Volatility and Heterogeneous Arbitrageurs in Government Bond Markets*

Oliver Ashtari-Tafti†
London School of Economics

Carlos Cañón Salazar‡
Bank of England

November 9, 2025

Link to the latest version

Do not quote without authors' permission

Abstract

Models with limits to arbitrage, increasingly used in international finance and macroeconomics, often rely on static participation by homogeneous arbitrageurs. Instead, this paper documents the existence of two distinct types of arbitrageurs—hedge funds and dealer banks—and shows that volatility affects the composition of arbitrageurs trading across different markets. We test the predictions of a two-arbitrageurs preferred-habitat model by leveraging detailed data on the quasi-universe of trades by UK financial institutions. Exploiting quasi-natural variation from one of the largest volatility shocks in UK bond history—the 2022 gilts market meltdown—we show that hedge funds traded nearly only nominal bonds, and within these, concentrated in shorter-term bonds whereas dealer banks traded inflation-linked and long-term nominal bonds. We attribute this specialization to the relative fragility of hedge funds' funding and to banks' access to the lender of last resort, which facilitates intermediation in long-term bonds. Finally, we show that the relationship between hedge funds' participation and volatility extends beyond large shocks. Our evidence points to a new channel that explains fragility in the market for long-term bonds.

Keywords: government bonds, hedge funds, volatility, maturity structure, limits of arbitrage.

JEL Codes: G11, G12, G23, E44.

*We are grateful to Liliana Varela and Dimitri Vayanos for their continued guidance and support throughout this project. We thank Elena Ashtari Tafti, Cynthia M. Balloch, Nicolas Garrido-Sureda, Rodrigo Guimaraes, Péter Kondor, Marvin Lecker, Mario Lupoli, Johannes Matt, Martin Oehmke, Niels K. Wagner and seminar participants at the LSE, EEA 2025 for helpful comments. The views expressed in this paper are those of the authors, and not necessarily those of the Bank of England or any of its committees.

†Email: o.ashtari-tafti@lse.ac.uk

‡Email: carlos.canonsalazar@bankofengland.co.uk

1 Introduction

Limits to arbitrage are increasingly invoked to explain a number of puzzles not only in finance but also in macroeconomics (Gabaix and Maggiori, 2015, Itskhoki and Mukhin, 2021, Vayanos and Vila, 2021). Despite the widespread adoption, fundamental questions remain open. Why do some markets attract more arbitrage capital than others? Under which conditions do arbitrageurs enter? Under which conditions do they exit?

Leading theories agree that volatility is a key determinant of arbitrageurs' participation but disagree on its direction. In Grossman and Miller (1988) volatility attracts arbitrageurs because these are periods with better investment opportunities, while in Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009) volatility deters arbitrageurs because it tightens financial frictions and amplifies the limits to arbitrage (Shleifer and Vishny, 1997). Crucially, both theories build on the assumption of homogeneous arbitrageurs, implying a single market-wide response to volatility. Instead, this paper shows empirically that arbitrageurs are heterogeneous, with hedge funds and dealer banks playing very different roles in response to volatility. It also shows that both theories are consistent with the data, but at different times and under different market conditions.

Our analysis leverages a detailed transaction-level dataset of UK financial institutions from 2019 to 2024 and proceeds in two parts. First, exploiting one of the largest volatility shocks in the United Kingdom bond market history, we show that high volatility deters hedge funds' participation in long-term bonds, who then retrench towards shorter-term bonds. This is driven by a preference for more liquid, and not only safer, bonds. In contrast, banks increase their participation in long-term bonds, we argue, because of direct access to lender of last resort. The existence of two distinct types of arbitrageurs bridges market microstructure, which looks at dealer banks, and asset pricing, which adopts a broader interpretation including hedge funds and other specialized intermediaries. This heterogeneity matters for aggregate prices, with markets where hedge funds are absent experiencing more violent fire sales. Second, we show that the relationship extends beyond a single large shock: hedge funds' participation responds nonlinearly to volatility, thus reconciling the risk-sharing view (Grossman and Miller, 1988) with the limits-to-arbitrage view (Shleifer and Vishny, 1997).

In Section 2, we present a discrete-time model of the term structure à-la-Vayanos and Vila (2021) around which we organize the empirical work. The model features two types of intermediaries—hedge funds (hereafter, arbitrageurs) and dealer banks (hereafter, banks)—that differ because arbitrageurs are less efficient at intermediating long-term bonds, and their inefficiency rises with volatility, consistent with a worsening in funding conditions and tighter risk management prac-

tices.

The model generates two sets of predictions, depending on the level of volatility. The first set of predictions concerns *market meltdowns*, namely episodes where volatility is so high that arbitrageurs do not participate in long-term bonds even though the term premium is attractive because funding costs are too high, deterring entry. Since banks are always present, in equilibrium we observe what looks like specialization: arbitrageurs only trade short-term bonds, banks hold the entire supply of long-term bonds, and the term premium rises as compensation for banks. Instead, in *normal times*, both arbitrageurs and banks participate in long-term bonds. In this case, volatility has a nonlinear impact on arbitrageurs' participation. Volatility initially induces greater participation because of the risk-sharing motive. However, when it becomes sufficiently high, funding liquidity deteriorates, making it too costly for arbitrageurs to trade long-term bonds, prompting a flight to short-term bonds.

One challenge in testing the model predictions is the paucity of data on arbitrageurs' positions, which we overcome using a granular trade-level dataset covering all the bond trades by UK-regulated financial institutions. Prior work largely infers participation indirectly, from prices or aggregate quantities. The key advantage of our dataset is that we observe all trades at daily frequency and at the security level, including the identity of the fund, offering an unparalleled view on the asset side of those agents. The sample covers 2019-2024, one of the most eventful periods in bond markets with the Covid-19 pandemic, the subsequent inflation and global interest rate cycle. Section 3 describes the data and presents descriptive evidence on the participation of arbitrageurs and banks.[1]

In Section 4, we test the first set of predictions using a quasi-natural experiment—the 2022 gilts *market meltdown*—where a fiscal announcement triggered a large negative demand shock from liability-driven investors and pushed gilts volatility above 40%. The identification exploits the forced selling and the resulting rise in non-fundamental volatility to test the model prediction that when volatility is excessively high, arbitrageurs do not trade long-term bonds, and banks are left as the only intermediary in the market.

Our main result is that arbitrageurs and banks respond to volatility by trading mostly different markets (nominal versus inflation-linked) and, within the same market, different maturities (short-term versus long-term). Arbitrageurs purchase only nominal bonds. Within nominal bonds, they largely avoid long-term ones (those with maturity above 15 years). Banks instead concentrate their purchases in long-term nominal bonds and are active across all maturities in

[1] Appendix D shows that the hedge funds in our sample are large global players, accounting for 26.7% of aggregate government bond trading volume in the United Kingdom, 25.2% in the Euro-area and 4.5% in the United States.

inflation-linked bonds. Consistent with the model predictions, we document larger price discounts in markets where arbitrageurs are absent: long-term versus short-term nominal; and nominal versus inflation-linked bonds.

The divergent choices by arbitrageurs and banks are consistent with a difference in their funding costs, which increases with volatility. As in the model, hedge funds' purchases concentrate in assets that are less costly to trade and hedge: either short-term bonds or medium-term *deliverable* bonds. Short-term bonds are less costly to fund because they have low volatility whereas deliverable bonds are more liquid (hence less costly to trade) because they are in high demand and they can be (indirectly) traded, even in a dysfunctional market, through the associated futures contract. Using a difference-in-differences design, we estimate a strong preference of hedge funds for more liquid bonds by comparing bonds that are otherwise identical except that one is deliverable. We find that over 80% of their purchases are in deliverable gilts. This concentration is hardly random since only five out of fifty-eight bonds were deliverable.

Banks' intermediation in long-term bond was supported by the lender of last resort, further widening the funding cost difference with arbitrageurs.[2] On 28 September, the Bank of England announced a temporary intervention to support market functioning, dubbed 'market maker of last resort' (MMLR).[3] Importantly, only banks were eligible counterparties to the MMLR. Through the lens of the model, the intervention represents a shift in the relative cost of long-term bonds, making banks even more efficient than arbitrageurs. Consistent with this view, in the cross section, banks purchases concentrate in bonds that are eligible under the temporary intervention. In the time series, banks' participation in long-term bonds increase only after the Bank of England announcement.

The second set of model predictions is that, in *normal times*, volatility has a nonlinear effect on arbitrageurs' participation: it initially attracts arbitrageurs, and then it repels them. In Section 5, we uncover two distinct volatility regimes using the VIX index as a proxy for liquidity conditions (Brunnermeier et al., 2008, Nagel, 2012). In the low-VIX regime, an increase in UK gilts volatility attracts arbitrageurs, as measured by more funds active in the market and larger exposures on a given day. In the high-VIX regime, the relationship turns negative, and volatility repels arbitrageurs. As predicted by the model, the nonlinearity is more pronounced in long-maturity bonds because of the higher volatility. The high-VIX regime is associated with a shift in arbitrageurs' intermediation away from long-term and into short-term bonds. Effectively, this implies a reallocation of duration

[2]The model features no asymmetric information nor moral hazard. As a result, there are no 'winners or losers' from the Bank of England intervention since agents' returns are purely compensation for bearing risk.

[3]For background on the market maker of last resort see Hauser (2021). For a distinction between market-functioning purchases and other asset-purchase programmes see Duffie and Keane (2023).

risk away from arbitrageurs towards banks, the residual agents, who are left holding long-term bonds when volatility increases because arbitrageurs fly towards short-maturity bonds, consistent with what we observe during the 2022 gilts market meltdown. In contrast, in the low-VIX regime, there is no difference between short-term and long-term bonds.

We exploit scheduled macroeconomic news releases to further identify the effect of volatility on arbitrageurs participation, disentangling fundamental volatility from endogenous volatility. Realized volatility conflates fundamental volatility with endogenous volatility, potentially introduced by the arbitrageurs themselves. To isolate fundamental volatility, outside of arbitrageurs' control, we use days with scheduled macroeconomic news releases (Anderson et al., 2003). Consistent with the model predictions, arbitrageurs' participation increases when fundamental volatility is higher but falls when this happens in the high-VIX regime. This is independent of whether news is positive or negative, ruling out informed trading. Instead, the size of the news (in absolute value), a direct proxy for fundamental volatility, reveals strongly the nonlinearity as predicted by the model.

The evidence suggests that a volatility shock can have opposite effects depending on the sign of the bond-futures basis. In the US, a positive basis (where futures are expensive and bonds are cheap) forced hedge funds to sell Treasuries in response to the March 2020 shock, amplifying the Treasury selloff. In the UK, the basis was negative before the 2022 market meltdown, with arbitrageurs long futures and short gilts. The volatility shock pushed bond prices below the futures price and created an incentive to buy bonds, stabilizing bond markets.[4]

The analysis also highlights that hedge funds are fundamentally different than banks, and have not replaced them. There is a lively debate on whether hedge funds are taking over functions previously carried out by banks, e.g., Bailey (2025). By focusing on the maturity choice of hedge funds and banks, this work shows a clear distinction between the two types, echoing the discussion in Grossman and Miller (1988, p. 633).[5]

[4] A number of papers discuss the role of hedge funds as (de)stabilizing. In equity markets, Brunnermeier and Nagel (2004) find that hedge funds were destabilizing during the 2000 tech bubble, riding the bubble and reducing exposure right before the crash. Similarly, Ben-David et al. (2012) show that hedge funds sold stocks during the US equity market crash in 2007-2008. In bond markets, during March 2020, Kruttli et al. (2023) find that hedge funds reduced exposure to US Treasury by 20%, that is they did not provide liquidity. Barth and Kahn (2025) find that through the basis trade, hedge funds provide liquidity to asset managers. However they turned to liquidity demanders in March , as volatility spiked and funding conditions tightened, destabilizing bond markets.

[5] This view of arbitrageurs conforms to the conjecture of Shleifer and Vishny (1997) that explains participation only in markets where volatility is not excessive and fundamental value easier to ascertain, e.g. relative-value fixed income. The view of banks as 'toll-takers' is explored in Lu and Wallen (2024).

Related literature. This paper belongs to the preferred-habitat tradition and intermediary asset pricing. In contrast to preferred-habitat models (Vayanos and Vila, 2021, Greenwood et al., 2023, Kekre et al., 2024, Ray et al., 2024, Gourinchas et al., 2025), we emphasize volatility episodes. In contrast to the intermediary asset pricing literature, we focus on the term structure of government bonds and away from risky assets such as equities, corporate bonds and mortgage-backed securities (He and Krishnamurthy, 2013, Brunnermeier and Sannikov, 2014, Adrian and Shin, 2014, Kondor and Vayanos, 2019).

There is growing recognition that different intermediaries matter for different asset markets (Haddad and Muir, 2025). An important contribution is Siriwardane et al. (2025) who find low correlations across arbitrage spreads, the opposite of what would be predicted by a model with a representative intermediary. Donaldson et al. (2021) rationalize the existence of multiple types of intermediaries with funding differences. Hanson et al. (2015) attribute it to costly equity capital and access to the lender of last resort, a view that is shared by this paper.[6] Our findings complement these studies by documenting the delicate interaction between two types of intermediaries within the same market.[7]

This paper is also close to the literature on the safety and liquidity of government bonds. A critical data point for this literature is the March 2020 dash-for-cash, where US Treasuries experienced illiquidity and reverse flight to safety (Ma et al., 2022, Duffie, 2025). While much of this literature emphasizes dealer banks' constraints (Duffie et al., 2023), we examine hedge funds as a distinct class of intermediaries. Barth and Kahn (2025) study US hedge funds engaging in basis trade. Kruttli et al. (2023) find that internal risk limits, such as value-at-risk constraints, were binding. Kashyap et al. (2025) propose that, in response to Treasury market disruptions, the central bank intervenes carrying out a 'reverse basis trade'. We complement those by showing that the impact of a volatility shock depends on the sign of the basis.

Finally, our analysis of the 2022 UK gilts crisis connects to recent studies of that episode. Pinter et al. (2024) estimate the price pressure due to pension funds' selling. Alfaro et al. (2024) attribute the forced selling to a peculiar hedging need and Czech and Monroe (2025) study dealers' price

[6] Farhi and Tirole (2021) study optimal regulation and lending of last resort in a model with banks and shadow banks.

[7] A number of recent papers emphasize compositional effects in financial markets. Bryzgalova et al. (2023) study arbitrageurs segmentation in a game theory setting and show that arbitrageurs specialize to avoid diluting each others' profits. Eisfeldt et al. (2023) study limited participation in a complex asset market, e.g. hard-to-value mortgage backed securities, and attribute specialization to skills. In a different context, Haddad et al. (2025) quantifies in a demand-based setting how much the market elasticity has changed due to the rise in passive investing. Coimbra and Rey (2024) study asset price booms and busts driven by the composition of financial intermediaries that differ in risk aversion. We add to these papers by showing the interaction between banks and arbitrageurs, due to differential funding costs, in non-complex asset markets.

setting and relate it to asymmetric information. We contribute to this literature by documenting novel facts on arbitrageurs' participation across the term structure.

