements. This distinction is important as a APPs' announcement and implementation may work via different channels. For example, the former via a signalling channel, while the latter via a portoflio balance channel (Busetto et al. 2022).

Furthermore, and particularly relevant in the case of mutual funds, APPs can help to mitigate redemption dynamics which, in general, amplifies the effects of negative shocks. Therefore APPs are also particularly relevant for this corner of financial market.

In the next sections, we use the UK budget's shock in 2022 as a laboratory to study these important issues. Differently than other shocks, studying the effects of APPs during UK gilt market shock of 2022, provides a clearer shock. The 2022 shock was a market-driven event, free from many of the confounding economic factors present during the pandemic. Furthermore, it was a

[3]Bank of England offcial website about asset purchase facility. https://www.bankofengland.co.uk/markets/bank-of-england-market-operations-guide/our-tools

[4]Long-dated Gilt purchase operational results. https://www.bankofengland.co.uk/-/media/boe/files/markets/other-market-operations/long-dated-uk-government-bond-purchase-time-series.xlsx

period where the BoE was carrying a quantitative tightning policy.

We start designing a simple DID approach to analyze the impact of the gilt market and the Bank of England's APP on the cumulative performance of pension funds during the mini-budget crisis.

4.1 Empirical Identification

We use fund-level data to obtain a fund performance indicator to analyze the role of the Bank of England's large-scale purchases over the 2022 mini-budget period — the net asset value (NAV). We conjecture that APPs can break the dawnward spiral of prices and have positive effects on funds' performance. In this section, we use daily data to construct cumulative fund performance, normalized to September 1, 2022.

$$\Delta\mathrm{NAV}_{i,t} = \frac{\mathrm{NAV}_{i,t} - \mathrm{NAV}_{i,t-1}}{\mathrm{NAV}_{i,t-1}} \tag{1}$$

$$\mathrm{Performance}_{i,t}^{\mathrm{cum}} = \left(\prod_{k=0}^{t} \left(1 + \Delta\mathrm{NAV}_{i,k}\right) \right) - 1 \tag{2}$$

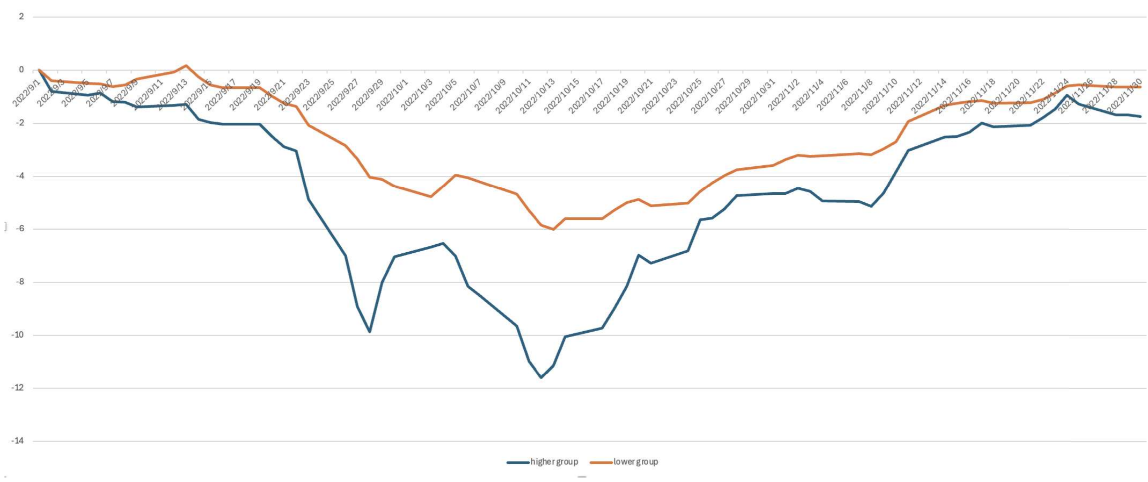
To assess the impact of the APP on fund performance, we focus on funds that satisfy two criteria: (i) they invest in investment-grade securities, and (ii) they hold a nonzero share of UK securities in their portfolios; the latter ensures material exposure to the Bank of England's interventions.

These criteria will be useful for identification. We split funds into two groups by ex-ante exposure to the APP: funds with above-median shares of gilts in September 2022 (high-exposure) and those with below-median shares (low-exposure). As shown in Figure 5, the performance of the two groups of pension funds followed a strikingly similar trend prior to the APP's action on October 3, 2022. In Figure 5, the blue (orange) line traces the performance of funds with higher (lower) gilt shares, with performance normalized to zero on September 1, 2022. Performance in both groups starts declining around September 13, 2022; the decline accelerates with the onset of the crisis around September 23, reaching about −3% by September 28, 2022. In other words, focusing on investment-grade funds delivers an ex-ante homogeneous set of funds, allowing us to zoom in on the effects of central-bank interventions during late September 2022.

Figure 5: Cumulative Performance of Two Pension Groups

We use the same approach to construct the performance measure for mutual funds, see the Online Appendix 4. As shown in Figure 6, the performance of these two groups of mutual funds followed a similar trend prior to the mini-budget on September 23, 2022.

Figure 6: Cumulative Performance of Two Mutual Groups



4.2 A Difference-in-Differences set-up

To further mitigate confounding factors, we compare pension funds across time and across gilt holdings in a difference-in-difference (DiD) set-up. To assess the dynamics of fund performance, we estimate the following specification:

$$\text{performance(cum)}_{i,t} = \beta_0 + \sum_{k=1}^{5} \beta_k \, \text{CrisisPeriod}_{k,t} \times \text{Higher}_i + \sum_{k=1}^{5} \varphi_k \, \text{CrisisPeriod}_{k,t} + \mu_i + \varepsilon_{i,t} \quad (3)$$

where $\text{performance(cum)}_{i,t}$is the cumulative fund performance, scaled[5] to September 1, 2022. The dummy variables $\text{CrisisPeriod}_{k,t}$ take on the value of 1 for period k and zero otherwise. We consider 5 periods: crisis onset (Sep 23– Sep 27), an asset purchase announcement period (Sep 28 – Oct 2), two purchase implementation periods and the end period. The two implementation periods are action5 (Oct 3 – Oct 10), and the periods action10 (Oct 11 – Oct 14). The variable Higher_i is equal to 1 if a fund held, at the end of August 2022, above-the-median amounts in gilts as a percentage of total portfolio. Lastly, μ_i are fund level fixed effects and $\varepsilon_{i,t}$ is the error term. In this section i refers to pension funds.[6]

Our DiD specification identifies the causal effect of the BoE's gilt purchases on pension funds' performance under a standard parallel-trends assumption: absent the mini-budget shock and the subsequent APP, high- and low-gilt-exposure funds would have followed similar trends in cumulative performance, conditional on fund fixed effects and controls. We view this as plausible in our setting. First, the treatment is a sharp, policy-driven event: the September 2022 mini-budget and the emergency BoE purchases are unlikely to be anticipated by pension (mutual) funds and were unrelated to their idiosyncratic performance before September 2022. Second, as we said, we focus on investment-grade funds with non-zero UK exposure, yielding a relatively homogeneous sample of institutions that move closely together before the shock (Figure 5). Finally, we show

[5]Scale: using the NAV on 1 September 2022 as the benchmark, record the cumulative performance on that day as 0. Calculate the cumulative performance of the fund after that date.

[6]The online appendix 4 focuses on mutual funds. Same specification is used for mutual funds including DiD, event-study, parallel-trend plots, portfolio sorting.

that remaining pre-trend differences can be largely accounted for by a small set of observable characteristics – in particular size and leverage – and that DiD results are robust to their inclusion as time-varying controls and to a battery of placebo tests.

Our specification, in this section, uses fund-level outcomes (returns, flows, leverage, etc.) rather than bond prices. Compares high-exposure funds (to eligible gilts) with low-exposure controls, before vs after the BoE's 2022 gilt purchases. It includes fund fixed effects, event-study parallel-trend plots, and robustness with alternative windows.[7] Tests parallel trends visually and statistically, showing no significant pre-treatment differences (see Fig. 7 and Fig. 8).

We aknowledge possible methodolical limitations of our specification. For example, although pre-treatment trends are statistically indistinguishable, high-exposure funds may differ structurally from low-exposure funds in leverage and investment. We therefore interpret the DiD estimates as capturing the average causal effect for this specific group of highly exposed institutions rather than a fully "homogeneous fund population."

Because the BoE's actions restored overall gilt-market liquidity, low-exposure funds may also have experienced indirect improvements. While the DiD estimates should be viewed as conservative lower-bound effects of the intervention on directly exposed funds, we also consider this rebalance effect in several ways in the next sections.

We checked if some funds may have adjusted positions before the official start of the BoE purchases (anticipation). But our results using the announcement do not support this conjecture. Furthermore the results using our DiD strategy in this section and appendix, are furtehr extended using an instrumental variable approach in the Section 6 of this paper, confirming the main results in this section.

[7] In Appendix B, we categorised funds into three groups based on their bond holdings, illustrating the pressure exerted on cumulative fund performance during the crisis under varying exposure levels. As part of the robustness analysis for our results.

4.3 Empirical results

Table 4 shows the results for the impact of the APP on daily cumulative performance of pension funds. Columns (1) consider funds that have below-the-median holdings of gilts, while columns (2) provides estimates for the funds that have above-the-median holdings of gilts. Columns (3) gives differences between the funds with higher versus funds with lower gilts holdings.

Table 4 documents that both groups of funds experienced a large drop in performance since the onset of the crisis (columns 1 and 2).The cumulative performance of the group of pension funds holding a lower percentage of gilt fell by 2.25% at the onset of the Mini-budget crisis. Pension funds holding a higher proportion of gilt faced a worse negative impact. Their cumulative performance fell by 5.45%. The key results are in the differential effects between the two groups (columns 3). There is a significant difference between the two groups during the crisis onset.

Pension funds more exposed to gilts are more severely affected. Their cumulative performance was 3.2 p.p. lower than that of pension funds holding less gilt. It is interesting to note that there is no significant difference between the two groups during the announcement of the APP. This suggests that announcement "per se" did not work to mitigate the effects of the shock. A large performance gap between the two groups emerges after the APP 5 billion/day action on Oct 3, 2022: funds with higher gilt holdings recovered by an additional 0.73 p.p. (at the 99% confidence interval) than funds with lower gilt holding (column 3). When the APP size increases to 10 billion/day, the additional recover expanded to 0.51 p.p. at a confidence interval 99%.

These results are economically sizeable. The estimated 0.73 percentage-point cumulative outperformance of high-gilt-exposure funds implies substantial mark-to-market benefits. A 0.73% increase in net asset value, the implied gain equals 0.0073×AUM. For a £1 billion pension fund, this translates to about £7.3 million, while for the sector as a whole (≈ £150 billion of affected assets), it amounts to roughly £1.1 billion in additional value. These back-of-the-envelope figures suggest that the BoE's intervention generated a material improvement in non-bank balance sheets, mitigating forced asset sales and margin stress. The magnitude highlights the real economic relevance of the portfolio-balance transmission channel identified in the next sections.

If we compare this to the impact on bond funds' cumulative performance of the market liquidity shock caused by the March 2020 epidemic outbreak and the massive asset purchases (PEPP) announced by the ECB on 18 March (Breckenfelder and Johannes, 2021), we note two main differences 1) The cumulative performance of European bond funds all fell significantly during the epidemic phase, and there was no statistically significant difference in the magnitude of the fall. In contrast, in the UK, pension funds holding a large proportion of gilts were hit harder during the UK mini-budget crisis. This suggests that, unlike the full-blown impact of the epidemic on the bond market, the mini-budget shock in UK, initially, affected only the gilt market. Pension funds holding a significant proportion of gilts, the ones relying on LDI strategies, became the main target of the crisis.

While European bond funds reacted significantly when similar temporary policies were issued, UK pension funds did not show a different performance. However, the similarity lies in the fact that both the BoE's and the ECB's temporary purchase facilities were significantly supportive and successfully penetrated non-bank financial intermediaries at the time they were implemented. In the Appendix Appendix B, we also complement these results by using alternative methodologies. For example portfolio sorting based on funds' bond holdings. We obtain very similar results.

The online Appendix 4 shows results for mutual funds. We find that mutual funds with higher gilt holdings experienced significantly greater performance deterioration at the onset of the crisis. Again we find that the announcement of the Bank of England's APP alone did not mitigate the risk. We conjecture that this is the case because purchases go beyond signaling by influencing the supply and demand for assets. This triggers a different channel for how APPs work (Bank of England, Quarterly Bulletin 2022 Q1). Following the gilt purchases (on October 3), funds with higher bond exposure exhibited a stronger recovery - 0.36 p.p. initially, rising to 0.38 p.p. as the purchase size increased - relative to lower bond-holding funds. This suggests that asset purchase program more than the announcement, was effective in stabilizing mutual fund performance, with larger interventions being more effective. These results are in line with our stylised model suggesting a wealth effect following the APP. The online Appendix 3 shows additional results in support of this

Table 4: The DiD Result to Pension Funds' Performance(cum)

	(1) lower gilt group	(2) higher gilt group	(3) diff in diff
onset	-2.251^{***}	-5.452^{***}	-2.251^{***}
	(-20.04)	(-26.39)	(-20.75)
announce	-1.435^{***}	-1.402^{***}	-1.435^{***}
	(-9.85)	(-5.23)	(-10.19)
action5	-0.175	0.555^{**}	-0.175
	(-1.39)	(2.39)	(-1.44)
action10	-0.588^{***}	-0.0769	-0.588^{***}
	(-6.82)	(-0.48)	(-7.06)
treat_onset			-3.201^{***}
			(-20.87)
treat_announce			0.0324
			(0.16)
treat_action5			0.730^{***}
			(4.23)
treat_action10			0.511^{***}
			(4.34)
_cons	-0.540^{***}	-1.609^{***}	-1.074^{***}
	(-12.09)	(-19.60)	(-35.25)
N	8987	8987	17974
F	1353.6	934.9	2420.7
r^2	0.376	0.294	0.525

t statistics in parentheses,

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: We compare pension funds across time and across gilt holdings in a difference-in-difference set-up. To assess the dynamics of fund performance, we estimate the following specification:

$$\text{performance(cum)}_{i,t} = \beta_0 + \sum_{k=1}^{5} \beta_k \, \text{CrisisPeriod}_{k,t} \times \text{Higher}_i + \sum_{k=1}^{5} \varphi_k \, \text{CrisisPeriod}_{k,t} + \mu_i + \varepsilon_{i,t}$$

where $\text{performance(cum)}_{i,t}$ is the cumulative fund performance, scaled to September 1, 2022. The dummy variables $\text{CrisisPeriod}_{k,t}$ take on the value of 1 for period k and zero otherwise. We consider 5 periods: crisis onset (Sep 23– Sep 27), an asset purchase announcement period (Sep 28 – Oct 2), two purchase implementation periods and after finish period. The two implementation periods are action5 (Oct 3 – Oct 10), and the periods action10 (Oct 11 – Oct 14). The variable Higher_i is equal to 1 if a fund held, at the end of August 2022, above-the-median amounts in gilts as a percentage of total portfolio. Lastly, μ_i are fund level fixed effects and $\varepsilon_{i,t}$ is the error term. Standard errors are clustered at fund level.

evidence.

4.4 Robustness

4.4.1 Parallel trend test - event study

Figure 5 presents a preliminary graphical representation of the parallel trends for the two groups of funds. In this subsection we further test the parallel trends before treatment for the sample of pension funds using an event study. To increase the sample size, we extend the sample period from 5 weeks pre-crisis to 10 weeks post-crisis. We construct the following regression model for parallel trend test:

$$\text{performance(cum)}_{i,t} = \beta_0 + \sum_{w \neq 38} \beta_w \times 1(t \in w) \times D_i + \mu_i + \varepsilon_{i,t} \tag{4}$$

where $\text{performance(cum)}_{i,t}$ is the cumulative fund performance, scaled to August 1, 2022. $1(t = s)$ is an indicator variable for whether date t is in week w. We use the week in which the Mini-budget Crisis occurs as the baseline, i.e. week 38 of 2022. And the sample period[8] is selected to be 5 weeks before crisis and 10 weeks after crisis to test for parallel trends. So the range of values for w is 33 to 48. D_i in the regression is an indicator variable for whether a fund held above-the-median amounts in gilts as a percentage of total portfolio at the end of August 2022. μ_i is a fixed effect for fund i explaining unobserved fund-level characteristics. $\varepsilon_{i,t}$ is the error term.

As with any difference-in-difference estimator, the β_w's trace out the causal impact of Mini-budget Crisis on pension fund performance under the assumption of parallel trends: absent Mini-budget Crisis, fund with different percentage of gilt holding would have followed similar price trends from early September through the mid of November.

We estimate the period from five weeks before the Mini-budget Crisis to ten weeks after its occurrence. The key focus are the estimated coefficients β_w and they are normalized such that $\beta = 0$

[8]We look at the cumulative performance scatterplot for each fund in the sample to rule out the effect of outliers on the regression estimates. Only five funds out of a sample of 227 funds have outlier performance observations. We choose to drop them sensibly.

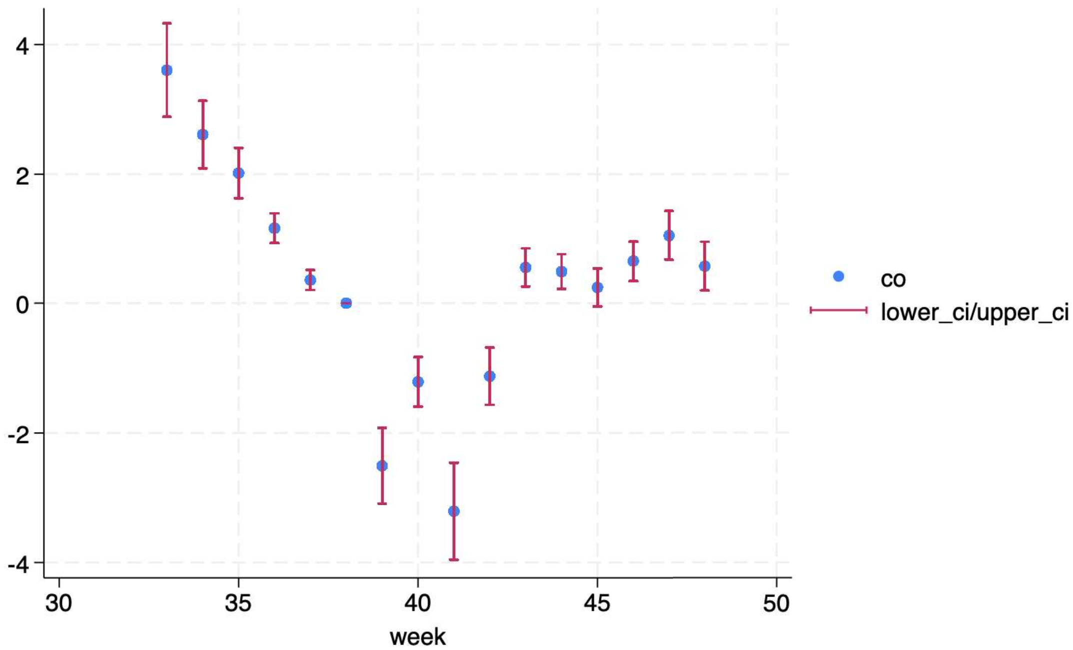
for the week in which the Mini-budget was announced (2022w38). They are plotted in Figure 7 along with 95% confidence intervals based on standard errors that are clustered by fund.