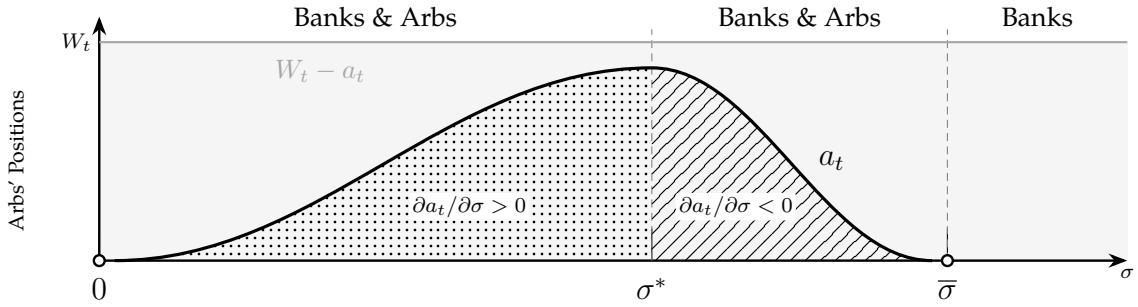
2 A Model of the Bond Market with Two Types of Intermediaries

In this section, we present a discrete-time model of the term structure of interest rates following Greenwood et al. (2023). The model captures a key tradeoff in how volatility affects arbitrageurs: while it increases profit opportunities as in Grossman and Miller (1988), it also magnifies the limits of arbitrage as in Shleifer and Vishny (1997). Which force dominates ultimately depends on the level of volatility.

As in the preferred-habitat tradition of Vayanos and Vila (2021), the market is populated by preferred-habitat investors and intermediaries. The key innovation from the preferred-habitat tradition is that intermediaries are heterogeneous. Specifically, they are of two *types*: type-A intermediaries, like hedge funds and type-B, like banks. As shorthand, we refer to type-A as arbitrageurs and type-B as banks. Arbitrageurs are identical to banks except that they face a financial friction on their long-term bond position. The financial friction captures the *relatively more fragile* funding of arbitrageurs relative to banks. The assumption of heterogeneous intermediaries is consistent with Siriwardane et al. (2025) who distinguish between funding and balance sheet segmentation. In our model, the two dimensions coincide, with hedge funds exposed to different funding conditions than banks. This type of funding heterogeneity is consistent with the evidence in Hanson et al. (2015), showing that banks hold more (costly) equity than hedge funds, as part of an institutional arrangement that grants them access to lender of last resort.

Figure 1 summarizes the model and the main intuitions. The figure plots the total allocation to the long-term bond (a_t), the solid black line. The gray region represents the holding of short-term bonds, defined residually, as the difference between total wealth and the allocation to the long-term bond, $W_t - a_t$. Arbitrageurs' participation depend on the level of volatility (σ), plotted on the x-axis. Arbitrageurs will not participate in long-term bonds when volatility is too high ($\sigma > \bar{\sigma}$). We label *market meltdown* the critical level of volatility $\bar{\sigma}$, above which arbitrageurs exit. During a market meltdown, banks are the only intermediaries in the market for long-term bonds. At intermediate levels of volatility ($\sigma \leq \bar{\sigma}$), labeled *normal times*, banks and arbitrageurs jointly intermediate long-term bonds. In this region, an increase in volatility has a nonlinear effect: first it attracts participation from the arbitrageurs (dotted region), then it deters participation as financial friction becomes severe (dashed region). We label the level of volatility that separates the two regions (σ^*) as *funding liquidity stress*.

Figure 1: Participation Regions



Note: The solid black curve shows the arbitrageurs allocation to the long-term bond, a_t (with net supply $z_t > 0$). The gray line is total wealth W_t; the residual $W_t - a_t$ is the short-term bond allocation.

In principle, banks could absorb the entire supply coming from the preferred-habitat investors. However, because of risk aversion this would require a large drop in the price of the long-term bond. Arbitrageurs alleviate pressure from banks and avoid some of the price drop. Arbitrageurs are more likely to participate when volatility increases, as on those occasions banks require larger price discounts to induce them to hold the supply. It is precisely this price discount that induces arbitrageurs to participate.

2.1 Setup

Time is discrete and runs forever, $t = 1, 2, \cdots$.

Assets. There is a term structure comprising two zero-coupon bonds: a short-term bond, maturing next period $(t+1)$ and a long-term bond, maturing in two periods $(t+2)$. Both bonds pay off one unit of the numeraire at maturity.

The short rate evolves according to an auto-regressive process

$$r_{t+1} = \bar{r} + (1-\kappa)(r_t - \bar{r}) + \sigma\varepsilon_{t+1}, \tag{1}$$

where $\bar{r}$ is the natural rate, κ is the speed of mean reversion towards $\bar{r}$, $\varepsilon_{t+1} \sim N(0,1)$ is a short-rate shock and σ is its volatility. We vary the volatility of the shock to derive our main empirical predictions.

The short-term bond is available in elastic supply and its price is pinned down by the short rate, $P_t^{(1)} = e^{-r_t}$.[8] The long-term bond is instead in zero net supply and its price, $P_t^{(\ell)}$, is determined

[8] In what follows, we approximate $e^{-r_t} \approx (1+r_t)^{-1}$.

in equilibrium. We let $r_{t+1}^{(\ell)}$ denote the log holding period return on the long-term bond and its volatility by σ_ℓ.[9]

Agents. The market is populated by three agents: (i) preferred-habitat investors, who only trade the long-term bond; (ii) banks, which always participate in both short-term and long-term bond markets; (iii) arbitrageurs, which participate opportunistically in the long-term bond market. We describe each one in detail below.

Preferred-habitat investors have exogenous demand for the long-term bond, z_t. We consider the case where their demand is not random to focus on the interaction between the two types of arbitrageurs.

There is a unit mass of banks, with mean variance utility and risk aversion parameter γ. Other than risk aversion, they face no frictions for trading long-term bonds. They maximize their next-period wealth, W_{t+1}, by choosing their position in the long-term bond, b_t:

$$\mathbb{E}_t(W_{t+1}) - \frac{\gamma}{2}\,\mathbb{V}\mathrm{ar}_t(W_{t+1}). \tag{2}$$

Their wealth evolves as:

$$W_{t+1} = W_t(1 + r_t) + b_t(r_{t+1}^{(\ell)} - r_t), \tag{3}$$

where b_t denotes their demand for the long-term bond.

Similarly to banks, arbitrageurs have mean variance utility with risk aversion parameter γ. In contrast to banks, they face a financial friction to intermediate long-term bonds that increases with volatility, $\phi(\sigma_\ell) \geq 0, \phi'(\sigma_\ell) > 0, \phi''(\sigma_\ell) > 0$. Arbitrageurs' wealth evolves as:

$$W_{t+1} = W_t(1 + r_t) + a_t(r_{t+1}^{(\ell)} - r_t) - \phi(\sigma_\ell)|a_t|, \tag{4}$$

where a_t is the arbitrageurs' position in the long-term bond. The friction makes arbitrageurs less efficient than banks in carrying out arbitrage trades in long-term bonds. To see this, suppose arbitrageurs take a long position in long-term bonds, $a_t > 0$. The effective return that they earn is $r_{t+1}^{(\ell)} - (r_t + \phi(\sigma_\ell))$, implying that they fund the trade at a spread $(\phi(\sigma_\ell))$ over the short rate, r_t. In contrast, banks have direct access to funding at the short rate r_t and, on the same position, they earn $r_{t+1}^{(\ell)} - r_t$. We emphasize that the friction captures the inefficiency of arbitrageurs *relative* to

[9] Following Greenwood et al. (2023), we use the approximation $R_{t+1}^{(\ell)} \approx \tilde{r}_{t+1}^{(\ell)} + 0.5\sigma_\ell^2 \equiv r_{t+1}^{(\ell)}$, with $\sigma_\ell^2 \equiv \mathbb{V}\mathrm{ar}_t\left(r_{t+1}^{(\ell)}\right)$.

banks in trading long-term bonds. An increase in $\phi(\sigma_\ell)$ can be interpreted as either a decrease in efficiency of arbitrageurs, or an increase in efficiency of banks.

Following Gabaix and Maggiori (2015), the friction depends directly on volatility, extended to include a common and an asset-specific component:

$$\phi(\sigma_\ell) = (\phi_t + \phi_\ell)\sigma_\ell^\alpha, \tag{5}$$

where the parameters ϕ_t and ϕ_ℓ determine the liquidity of the asset. ϕ_t captures aggregate, time-varying liquidity conditions, and ϕ_ℓ captures asset-specific liquidity. Assets with a low ϕ_ℓ are easier to finance and trade, that is they are more liquid. One example is a bond in high demand from the market, such as on-the-run or cheapest-to-deliver which are often on "special" and therefore can be financed at a lower cost (Duffie, 1996).

Crucially, the financial friction depends on the asset's volatility, σ_ℓ.[10] The parameter α captures the sensitivity of the constraint to the volatility of the long-term bond. The constraint nests two notable cases. If $\alpha = 0$, then the liquidity of the asset does not depend on volatility. If $\alpha > 0$, then the liquidity of the asset deteriorates with volatility and it becomes costlier to trade it. We will adopt this functional form only in the empirical analysis in Section 4.

Market clearing. Long-term bonds are in zero net supply and, assuming both banks and arbitrageurs participate, market clearing requires:

$$a_t + b_t = z_t. \tag{6}$$

The rest of the equilibrium definition is standard.

2.2 Discussion of Assumptions

We discuss the choice of modeling arbitrageurs as constrained, and banks as unconstrained; we also discuss the interpretation of the financial friction.

Hedge Funds vs Banks. Banks face a number of regulatory constraints, e.g., the supplementary leverage ratio, which hedge funds are exempt. The supplementary leverage ratio matters both in good and bad times, and it does not depend on volatility. Our modelling captures that in bad

[10] In Appendix E.7, we show that a similar constraint emerges from a financier setting margins using a value-at-risk constraint.

times –when the constraint binds and volatility is high– liquidity deteriorates and hedge funds are reluctant to participate. Introducing a constraint on banks that does not tighten in bad times, e.g. with volatility, would not alter the conclusions of the model. For example, we can show that adding a quadratic cost to the banks' problem as in D'Avernas and Vandeweyer (2024) does not alter our result as long as the cost does not increase with volatility.

The Financial Friction. We interpret the friction in broad terms to capture any (agency) cost that prevents efficient capital raising. The literal interpretation, and the one we stress throughout the text, is that of a funding spread. Interpreting the cost as a differential funding advantage is in line with Hanson et al. (2015), and it is indeed a key distinguishing features of banks relative to hedge funds. Access to lending of last resort is particularly valuable in bad times, when volatility rises.

2.3 Equilibrium Characterization

In this section, we solve the model for the case $z_t > 0$–the empirically relevant one–and state the main results, with all the proofs relegated in Appendix E.1. Note that when preferred-habitat demand is not random, as in our case, $\sigma_\ell = \sigma$.

Agents' demand. By standard arguments, banks' demand is

$$b_t = \frac{\mathbb{E}_t(r_{t+1}^{(\ell)}) - r_t}{\gamma\,\sigma^2}, \tag{7}$$

while arbitrageurs' demand is

$$a_t = \frac{\mathbb{E}_t(r_{t+1}^{(\ell)}) - r_t - \phi(\sigma)}{\gamma\,\sigma^2} \quad \text{if } \mathbb{E}_t(r_{t+1}^{(\ell)}) - r_t \geq \phi(\sigma), \tag{8}$$

and $a_t = 0$ otherwise.

The friction generates a participation wedge: banks participate as long as the term premium is positive, arbitrageurs require an additional compensation. The next lemma provides the conditions under which the additional compensation is sufficient to induce arbitrageurs to participate in the long-term bond market.

Lemma 1 (Cutoffs for Arbitrageurs' Participation)**.** *Suppose $z_t > 0$. Let $\phi : \mathbb{R}_+ \to \mathbb{R}_+$ be convex and*

continuous with $\phi(0) = 0$*, and assume*

$$\lim_{\sigma \to 0} \frac{\phi(\sigma)}{\sigma^2} = 0 \quad \textit{and} \quad \lim_{\sigma \to \infty} \frac{\phi(\sigma)}{\sigma^2} = +\infty.$$

If $\sigma < \bar{\sigma}$*, then arbitrageurs participate in the long bond market, where* $\bar{\sigma}$ *is the root of*

$$\underbrace{\gamma \sigma^2 z_t}_{\textit{Risk premium}} - \underbrace{\phi(\sigma)}_{\textit{Funding friction}} = 0. \tag{9}$$

There is a tradeoff in arbitrageurs' participation in long-term bonds. On the one hand, an increase in volatility increases the risk premium, the first term in equation (9), inducing participation. The higher risk aversion, γ, and the larger supply z_t, the larger the increase in risk premium effect for a given increase in volatility. On the other hand, an increase in volatility also makes funding costlier, the second term in equation (9), deterring participation in long-term bonds.

The level of volatility determines which effect dominates. In normal times ($\sigma < \bar{\sigma}$), banks and arbitrageurs jointly provide liquidity to preferred-habitat investors. This happens because volatility is low, and the funding cost low. However in a market meltdown ($\sigma > \bar{\sigma}$), and because of the convexity of $\phi(\sigma)$, arbitrageurs find too costly to trade long-term bonds and exit long-term bonds. The assumptions on $\phi(\sigma)$ in Lemma 1,[11] are needed for the limits-to-arbitrage channel to rise faster than the risk-premium channel when volatility is high. When this is the case, condition (9) holds for all sufficiently small σ and fails for all sufficiently large σ.[12]

Using this lemma, we now define the equilibrium. We conjecture first that type-A do not participate and solve for the equilibrium.

Proposition 1 (Equilibrium Term Premium and Long-Term Bond Holdings)**.** *Suppose* $z_t > 0$*. Then,*

- *If* $\sigma \leq \bar{\sigma}$*, arbitrageurs participate, the term premium is* $\mathbb{E}_t\, r_{t+1}^{(\ell)} - r_t = \frac{\gamma \sigma^2}{2} z_t + \frac{\phi(\sigma)}{2}$ *and positions are:*

$$a_t = \frac{z_t}{2} - \frac{\phi(\sigma)}{2\gamma\sigma^2}, \qquad b_t = \frac{z_t}{2} + \frac{\phi(\sigma)}{2\gamma\sigma^2}. \tag{AB-Eq'm}$$

- *If* $\sigma > \bar{\sigma}$*, arbitrageurs do not participate, the term premium is* $\mathbb{E}_t\, r_{t+1}^{(\ell)} - r_t = \gamma \sigma^2 z_t$ *and positions are*

$$a_t = 0, \qquad b_t = z_t. \tag{B-Eq'm}$$

The proposition shows how arbitrageurs and banks share the supply coming from preferred-

[11] The conditions in the lemma are equivalent to $\alpha > 2$ using functional form (5).

[12] If, in addition, $\phi(\sigma)/\sigma^2$ is non decreasing, and there is only one cutoff solving $\gamma z_t\, \bar{\sigma}^2 = \phi(\bar{\sigma})$.

habitat investors. In the absence of the financial friction, they split supply (z_t) in half (the first term in (AB-Eq'm).[13] In the presence of the financial friction, the allocation of long-term bonds is tilted towards the most efficient agent. The larger the funding gap ($\phi(\sigma)$), the larger the tilt in favor of banks and away from hedge funds. A large enough increase in volatility (so that $\sigma > \bar{\sigma}$), drives a complete exit of arbitrageurs from the long-term bond ($a_t = 0$) and fully into the short-term bond (note that the allocation to the short-term bond is $W_t - a_t$), while banks absorb the entire long-term supply ($b_t = z_t$). In other words, volatility induces specialization across the term structure.

The term premium takes an intuitive shape. Consider first the case where arbitrageurs participate in the long-term bond market. The first term is a risk compensation for holding the long-term bond supply ($\frac{\gamma\sigma^2}{2} z_t$). The second term is a 'liquidity' discount to compensate arbitrageurs for paying the cost $\phi(\sigma)$. Both terms are divided by two, since there is a total mass of two agents in the market which effectively means a higher risk-bearing capacity.[14] When arbitrageurs do not participate, the term premium only reflects risk compensation.

The next two propositions show how market structure and term premium respond when volatility increases.

Proposition 2 (The Impact of Volatility on Market Structure)**.** *Suppose that volatility increases in the interval* $(0, \bar{\sigma})$*. Then, arbitrageurs' holding of long-term bond changes by*

$$\frac{\partial a_t}{\partial \sigma} = \frac{1}{\gamma\sigma^2}\left(\frac{\phi(\sigma)}{\sigma} - \frac{1}{2}\frac{\partial \phi(\sigma)}{\partial \sigma}\right).$$

Moreover, there exists a bliss point σ^* *such that* $\frac{\phi(\sigma)}{\sigma} - \frac{1}{2}\frac{\partial \phi(\sigma)}{\partial \sigma} = 0$.

- *If* $\sigma \leq \sigma^*$, $\partial a_t / \partial \sigma \geq 0$.
- *If* $\sigma > \sigma^*$, $\partial a_t / \partial \sigma < 0$.

Arbitrageurs face a trade-off when participating in long-term bonds. The first force is that, for a given level of the friction $\phi(\sigma)$, an increase in volatility raises the Sharpe ratio on the long-term bond. This happens because of risk aversion and induces arbitrageurs' participation, as in Grossman and Miller (1988). The second force is that when volatility rises, also the financial friction tightens, as in Shleifer and Vishny (1997), and arbitrageurs find it costlier to intermediate long-term bonds. Which force dominates depend on the level of volatility, via its impact on funding liquidity. Funding liquidity stress (σ^*) divides the volatility space into these two regions, as shown

[13] This is because they have the same risk aversion. If they were heterogeneous in risk aversion, they would split it in proportion to risk aversion. This heterogeneity would not affect the main results.

[14] Specifically, there is a unit mass of banks and a unit mass of arbitrageurs.

in Figure 1.

2.4 Testable Implications

We derive four testable implications from the model. We discuss each one in turn and briefly outline the empirical strategy for testing it.

Prediction 1. *In a market meltdown, arbitrageurs will not participate in long-term bonds. When this happens arbitrageurs and banks specialize: arbitrageurs are only active in short-term bonds, while banks trade both long-term and short-term bonds.*

This can be seen in Figure 1, where arbitrageurs take no position in long-term bonds in a market meltdown, $\sigma > \bar{\sigma}$. In this case, the financial friction is too severe and arbitrageurs are unable to fund their trades at a sufficiently attractive rate. As a result, they only trade short-term bonds. The strategy for testing this implication is to identify an event where volatility was sufficiently high *and* financial frictions were binding. The 2022 gilts market meltdown satisfies both criteria.

Prediction 2. *When arbitrageurs exit long-term bonds, the (term) risk premium is higher.*

This is the result of the decrease in the market risk-bearing capacity. With only banks left to absorb the demand shock from preferred-habitat investors, the yield curve has to steepen as a compensation. We will show that in the 2022 gilts crisis, where arbitrageurs exited the long-term bond, there was a large increase in term premium. An equivalent way to see this is that excess returns on long-term bonds increased substantially more than on shorter maturity bonds.

Prediction 3. *Conditional on participation, arbitrageurs tilt their demand towards more liquid assets:*

$$\frac{\partial a_t}{\partial \phi_\ell} = -\frac{\sigma^\alpha}{2\gamma\sigma^2} \leq 0 \qquad \frac{\partial a_t}{\partial \sigma \partial \phi_\ell} = -(\alpha - 2)\frac{\sigma^{\alpha-1}}{2\gamma\sigma^2} \leq 0,$$

since $\sigma, \gamma \geq 0$ *and* $\alpha > 2$.

Arbitrageurs hold larger positions in assets that are less costly to trade, a lower ϕ_ℓ in equation (5), and the tilt increases with volatility. We provide two tests of this prediction. In the first test, we look at deliverable bonds, which are bonds easier to trade (a lower ϕ_ℓ), and show that despite similar risk-return profiles arbitrageurs tilt their demand towards those assets. In the second test,

we use the Bank of England intervention as a shift in the relative efficiency of banks in trading long-term bonds.

Prediction 4. *Conditional on participating in long-term bonds, arbitrageurs optimal demand first increases with volatility, then decreases.*

This follows from Proposition 1. The model clarifies the existence of two forces shaping arbitraguers' participation: the Grossman and Miller (1988) view and the Shleifer and Vishny (1997) view, tracing the shape of arbitrageurs' demand in the dotted and in the dashed area in Figure 1.

3 Data

In this section, we describe the main dataset used in our analysis: the MiFID II Transaction Reporting Dataset. Then, we provide summary statistics on hedge funds and banks in the UK government bond market. In Appendix D, we provide summary statistics of hedge funds across not just the UK but also the US and Euro-area.

Secondary Market Trading Data. We use the MiFID II database held by the Financial Conduct Authority (FCA) in the United Kingdom, covering all the bond trades by UK-regulated investment firms and shared with the Bank of England.[15]

We focus mainly on trades by hedge funds, using a novel cleaning procedure, and complement it with trades by dealer banks in UK government bonds. We identify all the hedge funds directly reporting to the FCA from names and legal entity identifier (LEI) using the Bank of England internal classification and extensive manual checks, and keep trades across all instruments. Appendix A provides a detailed description of this procedure.

Using this novel procedure, we are able to measure the global footprint of UK-reporting hedge funds, overcoming common pitfalls of transaction-level dataset.[16]

[15]The Markets in Financial Instruments Directive II (MiFID II) came into force across the European Union in January 2018. A central objective of the regulation was to increase transparency, oversight, and investor protection in European financial markets following the global financial crisis. Among its key innovations was the introduction of a harmonized transaction reporting regime: all investment firms executing trades in financial instruments admitted to trading on an EU venue must report detailed information. These reports include identifiers for the buyer and seller, instrument characteristics, transaction size, price, and time of execution. As a result, MiFID II has generated a uniquely comprehensive dataset on secondary market activity.

[16]See Jurkatis (2024) for a detailed description.

Other Macroeconomic and Financial Datasets. We complement the MiFID II dataset with standard macroeconomic and financial series, described in detail in Appendix B.

3.1 Hedge Funds and Banks in the United Kingdom

How large is hedge funds' intermediation relative to (dealer) banks? We answer this question for the UK government bond market, for which we have full coverage of banks. We call (dealer) banks the Gilt-edged market makers (GEMMs), which are the equivalent of primary dealers in United States.[17]

Table 1 shows that banks and hedge funds are active across all maturities, but hedge funds are slightly tilted towards shorter ones. Combining banks and hedge funds, we observe approximately £5 billion daily traded *notional* amount.[18] Hedge funds account for 43-56% of volume in the 1-12Y segment, and 33-41% in the segment above 13Y, see Panel (a). The opposite pattern holds for banks which are relatively more active in bonds with maturity 19Y and above. Panel (b) shows that 71.4% of hedge funds' trading is in maturities below 12Y, against 58.7% for banks. But they also trade long-term bonds, and around 18.1% of their trading is in bonds with maturity above 19Y, while the same figure stands at 30.8% for banks.

When banks increase their trading, also hedge funds do. We compute the correlation between the daily traded quantity (in absolute value) by banks and hedge funds. In Panel (c) shows that the correlation coefficient is positive and stable across maturities, varying between 0.216 and 0.382. This is the first suggestive evidence that, unconditionally, banks and hedge funds complement each other. However, in periods of heightened volatility, there is a divergence between hedge funds and banks. Also in Panel (c), we compute the correlation of banks' daily traded quantity (in absolute value) with the VIX; and the same for hedge funds' with the VIX. Banks' participation has a small, but positive, correlation with the VIX, and more so at long-term maturities. Instead, hedge funds' participation is negatively correlated with the VIX. This is suggestive evidence that periods of heightened volatility see distinguish the behaviour of hedge funds and banks.

4 Evidence from a Market Meltdown

In this section, we use the 2022 UK gilts market meltdown as a quasi-natural experiment to test Implication 1 of the model—arbitrageurs avoid trading long-term bonds when volatility is excessively

[17] There are currently 18 active GEMMs, see the official list on DMO Gilt-edged Market Makers.

[18] The dataset covers trades in the dealer-to-client segment. To avoid double counting trades, Banks exclude trades where the counterparty was a hedge fund.

Table 1: Participation Shares by Maturity Bucket

	1–6Y		7–12Y		13–18Y		19Y+	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	Panel (a): Share across types (within maturity)							
Hedge Funds	0.433	0.193	0.558	0.207	0.410	0.244	0.331	0.187
Banks	0.576	0.191	0.448	0.208	0.614	0.250	0.676	0.180
	Panel (b): Share within type (across maturities)							
Hedge Funds	0.317	0.161	0.397	0.170	0.115	0.119	0.181	0.110
Banks	0.338	0.124	0.249	0.117	0.112	0.071	0.308	0.109
	Panel (c): Correlation of daily quantity (abs. value)							
ρ(Banks, Hedge Funds)	0.316		0.216		0.329		0.382	
ρ(Banks, VIX)	0.016		0.014		0.018		0.103	
ρ(Hedge Funds, VIX)	−0.117		−0.171		−0.114		−0.199	

Note: Means and standard deviations (SD) are computed from daily data across nominal gilts by maturity buckets. Quantities are in absolute value. Panel A reports, for each maturity bucket, the share split across participant types. Panel B reports, for each type, the distribution of activity shares across maturity buckets. Panel C reports correlations of daily traded quantities.

high ($\sigma > \bar{\sigma}$)—and show the emergence of specialization between banks and arbitrageurs. Using the cross-section of assets, we test Implication 3—arbitrageurs tilt their demand towards assets with lower $\phi(\sigma)$—showing that the arbitrageurs tilt demand towards more liquid assets, while access to the MMLR, acting as a decrease in cost for banks only, was crucial for banks' participation in long-term bonds. Finally, testing Implication 2, we show larger price discounts when arbitrageurs are absent.

4.1 The Volatility Shock

In September 2022, the UK gilts market experienced one of the largest financial volatility events in recorded history. Following an expansionary fiscal policy announcement on 23 September, bond yields spiked. Both the speed and scale of the spike were unprecedented, with yields rising by 30-40 bps per day.[19] In a matter of days, yields rose by ≈100 bps reaching 4.5% on the 30Y.

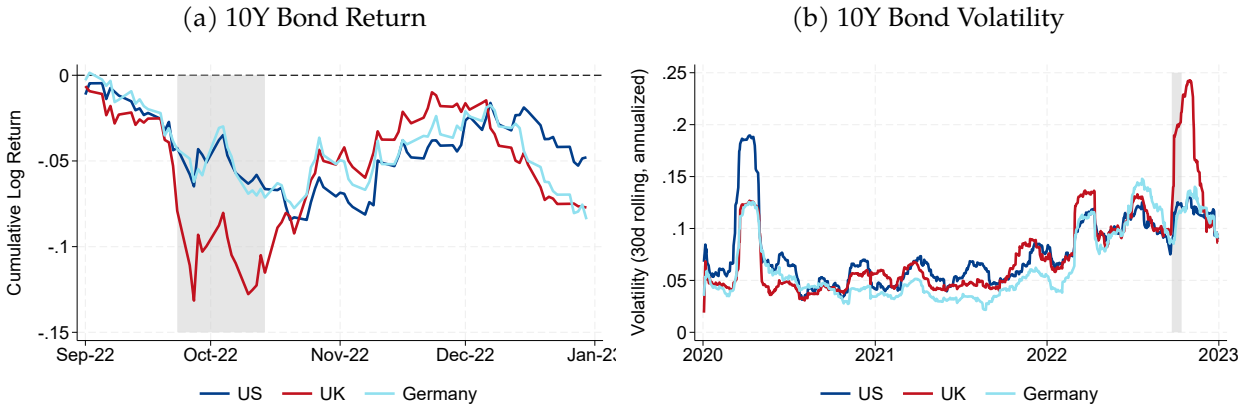
The initial spike in yields led to a fire sale of UK gilts by liability-driven investment (LDI) funds.

[19]The biggest daily increase since 2000 was 29 bps. The September 2022 jump in yields was more than four times larger than the jump during dash-for-cash spike in March 2020, see Cunliffe (2022).

These funds' strategies involve leverage to increase gilts exposure and are mainly run by large asset managers on behalf of pension funds. The spike in yields was followed by capital losses, which then triggered margin calls. Pension funds had two ways to meet these margin calls: either through capital injections or by selling assets, e.g., gilts. The speed of repricing outpaced the speed at which LDI investors could raise capital and therefore turned them into forced sellers of both nominal and inflation-linked UK government bonds.[20] We exploit this mechanism in the identification.

Figure 2 shows the time series of bond returns and volatility around this episode. Panel (a) shows that while bond returns had started declining earlier in the month, UK bonds saw large movements during the crisis (gray shaded area) compared to the US and Germany. The price drop is large, around 8.7% in excess of a maturity–matched global bond portfolio. Panel (b) shows volatility over a longer sample. While generally range–bound between US and Germany, UK volatility visibly spikes in late 2022. US and German bonds see no comparable spike. This reflects the localized nature of this shock and contrasts with global shocks, e.g. Covid-19, where the UK did not experience any excess volatility.[21]

Figure 2: Asset Price Movements in the Crisis



Note: Panel (a) shows the cumulative log return of the 10Y bond in UK, US and Germany between 01/09/2022 and 31/12/2022. Panel (b) shows the volatility of the 10Y total return computed over a 30-day rolling window between 01/01/2020 and 31/12/2022. The underlying assets are the FTSE 10Y Government Bond Indices of the respective country. The gray shaded area is the 2022 gilts market meltdown, 23/09/2022-14/10/2022.

The Bank of England intervened on 28 September in a targeted operation that lasted for two weeks, until 14 October 2022. Therefore, we take 23 September-14 October as the crisis window. The Bank of England will temporarily purchase eligible assets, selling them back to the market as

[20] See the letter from the Deputy Governor for Financial Stability to the Treasury Select Committee on 5 October.

[21] Figure 17a in the Appendix uses swaptions *implied volatility*. There, we also see a sharp rise in UK volatility relative to US volatility.

soon as LDI investors recapitalized, acting as a *market maker of last resort* (MMLR). The intervention was crucial in sustaining market functioning.

Identification of Arbitrageurs' Response to Volatility

This crisis is an ideal setting for studying the response of arbitrageurs to a volatility shock. We identify their response by exploiting the quasi-exogenous volatility generated by liability-driven investors.[22] This means that the volatility shock is plausibly exogenous with respect to arbitrageurs' participation, and therefore their trading is driven by the exogenous shock. In contrast to Covid-19, this shock is localized to UK government bonds, which allows a *ceteris paribus* comparison. The scale of the shock implies that in these two-week window the UK episode dominates.

This volatility shock closely maps into our model, with a direct link to its testable implications. The demand shock is unambiguously negative, because of forced selling, equivalent to a net supply shock to the intermediaries: $z_t > 0$. Given the unprecedented volatility, perhaps no other event so closely resembles the cutoff point of participation, from $\sigma \to \bar{\sigma}$. Importantly, global funding conditions were tight (a high ϕ_t in (5)), as proxied by the VIX index (see Figure 10), implying that funding and liquidity considerations were first-order concerns for arbitrageurs.