Figure 7: Coefplot of pension funds

We construct the following regression model for parallel trend test:

$$\text{performance(cum)}_{i,t} = \beta_0 + \sum_{w \neq 38} \beta_w \times 1(t \in w) \times D_i + \mu_i + \varepsilon_{i,t}$$

where performance(cum)$_{i,t}$is the cumulative fund performance, scaled to August 1, 2022. $1(t = s)$ is an indicator variable for whether date t is in week w. We use the week in which the Mini-budget Crisis occurs as the baseline, i.e. week 38 of 2022. And the sample period is selected to be 5 weeks before crisis and 10 weeks after crisis to test for parallel trends. So the range of values for w is 33 to 48. D_b in the regression is an indicator variable for whether a fund held above-the-median amounts in gilts as a percentage of total portfolio at the end of August 2022. μ_i is a fixed effect for fund i explaining unobserved fund-level characteristics. $\varepsilon_{i,t}$ is the error term. Standard errors are clustered at fund level.



The Figure 7 shows the period before the Mini-budget crisis. There is a significant difference in the cumulative performance of these two groups of pension funds. Given this, we include exra factors which we believe could belp to mitigate this issue.

A number of studies have shown that fund size affects fund performance, e.g., (Joseph et al., 2004; Joshua et al., 2008; Arhinful et al., 2023) an increase in fund size raises execution and opportunity costs, leading to more inefficient decision making and execution by fund managers. Also, large-scale funds buying and selling assets can have greater shocks to asset prices, leading to lower returns than smaller funds. According to Arhinful (2023) the company's degree of financial leverage has a negative impact on ROE. Based on the data nodes available in the Morningstar database, we obtained size and leverage time series data for the pension fund sample. They are added as controls to the regression model.

By comparing the pre-crisis part of the coefficient plot we can see that, the inclusion of size and leverage do mitigate the difference in cumulative performance between the two groups of pension funds. Size and leverage explain 45.9% of the cumulative performance difference in pre-crisis.[9]

Overall, Figures 7 and 8 show that unconditional pre-trends differ somewhat between high- and low-gilt funds, but that these differences are substantially reduced once we control for size and leverage. Adding size and leverage explains roughly 46% of the pre-crisis performance gap, and the remaining differences are statistically small relative to the large post-intervention responses.[10] Based on these reesults, we therefore interpret our DiD estimates as capturing the average causal effect of the APP on funds with similar observable characteristics, and we emphasise this as a conditional parallel trends design rather than unconditional randomisation (see also our earlier discussion).

As an additional, non-parametric test, Appendix B reports portfolio-sorting results that group funds into three bins by gilt holdings. The cross-group dynamics of cumulative performance in Figure 16 mirror our regression findings: performance gaps open sharply at the onset of the crisis, and funds with the highest gilt exposure benefit disproportionately once APP purchases begin. That pattern is difficult to reconcile with generic risk factors, while can be more directly reconciled with the effects of APP stabilising funds in proportion to their exposure to eligible gilts.

[9] Online appendix 2 shows further results

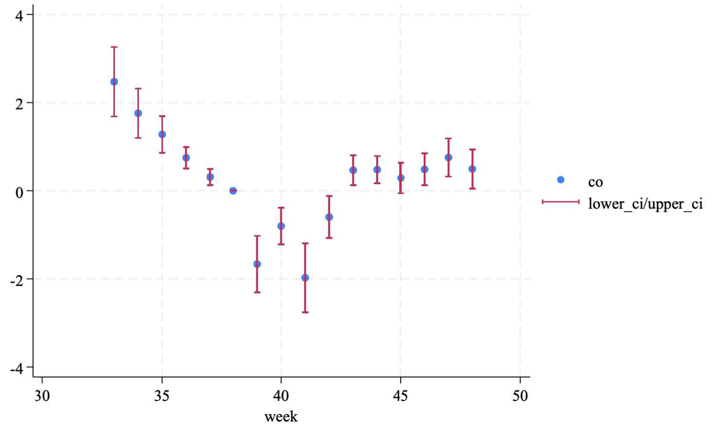
[10] See Online Appendix 2 for alternative window definitions and additional controls.

Figure 8: Coefplot of pension funds with controls

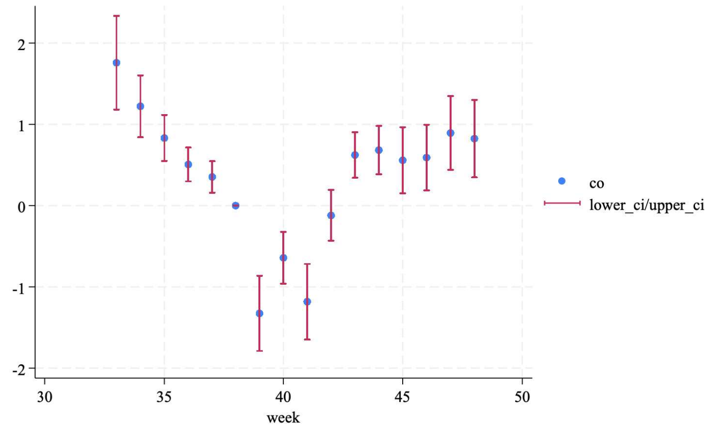
We construct the following regression model for parallel trend test:

$$\text{performance(cum)}_{i,t} = \beta_0 + \sum_{w \neq 38} \beta_w \times 1(t \in w) \times D_i + \alpha_{i,t} + \mu_i + \varepsilon_{i,t}$$

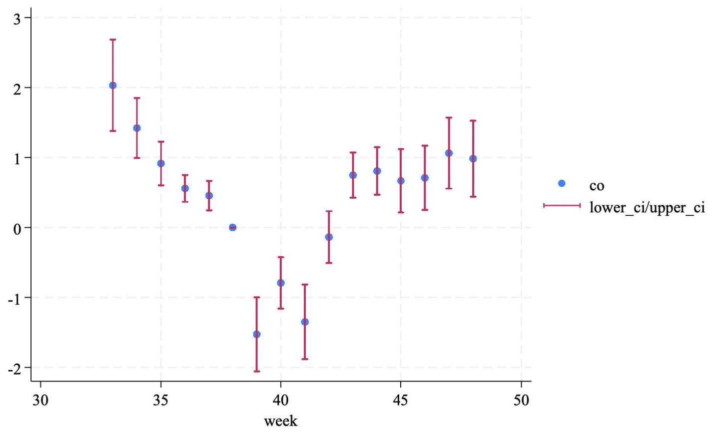
where $\text{performance(cum)}_{i,t}$ is the cumulative fund performance, scaled to August 1, 2022. $1(t = s)$ is an indicator variable for whether date t is in week w. We use the week in which the Mini-budget Crisis occurs as the baseline, i.e. week 38 of 2022. And the sample period is selected to be 5 weeks before crisis and 10 weeks after crisis to test for parallel trends. So the range of values for w is 33 to 48. D_i in the regression is an indicator variable for whether a fund held above-the-median amounts in gilts as a percentage of total portfolio at the end of August 2022. $\alpha_{i,t}$ is control variables. μ_i is a fixed effect for fund i explaining unobserved fund-level characteristics. $\varepsilon_{i,t}$ is the error term. Standard errors are clustered at fund level.



(a) control net asset



(b) control leverage



(c) control size & leverage

4.4.2 Placebo DiD Test using Equity Exposure

To rule out the possibility that 'the results merely reflect general risk exposure' rather than 'policy transmission associated with gilts', we constructed a treatment group using equity holdings instead of gilt holdings within the pension fund sample. Specifically: using the September 2022 equity asset allocation as the benchmark, funds were divided into two groups based on the median; those above the median were assigned to the high-equity exposure group (HighEquity=1), while those below constituted the control group (HighEquity=0). Subsequently, difference-in-differences (DiD) regressions were used for each time (onset, announcement, action5, action10), incorporating fund-level fixed effects and employing fund-level clustering robust standard errors.

As demonstrated in Table 5, the key interaction terms show no significant effect across all times except the initial crisis stage. This suggests that only during the initial phase of the crisis funds with higher equity exposure exhibit a slight relative deterioration, more likely attributable to the market-wide effect of 'risk asset beta. Conversely, the announcement and implementation windows (announce, action5, action10) more directly linked to the BoE policy did not yield significant results on the high- and low-equity exposure groups.

Weekly event studies further corroborate the parallel trend in Figure 9: prior to intervention, both groups exhibited weekly coefficients approaching zero with confidence intervals encompassing zero. Significant divergence emerged duringthe weeks of crisis outbreaks, subsequently receding within the following window—consistent with characteristics of a one-off shock rather than persistent intergroup disparities.

This placebo test indicates that no systematic differences associated with the announcement or bond purchase implementation phases are discernible when employing 'equity exposure' as the treatment. When combined with the main findings, this provides stronger support for BoE intervention.

Table 5: Placebo DiD Test for Equity Exposure

	(1) diff in diff
onset	−.3.674***
	(0.112)
announce	−1.426***
	(0.145)
action5	−0.142
	(0.125)
action10	−0.312***
	(0.0856)
treat_onset	−0.354*
	(0.158)
treat_announce	−0.0139
	(0.205)
treat_action5	−0.0959
	(0.177)
treat_action10	−0.0406
	(0.121)
_cons	−1.074***
	(0.0313)
N	17974
F	258.6
r^2	0.176

t statistics in parentheses,

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

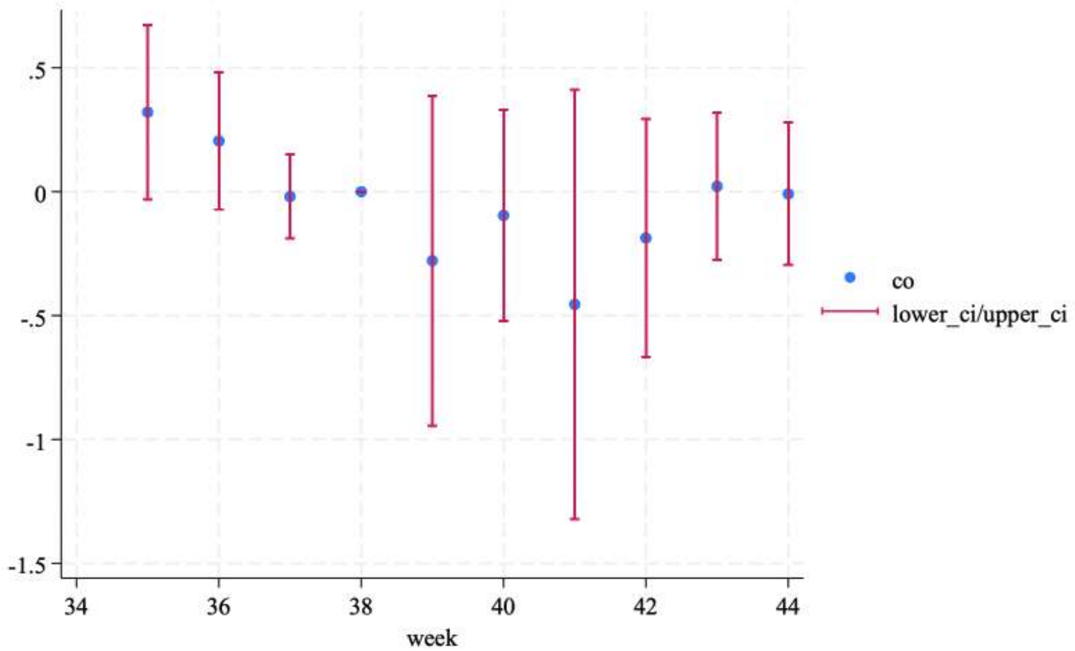
Notes: We compare pension funds across time and across equity holdings in a difference-in-difference set-up. To assess the dynamics of fund performance, we estimate the following specification:

$$\text{performance(cum)}_{i,t} = \beta_0 + \sum_{k=1}^{5} \beta_k \, \text{CrisisPeriod}_{k,t} \times \text{Higher}_i + \sum_{k=1}^{5} \varphi_k \, \text{CrisisPeriod}_{k,t} + \mu_i + \varepsilon_{i,t}$$

where $\text{performance(cum)}_{i,t}$ is the cumulative fund performance, scaled to September 1, 2022. The dummy variables $\text{CrisisPeriod}_{k,t}$ take on the value of 1 for period k and zero otherwise. We consider 5 periods: crisis onset (Sep 23– Sep 27), an asset purchase announcement period (Sep 28 – Oct 2), two purchase implementation periods and after finish period. The two implementation periods are action5 (Oct 3 – Oct 10), and the periods action10 (Oct 11 – Oct 14). The variable Higher_i is equal to 1 if a fund held, at the end of August 2022, above-the-median amounts in equity as a percentage of total portfolio. Lastly, μ_i are fund level fixed effects and $\varepsilon_{i,t}$ is the error term. Standard errors are clustered at fund level.

Figure 9: parallel trend

where performance(cum)$_{i,t}$ is the cumulative fund performance, scaled to August 1, 2022. $1(t = s)$ is an indicator variable for whether date t is in week w, $33 \leq w \leq 48$. D_b in the regression is an indicator variable for whether a fund held above-the-median amounts in bonds as a percentage of total portfolio at the end of August 2022. μ_i is a fixed effect for fund i explaining unobserved fund-level characteristics. $\varepsilon_{i,t}$ is the error term. Standard errors are clustered at fund level.



5 Leverage and Funds' Performance

Did leverage affect funds' performance? In the previous sections we discussed the role of leverage in the UK 2022 crisis. We re-do the analysis in section 4 but we now control for leverage. We show that the inclusion of leverage can explain about 52.7% ((3.7-1.75)/3.7) of the ex-ante difference (week33). This suggests that leverage did play somehow an important role in driving the performance of pension funds. The effect of leverage (see below the way we compute leverage), reinforces the case of a wealth effect following the APP. See also our model.

5.1 Leverage DID regression set-up

We change the DiD in Section 4.2. We replace Higher_i in the interaction term with a dummy variable indicating leverage. This is equal to 1 if a pension fund leverage is above the median at the end of August 2022, otherwise it is equal to 0. The specific settings are as follows:

$$\text{performance(cum)}_{i,t} = \beta_0 + \sum_{k=1}^{5} \beta_k \,\text{CrisisPeriod}_{k,t} \times \text{Higher\_Leverage}_i + \sum_{k=1}^{5} \varphi_k \,\text{CrisisPeriod}_{k,t} + \mu_i + \varepsilon_{i,t} \tag{5}$$

where $\text{performance(cum)}_{i,t}$is the cumulative fund performance, scaledScale: using the NAV on 1 September 2022 as the benchmark, record the cumulative performance on that day as 0. Calculate the cumulative performance of the fund after that date. to September 1, 2022. The dummy variables $\text{CrisisPeriod}_{k,t}$ take on the value of 1 for period k and zero otherwise. We consider 5 periods: crisis onset (Sep 23 – Sep 27), an asset purchase announcement period (Sep 28 – Oct 2), two purchase implementation periods and after finish period. The two implementation periods are action5 (Oct 3 – Oct 10), and the periods action10 (Oct 11 – Oct 14). The variable Higher_Leverage_i is equal to 1 if a pension fund leverage is above the median at the end of August 2022, otherwise it is equal to 0. Lastly, μ_i are fund level fixed effects and $\varepsilon_{i,t}$ is the error term.

5.2 DiD regression results

For the regressions in column (1) and (2), we use data - debt to cap (long)% to measure leverage. This ratio measures a fund's financial leverage. It is calculated by dividing long-term debt (excluding other liabilities) by total capitalization (the sum of common equity plus preferred equity plus long-term debt).

$$\text{Debt\_to\_cap(long)\%} = \frac{\text{Long\_term\_debt}}{\text{Equity} + \text{Preferred\_equity} + \text{Long\_term\_debt}} \tag{6}$$

And for regressions in column (3) and (4), leverage is debt to cap (short)%. It is calculated by dividing short-term debt (excluding other liabilities) by total capitalization (the sum of common equity plus preferred equity plus long-term debt).

$$\text{Debt\_to\_cap(short)\%} = \frac{\text{Short\_term\_debt}}{\text{Equity} + \text{Preferred\_equity} + \text{Long\_term\_debt}} \tag{7}$$

Table 6 shows the summary statistics for pension fund leverage. In terms of distribution, Debt to cap leverage of pension funds is in the 30%–40% range for both long and short term leverage.

Table 6: Summary statistic for pension fund leverage

	debt to cap (long)%	debt to cap (short)%
Mean	36.26	27.98
Median	37.38	35.14
Std. Dev.	7.27	15.56
Min	1.32	1.11
25th Pct	33.89	23.21
50th Pct	37.38	35.14
75th Pct	39.86	39.14
Max	88.70	49.80
N	7993	1215

Table 7 shows the effect of leverage on the cumulative performance of pension funds during the mini-budget shock. Colunm (1) and (2) are the DiD results using the Debt_to_cap(long)% as the grouping variable, where colunm (2) adds the size control variable to colunm (1). Colunm (3) and (4) are the DiD results using the Debt_to_cap(short)% as the grouping variable, where colunm (4) adds the size control variable to colunm (3).

Columns (1) shows that higher long-term leverage causes pension funds to incur additional cumulative performance declines during the mini-budget crisis. Each 1% increase in long-term financial leverage leads to a 0.44% decline in cumulative performance. The APP announcement did not make a significant difference for pension funds cumulative performance. But following the implementation of the APP, pension funds with higher long-term debt leverage had significantly better cumulative performance than those with lower long-term debt leverage, which improved by 1.12%. Controlling for fund size (column 2), pension funds with higher long-term debt leverage still maintain about 1.2% additional cumulative performance in the second period.

In columns (3) and (4), we focus on short term leverage. Pension funds with higher short-term debt leverage are more resilient to the mini-budget shock, and their cumulative performance is about 1% higher than that of pension funds with lower short-term debt leverage. Furthermore, during the first period when of Bank of England implemented the APP, they show the worse cumulative performance (around -0.5%). Refer to the online Appendix 2 for parallel test and further empirical evidence.

Overall, our findings provide some support to Breeden (2022).[11] Leverage was an important risk factor in UK during the crisis. Our results suggest that the level of leverage, concentrated into specif sectors of the UK financial system, should not be ignored by regulators.

6 Spillover effect to mutual funds

The analysis so far has shown that pension funds with significant gilt exposure experienced significantly larger NAV declines during the shock and that these losses reversed more quickly once the asset-purchase programme was implemented. These patterns indicate that the shock interacted

[11] Parallel trend tests for leverage DiD are shown in online appendix 3.

Table 7: The Leverage DiD Result to Pension Funds' Performance(cum)

	Performance(cum)			
	debt to cap (long)%		*debt to cap (short)%*	
	(1)	(2)	(3)	(4)
onset	-2.176^{***}	-2.417^{***}	-2.957^{***}	-2.449^{***}
	(-57.97)	(-30.93)	(-25.15)	(-14.84)
announce	-1.316^{***}	-1.528^{***}	-1.518^{***}	-1.290^{***}
	(-27.02)	(-15.91)	(-9.95)	(-6.50)
action5	-0.236^{***}	-0.165^{**}	0.0413	0.0537
	(-5.60)	(-1.99)	(0.31)	(0.31)
action10	-1.536^{***}	-1.527^{***}	-0.489^{***}	-0.509^{***}
	(-53.76)	(-25.82)	(-5.42)	(-4.21)
treat_onset	-0.443^{***}	-0.0404	0.955^{***}	1.200^{***}
	(-8.34)	(-0.38)	(6.53)	(6.03)
treat_announce	0.0484	0.0180	0.618^{***}	0.213
	(0.70)	(0.14)	(3.25)	(0.87)
treat_action5	0.0245	0.316^{***}	-0.517^{***}	-0.450^{**}
	(0.41)	(2.78)	(-3.14)	(-2.13)
treat_action10	1.124^{***}	1.209^{***}	-0.127	-0.221
	(27.82)	(14.88)	(-1.13)	(-1.47)
_cons	-0.0558^{***}	-1.743^{***}	-0.0961^{***}	-2.090^{***}
	(-5.29)	(-9.21)	(-3.46)	(-5.95)
N	80080	22204	6923	3097
F	14581.7	3334.5	1663.1	639.7
R-square	0.599	0.588	0.663	0.663
FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: We estimate the following specification:

$$\text{performance(cum)}_{i,t} = \beta_0 + \sum_{k=1}^{5} \beta_k \text{ CrisisPeriod}_{k,t} \times \text{Higher\_Leverage}_i + \sum_{k=1}^{5} \varphi_k \text{ CrisisPeriod}_{k,t} + \mu_i + \varepsilon_{i,t}$$

where performance(cum)$_{i,t}$ is the cumulative fund performance, scaled to September 1, 2022. The dummy variables CrisisPeriod$_{k,t}$ take on the value of 1 for period k and zero otherwise. We consider 5 periods: crisis onset (Sep 23–Sep 27), an asset purchase announcement period (Sep 28 – Oct 2), two purchase implementation periods and after finish period. The two implementation periods are action5 (Oct 3 – Oct 10), and the periods action10 (Oct 11 – Oct 14). The variable Higher_Leverage$_i$ is equal to 1 if a pension fund leverage is above the median at the end of August 2022, otherwise it is equal to 0. Lastly, μ_i are fund level fixed effects and $\varepsilon_{i,t}$ is the error term. Standard errors are clustered at fund level. Colunm (1) and (2) are the DiD results using the Debt_to_cap(long)% as the grouping variable, where colunm (2) adds the size control variable to colunm (1). Colunm (3) and (4) are the DiD results using the Debt_to_cap(short)% as the grouping variable, where colunm (4) adds the size control variable to colunm (3).

strongly with the balance-sheet positions of pension funds, generating heterogeneous valuation effects even among institutions holding broadly similar assets. A natural question is whether these valuation effects were confined to pension funds or whether they also affected other non-bank investors. We focus on mutual funds. In sum, based on our model, we argue that the portfolio re-balance channel generated (beneficial) spillover effects to other non-banking sectors.