The Bank of England intervention provides another source of variation in the intermediation cost incurred by banks relative to arbitrageurs. This is because banks had direct access to the Bank of England operations while hedge funds did not.[23]

4.2 The Response of Market Structure to the Volatility Shock

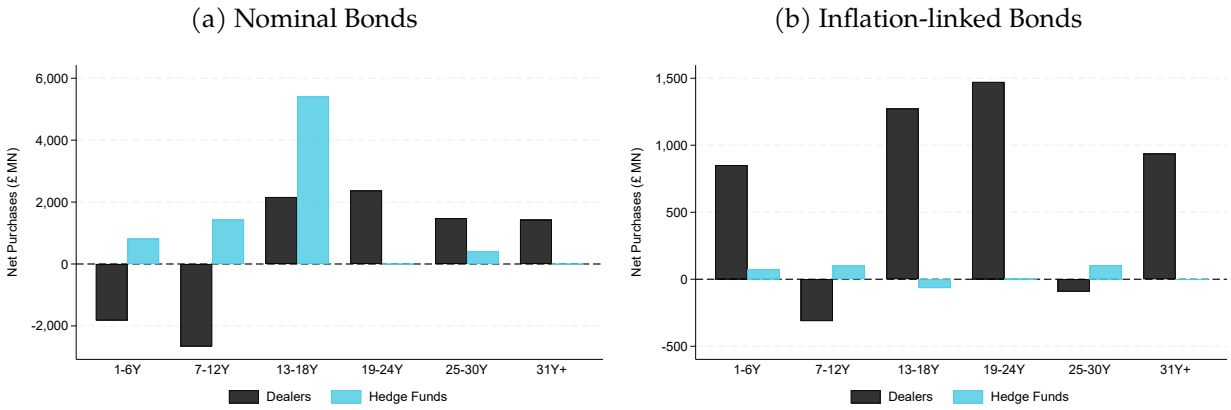
Proposition 2 says that when volatility increases, so does specialization across types of intermediaries. When volatility becomes extreme, as it was during the crisis, we approach the discontinuity where the equilibrium switches, from 'Banks & Arbs' to 'Banks' only in Figure 1, and arbitrageurs exit. We interpret this period as type-B only equilibrium in Proposition 1, where arbitrageurs hold no position ($a_t = 0$) and banks absorb the entire net supply of (very) long-term bonds ($b_t = z_t$).

Figure 3 shows the existence of two distinct types of financial intermediaries: hedge funds and banks. Although both nominal and inflation-linked assets were subject to fire sales, hedge funds bought exclusively nominal bonds, as can be seen in Figure 3. While arbitrageurs are completely absent in inflation-linked markets, banks are heavily involved across all maturities, as shown in

[22] While there was also a worsening of fundamentals, Pinter et al. (2024) find that more than half of the yield spike is driven by the fire sale. In addition the price patterns documented in Figure 2 are consistent with a temporary liquidity shock, with the price recovering to its pre-crisis level.

[23] See Bank of England: Market Notice 28 September 2022. and Bank of England: Market Notice 11 October 2022.

Figure 3: Two Types of Arbitrageurs



Note: Panel (a) shows the total quantity of nominal gilts purchased by hedge funds and dealers during the crisis. Panel (b) shows the same for inflation-linked bonds. The data includes bonds with more than one year of remaining maturity.

Panel (b). Panel (a) shows rich dynamics in the nominal bonds market. We observe three regions. (i) short maturities —arbitrageurs absorb supply including from banks, who are net sellers; (ii) intermediate maturities —banks and arbitrageurs jointly intermediate; (iii) long maturities — arbitrageurs exit and banks are the only (private) intermediary. In the model this occurs because volatility makes it infeasible for them to trade.[24] It is interesting to note that the Bank of England intervenes precisely where arbitrageurs are not participating, which we show in Figure 13 in the Appendix.

4.3 Arbitrageurs Stabilized Only Short- and Intermediate-term Bonds

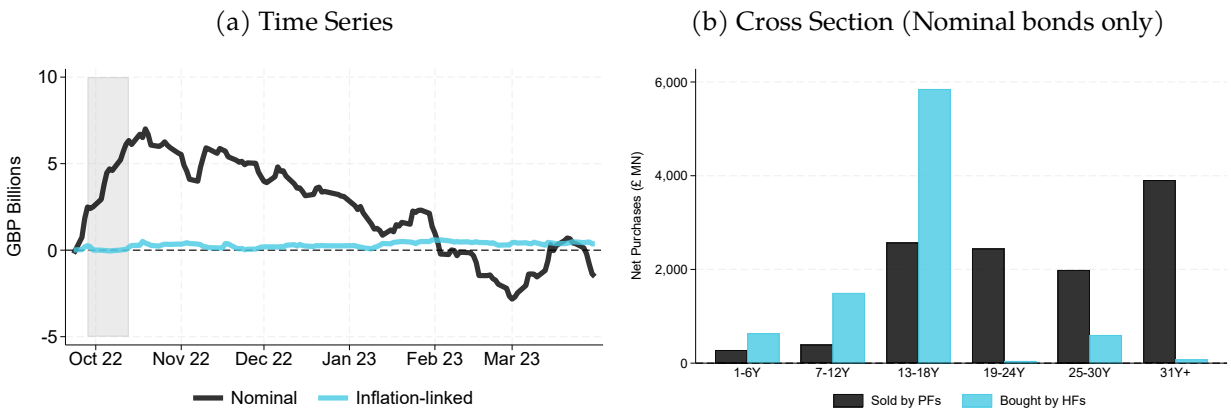
Following the shock, arbitrageurs rapidly accumulated a large position in UK government bonds, and slowly unwound it. Panel (a) cumulates arbitrageurs' net purchases from the day of the shock (23 September 2022) until six months later (01 April 2023). The position is large, peaking at around £6 billion. To get a sense of magnitudes, the Bank of England intervention will total £19 billion. While the buildup was rapid, the decumulation was gradual, over six months, consistent with the view that arbitrageurs smooth shocks across time (Grossman and Miller, 1988, Brunnermeier and Pedersen, 2009). This evidence is consistent with hedge funds behaving as the arbitrageurs in the model, stabilizing financial markets by absorbing demand shocks onto their own balance sheets.[25]

Panel (b) breaks down nominal purchases by maturity for arbitrageurs (light blue bars) and

[24] Volatility was indeed one of the criteria mentioned in the rationale for the intervention, see Alexander et al. (2023).
[25] Equivalently, this is a test of the market clearing condition: $a_t + b_t = z_t$.

pension funds (black bars) over the two weeks of the crisis.[26,27] Pension funds were selling across all maturities, but particularly concentrated in bonds with maturity 13Y and above. While arbitrageurs were actively trading, they did not participate in very long-term bonds, those with maturity above 19Y. This evidence is consistent with Proposition 1: excessive volatility renders very long-term bonds too costly for arbitrageurs to trade. Strikingly, the largest price discounts were precisely in very long-term nominal bonds and inflation-linked bonds, yet arbitrageurs avoided both.

Figure 4: Hedge Funds' Purchases During the Crisis



Note: Panel (a) shows the time series of cumulative purchases by hedge funds since 23/09/2022. The gray shaded area corresponds to the crisis period (23/09-14/10). Panel (b) shows the split of gilts purchased during the crisis across maturities. Pension fund sales are indicative.

4.4 Arbitrageurs Traded More Liquid Bonds

The financial friction, $\phi(\sigma)$, is a key driver of arbitrageurs' demand, and it increases with volatility. Long-term bonds, whether nominal or inflation-linked, load more on volatility. When volatility increases, trading such bonds becomes disproportionately costly, explaining the absence of arbitrageurs at the very long-end of the curve. In addition, inflation-linked bonds tend to have poor liquidity irrespective of risk, a high ϕ_ℓ, making even short-term inflation-linked bonds unattractive.

The challenge in testing this hypothesis is that liquidity is hard to measure. The ideal experiment would be to compare two assets that differ only in liquidity–i.e., different $\phi(\sigma)$. Consider two bonds, indexed by i and j, with the same maturity τ, hence the same risk ($\sigma_i = \sigma_j$) but different liquidity: $\phi_i(\sigma) = (\phi_t + \phi_i)\sigma^\alpha$ and $\phi_j(\sigma) = (\phi_t + \phi_j)\sigma^\alpha$. Arbitrageurs' demand for bond i is

[26] Pension fund sales are indicative and illustrate where selling concentrated across maturities.
[27] Figure 12 in the Appendix shows the amount sold in the inflation-linked market.

the sum of a common (within maturity) fundamental $f_t^{(\tau)} \equiv (\gamma\sigma^2)^{-1}\,\mathbb{E}_t\, r_{i,t+1}^{(\tau)}$ and a liquidity cost $\phi_i(\sigma)$. Using (8) and (5), since arbitrageurs exhibit a preference for liquid assets, we can isolate the demand due to the liquidity component as:

$$a_{it}^{(\tau)} - a_{jt}^{(\tau)} = \frac{1}{\gamma\sigma^2}(\mathbb{E}_t\, r_{i,t+1}^{(\tau)} - \mathbb{E}_t\, r_{j,t+1}^{(\tau)}) - (\phi_j - \phi_i)\frac{\sigma^{\alpha-2}}{\gamma} \tag{10}$$

$$= (\phi_j - \phi_i)\frac{\sigma^{\alpha-2}}{\gamma}. \tag{11}$$

In other words, the difference in demand of two otherwise identical assets reveals the liquidity component. The key identifying assumption is that the two bonds share fundamentals: $\mathbb{E}_t\, r_{i,t+1}^{(\tau)} = \mathbb{E}_t\, r_{j,t+1}^{(\tau)}$. The test rests on the existence of two assets that are otherwise identical except for their liquidity.

An Empirical Test using Deliverable Bonds

Government bonds provide precisely this laboratory since bonds of the same maturity are exposed to the same fundamental risk (Frazzini and Pedersen, 2014) and there are multiple bonds with the same maturity outstanding. Any difference between two bonds with the same maturity can be ascribed to liquidity,[28] as in equation (10). A notorious example is the *on-the-run* phenomenon, with bonds more recently issued trading at a premium relative to otherwise identical, but older, counterparts (Krishnamurthy, 2002, Vayanos and Weill, 2008).[29] A similar phenomenon occurs with *deliverable* bonds, that is bonds eligible to be delivered at expiration of a futures contract. Compared to other measures, deliverability has some key advantages. While repo specialness data is hardly available, deliverability is readily available. Moreover, deliverability is a contractual and pre-determined feature rather than an endogenous outcome such as specialness.[30]

We measure the liquidity value as the differential demand for deliverable bonds. In the UK, there are four futures contracts available on gilts, with only nominal bonds as underlying assets. Each quarterly contract specifies a basket of six deliverable bonds. While nominally there are four

[28] There is a long tradition of extracting liquidity premia as difference between assets, see for example Longstaff (2002), Krishnamurthy and Vissing-Jorgensen (2012), Fleckenstein et al. (2014) and the recent convenience yield literature, see among others Fleckenstein and Longstaff (2024), Krishnamurthy and Ma (2024).

[29] Often this happens because those bonds are in high demand, and so financiers offer better financing conditions. In jargon, they are on (repo) "special" (Duffie, 1996). This is consistent with our interpretation of liquidity as a funding wedge.

[30] Deliverable bonds are associated with the basis trade (Barth and Kahn, 2025), but this trade cannot explain all the observed trading during the crisis. See ICE Historically Delivered Bonds. The December-22 contract saw the second largest delivery on record of 74k contracts, in two distinct bonds. Hedge funds in our sample do not match the quantities observed.

contracts, the Long Gilt futures is the only actively traded contract.[31]

Equation (10) implies a difference-in-differences (DiD) approach. Specifically, we run two specifications:

$$a_{it}^{(\tau)} = \beta(\mathbb{1}\{\text{Del}_{it}\} \times \mathbb{1}\{\text{Crisis}_t\}) + \gamma\mathbb{1}\{\text{Del}_{it}\} + \delta\mathbb{1}\{\text{Crisis}_t\} + \alpha_t + \alpha_\tau + \varepsilon_{it}^{(\tau)}, \tag{12}$$

$$a_{it}^{(\tau)} = \beta(\mathbb{1}\{\text{Del}_{it}\} \times \mathbb{1}\{\text{Crisis}_t\}) + \gamma\mathbb{1}\{\text{Del}_{it}\} + \alpha_{\tau t} + \varepsilon_{it}^{(\tau)}, \tag{13}$$

where $a_{it}^{(\tau)}$ is the net amount purchased of bond i belonging to maturity bucket τ on day t.[32] $\mathbb{1}\{\text{Del}_{it}\}$ is a dummy variable that is equal to one if bond i is part of the deliverable basket on day t. $\mathbb{1}\{\text{Crisis}_t\}$ is a dummy variable that takes value one during the gilts market meltdown. α_t, α_τ and $\alpha_{\tau t}$ are respectively time, maturity-bucket and time times maturity-bucket fixed effects. The inclusion of the interacted fixed-effect, at the maturity-bucket times day level means that we are comparing bonds on the same day and the same maturity bucket, thus stripping out the common factor $f_t^{(\tau)}$.[33] The coefficient of interest is β, which measures the "treatment effect" of being more liquid when volatility increases, as proxied by the deliverable status interacted with the crisis dummy.[34]

Table 2 shows that liquidity is a key determinant of arbitrageurs' demand. To get a sense of magnitude, column (1) shows the results without fixed effects and the deliverable dummy. Arbitrageurs are selling on average £900 thousand per day for the average bond. During the crisis they purchased £7.41 million on the average bond (δ). The behaviour of arbitrageurs was exceptionally different in this event, both in direction, from net sellers to net buyers, and in magnitude. Once we account for liquidity in column (2), the crisis dummy is no longer statistically significant and all the effect is absorbed by the interaction of deliverable and crisis. Therefore, purchases are exclusively concentrated in deliverable bonds, with the coefficient β doubling in size. The coefficient is quantitatively large: on a given day they purchased £14.49 million more of deliverable bonds relative to non-deliverable ones, column (2).[35] This is not driven by specific days, the composition

[31] In the Appendix, we show the open interest and volume of each contract.

[32] Throughout we always use 5Y maturity buckets, as in the main analysis: 1-6Y, 7-12Y, 13-18Y, 19-24Y, 25Y-30Y, 31Y+.

[33] The inclusion of the interacted fixed-effects can be interpreted in the context of demand-based asset pricing. Haddad et al. (2025) show that fixed effects, together with the constant relative elasticity assumption, are needed to isolate the elasticity of demand.

[34] More formally, the β picks up the difference of being deliverable (Del_{it}) when volatility is high ($\text{Crisis}_t = 1$) relative to when volatility is low ($\text{Crisis}_t = 1$): $\beta = \mathbb{E}(a_{it}|\text{Del}_{it} = 1, \text{Crisis}_t = 1) - \mathbb{E}(a_{it}|\text{Del}_{it} = 0, \text{Crisis}_t = 1) - \mathbb{E}(a_{it}|\text{Del}_{it} = 1, \text{Crisis}_t = 0) + \mathbb{E}(a_{it}|\text{Del}_{it} = 0, \text{Crisis}_t = 0)$.

[35] According to the DMO, between the 23/09-14/10 the average daily turnover in UK government bonds was £98.02 billion. Given 88 bonds outstanding across nominal and inflation-linked bonds, this amounts to a daily bond turnover of £1.11 billion.