Our model generates three main hypothesis. Hypothesis 1 predicts that central-bank purchases lead stronger price reactions by institutions with greater pre-crisis exposure to government bonds. This reflects our model's downward-sloping demand structure, in which exogenous reductions in effective supply raise prices more sharply when investors are constrained by binding margin requirements.

Hypothesis 2 predicts that as rising bond prices mitigates funding pressures, and constrained investors rebalance their portfolios toward other assets not directly targeted by the intervention (ineligible). This is also captured by our model via improved wealth effects.

Hypothesis 3 predicts that these effects extend beyond the direct holders of government bonds, affecting the valuation and performance of other market participants, in our case mutual funds, through spillover effects embedded in market prices. This occurs because the rebalancing behaviour of constrained investors influences prices in segmented markets, transmitting the original demand shock beyond its initial source.

Together, these hypotheses operationalise the model's central prediction that asset prices under stress are shaped not only by fundamentals but also by the funding constraints and portfolio adjustments of dominant investor groups.

Breckenfelder and De Falco (2023) studied the APP launched by the ECB during the COVID-19 shock, providing support for a portfolio balance type of mechanism in place. Given that both with the COVID-19 and the UK budget shocks, APPs have operated mainly to mitigate dysfunctions in an important core market, that is safe asset market, rather than monetary policy tools, results in these papers should also help policy makers to better target policy interventions, that is "market-function asset purchases programs"(Duffie and Keane 2023).

The shift share instrumental variable in the next sections follows Breckenfelder and Falco (2024). This rests on the assumption that aggregate shocks to eligible assets (e.g., BoE purchases) are exogenous to unobserved fund-level determinants of performance. However, because the BoE targeted stressed maturities, this exogeneity may be imperfect. We therefore interpret our IV as exploiting plausibly exogenous, but not strictly random, variation in exposure intensity across funds.[12]

One of the concern with shift–share IVs is that exposure weights might be endogenous — chosen by agents in anticipation of the shock or correlated with omitted characteristics. In our specific case this concern should be mitigated as pension (mutual) funds, in general, have fixed long-term mandates. They allocate to gilts and derivatives to match liability durations and regulatory solvency ratios, not tactical alpha. These allocations are typically governed by investment mandates and trustees rather than portfolio managers responding to short-run market views. Greenwood and Vayanos (2014); Greenwood et al. (2018).

Finally, to be explictly in what we do, while our design resembles a shift-share instrument, our setting involves a single monetary policy intervention. As recent econometric work shows Borusyak et al. (2022*a*), the many-shocks justification does not apply in this case, and validity relies on the exogeneity of exposure shares. We therefore conduct extensive tests of predeterminedness and pre-trends, and explore alternative specifications to support our identification strategy.

6.1 Pension funds' exposure and portfolio re-balancing

We start with hypothesis I. To test this hypothesis we need an exogenous instrument. We follow Breckenfelder and Falco (2024) to design a shift-share instrument. For each pension fund we create a quasi-exogenous measure of investor exposure to the APP, the Exposure index. This is the amount of gilts, each pension fund sells, in each month, to the BoE

$$\text{Exposure}_{p,t} = \frac{\sum_g \Delta\text{Amount}_{p,g,t}}{\text{TotPortfolio}} \tag{8}$$

[12] We provide some falsification tests to mitigate this possibility.

where g stands for eligible gilt purchased by the BoE at time t and p refers to pension funds in our sample.

This quantity could be correlated with specific funds' investment strategy. Therefore, we construct an instrument to address this endogeneity following Breckenfelder and Falco (2024). We define the instrument as Predicted Exposure, this variable measures how much a fund can potentially sell to the BoE based on their portfolio allocation at the end of August 2022 (therefore exposure is pre-determined before APP started).

$$\text{PredExposure}_{p,t} = \frac{\sum_g \text{Share}_{p,\text{Aug2022},g} * \Delta\text{APP Amount}_{t,g}}{\text{TotPortfolio}} \tag{9}$$

For each eligible bond, we calculate the size of purchases in a given month (change in BoE security holdings in a month) and multiply it by the fund's share of that security in August 2022. This should provide us with a predicted quantity each pension fund would sell, based on the share of amount outstanding that they held of the bond at the end of Aug2022. The index is finally obtained by summing over gilts within each pension fund. Under the assumption that BoE decision to buy certain securities is random from the investor's perspective, this instrument should help to mitigate the effect of counfounding factors.

This is a shift–share instrument where the "shares" are given by the pre-determined portfolio weights of each pension fund in August 2022, while the "shifters" are the security-level BoE purchase amounts during the APP window. Intuitively, from the perspective of an individual fund, the cross-sectional pattern of BoE purchases across eligible gilts should be quasi-random, whereas its own pre-APP gilt allocation should be predetermined and evolves smoothly prior to the shock. Our tests below support this assumption.

This should give us a sense of the predicted exposure of pension fund to BoE purchases. The main assumption is that $\text{Share}_{p,\text{Aug2022},g}$, the ex-ante exposure, is uncorrelated with unobserved determinants of the outcome variable. As in Breckenfelder and Falco (2024), both exposure measures are normalized by the total portfolio amount held by each pension fund.

We start testing whether predicted exposure can predict pension funds' exposure to BoE purchases.

$$\text{Exposure}_{p,t} = \gamma_t + \omega\, \text{PredExposure}_{p,t} + \nu_{p,t} \tag{10}$$

Table 16 in Appendix C, we report first stage results. A significant coefficient at the 1% level suggests that the instrument variable does have strong explanatory power or relevance. Also, IV test result shows it is not significantly weak[13].

We test whether pension funds more exposed to APP re-balanced more towards non-eligible assets. The variable ΔWeight is the change in portfolio weights of ineligible securities, denoted by n. In Table 8 we show the results based on:

$$\mathbb{E}_n\left[\Delta\text{Weight}_{n,p,t}\right] = \alpha_p + \gamma_t + \beta\, \text{Exposure}_{p,t} + \nu_{p,t}\,. \tag{11}$$

Column (1)(3)(5) report OLS results, while in column (2)(4)(6) show 2SLS results, where we use predicted exposure as an instrument for the right-hand-side variable.

The ΔWeight in Table 8 coloum (1)(2) is the mean value of the change in the portfolio weight of all assets[14] held by the pension fund. The dependent variable in coloum (3)(4) is based on the fraction of bonds[15] that we identify from all assets of the pension fund. The results of the regression using equity assets as ineligible assets are in coloum (5)(6).

In Table 8 we control for month and fund fixed effects. These controls are important to make sure we identify re-balancing towards ineligible securities that is driven only by exposure to APP rather than other factors. This identification strategy has also been used in many papers (Breckenfelder and De Falco, 2023 and many others).

We do not consider clustering standard errors along both the fund and time dimensions given the short time dimension of our panel. Cluster-robust standard errors are not reliable and may even

[13] See online Appendix 5 - Table 22.

[14] All assets include Equity, Bond, Derivatives, Currency, Cash and other kinds of asset.

[15] Including: asset backed bond, capital contingent debt bond, commercial mbs bond, corporate bond, covered bond, global non-agency mbs bond, gov't agency debt bond, gov't inflation protected bond, gov't/treasury bond, short-term government bills bond, sub-sovereign government debt bond, treasury future bond. (These catagories are defined by Morningstar Direct.)

Table 8: Pension funds' rebalancing

	Performance(cum)					
	(1)	(2)	(3)	(4)	(5)	(6)
	All assets	*All assets*	*Bond*	*Bond*	*Equity*	*Equity*
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	ΔWeight	ΔWeight	ΔWeight	ΔWeight	ΔWeight	ΔWeight
Exposure	0.0002143***	0.0000242***	0.0002147***	0.0000251***	0.00318	0.00578
	(0.000000762)	(0.00000395)	(0.000000010)	(0.00000526)	(0.00286)	(0.00718)
Observations	796	796	782	782	364	364
R^2	0.7641	0.7519	0.8332	0.7481	0.1214	0.0402
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

*Notes:*The table reports regressions of the form $\mathbb{E}_n\left[\Delta\text{Weight}_{n,p,t}\right] = \alpha_p + \gamma_t + \beta Exposure_{p,t} + \nu_p$. Time frame is 1 Sep2022 to 31 Oct2022. $\Delta Weight$ corresponds to the change in portfolio weight of ineligible assets. Column (1)(3)(5) report OLS results. Column (2)(4)(6) report 2SLS results, where Exposure is instrumented by Predicted Exposure as in Table 16. We control for month and fund fixed effects. t statistics are reported in parentheses. Standard errors are clustered at the pension fund level. *,**,*** indicate significance at the 5%, 1%, 0.1% level, respectively.

be severely downward biased. For this reason, we follow standard practice in short panels (large N, small T) and cluster only at the fund level. This approach allows for arbitrary correlation of residuals within each fund across the two months, while maintaining valid inference.[16]

We can see that for all ineligible assets, the change in their holding weight is significantly and positively correlated with the pension fund's exposure to BoE purchases by about 0.024 basis points. We categorize their ineligible assets into bonds and equity for further analysis. We find that bond assets are the main target assets for pension funds' re-balancing operations. In fact, its correlation coefficient of 0.025 basis points is very close to the coefficient for all ineligible assets. The fund's exposure to APP does not significantly influence changes in the weighting of equity holdings. Moreover, the estimated coefficients for all assets are very similar to those for bonds.

The coefficient on the 2SLS specification suggests that a fund that is 1 pp more exposed to APP increases the portfolio weight of the average ineligible bonds in their portfolio by 0.025 basis points. Our results suggest that pension funds use ineligible bonds to re-balance their portfolios at the time of the APP. As a sort of falsification test, we also report the empirical results using equity in the Appendix C.[17]

Online appendix 5 provides further robustness tests. Table 22 and Table 23 presents the effect of exposure on changes in portfolio weights of ineligible assets between September and October 2022. The OLS estimate is positive and highly significant, and the IV estimates from both 2SLS and LIML are very similar, reinforcing the robustness of the results. We also provide diagnostic tests to confirm that the instrument is relevant. Wild cluster bootstrap inference shows that IV estimates remain consistent with conventional clustered inference, and Anderson–Rubin inference strongly rejects the null of no effect, with a 95% confidence interval entirely in the positive domain. Overall, the results provide robust evidence that higher exposure leads to an increase in the portfolio

[16]For our short panel, we have considered whether this inreoduces bias in the estimation. However, from a asymptotic perspective, the large cross-section of pension funds should be helpful to mitigate this possibility. To reach convergence of sample moments, a large number of shock samples are required, but they do not need to be driven by time series changes. An example is Chodorow-Reich (2014), 'The Impact of Credit Market Turmoil on Employment', whow use a large cross-section of banks and borrowers rather than long time series and employs a transfer share design in a single crisis context.

[17]Table 18: first stage on equity for hypothesis II. Table 19: OLS and 2SLS results on equity for hypothesis II. Table 20: result on equity for hypothesis III:

weight of ineligible assets.

Overall, the results in this section, jointly with robust tests reported in the next sections and Online Appendix 5, suggest that our rebalancing estimates are not driven by spurious correlation. Instead, they capture genuine variation in gilt sales induced by the BoE APP, which in turn triggers reallocation into ineligible bonds.

Our results have important policy implications as they help central banks to understand the effectiveness of the APPs by observing key investors such as pension (mutual) funds' risk shift to search for higher yields. For example, using bank's reserves to buy riskier assets. In the next section we shall focus on the price impact of the APP programme.

6.2 The Price Mechanism of the APP

We now study whether purchase flows induced by APP had also an effects on prices of assets not targeted by the BoE (i.e. ineligible). This is what we would expect if the APP operates via a portfolio rebalance channell.

We define the change in nominal amount that pension funds hold of each security. This variable quantifies how much each security is purchased by pension funds.

$$\Delta log(NomAmount)_{n,t} = \Delta log \sum_{p} NomAmount_{n,p,t} \tag{12}$$

Secondly, we define an instrument controlling for the change in quantity that is driven by pension funds re-balancing due to BoE gilt purchases.

As before, we construct Predicted Flow as the predicted quantity change for each ineligible security by each pension fund due to exposure to APP.

$$\text{PredictedFlow}_{n,p,t} = (\sum_{g} \text{Share}_{p,\text{Aug2022},g} * \Delta\text{APP Amount}_{t,g}) * \text{Weight}_{n,p,t-1} \tag{13}$$

where

$$\text{PredExposure}_{p,t} = \frac{\sum_g \text{Share}_{p,\text{Aug2022},g} * \bigtriangleup \text{ APP Amount}_{t,g}}{\text{TotPortfolio}} \tag{14}$$

This is a shift-share instrument with "Predicted exposure" computed previously, and the shares are portfolio weights of ineligible securities in the previous month, that is before the APP program. The shifter instrument given our design is quasi-exogenous (see also discussion in Breckenfelder and De Falco, 2023 for further discussion and (Borusyak et al. 2022*b*).

This design follows the same shift–share logic as our fund-level instrument, but now at the security level. The shifter is again the cross-section of BoE gilt purchases, while the shares are given by the pre-APP portfolio weights of ineligible securities across pension funds. Note that weights are measured before the crisis and evolve smoothly in normal times. Therefore, they provide a plausibly exogenous allocation of the BoE-induced demand shock across ineligible assets. Conditional on time fixed effects, variation in PredictedFlow is likely to be driven by how strongly each ineligible security is connected to funds that are exposed to the APP, rather than by unobserved, concurrent shocks to a security.

We can now calculate the change in ineligible securities nominal amounts held by funds.

$$\Delta log(PredNomAmount)_{n,t} = \Delta log \sum_p (NomAmount_{n,p,t-1} + PredictedFlow_{n,p,t}) \tag{15}$$

$$\Delta log(NomAmount)_{n,t} = \gamma_t + \beta \Delta log(PredNomAmount)_{n,t} + \nu_{n,t} \tag{16}$$

In Table 17 in Appendix C, we report first stage results. A significant coefficient at the 5% level implies that the instrument variable does have strong explanatory power or relevance.

Finally we test how the shock impacted prices of ineligible securities with the following specification.

$$\Delta log(P)_{n,t} = \gamma_t + \beta \Delta log(NomAmount)_{n,t} + \nu_{n,t} \tag{17}$$

In Table 9 we show the results: in column (1) we run an OLS regression while in column (2) the 2SLS specification.

Table 9: Effect on prices of indirect demand shock

	(1)Bond OLS Δlog(P)	(2)Bond 2SLS Δlog(P)
Δlog(NomAmount)	0.178**	1.016***
	(0.0539)	(0.184)
Observations	1,224	1,224
R^2	0.1071	-2.2559
Month	Yes	Yes

Notes: The table reports regressions of the form $\Delta log(P)_{n,t} = \gamma_t + \beta \Delta log(NomAmount)_{n,t} + \nu_n$ from 1 Sep2022 to 31 Oct2022. $\Delta log(NomAmount)$ corresponds to the change in nominal amount of each security held by pension funds. In column (1) we report OLS results. In column (2) we report 2SLS results where the first stage is reported in Table 17. We control for month and security fixed effects. t statistics are reported in parentheses. Standard errors are clustered at the security level. *,**,*** indicate significance at the 5%, 1%, 0.1% level, respectively.

The coefficient in Table 9 implies that for a 1% increase in demand by pension funds, the price of ineligible assets increases by 1.04%[18].

It is interesting to compare these results with some papers focusing on the COVID-19 shock. In comparison to the large-scale asset purchases (APP and PEPP) policies implemented by the European Central Bank (ECB) since 2015 and discussed in Breckenfelder and Falco (2024).

Breckenfelder and Falco (2024)suggest that when central banks buy large amounts of certain ‘eligible’ securities, private sector investors (e.g. mutual funds) will invest in other assets that were not purchased by the central bank (ineligible), leading ‘non-eligible assets to increase in prices.

Our empirical results show a similar spillover effect taking place during the UK’s 2022 mini-budget crisis. The Bank of England bought a large amount of gilts to support dysfunctions in this

[18]Detailed diagnostics and robustness checks are reported in the Online Appendix 5.

market which was making liquidity pressures on pension funds, with the risk of spreading to the rest of the UK financial market. Pension funds used that liquidity to top up margin calls but also, and this is new, to buy ineligible assets, increasing their prices. This is the first paper to document this portfolio balance effect for the 2022 UK budget shock.

6.3 Mutual funds performance change due to ineligible

We take one step further and discuss whether changes in the prices of ineligible securities held by pension funds had also an impact on the cumulative performance of mutual funds (see results in Online Appendix 4). Therefore, we study if the portfolio re-balance channel can also reach other corners of the UK non-banking system (i.e. mutual funds).

We introduce a dummy variable, $w_{n,i}$, to distinguish 'cumulative performance increases due to actual holdings' from 'cumulative performance increases due to sectoral or macro-level effects'. $w_{n,i}$ is equal to 1 if bond n is held by mutual fund i and 0 if not held. We use the following specification:

$$\text{Performance(cum)}_{i,t} = \gamma_t + \beta \frac{\sum_n \Delta log(P)_{n,t} * w_{n,i}}{\sum_n 1 * w_{n,i}} + \nu_{i,t} \tag{18}$$

where i is used to distinguish mutual funds, n is ineligible bond assets, and t is the time of month.

The results in Table 10 show that a 1% increase in average bond prices leads to a 5.49% increase in the cumulative performance of mutual funds. This is a a significant and sizeable increase.

Mutual funds were also supported by the BoE APP during the mini-budget crisis, and our analysis suggests that spillover effect from pension fund portfolio re-balancing their portfolios was instrumental. This is a new and important result that has also important policy implications for central banks as it suggests that APPs that are well targeted can effectively reach the non-banking sector and contribute to stabilise financial markets in times of market stress.

Table 10: Effects on mutual funds' performance

	(1)Bond Performance(cum)
Δlog(P)	5.493**
	(2.026)
R^2	0.1282
MonthXIsin	Yes

Notes: The table reports regressions of the form $\text{Performance(cum)}_{i,t} = \gamma_t + \beta \frac{\sum_n \Delta \log(P)_{n,t} * w_{n,i}}{\sum_n 1 * w_{n,i}} + v_{i,t}$ from 1 Sep2022 to 31 Oct2022. Performance(cum) is the cumulative mutual fund performance, scaled to 1 Aug2022. By using $w_{n,i}$, we construct the average price change of ineligible bond assets held by each mutual fund. $w_{n,i}$ is equal to 1 if bond n is held by mutual fund i and 0 if not held. We control for month and mutual fund fixed effects. t statistics are reported in parentheses. Standard errors are clustered at the mutual fund level. *,**,*** indicate significance at the 5%, 1%, 0.1% level, respectively.

6.4 Robustness

6.4.1 Placebo for spillover

We reconstructed the instrumental variable - predicted exposure - for robustness testing. We instead used the share of ineligible bonds held by the fund in August 2022 to construct the instrument. To multiply share and APP Amount, we needed to match their subscript g.[19] We match based on bond maturity. First, we allocate the ineligible bonds into 7 maturity baskets: 0-5 years, 6-10 years, 11-15 years, 16-20 years, 21-25 years, 26-30 years, and over 30 years. Simultaneously, we allocate the eligible gilts portion of the APP amount to these seven maturity baskets. Based on this, the share represents the proportion of ineligible bonds held by the fund across different maturities in August 2022. The APP Amount denotes the BoE's purchase volume of eligible gilts across different maturities in a given month. Finally, we multiply these two variables for matching

[19]In the original instrumental variables, both share and APP Amount were based on eligible gilt, allowing them to be matched against the same eligible gilt. However, in this test, share is based on ineligible bonds while APP Amount remains the size of purchases by the BoE on eligible gilt. Therefore, we must match these two values.

maturities to derive the core component of the instrumental variable.

Table 11 shows the 2SLS regression using the new instruments and it yields insignificant results, suggesting weak instrument. KP, rk, Wald, and F statistics (reflecting weak instrument identity) decrease from 14.708 to 0.730. That is, new instruments fail the weak instrumental variable test.

Table 11: placebo on the IV for pension funds' rebalance

	ΔWeight
$Exp\hat{o}sure$	0.0005354
	(0.000319)
Observations	782
Month	Yes
F	0.73

Notes: This table reports the placebo test for the instrument variable in section 6.1. Instead of using share of eligible assets, we used the share of ineligible bonds held by the pension funds in August 2022 to construct the instrument - $PredExposure$. Here is the 2SLS result using the new IV. t statistics are reported in parentheses. We control for month and fund fixed effects. Standard errors are clustered at the pension fund level. *,**,*** indicate significance at the 5%, 1%, 0.1% level, respectively.

Table 12 shows the test result for Section 6.2. Although still significant, the strength of the instrumental variables weakened.

6.4.2 Exogeneity test for shares

We estimate the following specification:

$$\text{Share}_{p,g,\text{Aug2022}} = \alpha + \beta\,\text{Share}_{p,g,\text{Jul2022}} + \mu_p + \gamma_g + \varepsilon_g, \tag{19}$$

where μ_p denotes pension-fund fixed effects and γ_g denotes security fixed effects. The reault is reported in 13 colunm (1).

A rolling window analysis was conducted and it is reported in Table 13 where we report the p-value obtained from testing the unit coefficient hypothesis $H_0 : \beta = 1$.

Table 12: placebo on the IV for indirect demand shock

	Δlog(P)
$\Delta log(No\hat{m}Amount)$	1.224318
	(0.22396)
Observations	782
Month	Yes
F	29.343

Notes: This table reports the placebo test for the instrument variable in section 6.2. Instead of using share of eligible assets, we used the share of ineligible bonds held by the pension funds in August 2022 to construct the instrument - $\Delta log(PredNomAmount)$. Here is the 2SLS result using the new IV. t statistics are reported in parentheses. We control for month and fund fixed effects. Standard errors are clustered at the security level. *,**,*** indicate significance at the 5%, 1%, 0.1% level, respectively.

Columns (2) and (3) represent the two months (Sep & Oct) impacted by the shock. The coefficients are significant and stands at 0.850 and 0.797, which are further away from 1, compared to other months. Meanwhile, the p-values are 0.0108 and 0.0001, respectively. This indicates that shares experienced a significant abnormal fluctuation during the two months of the crisis.

However, in columns (1), (4) and (5), the hypothesis of beta=1 cannot be rejected at the 5% significance level. That is, the share for other months is almost entirely determined by the preceding month's share on a one-to-one basis. This indicates that during normal periods, the proportion of eligible assets held by pension funds remains stable. Simultaneously, column (1) also demonstrates that the share at the end of August is exogenous relative to the share during the crisis period.

We report below the specification for reg (3) in Table 14:

$$\text{Return}_{p,\,t=\text{Jul2022}} = \alpha + \beta\,\text{PreShare}_{p,\,t=\text{Aug2022}} + \gamma X_p + \varepsilon_p. \tag{20}$$

Whether or not control variables are included, the regression results meet the requirements: coefficients are insignificant, and the explanatory power of the pre-sharing variable is weak.

Table 13: Rolling window Beta

	(1) Aug on Jul	(2) Sep on Aug	(3) Oct on Sep	(4) Nov on Oct	(5) Dec on Nov
beta	0.9274832	0.8499314	0.7974311	0.9766406	0.9327375
p_value	0.1392	0.0108	0.0001	0.4524	0.0772
upper_ci	1.024512	0.9635431	0.89213	1.038732	1.007643
lower_ci	0.830454	0.7363197	0.7027321	0.914549	0.8578319
R-squared	0.9636	0.9259	0.9221	0.9447	0.9608

Notes: Rolling regressions of Share_t on Share_{t-1} with pension-fund and security fixed effects. The share refers to eligible assets' proportion held by the pension fund. Reported are point estimates (Beta), 95% confidence intervals (upper_ci/lower_ci), and the p-value obtained from testing the unit coefficient hypothesis $H_0 : \beta = 1$. Standard errors are clustered at the gilt level.

Table 14: Funds' return on pre-share

	Return			
	(1) July2022	(2) June2022	(3) July2022	(4) June2022
Pre-share	-2.924	0.0114	-6.236	0.0328
	(4.945)	(0.0652)	(6.360)	(0.0833)
Fund size	–	–	-24.26	0.704
			(56.52)	(0.738)
Fund risk	–	–	11.81	-0.0850
			(11.97)	(0.157)
R-square	0.0047	0.0004	0.0146	0.0023

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
The independent variable is the monthly returns of the pension fund for June and July 2022. The pre-share is the eligible assets held by the fund in August 2022.

6.4.3 Asset pricing

In this section, we move from fund-level variation to security-level evidence to assess whether institutional demand shocks translate into predictable cross-sectional price movements. Because gilt holdings differ substantially across investors, the stress episode generates high-frequency, quasi-exogenous variation in the intensity of sales at the individual-security level. These dynamics will allow us to estimate demand curves for specific gilts and to test whether securities disproportionately held by more exposed investors exhibit sharper price dislocations and subsequent reversals. By doing this, this section provides the cleanest asset-pricing test of the mechanism and findings we discussed in the previous sections.

We compare the yields of eligible and ineligible gilts in a difference-in-difference set-up. We estimate the following specification:

$$\ln(\text{price})_{g,t} = \alpha_g + \lambda_t + \sum_{k=1}^{4} \beta_k \, \text{CrisisPeriod}_{k,t} \times \text{Eligible}_g + \varepsilon_{g,t}$$

where $\ln(\text{price})_{g,t}$ is the yield of securities. The dummy variables $\text{CrisisPeriod}_{k,t}$ take on the value of 1 for period k and zero otherwise. We consider 4 periods: crisis onset (Sep 23– Sep 27), an asset purchase announcement period (Sep 28 – Oct 2), two APPs periods. The two periods when BoE implement the APP are named action5 (Oct 3 – Oct 10), and action10 (Oct 11 – Oct 14). The time-period used uses 10 days prior the mini-budget until 10 days after the APP. The variable Eligible_g is equal to 1 if a security is one of the aiming assets of APP. Lastly, α_g are security level fixed effects, λ_t are time level fixed effects and $\varepsilon_{i,t}$ is the error term. Standard errors are clustered at security level.

Table 15 shows strong and economically meaningful price effects associated with variation in predicted selling pressure. Gilts with higher ex-ante exposure experience significantly larger yield increases during the stress period: during the crisis, eligible securities experienced an additional 16.1% decline in price relative to ineligible securities. The Bank of England's announcement of its Asset Purchase Programme (APP) resulted in an additional 12.6% increase in the price of eligible securities. This shows that the announcement of the APP provided significant support to eligible securities. These estimates are consistent with steep and state-dependent demand curves for government bonds, in line with segmented-market asset-pricing models. Crucially, the magnitude of the effects is robust across maturity buckets and liquidity controls. Even after conditioning on security-level characteristics, the coefficient on predicted selling pressure remains large and statistically significant. This indicates that the cross-sectional variation in returns is not simply a reflection of differential liquidity or duration risk, but is driven by heterogeneity in investor holdings and the intensity of sales.

In contrast to earlier results, we now find that announcements also generate significant market responses. While the effects of actual investor flows remain much stronger, the estimates show that announcements alone lead to measurable adjustments in security-level yields and cross-sectional returns. This is consistent with asset-pricing models in which prices incorporate expected future demand and liquidity provision

To provide some robustness for our results, we also conducted an event study:

$$\ln(\text{price})_{g,t} = \alpha_g + \lambda_t + \sum_{d=1} \beta_d \times 1(t \in d) \times \text{Eligible}_g + \varepsilon_{g,t}$$

where $\ln(\text{price})_{g,t}$ is the yield of securities. $1(t = d)$ is an indicator variable to specify the date. The time spans from 10 days prior the mini-budget to 10 days following the the APP. Eligible_g in the regression is a dummy variable to capture whether a security is eligible or not. α_g and λ_t are fixed effects for security g and time t. $\varepsilon_{g,t}$ is the error term. Standard errors are clustered at security level.

The event-study estimates in Figure 10 show clear and timely security-level responses to the shock. Securities with higher predicted selling pressure begin to underperform immediately in the pre-announcement window, and the divergence sharply increases at the onset of deleveraging. The absence of pronounced pre-trends in the cross-section indicates that the subsequent yield movements are not driven by gradual buildup of differential risk but by the discrete jump in

Table 15: DiD for eligible and ineligible securities

	(1) diff in diff
onset	-0.147^{***}
	(0.0148)
announce	0.138^{***}
	(0.0170)
action5	-0.144^{***}
	(0.0170)
action10	0.202^{***}
	(0.0196)
treat_onset	-0.161^{***}
	(0.0186)
treat_announce	0.126^{***}
	(0.0169)
treat_action5	-0.0547^{***}
	(0.00548)
treat_action10	-0.0283^{***}
	(0.00351)
_cons	4.561^{***}
	(0.00368)
N	2126
F	227.48
r^2	0.6863
bond FE	Yes
time FE	Yes

t statistics in parentheses,

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Notes: We compare the yields of eligible and ineligible gilts in a difference-in-difference set-up. To assess the dynamics of security level price, we estimate the following specification:

$$\ln(\text{price})_{g,t} = \alpha_g + \lambda_t + \sum_{k=1}^{4} \beta_k \, \text{CrisisPeriod}_{k,t} \times \text{Eligible}_g + \varepsilon_{g,t}$$

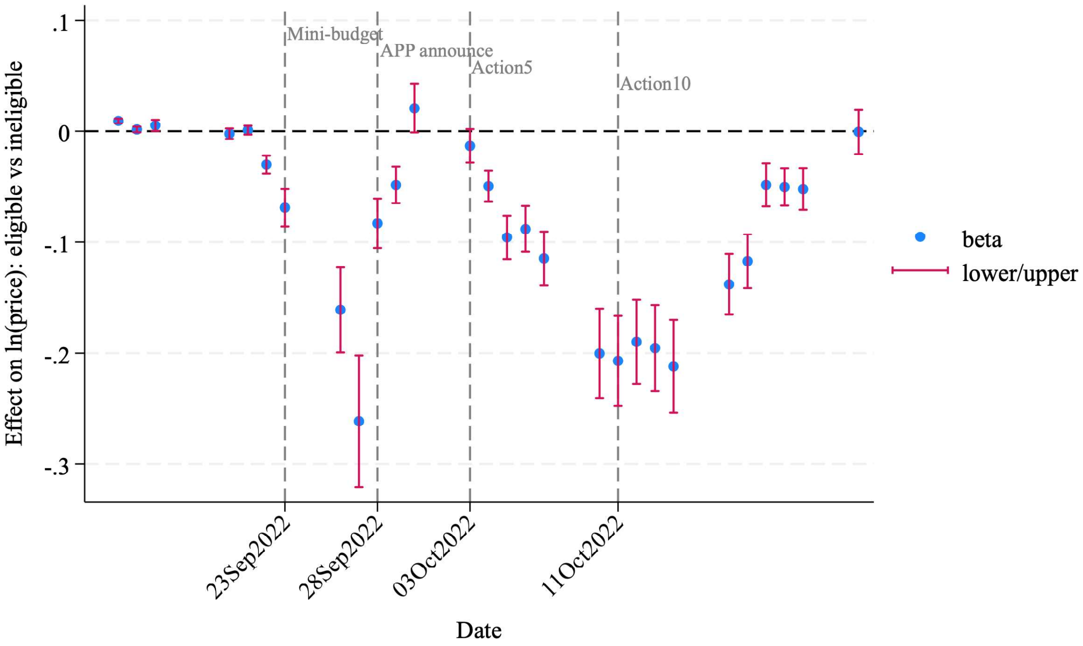
where $\ln(\text{price})_{g,t}$ is the yield of securities. The dummy variables $\text{CrisisPeriod}_{k,t}$ take on the value of 1 for period k and zero otherwise. We consider 4 periods: crisis onset (Sep 23– Sep 27), an asset purchase announcement period (Sep 28 – Oct 2), two purchase implementation periods and after finish period. The two implementation periods are action5 (Oct 3 – Oct 10), and the periods action10 (Oct 11 – Oct 14). The timeframe spans from 10 days prior to the enactment of the mini-budget to 10 days following the completion of the APP. The variable Eligible_g is equal to 1 if a security is one of the aiming assets of APP. Lastly, α_g are security level fixed effects, λ_t are time level fixed effects and $\varepsilon_{i,t}$ is the error term. Standard errors are clustered at security level.

expected selling intensity. This is consistent with asset pricing models showing steep demand curves, the yield impact peaks within the first few trading days and is concentrated precisely around the event window.

Following the APP, we observe partial price reversals for the most exposed securities, suggesting that the initial dislocations reflected temporary demand-driven pressure rather than changes in fundamentals. In sum, the event-study patterns provide clean visual and statistical evidence that the cross-sectional gilt price movements are tightly aligned with the timing of the demand shock. This result reinforces results in Table 15.

Figure 10: Event study of security price

where $\ln(\text{price})_{g,t}$ is the yield of securities. $1(t = d)$ is an indicator variable to specify the date. The timeframe spans from 10 days prior to the enactment of the mini-budget to 10 days following the completion of the APP. Eligible_g in the regression is an indicator variable to show whether a security is eligible gilt or not. α_g and λ_t are fixed effects for security g and time t. $\varepsilon_{g,t}$ is the error term. Standard errors are clustered at security level.



7 Stylised Model

The stylised model in this section provides a structural interpretation of the asset-pricing mechanism underlying our empirical findings. Rather than capturing features unique to the UK pension system, the model introduces a general setting where asset prices are determined by downward-sloping investor demand interacting with binding balance-sheet constraints. Therefore, APPs act as exogenous demand shocks that shift the effective supply faced by constrained investors. When margin constraints bind, the new price relaxes funding constraints and inducse portfolio rebalancing, generating spillovers across segmented markets. IN sum, the model stresses the notion that asset prices during stress reflect investor capacity and funding conditions rather than fundamentals alone.

In the model, APPs work as outward shifts in the demand curve for government bonds, raising prices through reduced private-sector supply (Equation (3)). Under margin constraints, shifts in price affect directly investors' wealth trigging portfolio rebalancing toward other risky assets, and leading to price spillovers (Equation (7) and subsequent discussion). This framework, although simple, provides a structural interpretation of our empirical results as evidence of constrained investor demand and market segmentation in safe asset markets.

The model is a one period model and it captures (i) how central-bank purchases affect gilt prices, (ii) how price changes affect non-bank (NBFI) balance-sheet/margin outcomes, and (iii) the rebalancing/spillover channel. The model rests on Vayanos and Vila (2021) and Greenwood and Vayanos (2014) and using Brunnermeier–Pedersen (2009)–type margin constraint to capture the fire-sale mechanism.

It's a single-period economy with date 0 and date 1. There is a fixed gross supply of gilts S (which can be normalized to 1). The central bank purchases $G \geq 0$ units of gilts at date 0. The remaining private sector holdings of gilts are $Q = S - G$.

There are two representative private agents: Banks (intermediaries) providing short-term funding and holding some safe assets. They set margin requirements and can withdraw funding. Non-bank financial institutions (NBFIs) hold gilts financed in part with short-term funding. Representative NBFI initially holds q0 gilts (a fraction of Q).

Gilts pay a random payoff at date 1; for simplicity let the gross payoff be normalized to 1 (so price is effectively related to yield). The market price p of gilts at date 0 is given by a downward-sloping linear inverse demand:

$$p = A - B \cdot Q_{ps}, \tag{21}$$

where Q_{ps} = private sector holdings of gilts available for trading at date 0 (i.e., supply to private buyers), $A > 0$, $B > 0$. Since the central bank withdraws G, $Q_{ps} = S - G$. Thus:

$$p(G) = A - B(S - G). \tag{22}$$

Larger central-bank purchases reduce private supply, so price rises. APPs function as supply shocks.

Margin constraints, Each NBFI finances a fraction of its gilt position with short-term funding. Let an NBFI hold q gilts and finance ϕq via short term funding (leverage fraction $\phi \in (0, 1)$). Lenders require a margin (haircut) h so that available collateral value must satisfy $(1 - h)pq \geq \phi q$ otherwise a margin shortfall triggers asset sales. Rearranging, the margin constraint, we obtain:

$$(1 - h)p \geq \phi \iff p \geq \frac{\phi}{1 - h} \equiv \bar{p}.$$

If $p < \bar{p}$,lenders issue margin calls and the NBFI must sell an amount s of gilts to restore the constraint (for simplicity assume they sell until equality holds).

Suppose a margin shock at date 0 causes lenders to raise ϕ to $\phi + \Delta\phi > 0$ or raises haircuts h (equivalent). This creates downward pressure on prices via forced sales by some agents. Central bank may intervene by choosing G (buying from the market), which reduces private supply and raises p. What is the effect on prices and margins?

Using the inverse demand equation with private supply $S - G$:

$$p(G) = A - B(S - G).(3) \tag{23}$$

And taking the derivative:

$$\frac{\partial p}{\partial G} = B > 0.$$

Central bank APPs raise the market price. Define the price to avoid margin shortfall as:

$$\bar{p} \equiv \frac{\phi}{(1-h)}. \tag{24}$$

If $p(G) \geq \bar{p}$, NBFIs do not face immediate margin shortfalls. If $p(G) < \bar{p}$, they must sell an amount s to make the constraint holding. For simplicity, suppose the NBFI reduces holdings from q to $q - s$, and the market clears:

$$\text{market clearing:} Q_{ps} = S - G + s,$$

because sales s increases the effective supply to private buyers. Price with sales s is:

$$p = A - B(S - G + s).(5) \tag{25}$$

The sales are determined by restoring the margin constraint at equality:

$$(1-h)p = \phi \ \Rightarrow \ p = \bar{p}. \tag{26}$$

Plugging it into price equation:

$$\bar{p} = A - B(S - G + s) \ \Rightarrow \ s = \frac{(A - \bar{p})}{B} - (S - G).(7) \tag{27}$$

Feasible s must satisfy $0 \leq s \leq q$ (can't sell more than holdings). Fire-sales occur only if $A - B(S - G) < \bar{p}$ (i.e., without sales price would be below $\bar{p}$).