Table 2: Hedge Funds Purchased More Liquid Bonds

	Dep var: $a_{it}^{(\tau)}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Crisis$_t$ (δ)	7.41***	1.39		1.38		
	(1.51)	(0.83)		(0.84)		
Deliverable$_{it}$ (γ)		-2.47*	-2.47*	-2.98*	-2.98*	-3.66**
		(0.96)	(0.96)	(1.31)	(1.31)	(1.33)
Deliverable$_{it}$ $\times$ Crisis$_t$ (β)		14.49***	14.49***	14.48***	14.48***	26.52***
		(3.60)	(3.60)	(3.61)	(3.61)	(6.44)
Constant	-0.90*	0.13				
	(0.38)	(0.40)				
Time FE	No	No	Yes	No	Yes	No
Maturity FE	No	No	No	Yes	Yes	No
Maturity X Time FE	No	No	No	No	No	Yes
R2	0.00	0.00	0.01	0.00	0.01	0.06
N	15,600	15,600	15,600	15,600	15,600	15,600

Note: The dependent variable is the net purchases (in £000). Deliverable is a dummy that takes value of one if the bond is in the basket of the front-month or next-month deliverable UK Gilts Futures. Crisis is a dummy equal to one in the period 23 September 2022 - 14 October 2022. There are 6 maturity buckets. The sample period is 01/01/2022-31/12/2022. Standard errors clustered at the day level.

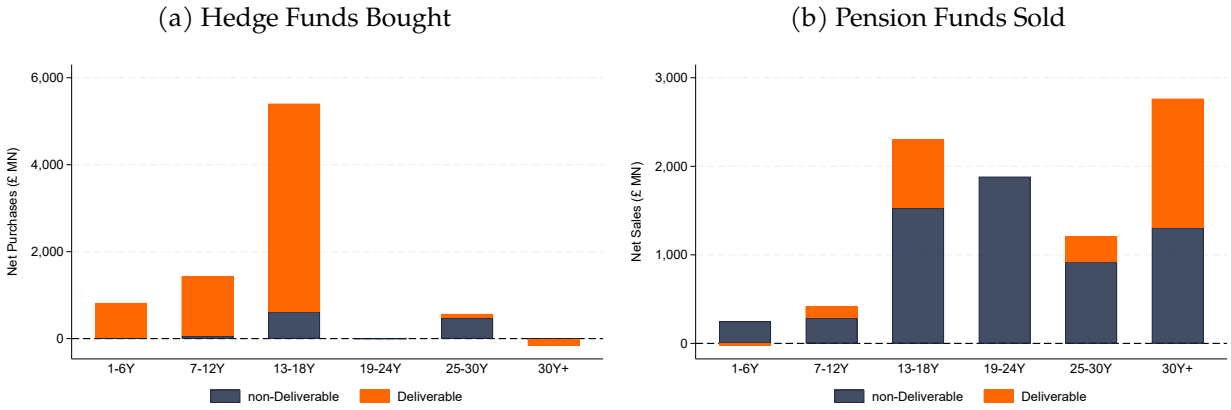
of maturities purchased or by a combination of the two (columns 3, 4, 5). Finally once we compare bonds within the same maturity bucket and day, the coefficient β almost doubles to £26.52 million.

Figure 5 shows that pension funds were mostly selling non-deliverable bonds, while arbitrageurs purchased mostly deliverable bonds.

Deliverable bonds are less volatile in a crisis, and therefore easier to fund and trade. Figure 6 shows the price of an equally-weighted portfolio of deliverable and non-deliverable bonds. The non-deliverable portfolio is composed of maturity–matched bonds to remove any effect of comparing long- and short-term bonds. The larger price discount was in non-deliverables, but arbitrageurs did not trade those. Even though non-deliverables were cheaper, their volatility was 13 pp higher than deliverables.

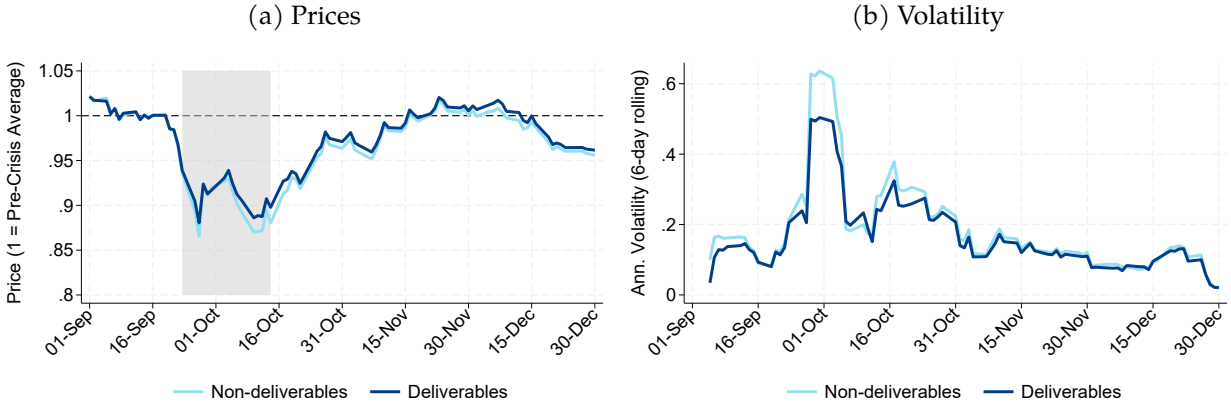
Table 2 suggests liquidity was an important consideration, but one might worry that the relationship is mechanical because deliverable bonds are only available on shorter maturity bonds. We show that this is not the case in Figure 7. We plot all the individual UK nominal bonds out-

Figure 5: Mismatch within the Same Maturity



Note: Panel (a) shows the total amount purchased by hedge funds during the crisis (23/09-14/10) split by maturity and deliverable status; Panel (b) shows the same split for pension funds. Pension fund sales are indicative.

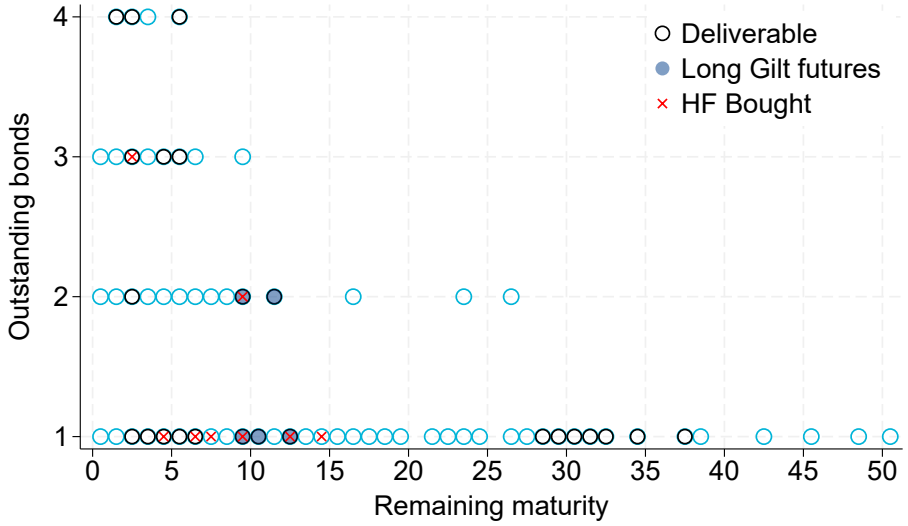
Figure 6: Maturity-Matched Deliverable vs Non-deliverable Bonds



Note: Panel (a) shows the price of a maturity-matched equally-weighted portfolio of deliverable and non-deliverable UK bonds. The price is normalized to equal one in the week prior to the crisis. Volatility is computed using a 6-day rolling window and annualized. The gray shaded area corresponds to the crisis period (23/09-14/10).

standing at the beginning of the crisis, ordered by time to maturity (light blue circles). There are 58 nominal bonds (ISIN) outstanding at the start of the crisis. For example, there are five nominal bonds outstanding with one year to maturity on the 22 of September. Around 40% of the bonds are associated with a futures contract (dark blue circles), of which only 5 bonds associated with an actually traded futures contract, the Long Gilt contract (shaded in blue). Arbitrageurs purchased only 8 out of 58 outstanding bonds (red crosses) and of those 6 were deliverable, of which only 3 associated with the traded futures contract. The regression showed that the intensity of purchases was concentrated in deliverable bonds, while this plot shows that also on the extensive margin liquidity was an important driver.

Figure 7: UK Nominal gilts Outstanding (22 Sep 2022)



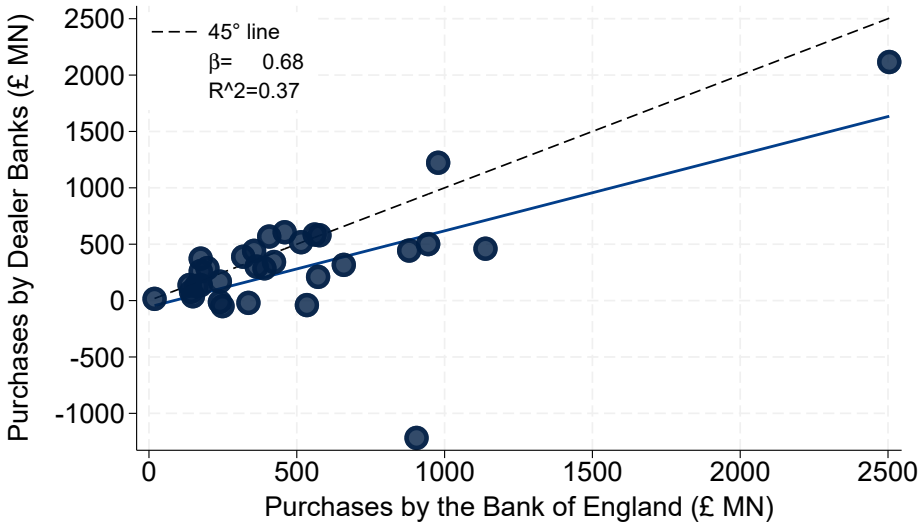
Note: Each dot represents an outstanding bond (ISIN). Circles in dark blue are bonds that are part of a deliverable basket. Red crosses are bonds that were purchased by the hedge funds accounting for 80% of their total purchases.

4.5 Banks, the Lender of Last Resort and Long-term Bonds

The presence of banks in markets (maturities) where arbitrageurs are absent suggests that they do not face the same friction. Consider the case of long-term bonds. They are particularly difficult to arbitrage because of the long horizon. In the interim, there is the risk that the arbitrageurs may need to exit the position and incur a costly liquidation, through an asset fire sale (Shleifer and Vishny, 1990). In those circumstances, stable funding is valuable as it allows to ride out the turbulence. Access to the lender of last resort is a particular form of funding stability (Hanson et al., 2015). Only banks have direct access to the lender of last resort. Under this view, the Bank

of England intervention on 28 September represents a shift in the intermediation cost of banks, increasing their efficiency relative to arbitrageurs in trading long-term bonds. This then reinforces the specialization result of Proposition 1, through an increase in $\phi(\sigma)$.[36]

Figure 8: Banks' Secondary-Market Purchases and Market Maker of Last Resort



Note: The figure shows the total purchases by the Bank of England through the reverse auction and the total purchases by dealer banks in the secondary market at the bond level. The solid line is the line of best fit. The dashed line is the 45 degree line.

There is a strong complementarity in bonds traded by the Bank of England and banks. Figure 8 shows for each bond (ISIN), the amount that was bought by the Bank of England (x-axis) and the amount purchased by banks in secondary markets (y-axis), for both nominal and inflation-linked bonds, over the two weeks of the intervention.[37] There is a strong positive relationship with most points lying close to the 45° line, suggesting that the bonds that banks purchased coincided with the ones that were sold to the Bank of England. This figure only uses the cross-section of bonds, and it is possible that banks' purchases happen at different times than those of the Bank of England.

Banks increased their intermediation of long-term bonds after the Bank of England interven-

[36] Since arbitrageurs and banks are identical, the model would ascribe the heterogeneity to the cost.
[37] The chart only includes bond that were eligible to be purchased.

Table 3: The Effect of the Lender of Last Resort on Banks' Purchases

	Dep var: $b_{it}^{(\tau,\pi)}$				
	(1)	(2)	(3)	(4)	(5)
Crisis_t	10.153*				
	(4.493)				
$\text{Crisis}_t \times \tau < 20\text{Y}$		2.884			
		(6.419)			
$\text{Crisis}_t \times \tau \geq 20\text{Y}$		19.544***			
		(5.835)			
$\text{Crisis}_t \times \text{Pre-BOE}_t$			-2.894		
			(9.761)		
$\text{Crisis}_t \times \text{Post-BOE}_t$			13.141**		
			(4.664)		
$c_{it}^{(\tau,\pi)}$				0.460***	
				(0.069)	
$C_t \times \text{Not Eligible}_{it}$					-0.004
					(0.007)
$C_t \times \text{Eligible}_{it}$					0.008**
					(0.002)
Constant	-3.513***				
	(0.323)				
Maturity FE	No	Yes	Yes	Yes	Yes
Inflation-linked FE	No	Yes	Yes	Yes	Yes
R2	0.00	0.00	0.00	0.33	0.02
N	118,698	118,698	118,698	309	1,045

Note: The table reports the OLS coefficients of regressions $b_{it}^{(\tau,\pi)} = \beta \mathbb{1}\{\text{Crisis}_t\} + \gamma \mathbb{1}(\{\text{Crisis}_t\} \times \mathbb{1}\{\tau\text{Dimension}_{it}\}) + \alpha_\tau + a_\pi + \varepsilon_{it}^{(\tau,\pi)}$, where $b_{it}^{(\tau,\pi)}$ is the daily net purchase of bond i in maturity bucket τ of type $\pi \in \{\text{Nom., Inf. Link.}\}$, $\text{Dimension}_{it} \in \{\tau \geq 20, \text{Post-BOE}_{it}\}$. Sample includes both nominal and inflation-linked bonds. Pre-BOE refers to the period 23/09-27/09. Post-BOE refers to the period 28/09-14/10. Eligible assets have maturity equal or above 20Y and are nominal only before 10/10. Afterwards inflation-linked with maturity above 20Y are included. Standard errors are clustered at the day level.

tion. We decompose banks' purchases during the crisis using the following regressions:

$$
\begin{aligned}
b_{it}^{(\tau,\pi)} &= \beta_0 + \beta_1 \mathbb{1}\{\text{Crisis}_t\} + \varepsilon_{it}^{(\tau,\pi)}, \\
b_{it}^{(\tau,\pi)} &= \gamma_0 + \gamma_1\big(\mathbb{1}\{\text{Crisis}_t\} \times \mathbb{1}\{\tau < 20\}\big) + \gamma_2\big(\mathbb{1}\{\text{Crisis}_t\} \times \mathbb{1}\{\tau \geq 20\}\big) + \varepsilon_{it}^{(\tau,\pi)}, \\
b_{it}^{(\tau,\pi)} &= \delta_0 + \delta_1\big(\mathbb{1}\{\text{Crisis}_t\} \times \mathbb{1}\{\text{Pre-BOE}_t\}\big) + \delta_2\big(\mathbb{1}\{\text{Crisis}_t\} \times \mathbb{1}\{\text{Post-BOE}_t\}\big) + \varepsilon_{it}^{(\tau,\pi)}.
\end{aligned}
$$

While on average banks are net sellers of UK government bonds, column (1) in Table 3, shows that, during the crisis, they become net buyers, a pattern similar to the arbitrageurs. Unlike arbitrageurs, they become large buyers of very long-term bonds (maturity $\tau \geq 20$Y) and do not alter their behaviour at other maturities ($\tau < 20$Y). Crucially, this change occurs only after the Bank of England intervention. Column (3) shows that all the purchases of long-term bonds occur after 28 September (Post-BOE$_t$) with no change before this date. This result is consistent with interpreting the Bank of England intervention as a shift in the intermediation cost of long-term bonds due to the lender of last resort.

The effect is primarily driven by purchases of eligible securities, consistent with a narrow transmission channel.[38] Specification 14 measures the pass-through of the Bank of England's purchase of a specific security (ISIN), $c_{it}^{(\tau,\pi)}$, to the banks' purchase of *that same security*, $b_{it}^{(\tau,\pi)}$. Specification 15 measures the spillovers of the total purchases (excluding the same security, $C_t - c_{it}^{(\tau,\pi)}$) to *any other security*. Both specifications include maturity bucket τ and inflation-linked fixed effects, α_τ, α_π.

$$
b_{it}^{(\tau,\pi)} = \theta c_{it}^{(\tau,\pi)} + \alpha_\tau + \alpha_\pi + \varepsilon_{it}^{(\tau,\pi)}, \tag{14}
$$

$$
b_{it}^{(\tau,\pi)} = \xi\big(C_t - c_{it}^{(\tau,\pi)}\big) + \alpha_\tau + \alpha_\pi + \varepsilon_{it}^{(\tau,\pi)}. \tag{15}
$$

Column (4) in Table 3 shows that for each £1 purchased by the Bank of England, banks purchased £0.46 of that same bond. The spillovers were localized to long-term bonds. Column (5) shows that an increase in total purchases by the Bank coincided with an increase in banks' purchases only on eligible assets, with no effects on ineligible ones.[39] In other words, banks were willing to purchase long-term bonds but only if they were eligible at the Bank of England facility.

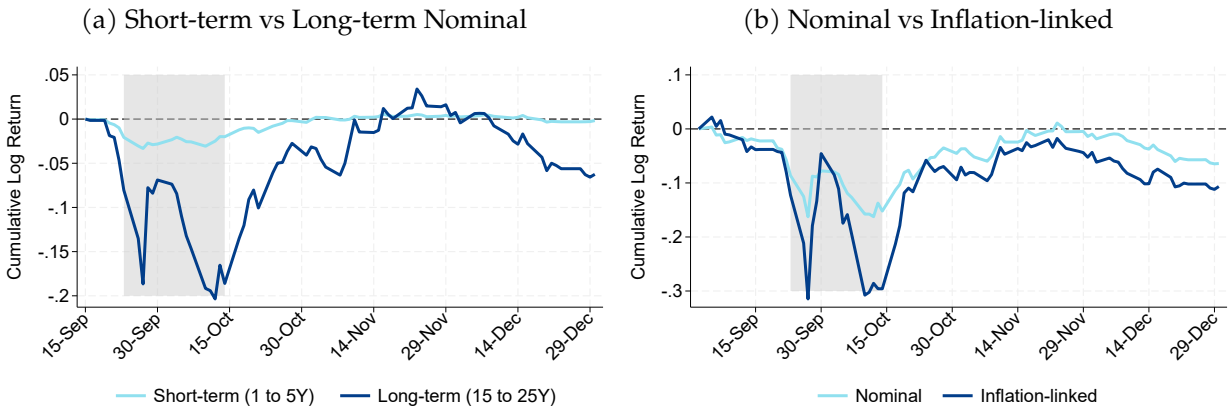
[38] See Lucca and Wright (2024) for a description of broad and narrow channels of asset purchases.

[39] Nominal bonds with maturity above 20Y were eligible from the 28/09 until the 14/10. Inflation-linked bonds with maturity above 20Y were eligible from the 11/10-14/10.

4.6 Risk Premia are Larger in Markets where Arbitrageurs are Absent

Consistent with Implication 1, risk premia are larger in markets where arbitrageurs do not participate, compensating banks for intermediating alone. Figure 9 shows this pattern consistently across different markets: long-term bonds offered larger returns than short-term bonds and inflation-linked bonds offered larger returns than nominal ones. In either case, the excess return (relative to the comparable asset) is large and persists throughout the crisis. At the height of the crisis, long-term bonds were offering an ≈18% discount, which then close by mid-November.

Figure 9: Larger Risk Premium where Arbitrageurs were Absent



Note: Panel (a) shows the cumulative log return from 01/09/2022-31/12/2022 of short-term nominal bonds relative to long-term nominal bonds. The assets are FTSE UK Treasury 1-5Y index; FTSE UK Treasury Bond 15-25Y index. Panel (b) shows the same for nominal bonds relative to inflation-linked bonds. The assets are FTSE UK Treasury Bond Index; FTSE UK Inflation-linked UK Bond Index. The gray shaded area corresponds to the crisis period (23/09-14/10).

Taking Stock

The difference between arbitrageurs and banks as marginal intermediaries emerges when volatility rises, liquidity tightens, and capital becomes scarcer. Consistent with Implication 1, following the volatility shock, two types of intermediaries emerge: arbitrageurs, concentrated in shorter-term bonds, and banks, concentrated in long-term bonds.

Arbitrageurs' preference for short-term bonds was not a flight to safety but rather a flight to liquidity. Consistent with Implication 3, arbitrageurs participated in short- and intermediate-term bonds by selecting the most liquid ones. In contrast to a risk-based explanation, the liquidity-based explanation can rationalize the non-participation in inflation-linked bonds and the concentration of purchases of nominal bonds at intermediate-term bonds, precisely where the deliverables of the

Long Gilt futures are. The spike at the 13-18Y mark in Figure 4 is thus largely explained by the liquidity of those assets (a lower $\phi(\sigma)$).

Banks' intermediation of long-term bonds was supported by access to the market maker of last resort, which increased their efficiency relative to arbitrageurs. The findings are consistent with the view in Hanson et al. (2015) that different liability structures give rise to different preferences for liquid assets. Consistent with Implication 2, risk premia were larger in markets where arbitrageurs did not participate.

5 Evidence from Normal Times: Bond Volatility and the VIX

In this section, we test Prediction 4 and show that the relationship between volatility and arbitrageurs participation extends beyond large volatility shocks. In normal times ($\sigma < \bar{\sigma}$), volatility has a nonlinear effect on arbitrageurs' participation in long-term bonds. This follows from Proposition 2 and traces the shape of arbitrageurs' demand in the dotted and in the dashed region in Figure 1.

We seek to trace out this nonlinearity in the data. Two forces operate when volatility increases: an increase in profit opportunities and a tightening in the funding friction. The balance of the two forces depends on the level of volatility. The idea is to compare arbitrageurs' participation at times when $\phi(\sigma)$ is high and when $\phi(\sigma)$ is low. The model predicts that periods when $\phi(\sigma)$ is high, arbitrageurs participation decreases, and vice versa when $\phi(\sigma)$ is low. The challenge is that we do not observe $\phi(\sigma)$ directly.

We proxy liquidity stress, a high $\phi(\sigma)$, using the VIX index, a well-known proxy for liquidity and financial conditions. Since the VIX is computed using US equity options, it bears no direct relationship to UK bonds other than through its effect on general financial conditions. If arbitrageurs, such as hedge funds in our sample, are global players then they will display sensitivity to global, rather than local, financial conditions as encapsulated by the VIX. This view is consistent with a large literature highlighting the special role of the VIX as barometer of the global financial cycle (Rey, 2015) and in specific asset markets, such as equities (Nagel, 2012), currencies (Brunnermeier et al., 2008), sovereign CDS (Longstaff et al., 2011) and corporate bonds (Bao et al., 2011).

5.1 Tracing Out the Shape of the Nonlinearity

We capture the balance of the two forces using a linear regression:

$$\ln a_t = \beta(\text{VIX}_t)\ln(\sigma_t) + \delta(\text{VIX}_t) + \varepsilon_t, \tag{16}$$

where $\beta(\text{VIX}_t), \delta(\text{VIX}_t)$ are functions of the financial friction, as proxied by the VIX, and we allow the asset's volatility (σ_t) to vary over time, as in the data. The slope is state dependent, and the state is captured by the financial friction.

Since the VIX captures *aggregate* liquidity conditions, as opposed to asset-specific liquidity, we pool across all bonds, shrinking the cross section to two maturity buckets, above or below 15Y of remaining maturity.[40] We approximate $\beta(\text{VIX}_t)$ with a step function that allows the slope to vary with the level of the VIX:

$$\beta(\text{VIX}_t) \approx \beta + \sum_{k=2}^{J} \gamma_k \mathbb{1}\{Q^{(k)}_{\text{VIX}_t}\} \qquad \delta(\text{VIX}_t) \approx \delta + \sum_{k=2}^{J} \delta_k \mathbb{1}\{Q^{(k)}_{\text{VIX}_t}\}, \tag{17}$$

where $\mathbb{1}\{Q^{(k)}_{VIX_t}\}$ is a binary variable that equals one if the VIX on day t is in J-tile k. We set $J = 4$ for parsimony, as the smallest number which the data does not reject equality.

Replacing (17) into (16), then yields:

$$\ln(a_t) = \beta \ln(\sigma_t) + \sum_{k=2}^{4} \gamma_k \left(\mathbb{1}\{Q^{(k)}_{\text{VIX}_t}\} \times \ln(\sigma_t) \right) + \delta + \sum_{k=2}^{4} \delta_k \mathbb{1}\{Q^{(k)}_{\text{VIX}_t}\}. \tag{18}$$

The theory predicts $\beta \geq 0$, γ_k (weakly) decreasing in k, and potentially negative for some k.

We measure the asset volatility (σ_t) with the total return volatility of UK Gilts, using the FTSE UK Conventional gilts Index 5-10Y and compute daily volatility of squared returns using an exponentially-weighted moving average with smoothing parameter $\lambda = 0.06$, which is standard industry practice.[41] The main outcome variable is the total amount traded by hedge funds in UK gilts in maturity bucket τ on day t. We account for the (unknown) sign of the preferred-habitat demand shock z_t by taking absolute values: $|a_t^{(\tau)}|$. To control for changes in outstanding supply, we scale the total traded amount by the supply of gilts outstanding in the respective quarter as

[40] We choose 15 years as the nearest-5 number to the average maturity of UK government debt. The results are unchanged with a cutoff of 10Y.

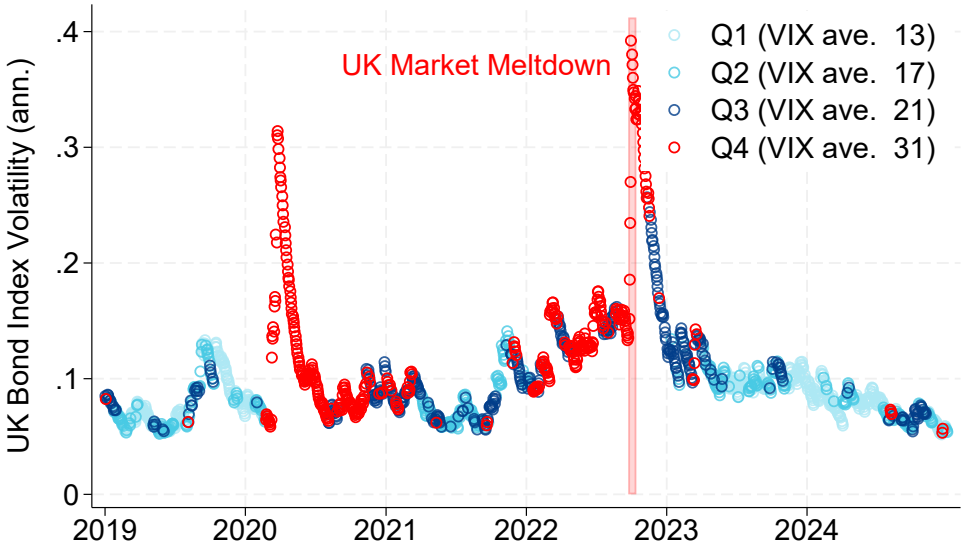
[41] This parametrization is known as the JP Morgan Risk Model (Danielsson, 2011). We experiment with more complex volatility models such as a generalized autoregressive conditional heteroskedasticity (GARCH) model and the results are unchanged.

reported by the Bank for International Settlement (BIS).[42]

5.1.1 UK Bond Volatility and the VIX

Figure 10 shows UK gilts volatility, color coded based on the level of the VIX on the given day. In other words, we intersect periods of tight global financial conditions (VIX) with volatility in the local UK bond market (gilts volatility). There are two visible spikes: Covid-19 and the UK gilts market meltdown. Both of those occurs during a high VIX period (in red) but for different reasons. Covid-19 was a global shock and the spike is immediate in March 2020. In contrast, as we already argued, the UK gilts market meltdown was a local shock that happened to occur on a backdrop of tight funding conditions.[43] Second, periods of high VIX (in red) tend to be persistent, consistent with its use as a slow-moving state variable. However, there are many switches between quartiles, which are often periods of subdued UK volatility.[44]

Figure 10: UK Government Bond Volatility and the VIX



Note: The figure shows the daily realized volatility (annualized) of the FTSE UK Conventional gilts Index. Volatility is computed as an exponentially-weighted moving average with smoothing parameter $\lambda = 0.06$. The colors correspond to the level of the VIX in a given day.

[42] As another proxy of arbitrageurs' participation, we use the number of unique funds trading in UK gilts market in maturity bucket τ on day t: $N_t^{(\tau)}$.

[43] The VIX had been hovering around its highest level since the start of the year, as central banks around the world started hiking interest rates.

[44] It is interesting to note that splitting into quartiles result in reasonable cutoffs. It is a widely held belief that VIX above 30 is means market stress. See S&P Global: A Practitioners Guide to Reading VIX.

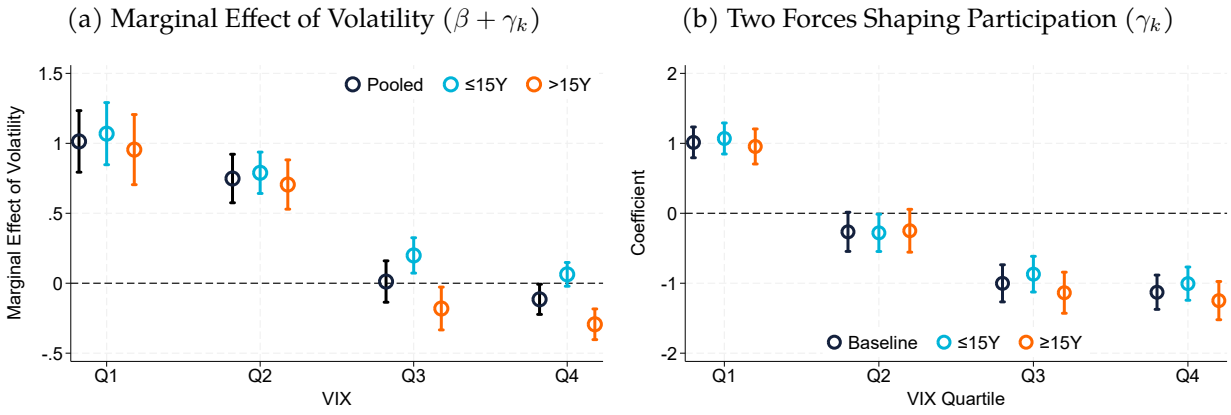
5.2 Baseline Result: Bond Volatility and the VIX

We run panel regressions at the daily frequency based on equation (18), first pooled and then split by maturity:

$$\ln\left(|a_t^{(\tau)}|\right) = \beta \ln(\sigma_t) + \sum_{k=2}^{4} \gamma_k \left(\mathbb{1}\{Q^{(k)}_{\text{VIX}_t}\} \times \ln(\sigma_t)\right) + \delta + \sum_{k=2}^{4} \delta_k \mathbb{1}\{Q^{(k)}_{\text{VIX}_t}\} + \varepsilon_t^{(\tau)}. \tag{19}$$

Figure 11 shows that the marginal effect of an volatility is positive when the VIX is low but turns negative when the VIX is high. Panel (a) plots $(\beta + \gamma_k)$, at different quartiles of the VIX (k), Panel (b) shows separately the coefficients β and γ_k, and Table 4 shows the full regression. Starting with the pooled regression, the black circle in Panel (a), we see that when the VIX is low (Q1 and Q2), volatility attracts arbitrageurs: an increase in UK bond volatility is associated with larger arbitrageurs participation as captured by the total amount traded. As the VIX increases, however, arbitrageurs become less responsive to volatility. When the VIX is in Q3, volatility ceases to attract arbitrageurs. When the VIX is in its highest quartile (Q4), volatility becomes repelling with arbitrageurs decreasing trading when the asset's volatility is higher.[45] These results trace out empirically the nonlinear relationship depicted in Figure 1. Consistent with the theory, volatility becomes repelling when the financial friction is tight, as proxied by the VIX.