7.1 Discussion

Our stylised model is simplistic but highlights the mechanism surrounding our results. For example, APPs raise gilt prices:

$$\frac{\partial p}{\partial G} = B > 0.$$

Every unit the BoE buys reduces private supply, mechanically increasing price and lowering the yield. If, in the absence of intervention, the price would be below the margin threshold (i.e., $p(0) < \bar{p}$), then there exists a minimal G^* such that $p(G^*) = \bar{p}$. Specifically

$$G^* = S - \frac{A - \bar{p}}{B}.$$

For any $G \geq G^*$, fire-sales are avoided ($s = 0$). Hence:

$$\frac{\partial s}{\partial G} = -1 (\text{while } p < \bar{p}, \text{through the mapping above}),$$

i.e. increasing G by the amount of averted forced sales reduces the forced sales dollar for dollar (in this linear model).

Central-bank purchases can directly reduce or eliminate NBFI forced sales by raising the market price above margin thresholds — this is the stabilisation channel that prevents deleveraging. From an asset-pricing perspective, this mechanism suggests that investor demand for bonds is highly sensitive to balance-sheet conditions. When margin constraints bind, the slope of effective demand steepens, and shifts in supply —see for example APPs- generate large price responses. In this context, central-bank intervention can be interpreted as relaxing a binding constraint that otherwise suppresses demand. IN this respect, the model shows how price effects in both eligible and ineligible assets emerge not from changes in fundamentals but from shifts in investor capacity. This is consistent with the interpretation of our empirical findings as evidence of inelastic demand and limits-to-arbitrage dynamics during crisis periods.

Suppose there is a second risky asset (ineligible assets) with price x determined by private investors' demand, which depends positively on their "excess" wealth or willingness to hold risky assets W. If central bank gilt purchases raise gilt prices and therefore raise NBFI equity/wealth (because the mark-to-market value of remaining holdings increases), private investors reallocate towards other risky assets: i.e.,

$$\frac{\partial W}{\partial G} > 0 \iff \frac{\partial x}{\partial G} > 0,$$

so central-bank purchases generate upward spillovers to other asset prices via portfolio rebalancing. This is similar to Stealth recapitalization" is a concept in economics, coined by Brunnermeier and Sannikov (2016). When CB purchases raise gilt prices and wealth, private portfolios tilt toward other risky assets—this is the rebalancing channel and explains observed spillovers from gilt purchases to ineligible assets.

Finally, the model motivates our hypothesis testing in this paper. First, investors with greater pre-crisis exposure to government bonds should experience stronger price effects from central-bank purchases, as demand shifts occur along a downward-sloping and constraint-amplified demand curve. Second, higher bond prices will relax binding constraints and it follows that constrained investors optimally rebalance their portfolios toward uneligible but closely related assets, generating spillover price effects in those markets. Finally, price adjustments will not only affect direct holders of government bonds, but spread to other market participants with exposure to the affected asset classes, influencing their valuation and performance.

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A Appendix A

A.1 Formation and reinforcement of the Mini-budget crisis

On 23 September 2022, following the introduction of the government's growth plan - the "mini-budget", UK government bond yields rose sharply. Figure 11 shows a line graph of average monthly yields on 1-, 5-, 10-, 20- and 30-year gilts. In September 2022, gilts rose sharply, with the 30-year nominal yield rising by 130 basis points in just a few days. The increase was particularly pronounced for medium- and long-term maturities compared to short-term ones.

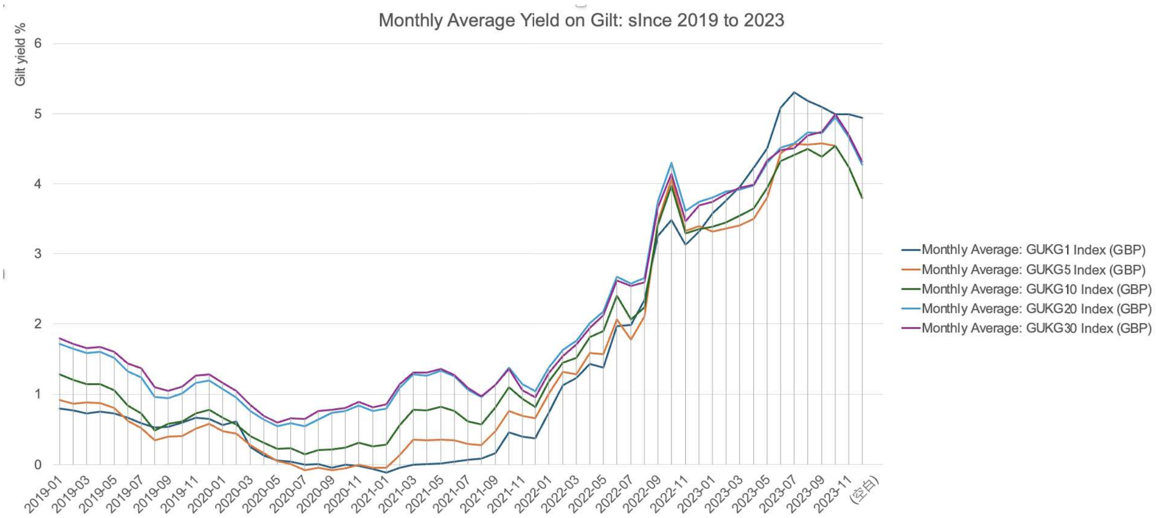
As we can see in Figure 12, the term structure of 30-year gilts rate (left panel) maintained a flat upward shape under all three periods. It is only after the mini-budget crisis that bank rates on 27 September were about 150-200 basis points higher than on 30 August at all maturities. By 27 October, bank rates significantly declined to near pre-crisis levels. This suggests that the onset of the mini-budget crisis caused interest rates to rise sharply, while they fell significantly after the central bank provided temporary purchase facilities.

A measure of gilts' liquidity during that period can be proxied by the swap rates (right panel) dynamics. The swap rate curve gradually decreased (inverted) at all the maturities. This is consistent with the fact that interest rates were already at nearly three-year highs at the time (Figure 11). Looking closely at the changes that occurred during that period, swap rates rose to their highest on September 27, which for the 30-year nominal gilts was a 200 basis points increase from the end of August. This is a significant increase and reflect the significant higher funding costs that pension funds were subject to. In fact, the immediate effect of this was that rising swap rates increased the quoted fixed rates and pension funds (fixed rate payers) were exposed to higher funding costs. This is another source of liquidity pressure for pension funds, in addition to repo agreements, which has not well investigated.

Figure 13 shows the monthly swap spreads which are calculated using swap rate minus gilts rate. There is a significant sharp increase between end of August with end of September in 2022. Based on the analysis of Figure 11, it can be seen that yields rose sharply during the mini-budget

Figure 11: Monthly average yield on gilt: since 2019 to 2023

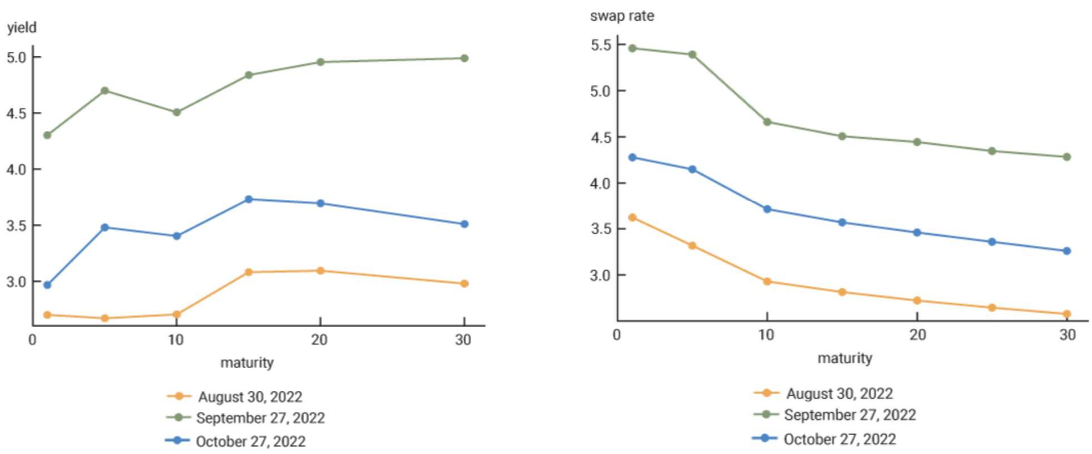
This is a line graph of the average monthly yields on 1-year, 5-year, 10-year, 20-year and 30-year gilts between 2019 and 2023.



Source: Data download from Bloomberg.

Figure 12: Change in gilt yields and GBP swap rates

This is a line graph of the 30-year gilts rate and swap rate at three points in time, 30 August, 27 September and 27 October 2022, indicating the state one month before the crisis, at the time of the crisis, and one month after the crisis, respectively.

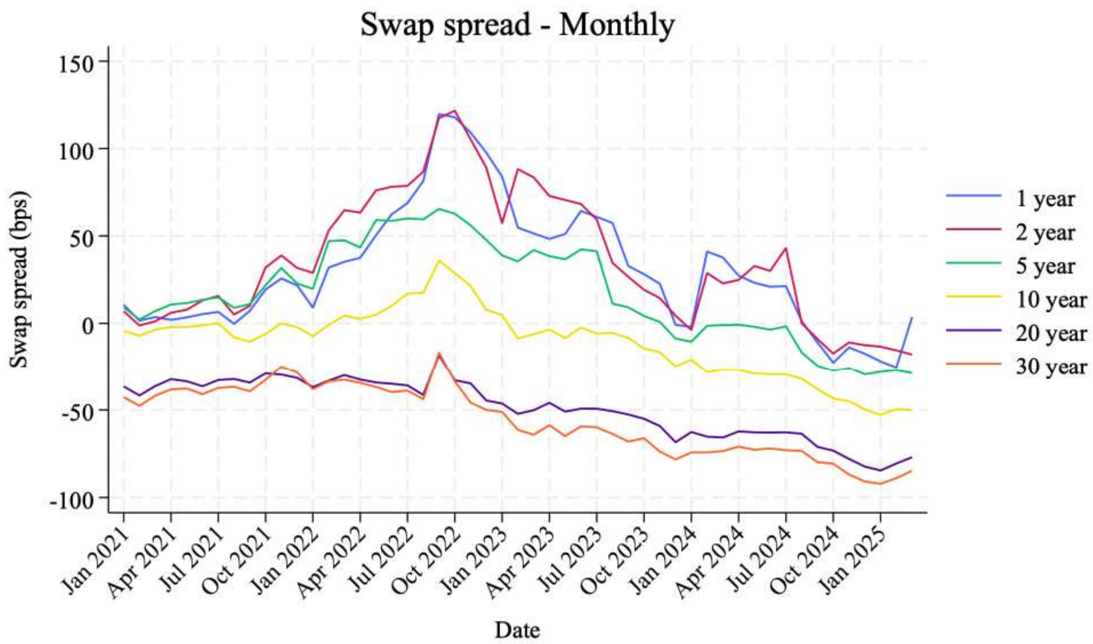


Source: Bloomberg.

crisis. The swap rate rose substantially during the same period. The rise in the swap rate indicates that the market expects the 'overall level of interest rates' or the 'future cost of finance' to be significantly higher in the short term. To explain the phenomenon, one reason might be markets took rising concerns about bank credit risk and liquidity risk. Given this significant and quick swings in funding markets, the BoE decide to intervene to restore market functioning.

Figure 13: Swap spread

This is a line graph of the average monthly yields on 1-year, 5-year, 10-year, 20-year and 30-year gilts between 2019 and 2023.



Source: Data from Bloomberg and calculated by authers.

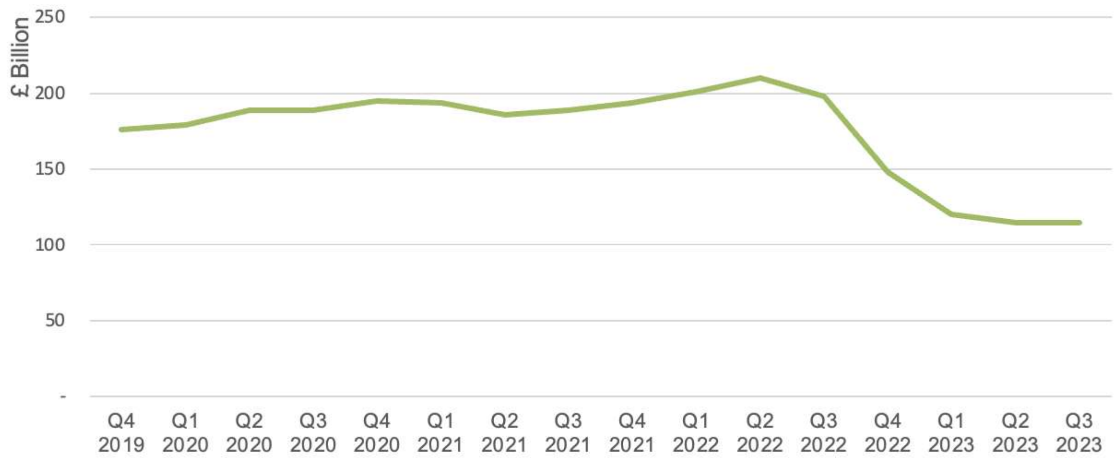
A.2 Impact on the funds

The sharp rise in gilt yields affected the net asset value of the leveraged LDI funds, and their leverage ratios increased considerably. In this case, the value of the fund's gilts in the repurchase agreement decreases massively, leading to margin calls[20]. Based on the high leverage, the fund

[20]This behaviour by banks is one of the ways in which they control counterparty default risk.

needs a large amount of cash to make the payment. Funds, in general, hold liquidity buffers for this purpose. But when the liquidity buffers are depleted, they then urgently needs to deleverage to prevent insolvency and to meet increasing margin calls. Figure 14 shows pension funds' holdings of repo contracts from Q4 2019 to Q3 2023. In the Q3 2022, the size of their repo contracts shrinks significantly, down 25.25% quarter over quarter. And it has remained stable for the 12 quarters prior to that. This suggests that the depreciation of gilts did have an impact on the repo leverage held by pension funds.

Figure 14: Repurchase agreements (Repos) that pension funds holding

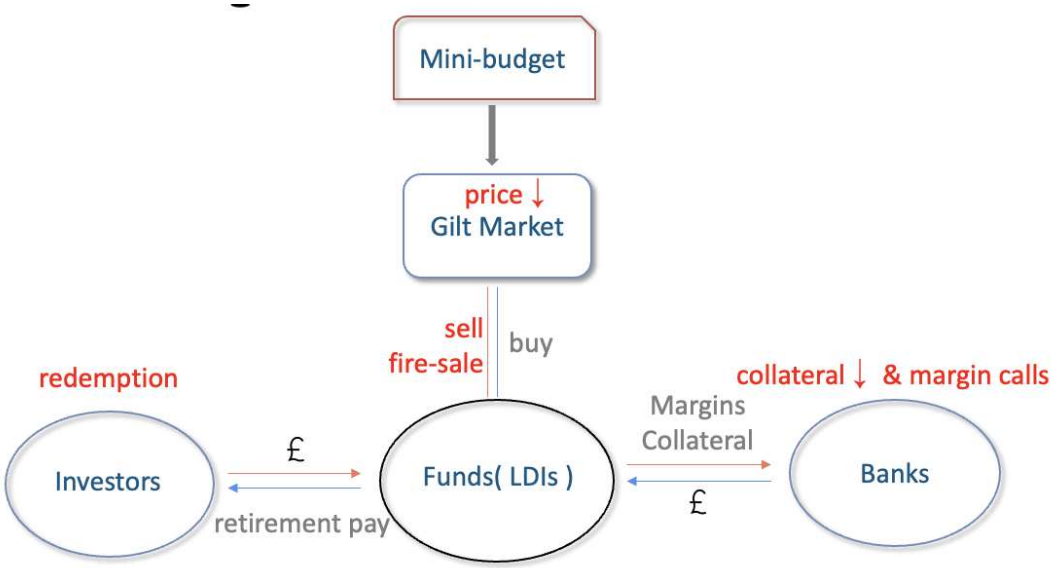


Source: Office for national statistics. Funded occupational pension schemes in the UK: July 2019 to September 2023: Reference table. Published 21st March 2024.

In such a situation, the fund would need to sell gilts into illiquid markets or ask DB pension scheme investors to provide additional capital. Eventually there is a situation where funds sell gilts to meet margin calls from banks (Figure 15). Analysing trading data from the UK government bond, repo and interest rate swap markets, Pinter (2023) finds that firms in the liability-driven investor sector, which had large repo and swap exposures prior to the crisis, sold more gilts during the crisis. This is consistent with Brunnermeier and Pedersen (2009) suggestion that funding conditions are important for market liquidity.

There are three main types of participants in the gilt sell-off: pooled funds, LDI funds, and counterparties that enter into repurchase agreements with the funds who holds gilt as collateral.

Figure 15: Changes of fund relationship under Mini-budget Crisis



Source: Drawn by author.

The problem of gilt selling is particularly acute in one small corner of the LDI industry - pooled funds. These funds represent around 10-15%[21] of the LDI market and manage assets for a large number of pension fund who have limited liability in the event of losses. Pooled fund small investors offering new funds typically take a week, sometimes two weeks, to rebalance their positions. But the speed and scale of yield movements during the mini-budget period far outstripped the ability of most pooled fund investors to raise funds. Limited liability also means that these pooled fund investors may choose not to provide support. As a result, pooled LDI funds were unable to raise sufficient funds from their investors and became forced sellers of gilts. Their selling rates could not have been absorbed under normal gilt trading conditions, let alone under the conditions that prevailed during the period of stress.

Other LDI funds, with separate mandates, have been able to raise funds from their personal pension scheme clients more easily. However, given their size of 85-90% of the market, some of these funds have also created selling pressure, making the task of pooled LDI funds even more

[21] Financial Survey of Pension Schemes 2022: Q2.

difficult. Also, if the pooled funds default, there is the possibility that the large number of gilts held as collateral by those who lent to these funds could be sold in the market.

B Appendix B

B.1 Portfolio sorting for Section 4

As a robustness for our results, we also use a simple classification of portfolios to understand the potential impact of the implementation of central bank intervention policies on the cumulative performance of pension funds. Specifically, we classify pension funds into three equally weighted portfolios based on the Hb value of their bond holdings, with each portfolio consisting of about 113 pension funds. Figure 16 plots the cumulative performance of portfolios with low and high bond holdings over time. The cumulative performance of the funds is relative to the NAV on 22 September, the day before the mini-budget. Portfolio performance is calculated using an equally weighted average of the cumulative performance of each fund in the portfolio.

Figure 16 shows that the performance of pension funds holding high gilt ratios declined sharply in performance relative to low gilt ratio funds after the mini-budget was happened. In just a few days, the cumulative performance of pension funds with high gilt exposure fell by 9.73% compared with the pre-Mini-budget announcement, while the cumulative performance of funds with low gilt exposure only fell by 2.42%. The difference in performance between the two portfolios means that the pension fund's gilt exposure caused an additional 7.31% drop in pension funds' performance when facing Mini-budge crisis. This result is supportive to the results we report in the paper. Table 4 where treat_onset interaction term coefficient is -3.2 strongly significant. Following the start of the BoE's APP intervention, the cumulative performance of funds with high gilt exposure clearly recovered to about the same level as funds with low gilt exposure. It suggests that the Bank of England's interventionist policy did play a supportive role for pension funds with high gilt exposure. But we can see that the difference in cumulative performance between pension funds with high gilt-holding ratios and those with low gilt-holding ratios continued to widen, which means the BoE's APP could not fully absorb the market sell-off of gilts during this time. The scale of purchases in the first week of the APP period was not enough to fully support the downward pressure on pension fund performance. This also provides an explanation for the central bank's expansion of purchases in the second week of APP. It is only after the larger purchases during the second week that the cumulative performance difference starts to narrow. At the end of the APP, the difference in cumulative performance between the two groups of portfolios gradually converges to the same level. Thus, the temporary policy effectively alleviated the liquidity pressure of the pension funds. This is consistent with our conclusion in Section 4.3.

Figure 16: Performance pressure of pension fund from Mini-budget - Portfolio Sorts

C Appendix C - Additional tables

In Table 16 we report first stage results for Section 6.1. we report first stage results for Section 6.1. The estimated coefficient implies that a pension fund that has a 1pp higher ex-ante exposure to BoE purchases, sells 1.3pp more of its portfolio compared to a less exposed pension fund. One

Table 16: Pension funds' exposure – first stage

	Exposure
Pred Exposure	1.274***
	(0.0538)
Observations	782
R^2	0.853
Month	Yes
F	14.708

Notes: The table reports regressions of the form $\text{Exposure}_{g,t} = \gamma_t + \omega\,\text{PredExposure}_{g,t} + \nu_{t,g}$ during APP from 1,Sep2022 to 31,Oct2022. Exposure is calculated as the amount each pension fund sells in a given month of gilts purchased by the BoE in that month. Predicted Exposure is a shift-share instrument that measures how much a pension fund can potentially sell to the BoE based on their portfolio allocation at the end of Aug2022. We control for month and fund fixed effects. t statistics are reported in parentheses. Standard errors are clustered at the pension fund level. *,**,*** indicate significance at the 5%, 1%, 0.1% level, respectively.

could interpret the coefficient ω as a measure of pension funds' sector demand sensitivity to supply shocks. It shows how much a pension fund is willing to sell given the APP.

In Table 17 we report the first-stage result for Section 6.2.

Table 17: Flows' predictability - first stage

	Δlog(NomAmount)
Δlog(PredNomAmount)	-0.00595^{**}
	(0.00227)
Observations	1,224
R^2	0.0200
Month	Yes
F	30.527

Notes: The table reports regressions of the form $\Delta log(NomAmount)_{n,t} = \gamma_t + \beta \Delta log(PredNomAmount)_{n,t} + \nu_{n,t}$ from 1Sep2022 to 31Oct2022. $\Delta log(NomAmount)$ corresponds to the change in nominal amount of each security held by pension funds. $\Delta log(PredNomAmount)$ corresponds to the predicted change in nominal amount of each security. We control for month and security effects. t statistics are reported in parentheses. Standard errors are clustered at the security level. *,**,*** indicate significance at the 5%, 1%, 0.1% level, respectively.

Table 18: Flows' predictability on equity - first stage

	Equity
	Δlog(NomAmount)
Δlog(PredNomAmount)	-0.00345^{***}
	(0.000905)
Observations	12,221
R^2	0.0018

Notes: The table reports regressions of the form $\Delta log(NomAmount)_{n,t} = \gamma_t + \beta \Delta log(PredNomAmount)_{n,t} + \nu_{n,t}$ from 1 Sep2022 to 31 Oct2022. $\Delta log(NomAmount)$ corresponds to the change in nominal amount of each security held by pension funds. $\Delta log(PredNomAmount)$ corresponds to the predicted change in nominal amount of each security. We control for month and security fixed effects. t statistics are reported in parentheses. Standard errors are clustered at the security level. *,**,*** indicate significance at the 5%, 1%, 0.1% level, respectively.

Table 19: Effect on prices of indirect demand shock

	(1)Equity OLS $\Delta\log(P)$	(2)Equity 2SLS $\Delta\log(P)$
$\Delta\log(\text{NomAmount})$	0.0322^{*}	-2.268^{***}
	(0.0158)	(0.557)
Observations	4,184	4,188
R^2	0.0846	0.0900
Month	Yes	Yes

The table reports regressions of the form $\Delta\log(P)_{n,t} = \gamma_t + \beta\Delta\log(\text{NomAmount})_{n,t} + \nu_{n,t}$. $\Delta\log(\text{NomAmount})$ corresponds to the change in nominal amount of each security held by pension funds. We control for month and security fixed effects. t statistics are reported in parentheses. Standard errors are clustered at the security level. *,**,*** indicate significance at the 5%, 1%, 0.1% level, respectively.

Table 20: Effects on mutual funds' performance

	(1)Equity Performance(cum)
$\Delta\log(P)$	4.862^{*}
	(2.253)
R^2	0.1270
MonthXIsin	Yes

The table reports regressions of the form $\text{Performance(cum)}_{i,t} = \gamma_t + \beta\frac{\sum_n \Delta\log(P)_{n,t} * w_{n,i}}{\sum_n 1 * w_{n,i}} + \nu_{i,t}$. Performance(cum) is the cumulative mutual fund performance, scaled to 1 Aug2022. By using $w_{n,i}$, we construct the average price change of ineligible equity assets held by each mutual fund. t statistics are reported in parentheses. We control for month and mutual fund fixed effects. Standard errors are clustered at the mutual fund level. *,**,*** indicate significance at the 5%, 1%, 0.1% level, respectively.

Online Appendix 1

The investments objectives of Defined Benefit (DB) pension schemes

Many UK Defined pension scheme, DB[22] had been in deficit for a significant period. Figure 17 shows the level of assets, liabilities and aggregate funding for private sector DB schemes in the UK, based on data from the Pension Protection Fund's 7800 index. From April 2011 to January 2021, the Aggregate balance of DB pension fund schemes in the UK is negative. This means that its liabilities (future commitments to pay pensions to pensioners) exceeded its asset holdings. Due to this situation investments by pension funds had two main objectives: 1) to hedge against interest rate risk and inflation risk that may arise from future payments on their liabilities; and 2) to reach an asset growth to mitigate the deficit.

Figure 17 shows this situation. From March 2006 (the beginning of the index) to February 2021, the aggregate balance was, generally, negative, which means most pension schemes were in deficit. In February 2021, the DB pension fund scheme's aggregate balance rose to 14.6 billions, the first surplus in a decade. It has maintained steady growth since then. According to House of Commons Library, in April 2023, 87% of schemes were in surplus.

Leverage was important during the crisis

As noted in Breeden (2022), leverage was at the core of the 2022 market turmoil in UK. We have already mentioned it in the previous section. Further discussion can be found in the online Appendix. In this section we dive deeper into the role that leverage had in the gilts' crisis. Leverage can be created in a variety of ways. The most obvious one is borrowing to buy assets - "financial leverage". But it can also be generated through "synthetic leverage" using derivatives[23][24]. This

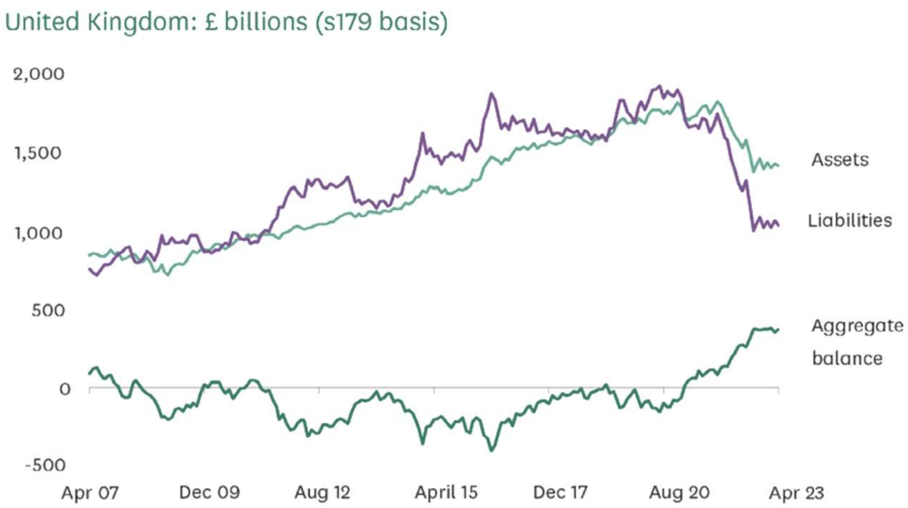
[22]Defined Benefit pension is a scheme in which an employer promises to pay a defined amount of pension to an employee upon retirement based on a predetermined formula (usually based on salary and length of service), with the investment risk being borne by the employer.

[23]Derivatives here generally refer to interest rate swaps and forward foreign currency contracts.

[24]For pension funds, as mentioned in Section 2.1 Figure 1, repos generate financial leverage and derivatives build synthetic leverage.

Figure 17: Asset and liability of defined benefit pension schemes

This line graph shows the change in assets and liabilities from April 2007 to April 2023 for defined benefit pension schemes.



Source: Chart produced by House of Commons Library from PPF 7800 index.

form of leverage is instrumental for pension funds as it allows the fund to adjust its risk profile by making relatively small initial outlays, while future gains or losses depend on changes in the underlying market prices.

The 2022 mini-budget event is also, probably, an example of vulnerability of the non-bank system driven by excessive leverage. For example, Figure 18 shows the trend in pension funds' derivative leverage and repo leverage from Q3 2019 to Q2 2023. Both the types of leverage were at historically high levels prior to the Mini-budget crisis, in the third quarter of 2022. By the fourth quarter of 2022, after the crisis, leverage, as a percentage of assets, declined significantly by 21.97% and 15.92%, respectively.

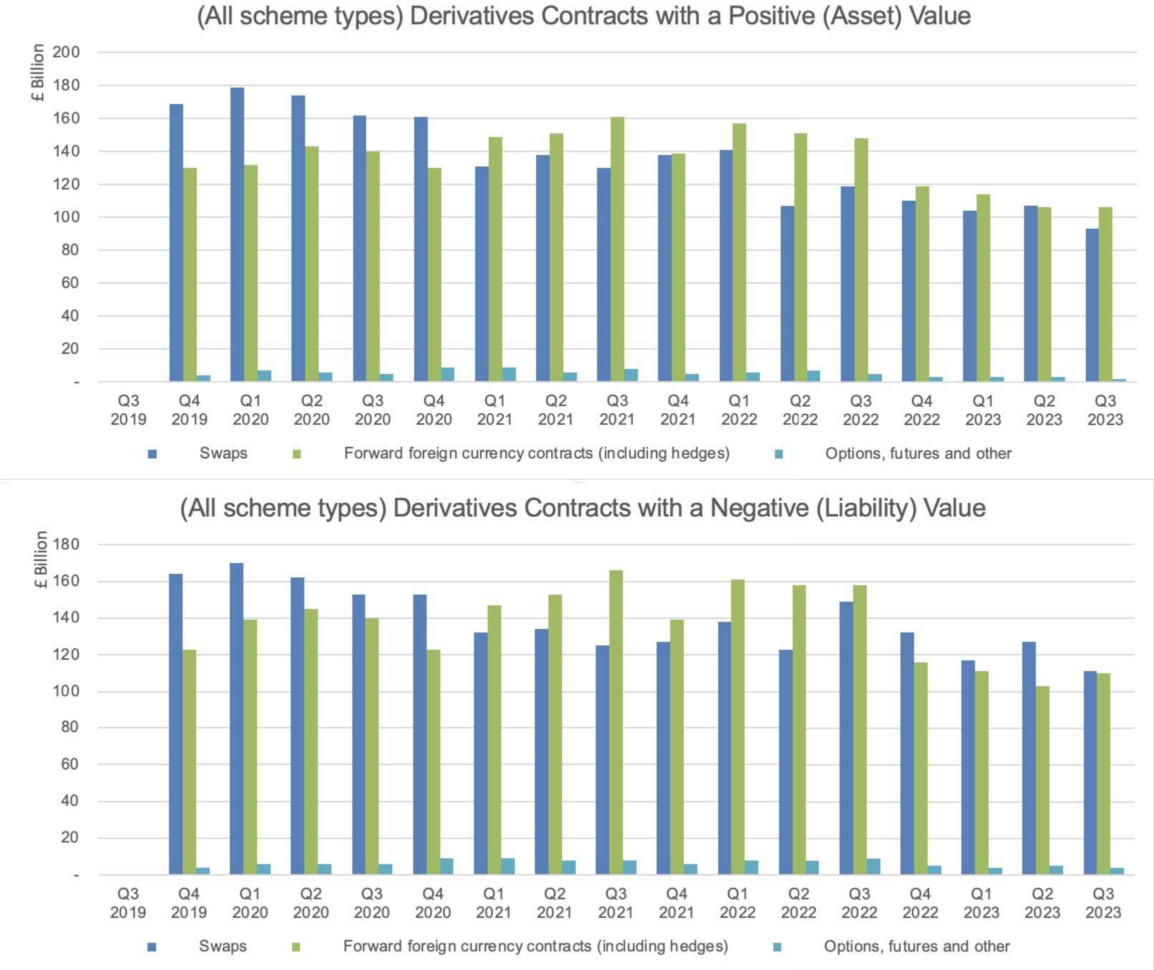
We also construct two (pension funds) leverage metrics. They are categorised according to the maturity of the debt: Debt_to_cap(long)% and Debt_to_cap(short)%. Theses two ratios measures a fund's financial leverage. Debt to cap (long)% is long-term debt (excluding other liabilities) to total capitalization (the sum of common equity plus preferred equity plus long-term debt).

Figure 18: Funds' derivative and repo leverage

This line graph shows the change in assets and liabilities from April 2007 to April 2023 for defined benefit pension schemes.

Source: Office for national statistics. Funded occupational pension schemes in the UK: July 2019 to September 2023: Reference table. Published 21st March 2024.

Figure 19: Pension funds' derivatives contracts



Source: Office for national statistics. Funded occupational pension schemes in the UK: July 2019 to September 2023: Reference table. Published 21st March 2024.

$$\text{Debt-to-cap (long) \%} = \frac{\text{Long-term debt}}{\text{Equity + Preferred equity + Long-term debt}} \tag{28}$$

Debt to cap (short)% is short-term debt (excluding other liabilities) to total capitalization (the sum of common equity plus preferred equity plus long-term debt).

$$\text{Debt-to-cap (short) \%} = \frac{\text{Short-term debt}}{\text{Equity + Preferred equity + Short-term debt}} \tag{29}$$

The Figure 20 illustrates the trends in these two financial leverage metrics over the mini-budget period for our sample of pension funds. Long-term leverage did not change significantly and remained rather stable. But short-term leverage, on the other hand, has a clear upward trend after the end of September 2022. Although it is not the objective of this paper to study whether excessive leverage caused the market turmoil in September 2022, the empirical evidence seems to support that conjecture.

Investment strategy for UK pension funds - LDI

In order to invest in a way that is appropriate for its expected pension payments, funds hold assets matching its liabilities.The DB Pension Scheme invests in long term gilts to hedge the interest rate and inflation risks associated with long term liabilities. The value of DB's liabilities is very sensitive to changes in the value of interest rates. When long-term interest rates fall, the present value of the DB pension plan liability also rises. Conversely, when long-term interest rates rise and gilt prices fall, the present value of the DB pension plan liability falls[25] This means that when the gilt assets held by the DB scheme fall in value, the value of its long-term liabilities also falls at the same time. However, funds need to invest in "growth assets", such as equities, in order to generate additional returns and grow their assets.

The liability driven investment (LDI) strategy utilises a leveraged gilt fund, allowing the scheme to maintain a substantial hedge while investing in growth assets, Aramonte and Rungcharoenkitkul

[25] Bank of England, Financial Stability Report, December 2022, section 5.1.

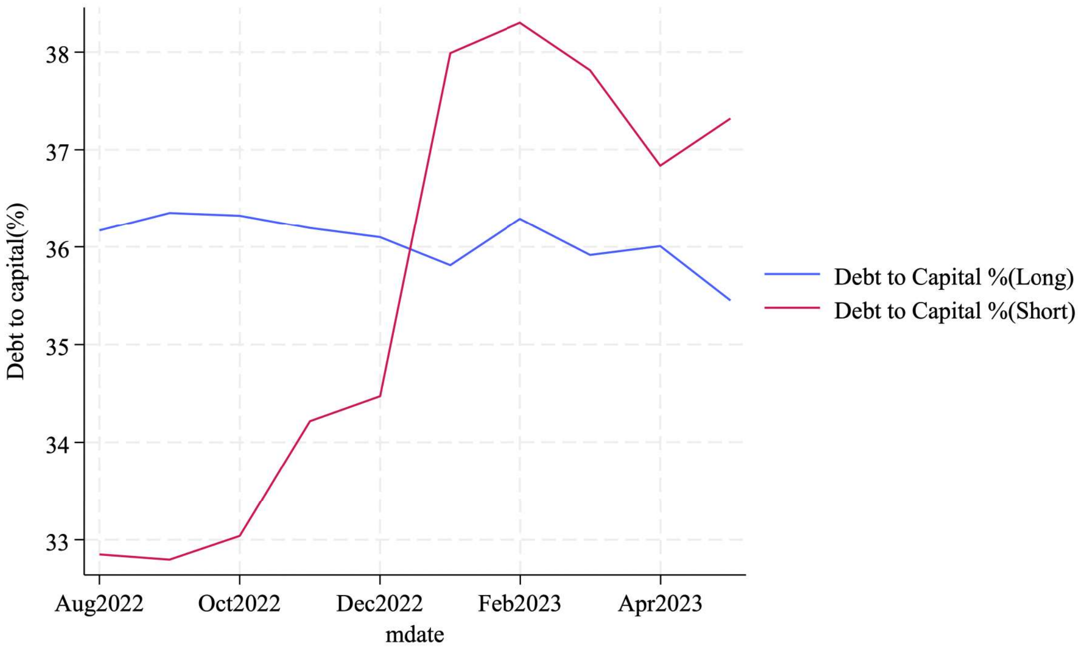
Figure 20: Trends in leverage variables in the crisis

The figure shows the monthly values (from August 2022 to May 2023) of leverage variables we have. The leverage ratio on the last trading day of each month is taken as the value for each month. Debt to cap (long)% is calculated by dividing long-term debt (excluding other liabilities) by total capitalization (the sum of common equity plus preferred equity plus long-term debt).

$$\text{Debt-to-cap (long) \%} = \frac{\text{Long-term debt}}{\text{Equity + Preferred equity + Long-term debt}}$$

Debt to cap (short)% is calculated by dividing short-term debt (excluding other liabilities) by total capitalization (the sum of common equity plus preferred equity plus long-term debt).

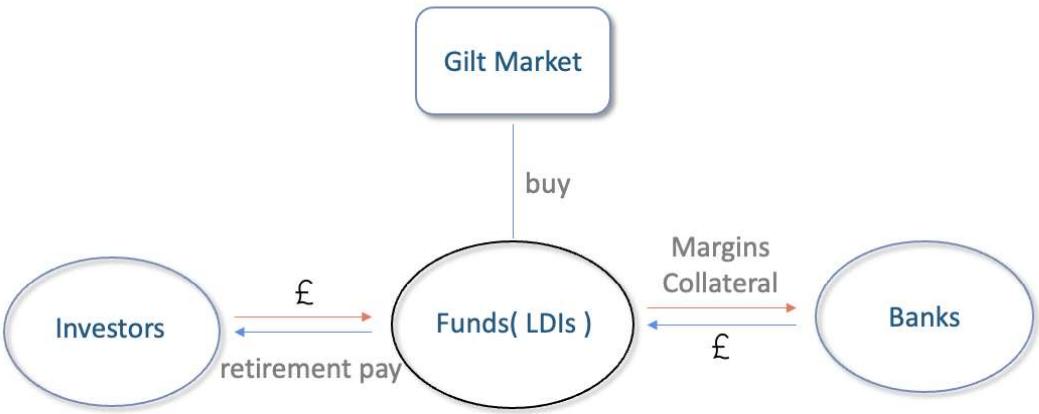
$$\text{Debt-to-cap (short) \%} = \frac{\text{Short-term debt}}{\text{Equity + Preferred equity + Short-term debt}}$$



(2022). Patel and Palacios (2023) explain that the UK gilt market is relatively small at $1.5 trillion compared to the $9.9 trillion US Treasury market. Therefore the LDI strategy portfolio includes synthetic leverage (i.e. derivatives). According to the Investment Association, the amount of UK pension fund liabilities hedged through LDI strategies grows from £400bn to £1.5 trillion (around two-thirds of UK GDP) between 2011 and 2020, with the majority of this concentrated in the gilt market (Chen and Kemp 2023).