Figure 11: Arbitrageurs' Trading, Bond Volatility and the VIX



Note: The figure reports the OLS coefficients estimated from the regression $\ln(|a_t^{(\tau)}|) = \alpha + \beta \ln(\sigma_t) + \sum_{k=2}^{4} \gamma_k (\ln(\sigma_t) \times \mathbb{1}\{Q^{(k)}_{VIX_t}\}) + \sum_{k=2}^{4} \delta_k \mathbb{1}\{Q^{(k)}_{VIX_t}\} + \varepsilon_t$. Specifically it reports $\beta + \gamma_k$ for $k = \{2, 3, 4\}$ and 90% confidence bands. The dependent variable is the absolute value of the total amount of UK nominal gilts traded on day t. The sample period is 2019-2024. Panel (b) reports the same coefficients this time estimated separately on short (≤15Y) and long (>15Y) maturity bonds. Standard errors are clustered at the day level.

[45] Appendix Table 10 formally tests the difference across quartiles.

The model predicts that this relationship is more pronounced for riskier assets, such as long-term bonds. In the low volatility environment (Q1, Q2), arbitrageurs are equally active across short-term and long-term bonds, as seen by the light blue and orange circles in Panel (a) of Figure 11. In a high volatility environment (Q3, Q4), however, a wedge opens up. Arbitrageurs participation in long-term bonds falls rapidly and, as soon as we reach Q3, the marginal effect turns negative. The marginal effect never turns negative in short-term bonds.

5.3 Realized, Fundamental and Endogenous Volatility

The previous analysis uses UK bond *realized* volatility. Realized volatility conflates fundamental volatility with endogenous volatility, potentially introduced by arbitrageurs' themselves (Brunnermeier and Sannikov, 2014). To identify the effect, we exploit scheduled macroeconomic announcements as a proxy for *fundamental* volatility (Anderson et al., 2003). We use the economic calendar provided by Bloomberg, Table 12 in the Appendix provides the full list of releases.[46] Since using scheduled macroeconomic news reduces the size of our sample, we use the VIX as a continuous variable.

We run the following regression:

$$\ln(|a_t|) = \alpha + \beta \text{News}_t + \gamma \ln(\text{VIX}_t) + \delta\big(\text{News}_t \times \ln(\text{VIX}_t)\big) + \varepsilon_t, \tag{20}$$

where News_t is a dummy variable equal to one if on day t there is a scheduled macroeconomic release. The coefficient of interest is δ, which captures the effect of fundamental volatility interacted with financial friction (VIX) on arbitrageurs' participation.

We then compare days with larger and smaller news, defined as the absolute value of the difference between the actual outturn and the survey expectation from Bloomberg. Arguably, this provides a sharper identification by comparing within news days. We run:

$$\ln(|a_t|) = \alpha + \beta \text{Large News}_t + \gamma \ln(\text{VIX}_t) + \delta\big(\text{Large News}_t \times \ln(\text{VIX}_t)\big) + \varepsilon_t, \tag{21}$$

where Large News_t is a dummy that takes value one if the surprise is above the median. The size of the news proxies more closely for volatility, and the model predicts $\beta \geq 0$ $\delta \leq 0$. Scheduled release days are high information days, and it is possible that arbitrageurs are informed and trade

[46] We keep only observations that have a survey estimate at the time of release, a Bloomberg relevance score above 30 (out of a 100), and drop news for which there are less than 30 observations over 2000-2025. We drop monetary policy news because we know from Hanson and Stein (2015) that there are systematic differences in demand conditions.

Table 4: Baseline Regression with Controls

	Dep var: $\ln(\lvert a_t^{(\tau)} \rvert)$				
	(1)	(2)	(4)	(5)	(6)
$\ln \sigma_t$	1.014***	0.548***	1.255***	0.971***	0.600***
	(0.126)	(0.149)	(0.135)	(0.127)	(0.153)
$\ln \sigma_t \times$ VIX Q2	-0.265	-0.181	-0.329*	-0.162	-0.078
	(0.150)	(0.147)	(0.147)	(0.151)	(0.148)
$\ln \sigma_t \times$ VIX Q3	-1.002***	-0.785***	-1.007***	-0.799***	-0.395**
	(0.145)	(0.145)	(0.140)	(0.145)	(0.147)
$\ln \sigma_t \times$ VIX Q4	-1.129***	-0.699***	-1.134***	-0.927***	-0.204
	(0.136)	(0.154)	(0.132)	(0.139)	(0.159)
VIX Q2	-0.768	-0.450	-0.966*	-0.481	-0.131
	(0.448)	(0.436)	(0.431)	(0.447)	(0.430)
VIX Q3	-3.231***	-2.456***	-3.229***	-2.639***	-1.201**
	(0.426)	(0.423)	(0.406)	(0.419)	(0.428)
VIX Q4	-3.658***	-2.247***	-3.667***	-2.991***	-0.597
	(0.397)	(0.455)	(0.377)	(0.402)	(0.475)
$y_t^{(10)} - y_t^{(2)}$		-0.232***			-0.349***
		(0.047)			(0.036)
Swap Spread$_t$			-0.123***		-0.187***
			(0.027)		(0.027)
R_{3m}^{HF}				0.113***	0.147***
				(0.024)	(0.019)
R2	0.050	0.057	0.064	0.056	0.089
N	2,993	2,993	2,989	2,993	2,989

Note: The dependent variable is the logarithm of total traded amount in UK nominal Gilts of maturity bucket τ, above or below 15Y. Volatility is computed as an exponentially-weighted moving average of the FTSE UK Conventional Gilts 5-10Y. Data is winsorized at 1% level. r_{3m}^{HF} is the cumulative return over the previous 3 months over the Barclay Hedge Fund Return Index. Column (6) excludes Covid and the UK Gilts crisis. The table omits the individual coefficient on the VIX quartiles. The sample period is 2019-2024. Standard errors are clustered at the day level.

Table 5: Continuous VIX and Macroeconomic News

	Dep var: $\log(\lvert a_t \rvert)$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln \sigma_t$	0.252*	3.464***				
	(0.099)	(0.750)				
$\ln(\text{VIX}_t)$		-3.359***		-0.221*	-0.482**	-0.240
		(0.755)		(0.097)	(0.187)	(0.155)
$\ln \sigma_t \times \ln(\text{VIX}_t)$		-1.033***				
		(0.243)				
News_t			0.188***	0.793*		
			(0.038)	(0.384)		
$\text{News}_t \times \ln(\text{VIX}_t)$				-0.205		
				(0.123)		
Positive News_t					-0.269	
					(0.396)	
Positive $\text{News}_t \times \ln(\text{VIX}_t)$					0.098	
					(0.136)	
Large News_t						1.252***
						(0.356)
Large $\text{News}_t \times \ln(\text{VIX}_t)$						-0.402***
						(0.120)
R2	0.021	0.075	0.016	0.036	0.047	0.059
N	1,499	1,499	1,499	1,499	721	721

Note: The table shows the OLS coefficients of daily regression using $\ln \sigma_t$ or a dummy variable News_t if on that given day a scheduled macroeconomic release as reported by the Bloomberg Calendar. Positive News_t is a dummy variable equal to one if news surprise (outturn - survey median) is positive. Large News_t is a binary variable capturing news with surprises (actual - survey median) above the median. Robust standard errors in parentheses.

on private signals. We test this using the sign of the news defined as actual outturn minus survey expectation, in a specification that mirrors (21).

Table 5 shows that higher fundamental volatility attracts participation, but repels arbitrageurs when the VIX is high. In column (1) and (2), we print baseline estimates for comparison. Days with news have on average 20.7% higher traded amounts, column (3).[47] When interacted with the VIX, in column (4), the point estimate is negative, in line with our hypothesis, although not statistically significant. In column (6), we find that higher fundamental volatility (Large News$_t$) has a large positive effect which turns negative effect when interacted with the VIX, as predicted by the theory. We find no evidence in favor of informed trading, in column (5).

5.4 Additional Exercises and Robustness

We perform two additional exercises and a robustness test. First, we check if the correlation between VIX and arbitrageurs' participation simply captures periods in which bond volatility is high. Second, since the VIX is an asset price, we decompose it into pure volatility and (variance) risk premium. Third, we add a three controls motivated by the literature to the baseline regression.

Alternative Sorting Variable. It is possible that when the VIX is high, bond volatility is also high and therefore the VIX simply captures times of high bond volatility. To check this possibility, we run the same regression while sorting on bond volatility itself rather than the VIX. Figure 6 in Appendix shows the result. In contrast to sorting on the VIX, bond volatility does not produce a the stable and decreasing pattern. The estimates are also noisier as evidenced by the large confidence bands, which suggest that the VIX contains information beyond the level of bond volatility.

Decomposing the VIX. We have interpreted the VIX as pure volatility but the VIX is risk-neutral volatility, and includes a risk premium. We validate our interpretation as pure volatility decomposing the VIX using Bekaert et al. (2013) methodology.[48] We then use the pure volatility measure and the variance risk premium as sorting variables. Figure 9 in Appendix shows that the repelling effect of volatility is driven by the conditional variance rather than by the risk premium. Instead, the variance risk premium produces a hump-shaped pattern.

[47] This is derived from $e^{0.188} - 1$.

[48] Specifically, we obtain the conditional expectation regressing the daily realized variance of the SP500 on its previous month's value and on the previous month's value of the VIX^2. That is, $\sigma^2_{SP500,t} = \alpha + \beta\sigma^2_{SP500,t-22} + \gamma \text{VIX}^2_{t-22} + \varepsilon_t$. The fitted value then corresponds to the expectation and the variance risk premium is defined as the difference between the VIX^2 and the conditional variance.

Adding Controls. We introduce controls motivated by the literature. In column (1) of Table 4, we repeat our baseline regression to aid comparison across specification. In column (2), we control for the term spread, which Campbell and Shiller (1991) find predicts bond returns. While the coefficients are smaller, the effect of volatility is still present. In column (3) we control for swap spreads to capture funding frictions and limits to arbitrage as in Jermann (2020). The effect is still there. Models with margins and debt, e.g. (Brunnermeier and Pedersen, 2009), predict that arbitrageurs' wealth is an important variable. We test this in column (5). We compute rolling 3-month cumulative hedge funds' returns as a proxy for hedge funds' wealth.[49] The coefficient on hedge funds' returns is positive and large, but controlling for hedge funds' cumulative returns over the previous 3 months also does not materially affects the effect of volatility. In column (6) we include all controls simultaneously. From here we conclude that the nonlinearity is fully spanned by a combination of arbitrageurs' wealth, funding frictions and the shape of the term structure and not driven by dark matter.

6 Conclusions

In this paper we studied the impact of volatility on arbitrageurs, taking into account the existence of two distinct types: hedge funds and banks. Hedge funds are more sensitive to volatility: they retrench to shorter-term bonds and extend to longer maturities only if they can hedge out some of the risk. In contrast, banks are less sensitive to volatility and, during the 2022 Gilts market meltdown, participated in long-term bonds.

We have attributed the differential response to volatility to their funding sources. In particular, hedge funds fund themselves in global markets, and therefore display sensitivity to global factors, such as the VIX. Banks have access to local funding, and are thus more insulated from global factors. Exclusive access to the lender/market-maker of last resort is a particularly powerful source of stability.

Our findings are relatively more benign than the US-based literature. Hedge funds did not amplify the volatility shock we studied. On the contrary, they were net buyers of UK bonds. The concern is that they did not participate where stress was most intense, namely long-term bonds. Under this new market structure, the long-end of the curve is more sensitive to global financial conditions, with consequences for dealer banks, who are systematically absorbing riskier bonds at riskier times.

Given the endogenous participation of hedge funds, it remains an open question remains what

[49] We use the Barclays Hedge Fund Index to compute the 3-month cumulative return.

the optimal policy is, and whether allowing hedge funds to access the lender of last resort could decrease their funding fragility and stimulate participation. We leave this area for future research.

References

Adrian, T. and H. S. Shin (2014). Procyclical leverage and value-at-risk. *The Review of Financial Studies 27*(2), 373–403.

Aguiar, M. and M. Amador (2014). Sovereign debt. In *Handbook of international economics*, Volume 4, pp. 647–687. Elsevier.

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

Alfaro, L., S. A. Bahaj, R. Czech, J. Hazell, and I. Neamtu (2024). Lash risk and interest rates. Technical report, National Bureau of Economic Research.

Anderson, T. G., T. Bollerslev, F. X. Diebold, and C. Vega (2003). Micro effects of macro announcements: Real-time price discovery in foreign exchange. *American Economic Review 93*(1), 38–62.

Bahaj, S., R. Czech, S. Ding, and R. Reis (2023). The market for inflation risk. *Working Paper*.

Bailey, A. (2025). Are we underestimating changes in financial markets? *Speech given at the University of Chicago Booth School of Business, London*.

Bao, J., J. Pan, and J. Wang (2011). The illiquidity of corporate bonds. *The Journal of Finance 66*(3), 911–946.

Barth, D. and R. J. Kahn (2025). Hedge funds and the treasury cash-futures basis trade. *Journal of Monetary Economics*, 103823.

Bekaert, G., M. Hoerova, and M. L. Duca (2013). Risk, uncertainty and monetary policy. *Journal of Monetary Economics 60*(7), 771–788.

Ben-David, I., F. Franzoni, and R. Moussawi (2012). Hedge fund stock trading in the financial crisis of 2007–2009. *The Review of Financial Studies 25*(1), 1–54.

Boehm, C. E. and T. N. Kroner (2023). The us, economic news, and the global financial cycle. Technical report, National Bureau of Economic Research.

Brunnermeier, M. and S. Nagel (2004). Hedge funds and the technology bubble. *The Journal of Finance 59*(5), 2013–2040.

Brunnermeier, M. K., S. Nagel, and L. H. Pedersen (2008). Carry trades and currency crashes. *NBER Macroeconomics Annual 23*(1), 313–348.

Brunnermeier, M. K. and L. H. Pedersen (2009). Market liquidity and funding liquidity. *Review of Financial Studies 22*(6), 2201–2238.

Brunnermeier, M. K. and Y. Sannikov (2014). A macroeconomic model with a financial sector. *American Economic Review 104*(2), 379–421.