In summary, UK pension funds held a large proportion of gilts via repo leverage. Therefore, leverage cannot be neglected to understand the market turmoil in UK in 2022, Figure 21.

Figure 21: Fund Relationship Network



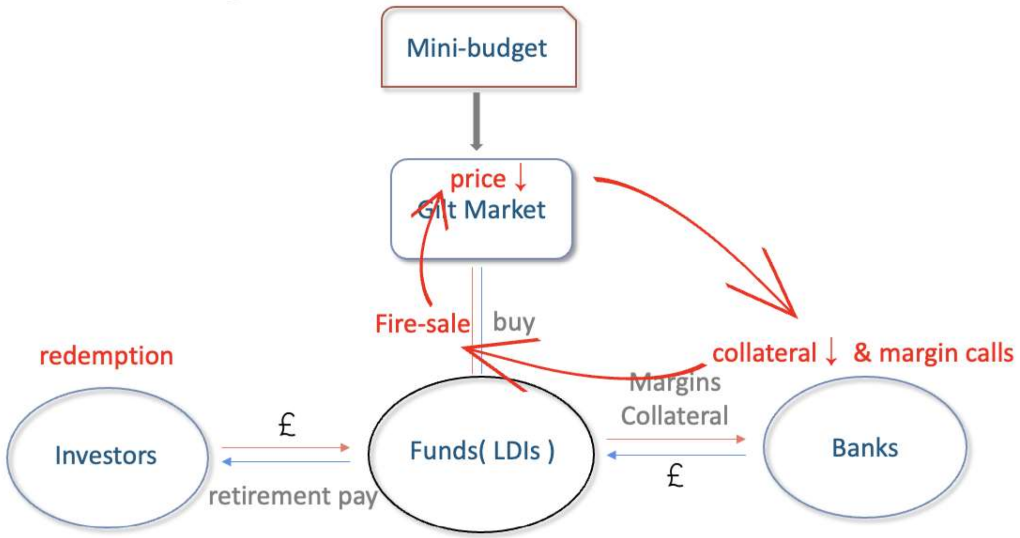
Source: Drawn by author.

Central bank intervention— self-reinforcing price spirals

As the gilt market is unable to absorb this forced sell-off, yields will increase leading to a vicious cycle of 'sell - price fall - further sell - further price fall' will develop in the gilt market, Patel and Palacios (2023) as in Figure 22.

In the aftermath of the Mini-budget crisis, the Bank of England intervened for 13 days, at a cost of £19.3 billion, for financial stability reasons. This was the first example of it achieving financial stability objectives through temporary, targeted intervention in the gilt market.

Figure 22: The self-reinforcing spiral under Mini-bydget Crisis



Source: Drawn by author.

The self-reinforcing price spiral mechanism, in that situation, was likely to lead to even greater disruption to the functioning of the gilt market. Breaking out of the price spiral and helping to restore the gilt market's pricing power was a key reason for the Bank of England's intervention.

Online Appendix 2

Controls selection for parallel trend test

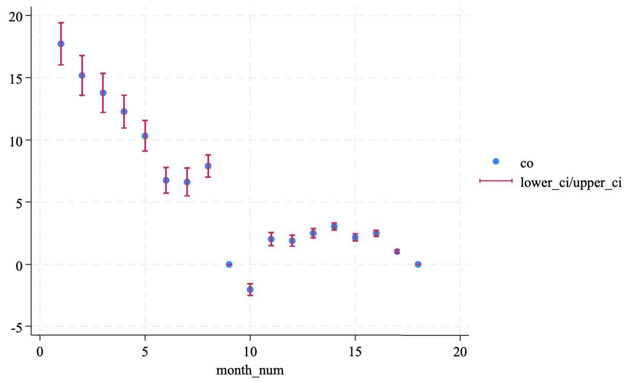
We have tried to adjust for the failure of the parallel trend test for pension funds. The following possibilities were proposed: 1) The setting of pre-crisis that only contains 5 periods and plots the coefficients in weeks may have the problem that the time interval of the test is too short, magnifying the short-term differences and ignoring the long-term trend. So we tried to extend pre to 1 January 2022 and change the weeks to coefficient plots in months.2) Factors that may have contributed to the difference between the control and treatment groups were controlled for to account for some of the trend differences.

Figure 23a shows that the ex ante parallel trend also does not hold for the control and treatment groups of pension funds for the nine-month period prior to the crisis. So the failure of the pension funds to satisfy the pre parallel trend assumption shown in the main text is not due to the sample period being too short. Figure 23b and Figure 23c present the results of the test with the inclusion of net asset and gilt yields. It can be seen that the addition of these two control variables does not significantly affect the coefficient results of the parallel trend test. For example, the coefficients for week33 remain between 3 and 3.5, which is not significantly different from the coefficient values without the control variables.

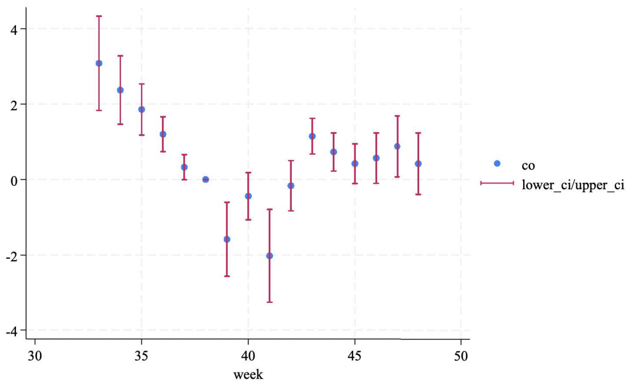
In summary, for the selection of effective control variables, size and leverage control effects are obvious (displayed in the main paper), while net asset and gilt yields do not produce effective control effects.

Figure 23: Parallel trend adjustment

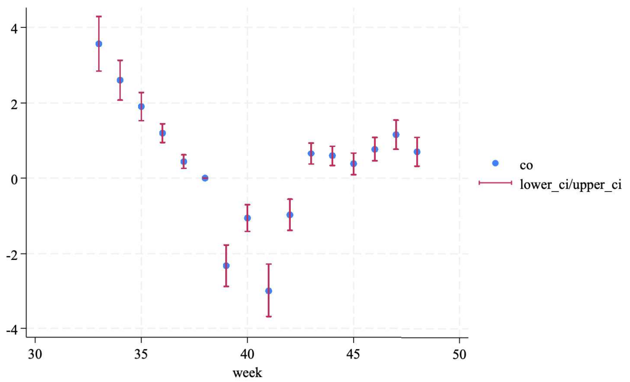
Sub-Figure a is a plot of the coefficients from 1 January 2022 to 30 June 2023, measured in months. The ninth month is the time of the crisis, which is used as the base for the regression analysis.
Sub-Figure b shows the coefficient plot considering the time series of net assets of pension funds. We obtained the time series of net assets of all the sample pension funds for the second half of 2022 from Morningstar direct database.
Sub-Figure c plots the coefficients controlling for long and short term gilt yields. We obtained the time series of yields on 1-year gilts and 20-year gilts for 2022 from Bloomberg.



(a) 9 months long pre-crisis test



(b) Control for net asset



(c) Control for 1 year and 20 year gilt yield

Online Appendix 3

Parallel trend tests for leverage DID

In this section we enhance on the parallel trends before treatment for the sample of pension funds. We use the following specification:

$$\text{performance(cum)}_{i,t} = \beta_0 + \sum_{w \neq 38} \beta_w \times 1(t \in w) \times D_i + \alpha_{i,t} + \mu_i + \varepsilon_{i,t}$$

We cover the period from the 33rd week to the 45th week in 2022. Week38 is when the Mini-budget announcement took place and it is regarded as treat time point. We assign 0 to its coefficient β_{33} and other coefficients β_w are normalized and estimated based on this. Performance(cum)$_{i,t}$ is the cumulative fund performance, scaled to August 1, 2022. $1(t = s)$ is an indicator variable for whether date t is in week w. We use the week in which the Mini-budget Crisis occurs as the baseline, i.e. week 38 of 2022. And the sample period is selected to be 5 weeks before crisis and 10 weeks after crisis to test for parallel trends. So the range of values for w is 33 to 48. D_i in the regression is an indicator variable for whether a fund held above-the-median amounts in leverage ratio at the end of August 2022. $\alpha_{i,t}$ is control variables. μ_i is a fixed effect for fund i explaining unobserved fund-level characteristics. $\varepsilon_{i,t}$ is the error term.

We do this parallel test on four samples in Table 7. They are plotted in Figure 24 along with 95% confidence intervals based on standard errors that are clustered by fund.

For the DIDs grouped by long-term debt leverage, the parallel trend of pension fund cumulative performance prior to the Mini-budget crisis is not entirely significant (shown in sub-figures a & b). But the difference in cumulative performance between the two ex ante samples is minimal compared to the large difference between the two groups after the crisis.

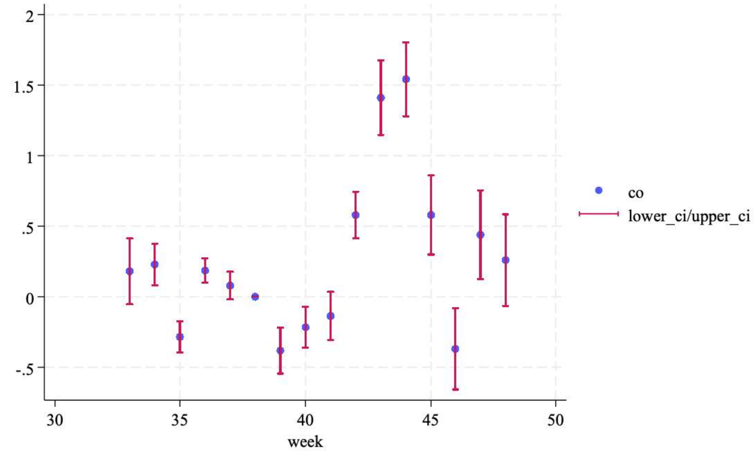
For DIDs grouped by short-term debt leverage, we can see a significant parallel trend in the cumulative performance of pension funds prior to the Mini-budget crisis (especially when controls for fund size are displayed in sub-figure d). This suggests that the regression results in Table 7 are robust. It further supports the conclusions of our analysis of the impact of short-term debt leverage

Figure 24: Coefplot of parallel tests for regressions in Table 7

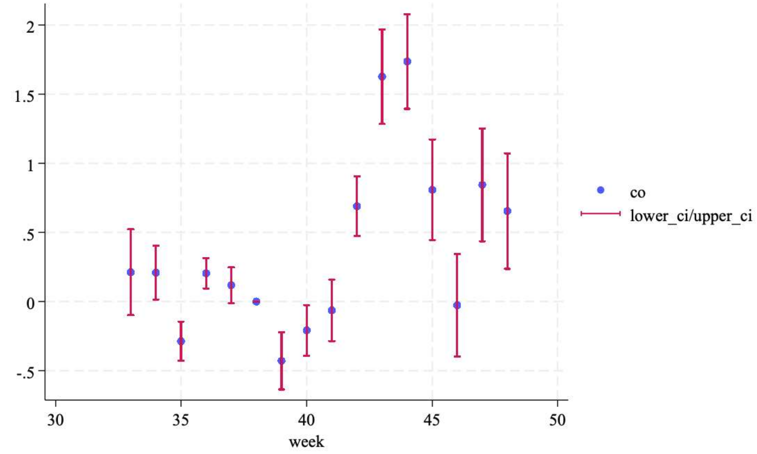
We construct the following regression model for parallel trend test:

$$\text{performance(cum)}_{i,t} = \beta_0 + \sum_{w \neq 38} \beta_w \times 1(t \in w) \times D_i + \alpha_{i,t} + \mu_i + \varepsilon_{i,t}$$

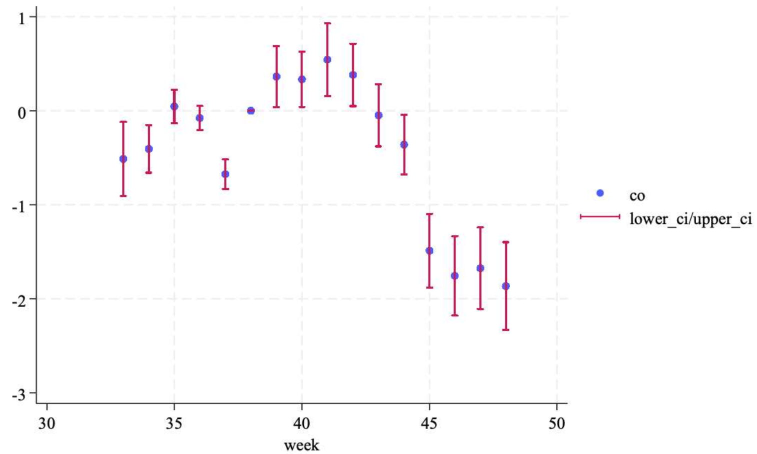
where performance(cum)$_{i,t}$ is the cumulative fund performance, scaled to August 1, 2022. $1(t = s)$ is an indicator variable for whether date t is in week w. We use the week in which the Mini-budget Crisis occurs as the baseline, i.e. week 38 of 2022. And the sample period is selected to be 5 weeks before crisis and 10 weeks after crisis to test for parallel trends. So the range of values for w is 33 to 48. D_i in the regression is an indicator variable for whether a fund held above-the-median amounts in leverage ratio at the end of August 2022. $\alpha_{i,t}$ is control variables. μ_i is a fixed effect for fund i explaining unobserved fund-level characteristics. $\varepsilon_{i,t}$ is the error term.



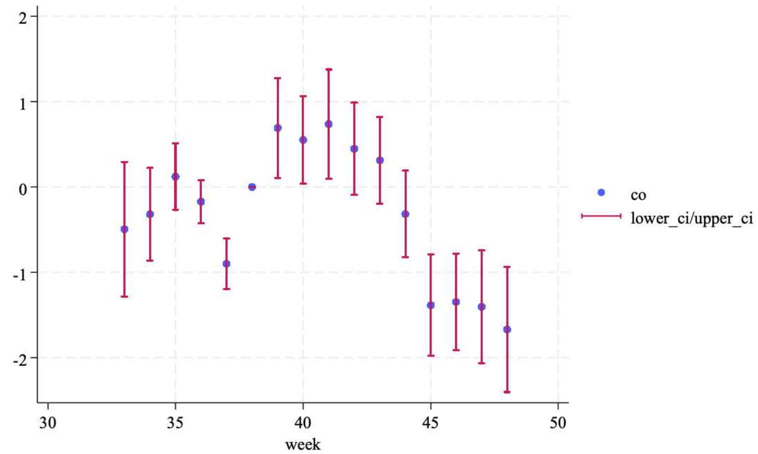
(a) (1)



(b) (2)



(c) (3)



(d) (4)

on the cumulative performance of pension funds.

Online Appendix 4

Impact of gilt market and BoE's interventions on mutual funds during the crisis

This section uses DID to analyse the impact of the gilt market and the Bank of England's Temporary Gilt Purchase Facility (also called Asset Purchase Programs) on the cumulative performance of mutual funds during the mini-budget crisis. We use the same method of constructing variables and regressions for mutual funds as before.

Table 21 shows the results for the impact of the APP on daily cumulative performance of mutual funds. Columns (1) provides estimates for the funds that have above-the-median holdings of bonds, while columns (2) consider funds that have below-the-median holdings of bonds. Columns (3) gives differences between the funds with higher versus funds with lower bonds holdings.

Table 21 documents that both groups of funds experienced a large drop in performance since the onset of the crisis (columns 1 and 2). The key results are in the differential effects between the two groups (columns 3). There is significant difference between the two groups during the crisis onset. Which means the liquidity risk for fund in Sep 2022 can be interpreted by bonds price fluctuation. By contrast, there is no significant difference between the two groups during the announcement of APP. A large performance gap between the two groups emerges after the APP 5 billion/day action on Oct 3, 2022: funds with higher bond holdings recovered by an additional 0.36 p.p. (at the 95% confidence interval) than funds with lower bond holding (column 3). When the APP size increases to 10 billion/day, the additional recover expanded to 0.38 p.p. at a higher confidence interval 99%. Therefore, during the Mini-budget Crisis, the APP announcement can't help to mitigate the decline in performance for funds with higher bond holdings.

Parallel trend test - event study

Table 21 presents a preliminary graphical representation of the parallel trends for the two groups of funds. In this subsection we further test the parallel trends before treatment for the sample of

Table 21: The DiD Result to Mutual Funds' Performance(cum)

	(1) Higher group	(2) Lower group	(3) performance
onset	-2.532^{***}	-2.180^{***}	-2.098^{***}
	(-36.67)	(-16.12)	(-21.85)
announce	-1.213^{***}	-1.153^{***}	-1.153^{***}
	(-13.62)	(-6.62)	(-9.33)
action5	-0.0853	-0.456^{***}	-0.456^{***}
	(-1.11)	(-3.02)	(-4.26)
action10	-1.597^{***}	-1.619^{***}	-1.198^{***}
	(-22.69)	(-11.75)	(-16.37)
treat_onset			-0.406^{***}
			(-2.99)
treat_announce			-0.0567
			(-0.32)
treat_action5			0.367^{**}
			(2.42)
treat_action10			0.383^{***}
			(3.69)
_cons	-0.554^{***}	-0.313^{***}	-0.468^{***}
	(-19.52)	(-5.61)	(-16.71)
N	4715	4743	9458
σ_u			0.932
σ_e			1.617
ρ			0.249
F	3003.3	855.5	1951.2
R^2	0.761	0.475	0.629

t statistics in parentheses,

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: We compare mutual funds across time and across gilt holdings in a difference-in-difference set-up. To assess the dynamics of fund performance, we estimate the following specification:

$$\text{performance(cum)}_{i,t} = \beta_0 + \sum_{k=1}^{5} \beta_k \, \text{CrisisPeriod}_{k,t} \times \text{Higher}_i + \sum_{k=1}^{5} \varphi_k \, \text{CrisisPeriod}_{k,t} + \mu_i + \varepsilon_{i,t}$$

where performance(cum)$_{i,t}$ is the cumulative fund performance, scaled to September 1, 2022. The dummy variables CrisisPeriod$_{k,t}$ take on the value of 1 for period k and zero otherwise. We consider 5 periods: crisis onset (Sep 23–Sep 27), an asset purchase announcement period (Sep 28 – Oct 2), two purchase implementation periods and after finish period. The two implementation periods are action5 (Oct 3 – Oct 10), and the periods action10 (Oct 11 – Oct 14). The variable Higher$_i$ is equal to 1 if a fund held, at the end of August 2022, above-the-median amounts in gilts as a percentage of total portfolio. Lastly, μ_i are fund level fixed effects and $\varepsilon_{i,t}$ is the error term. Standard errors are clustered at fund level.

mutual funds using an event study. Since there were only two full weeks before the mini-crisis occurred, we decided to extend the sample period from 5 weeks pre-crisis to 10 weeks post-crisis. We construct the following regression model for event study:

$$\text{performance(cum)}_{i,t} = \beta_0 + \sum_{w \neq 38} \beta_w \times 1(t \in w) \times D_i + \mu_i + \varepsilon_{i,t}$$

where $\text{performance(cum)}_{i,t}$ is the cumulative fund performance, scaled to August 1, 2022. $1(t = s)$ is an indicator variable for whether date t is in week w. We use the week in which the Mini-budget Crisis occurs as the baseline, i.e. week 38 of 2022. And the sample period[26] is selected to be 5 weeks before crisis and 10 weeks after crisis to test for parallel trends. So the range of values for w is 33 to 48. D_b in the regression is an indicator variable for whether a fund held above-the-median amounts in bonds as a percentage of total portfolio at the end of August 2022. μ_i is a fixed effect for fund i explaining unobserved fund-level characteristics. $\varepsilon_{i,t}$ is the error term.

As with any difference-in-difference estimator, the β_w's trace out the causal impact of Mini-budget Crisis on mutual fund performance under the assumption of parallel trends: absent Mini-budget Crisis, fund with different persentage of bond holding would have followed similar price trends from early September through the mid of November.

We estimate the period from five weeks before the Mini-budget Crisis to ten weeks after its occurrence. The key focus are the estimated coefficients β_w and they are normalized such that $\beta = 0$ for the week in which the Mini-budget was announced (2022w38). They are plotted in Figure 25 along with 95% confidence intervals based on standard errors that are clustered by fund.

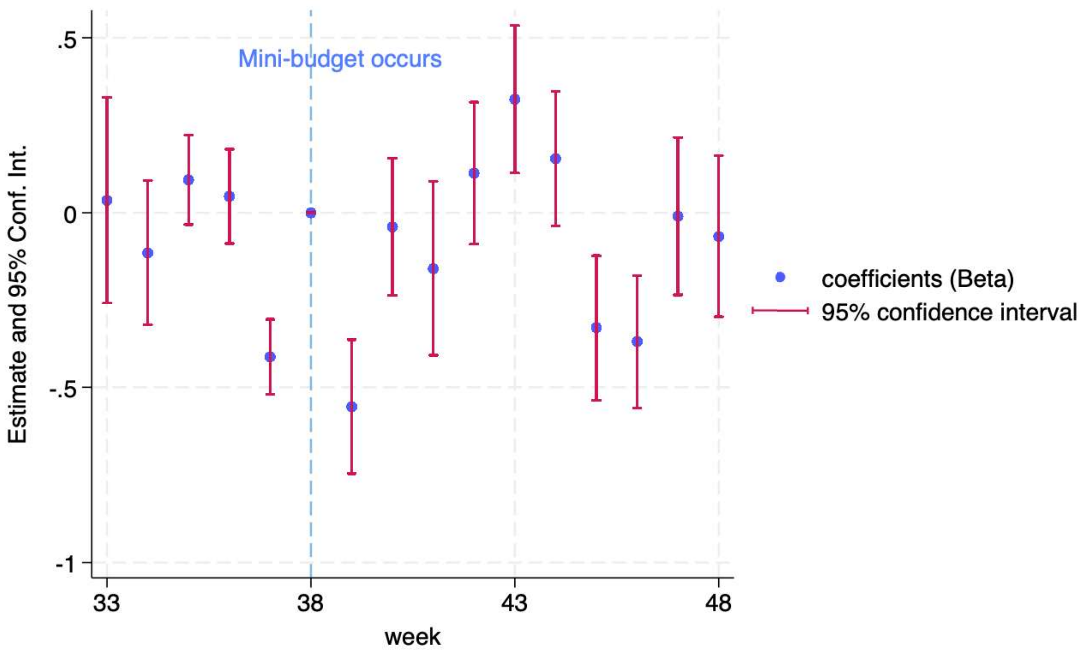
The Figure 25 shows that prior to the mini-budget, funds holding larger share of bonds followed a similar path to those that held less. The coefficients prior to the mini-budget are all close to zero and statistically insignificant (except week37), and we cannot reject the null hypothesis that they are equal.

The difference in cumulative performance between the two groups widened in the first week after

[26] We look at the cumulative performance scatterplot for each fund in the sample to rule out the effect of outliers on the regression estimates. Only five funds out of a sample of 227 funds have outlier performance observations. We choose to drop them sensibly.

Figure 25: Effect of Mini-budget Crisis

where performance(cum)$_{i,t}$ is the cumulative fund performance, scaled to August 1, 2022. $1(t = s)$ is an indicator variable for whether date t is in week w, $33 \le w \le 48$. D_b in the regression is an indicator variable for whether a fund held above-the-median amounts in bonds as a percentage of total portfolio at the end of August 2022. μ_i is a fixed effect for fund i explaining unobserved fund-level characteristics. $\varepsilon_{i,t}$ is the error term.



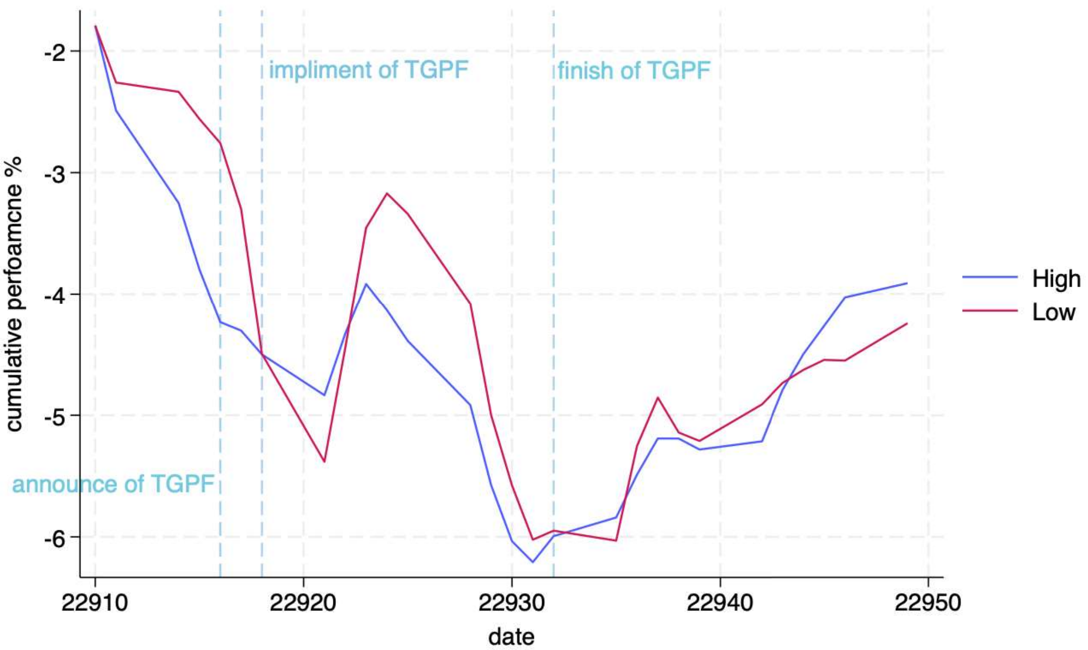
the mini-budget was announced to -0.55% and is statistically significant at conventional confidence levels. Funds holding more bonds performed significantly 0.55% worse than those holding fewer bonds. During this week the Bank of England announced the plan of government intervention but did not implement it. This suggests that simply announcing an intervention without implementing cannot help to alleviate the pressure. From week 40, the difference in cumulative performance between the two groups of funds diminishes and it is not significant. This was attributed to the two-week APP.

Portfolio sorting

In this section we provide robustness for our results. We use a simple classification of portfolios to understand the potential impact of the implementation of central bank intervention policies on the cumulative performance of mutual funds. Specifically, we classify mutual funds into three equal portfolios based on the Hb value of their bond holdings, with each portfolio consisting of about 70 mutual funds. Figure 26 then plots the cumulative performance of portfolios with low and high bond holdings over time. The cumulative performance of the funds is relative to the NAV on 22 September, the day before the mini-budget. Portfolio performance is calculated using an equally weighted average of the cumulative performance of each fund in the portfolio.

Figure 26 shows that the performance of mutual funds holding high bond ratios declined sharply in price relative to low bond ratio funds after the mini-budget was announced. In just a few days, the cumulative performance of mutual funds with high bond exposure fell by 2.44% compared with the pre-Mini-budget announcement, while the cumulative performance of funds with low bond exposure fell by 0.96%. The difference in performance between the two portfolios means that the Fund's bond exposure caused an additional 1.48% drop in performance. Following the start of the BoE's APP intervention, the cumulative performance of funds with high bond exposure clearly recovered to about the same level as funds with low bond exposure. It suggests that the Bank of England's interventionist policy does play a supportive role for mutual funds with high bond exposure.

Figure 26: Performance pressure of mutual fund from Mini-budget - Portfolio Sorts



Online Appendix 5

In Section 6.1, the key explanatory variable Exposure may suffer from endogeneity when regressed on the outcome meanweight. Given the short panel structure of the data (391 funds over only two time periods), standard fixed-effects estimation risks bias from reverse causality and omitted variables. To address this, we implement an instrumental variable strategy and conduct a series of specification and robustness tests (Table 22).

First, we report the results of two estimators under the fixed effects OLS (FE-OLS) and instrumental variables methods (FE-2SLS and FE-LIML). The OLS regression yields a coefficient of 0.0002147 under the control of fund and month fixed effects, which is highly significant. However, since OLS may be affected by endogeneity issues, we further instrumentalize Exposure using the instrumental variable predexposure. The results show that under FE-2SLS and FE-LIML, the coefficient increases to 0.000251 and remains at the 1% significance level, indicating that the estimation conclusions are robust to the estimation method.

Since the sample has only a single instrumental variable, under the setting of limited T, we first need to confirm whether the correlation between the instrument and the endogenous variable is strong enough. We use the Kleibergen-Paap rk LM test (under-identification test) to determine whether the model is identifiable. The p-value is 0.316, indicating that the model does not suffer from even the slightest 'under-identification' issue, and the instrument is statistically correlated with the endogenous variable.

Second, we conduct a weak instrument test. In short panel data, the weak instrument problem is particularly concerning, as the limited time dimension may reduce the instrument's effectiveness. The Kleibergen-Paap rk Wald F statistic is 14.7, slightly below the 10% critical value (16.38) provided by Stock-Yogo, but significantly above the 15% critical value (8.96). Therefore, we can conclude that the instrument strength is acceptable, and the weak instrument problem is not severe.

Even if the instrument is valid, we still need to verify whether Exposure is truly endogenous. If it is actually exogenous, then the estimation results of OLS and IV should not exhibit systematic differences. We employ the Durbin-Wu-Hausman (DWH) test to compare the two. The results

Table 22: Effect of Exposure on Weight — Bonds

	FE-OLS	FE-2SLS	FE-LIML
	(1)	(2)	(3)
exposure	0.0002147***	0.000251***	0.000251***
	(0.0000010)	(0.0000526)	(0.0000526)
Observations	782	782	782
Fund FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Cluster SE (Fund)	Yes	Yes	Yes
KP LM (under-ID)	—	0.3156	0.3156
KP rk Wald F (weak ID)	—	14.708	14.708
Endogeneity Chi2 (DWH, p-val)	—	0.3129	0.3129
Wild bootstrap p-value	0.5500	0.1590	0.1590
AR p-value (H0: $\beta = 0$)	—	0.0000	0.0000
AR 95% CI	—	[0.00013, 0.00050]	[0.00013, 0.00050]

Notes: The table reports regressions of the form $\sum_n \Delta Weight_{n,p,t} = \alpha_p + \gamma_t + \beta Exposure_{p,t} + \nu_p$. Time frame is 1 Sep2022 to 31 Oct2022. $\Delta Weight$ corresponds to the change in portfolio weight of ineligible assets. Fund fixed effects via within (OLS) or FWL (IV). Month fixed effects included via `i.month_id` (OLS) and absorbed in residualization (IV). Standard errors clustered at the fund level. The 2SLS/LIML columns report Kleibergen–Paap LM and rk Wald F statistics (heteroskedasticity- and clustering-robust). Endogeneity Chi2 is the Durbin–Wu–Hausman test. Wild cluster bootstrap p-values use Rademacher weights with 9,999 replications clustered at the fund level. Anderson–Rubin (AR) inference is computed in the residual space (after absorbing fund and month fixed effects). Exactly-identified model (one endogenous regressor, one instrument); hence overidentification tests (Hansen J) are not reported. *,**,*** indicate significance at the 5%, 1%, 0.1% level, respectively.

show a Chi-squared value of 1.018 and a p-value of 0.313, failing to reject the null hypothesis that "exposure1 is exogenous." This indicates that there is no statistically significant difference between OLS and IV. However, considering the possibility of reverse causality and omitted variables in an economic context, this paper still adopts the IV results as the main conclusion to ensure the robustness of the inferences.

Due to the sample structure of a large number of funds (N=391) but a very short time period (T=2), the conventional cluster robust standard error may be biased in a finite sample. Therefore, we adopt the wild cluster bootstrap method, which is particularly recommended in settings with many cross-sectional clusters but a very short time dimension. The results show that the bootstrap p-value for FE-OLS is 0.550, no longer significant; while the bootstrap p-values for FE-2SLS and FE-LIML are both 0.159, though not reaching the 10% significance level, their direction and magnitude align with the conventional clustering results, indicating that the conclusions from the instrumental variables (IV) approach possess a certain degree of robustness.

Finally, we employ the Anderson–Rubin (AR) test. The advantage of this test is that it can still provide valid inferences even when there is a weak instrumental variable problem. The test results indicate that under the null hypothesis β=0, the AR p-value is close to 0.0000, strongly rejecting the null hypothesis. At the same time, the 95% confidence interval constructed based on AR is [0.00013, 0.00050], which falls completely within the positive number range. This further confirms that the causal effect of Exposure on meanweight is a significant positive effect.

To conclude, these diagnostics provide strong evidence that the instrument is valid, sufficiently strong, and that the IV estimates are robust to weak instrument and finite-sample concerns. The consistent positive and significant coefficients across FE-OLS, FE-2SLS, and FE-LIML, reinforced by the AR test confidence interval, lead to the conclusion that Exposure exerts a robust positive causal effect on meanweight.

Table 23 reports the effect of exposure on portfolio weight changes across funds between September and October 2022. The dependent variable is the change in portfolio weight of all types of ineligible assets, while the key regressor is exposure. All specifications include fund and month

Table 23: Effect of Exposure on Weight — All assets

	FE-OLS	FE-2SLS	FE-LIML
	(1)	(2)	(3)
exposure	0.0002143***	0.000242***	0.000242***
	(0.00000762)	(0.00000395)	(0.00000395)
Observations	796	796	796
Fund FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Cluster SE (Fund)	Yes	Yes	Yes
KP LM (under-ID)	—	0.3157	0.3157
KP rk Wald F (weak ID)	—	14.708	14.708
Endogeneity Chi2 (DWH, p-val)	—	0.3218	0.3218
Wild bootstrap p-value	0.5062	0.1262	0.1262
AR p-value (H0: $\beta = 0$)	—	0.0000	0.0000
AR 95% CI	—	[0.000192, 0.000367]	[0.000192, 0.000367]

Notes: The table reports regressions of the form $\mathbb{E}_n\left[\Delta \text{Weight}_{n,p,t}\right] = \alpha_p + \gamma_t + \beta Exposure_{p,t} + \nu_p$. Time frame is 1 Sep2022 to 31 Oct2022. $\Delta Weight$ corresponds to the change in portfolio weight of ineligible assets. Fund fixed effects via within (OLS) or FWL (IV). Month fixed effects included via `i.month_id` (OLS) and absorbed in residualization (IV). Standard errors clustered at the fund level. The 2SLS/LIML columns report Kleibergen–Paap LM and rk Wald F statistics (heteroskedasticity- and clustering-robust). Durbin–Wu–Hausman test reports endogeneity p-value. Wild cluster bootstrap p-values use Rademacher weights with 9,999 replications clustered at the fund level. Anderson–Rubin (AR) inference is computed in the residual space (after absorbing fund and month fixed effects). Exactly-identified model (one endogenous regressor, one instrument); hence overidentification tests (Hansen J) are not reported. *,**,*** indicate significance at the 5%, 1%, 0.1% level, respectively.

fixed effects, with standard errors clustered at the fund level.

The FE-OLS estimates in column (1) show a positive and highly significant coefficient on exposure (0.0002147), suggesting that higher exposure is associated with an increase in the weight of ineligible assets. However, given potential endogeneity concerns, we instrument exposure with predicted exposure. Both the FE-2SLS and FE-LIML estimates in columns (2) and (3) yield very similar coefficients (0.000251), significant at the 0.1% level, indicating robustness across instrumental variable estimators.

Diagnostic tests support the validity of the instrument. The Kleibergen–Paap LM test indicates no under-identification, while the rk Wald F statistic (14.7) exceeds the 15% Stock–Yogo critical value, suggesting that weak instrument concerns are moderate but not severe. The Durbin–Wu–Hausman test produces a p-value of 0.313, failing to reject the null of exogeneity of exposure, implying that the OLS and IV estimates are not statistically different. Nevertheless, the IV framework is preferred as a conservative strategy to address potential endogeneity.

To account for the large number of fund clusters and very short time dimension (T=2), wild cluster bootstrap p-values are reported. The bootstrap inference shows that OLS estimates lose significance (p=0.55), while the IV estimates remain directionally consistent with conventional clustered inference (p=0.159). Finally, Anderson–Rubin inference, which is robust to weak instruments, strongly rejects the null of no effect ($p \approx 0.000$) and yields a 95% confidence interval of [0.000192, 0.000367], entirely in the positive domain.

Taken together, these results consistently point to a robust positive effect of exposure on the change in portfolio weight of ineligible assets, even after addressing potential endogeneity and accounting for weak instrument and finite-sample concerns.

To rigorously evaluate the validity of our instrumental variable (IV) model for estimating the effect of Δlog(NomAmount) on Δlog(P), we conduct a series of comprehensive diagnostic tests (Table 24). First, a comparison between the OLS results in column (1) and the 2SLS results in column (2) reveals a large and significant divergence between the OLS coefficient (0.178) and the 2SLS coefficient (1.016). This finding points to significant endogeneity bias in the OLS

Table 24: Effect on prices of indirect demand shock

	(1)Bond OLS $\Delta\log(P)$	(2)Bond 2SLS $\Delta\log(P)$	(3)Bond LIML $\Delta\log(P)$	(4)Bond Bootstrap $\Delta\log(P)$
$\Delta\log(\text{NomAmount})$	0.178^{**}	1.016^{***}	1.016^{***}	1.0413^{***}
	(0.0539)	(0.184)	(0.184)	(0.1894)
Observations	1,224	1,224	1,224	1,224
R^2	0.107	−2.2559	−2.2559	–
Fund FE	Yes	Yes	Yes	Yes
First stage F–statistic	–	30.527	30.527	–
LM statistic Chi-sq(1) p–val	–	0.00	0.00	–

Notes: The table reports regressions of the form $\Delta\log(P)_{n,t} = \gamma_t + \beta\,\Delta\log(\text{NomAmount})_{n,t} + \nu_n$ from 1 Sep2022 to 31 Oct2022. $\Delta\log(\text{NomAmount})$ corresponds to the change in nominal amount of each security held by pension funds. In column (1) we report OLS results. In column (2) we report 2SLS results where the first stage is reported in Table 17. t statistics are reported in parentheses. Standard errors are clustered at the fund level. *,**,*** indicate significance at the 5%, 1%, 0.1% level, respectively.

specification, justifying the use of an IV approach as both necessary and appropriate.

Crucially, tests for instrument validity provide strong support for our model specification. The underidentification test yields a p-value of 0.00 for the LM statistic, allowing us to strongly reject the null hypothesis that the model is underidentified. This confirms a significant association between our instrument and the endogenous variable. Furthermore, the weak instrument test yields a first-stage F-statistic of 30.527, which comfortably exceeds all conventional critical values (e.g., 10 or 16.38), indicating that our instrument is strong and not subject to weak instrument concerns.

Finally, to ensure the stability and reliability of our estimates, we further conduct a LIML estimation and a bootstrap procedure. The results show that the LIML coefficient in column (3) (1.016) is identical to the 2SLS result in column (2). Moreover, the coefficient (1.0413) and significance level derived from the clustered bootstrap with 1,000 replications, shown in column (4), are highly consistent with the 2SLS results in both economic and statistical terms. These findings confirm that our IV estimate is stable and not an artifact of a particular sample or estimation method.

Taken together, all diagnostic and robustness tests indicate that our IV model specification is valid, the instrument is both strong and relevant, and the resulting estimates are reliable.