Bryzgalova, S., A. Pavlova, and T. Sikorskaya (2023). Strategic arbitrage in segmented markets. *Available at SSRN*.

Campbell, J. Y. and R. J. Shiller (1991). Yield spreads and interest rate movements: A bird's eye view. *The Review of Economic Studies 58*(3), 495–514.

Coimbra, N. and H. Rey (2024). Financial cycles with heterogeneous intermediaries. *Review of Economic Studies 91*(2), 817–857.

Czech, R. and W. Monroe (2025). Dealers, information and liquidity provision in safe assets. *Bank of England Financial Stability Paper* (1,113).

Danielsson, J. (2011). *Financial risk forecasting: the theory and practice of forecasting market risk with implementation in R and Matlab*. John Wiley & Sons.

D'Avernas, A. and Q. Vandeweyer (2024). Treasury bill shortages and the pricing of short-term assets. *The Journal of Finance 79*(6), 4083–4141.

Donaldson, J. R., G. Piacentino, and A. Thakor (2021). Intermediation variety. *The Journal of Finance 76*(6), 3103–3152.

Du, W., J. Im, and J. Schreger (2018). The us treasury premium. *Journal of International Economics 112*, 167–181.

Du, W. and J. Schreger (2022). Cip deviations, the dollar, and frictions in international capital markets. In *Handbook of International Economics*, Volume 6, pp. 147–197. Elsevier.

Duffie, D. (1996). Special repo rates. *The Journal of Finance 51*(2), 493–526.

Duffie, D. (2025). How us treasuries can remain the worlds safe haven. *Journal of Economic Perspectives 39*(2), 195–214.

Duffie, D., M. J. Fleming, F. M. Keane, C. Nelson, O. Shachar, and P. Van Tassel (2023). Dealer capacity and us treasury market functionality. *FRB of New York Staff Report* (1070).

Duffie, D. and F. M. Keane (2023). Market-function asset purchases. *FRB of New York Staff Report* (1054).

Eisfeldt, A. L., H. Lustig, and L. Zhang (2023). Complex asset markets. *Journal of Finance 78*(5), 2519–2562.

Farhi, E. and J. Tirole (2021). Shadow banking and the four pillars of traditional financial intermediation. *The Review of Economic Studies 88*(6), 2622–2653.

Fleckenstein, M. and F. A. Longstaff (2024). Treasury richness. *The Journal of Finance 79*(4), 2797–2844.

Fleckenstein, M., F. A. Longstaff, and H. Lustig (2014). The tips-treasury bond puzzle. *Journal of Finance 69*(5), 2151–2197.

Frazzini, A. and L. H. Pedersen (2014). Betting against beta. *Journal of Financial Economics 111*(1), 1–25.

Gabaix, X. and M. Maggiori (2015). International liquidity and exchange rate dynamics. *Quarterly Journal of Economics 130*(3), 1369–1420.

Gourinchas, P.-O., W. Ray, and D. Vayanos (2025). A preferred-habitat model of term premia, exchange rates, and monetary policy spillovers. *American Economic Review*.

Greenwood, R., S. Hanson, J. C. Stein, and A. Sunderam (2023). A quantity-driven theory of term premia and exchange rates. *Quarterly Journal of Economics 138*(4), 2327–2389.

Greenwood, R., S. Hanson, and D. Vayanos (2023). Supply and demand and the term structure of interest rates. Technical report, National Bureau of Economic Research.

Gromb, D. and D. Vayanos (2002). Equilibrium and welfare in markets with financially constrained arbitrageurs. *Journal of Financial Economics 66*(2-3), 361–407.

Grossman, S. J. and M. H. Miller (1988). Liquidity and market structure. *Journal of Finance 43*(3), 617–633.

Haddad, V., Z. He, P. Huebner, P. Kondor, and E. Loualiche (2025). Causal inference for asset pricing. *Available at SSRN 5187305*.

Haddad, V., P. Huebner, and E. Loualiche (2025). How competitive is the stock market? theory, evidence from portfolios, and implications for the rise of passive investing. *American Economic Review 115*(3), 975–1018.

Haddad, V. and T. Muir (2025). Intermediaries and asset prices. Technical report, National Bureau of Economic Research.

Hanson, S. G., A. Shleifer, J. C. Stein, and R. W. Vishny (2015). Banks as patient fixed-income investors. *Journal of Financial Economics 117*(3), 449–469.

Hanson, S. G. and J. C. Stein (2015). Monetary policy and long-term real rates. *Journal of Financial Economics 115*(3), 429–448.

Hauser, A. (2021). From lender of last resort to market maker of last resort via the dash for cash: why central banks need new tools for dealing with market dysfunction. *Speech given at Reuters, London*.

He, Z. and A. Krishnamurthy (2013). Intermediary asset pricing. *American Economic Review 103*(2), 732–770.

Itskhoki, O. and D. Mukhin (2021). Exchange rate disconnect in general equilibrium. *Journal of Political Economy 129*(8), 2183–2232.

Jermann, U. (2020). Negative swap spreads and limited arbitrage. *The Review of Financial Studies 33*(1), 212–238.

Jurkatis, S. (2024). An approach to cleaning mifid ii corporate bond transaction reports. Technical report, Bank of England.

Kashyap, A. K., J. C. Stein, J. L. Wallen, and J. Younger (2025). Treasury market dysfunction and the role of the central bank. *Brookings Papers on Economic Activity*, 1.

Kekre, R., M. Lenel, and F. Mainardi (2024). Monetary policy, segmentation, and the term structure. *Working paper*.

Kondor, P. and D. Vayanos (2019). Liquidity risk and the dynamics of arbitrage capital. *The Journal of Finance 74*(3), 1139–1173.

Krishnamurthy, A. (2002). The bond/old-bond spread. *Journal of financial Economics 66*(2-3), 463–506.

Krishnamurthy, A. and Y. Ma (2024). The demand and supply of convenience assets. *Annual Review of Financial Economics 17*.

Krishnamurthy, A. and A. Vissing-Jorgensen (2012). The aggregate demand for treasury debt. *Journal of Political Economy 120*(2), 233–267.

Kruttli, M. S., P. Monin, L. Petrasek, and S. W. Watugala (2023). Ltcm redux? hedge fund treasury trading and funding fragility. *Available at SSRN 3817978*.

Longstaff, F. A. (2002). The flight-to-liquidity premium in us treasury bond prices.

Longstaff, F. A., J. Pan, L. H. Pedersen, and K. J. Singleton (2011). How sovereign is sovereign credit risk? *American Economic Journal: Macroeconomics 3*(2), 75–103.

Lu, L. and J. Wallen (2024). What do bank trading desks do? Technical report, Harvard Working Paper.

Lucca, D. O. and J. H. Wright (2024). The narrow channel of quantitative easing: Evidence from ycc down under. *The Journal of Finance 79*(2), 1055–1085.

Ma, Y., K. Xiao, and Y. Zeng (2022). Mutual fund liquidity transformation and reverse flight to liquidity. *The Review of Financial Studies 35*(10), 4674–4711.

Nagel, S. (2012). Evaporating liquidity. *Review of Financial Studies 25*(7), 2005–2039.

Pedersen, L. H. (2019). *Efficiently inefficient: how smart money invests and market prices are determined*. Princeton University Press.

Pinter, G. (2023). An anatomy of the 2022 gilt market crisis. *Working Paper*.

Pinter, G., E. Siriwardane, and D. Walker (2024). Fire sales of safe assets. *Bank of England Financial Stability Paper* (1,089).

Ray, W., M. Droste, and Y. Gorodnichenko (2024). Unbundling quantitative easing: Taking a cue from treasury auctions. *Journal of Political Economy 132*(9), 3115–3172.

Rey, H. (2015). Dilemma not trilemma: the global financial cycle and monetary policy independence. Technical report, National Bureau of Economic Research.

Shleifer, A. and R. W. Vishny (1990). Equilibrium short horizons of investors and firms. *The American Economic Review 80*(2), 148–153.

Shleifer, A. and R. W. Vishny (1997). The limits of arbitrage. *Journal of Finance 52*(1), 35–55.

Siriwardane, E. N., A. Sunderam, and J. Wallen (2025). Segmented arbitrage. *The Journal of Finance 80*(5), 2543–2590.

Vayanos, D. and J.-L. Vila (2021). A preferred-habitat model of the term structure of interest rates. *Econometrica 89*(1), 77–112.

Vayanos, D. and P.-O. Weill (2008). A search-based theory of the on-the-run phenomenon. *The Journal of Finance 63*(3), 1361–1398.

Appendix

A Data Construction

I filter the MIFID II data by reporting entity type rather than by asset (e.g., Gilts) as is commonly done. I first extract all the executing entity names using the new weekly files from 2022-2025. I filter in two stages. In the first stage, I identify those that are likely to be hedge funds using as criteria that the name includes keywords such as capital, advisor, LLP, LLC, or asset manager (excluding the obvious ones that are just asset managers). This first filter delivers 599 unique identities. I then cross check each of those to make sure they are actual hedge funds. In some instances they are execution services, or wealth managers, which I exclude. I also exclude private equity and private credit firms. This second filter delivers 398 unique identities, which are then extracted from the transaction-level raw data.

With the reporting entity I capture only entities that are reporting to the Financial Conduct Authority, hence avoid the problem of non-reporting entities appearing sporadically because they are trading with a UK counterparty. In other words, this is the best guess of keeping only UK-based entities.

I collect all the ISINs of the instruments traded and find static bond characteristics such as outstanding supply, issuer sector, maturity, coupon rate, rating and features such as callability and inflation protection from Reuters Datastream. Table 6 reports the frequencies. Before applying any filter at the asset level, we obtain dataset of hedge funds trades covering $\approx$ 60k unique ISINs and $\approx$ 4.25 million trades. A large number of bonds are corporate bonds (70.4%) however the majority of trading occurs in sovereign (73.7% of trades). The trading volume is largely concentrated in sovereign bonds (96%).

Since we are interested in government bonds, we restrict the dataset to sovereign ($SOVERGRN$). We drop bonds with rating withdrawn or defaulted ($\approx$ 1.3% of the trades) and bonds that are callable ($\approx$ 0.7% of trades). Since bonds are issued in multiple currencies, I convert all amounts in US Dollars using the previous end-of-day spot exchange rate.

Master-Feeder Consolidation I consolidate hedge fund structures where needed. For example, a hedge fund may report trades of both the firm-level and the master fund. When there is no doubt, for example in the case of a hedge fund that has only a single master fund, I consolidate the two.[50] The way reporting works is that the master feeder will report trading with the broker dealer and then a number of reallocation trades will be reported between the master fund and the feeder funds, see example in 7, identified by trading in the same instrument-day-price and quantities absorbed

[50] For non-UK assets, hedge funds report trades between the Feeder Fund and the Master Fund. For example it may report that the Feeder is purchasing from the Master. This trades is just reallocating from the Master to the Feeder. The Master Fund' trade with the external dealer is not observed.

Table 6: Summary Statistics by Asset Type

	Bonds		Trades		Volume	
	Freq	Pct	Freq	Pct	Freq	Pct
Corporate	36,468	70.5	996,892	23.4	3,553,763	3.4
Sovereign	6,388	12.3	3,145,262	73.9	99,400,000	96.1
Supranational	1,005	1.9	38,444	0.9	354,846	0.3
Municipal	518	1.0	7,170	0.2	41,413	0.0
Agency	1,310	2.5	19,649	0.5	110,763	0.1
NA	6,068	11.7	46,782	1.1	26,668	0.0
Total	51,757		4,254,199		103,487,453	

Note: Bonds is the count of unique ISINs, Trades is the number of trades (or equivalently observations), Volume is the unsigned volume, expressed in million US Dollars.

by the individual feeder funds totalling the trade size of those of the master fund.

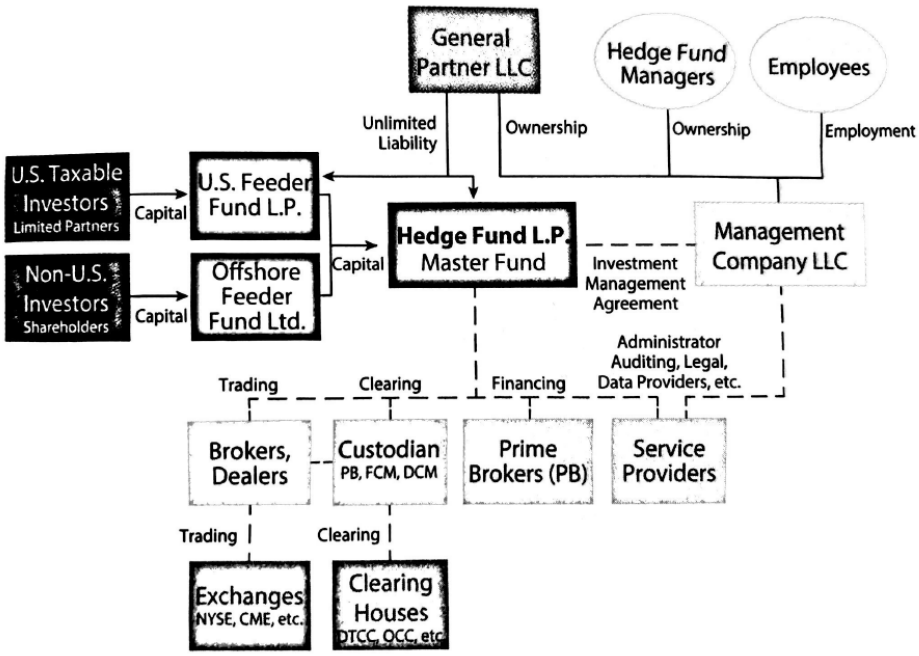


Figure 1.1. The master–feeder hedge fund structure.

Figure 1: Source: Pedersen (2019).

To remove potentially noisy observations, I drop funds that trades less than 35 times in my

Table 7: Master-Feeder Structure: The Case of a Fictitious Trade

Date	Instrument	Reported by	Buyer	Seller	Quantity	Price
12-Mar-24	Italian Bond	HF LLP	Broker Dealer X	HF LLP	5,500	97.75
12-Mar-24	Italian Bond	HF LLP	HF LLP	Feeder Fund 1	2,200	97.75
12-Mar-24	Italian Bond	HF LLP	HF LLP	Feeder Fund 2	1,100	97.75
12-Mar-24	Italian Bond	HF LLP	HF LLP	Feeder Fund 3	2,200	97.75

sample. This is a mild filter and corresponds to observations trading only 1.9% of days in the sample, which consists of 1'825 trading days (2019-2024). This filter drops 0.08% of trades.

The final dataset consists of ≈ 2.97 million trades on sovereign, agency and supranational bonds from 2018m1 to 2024m12. There are 188 fund families (reporting entities) and 554 unique funds. Each fund family reports between 1 and 63 unique funds.

B Other Data Sources

Bond Indices. We obtain bond prices from Datastream/Refinitiv. We use the FTSE Government Bond Index and its country-level sub-indices to compute log returns and volatility. We use: FTSE Act UK CG 10-15Y Index (FTBGTTF); FTSE Act UK CG 5-10Y Index (FTBG5TT); FTSE Act UK CG 15-25Y Index (FTBGFTT); FTSE Act UK CG over 25Y Index (FTBGOVT); FTSE Act UK CG up to 5Y Index (FTBGSHT).

Individual Bonds. We also obtain individual bond prices at the ISIN level from Datastream/Refinitiv. We source the list of ISINs outstanding from the Gilts in Issue report from the Debt Management Office (DMO).

Government Bond Supply. We obtain the S1311:Central government excluding social security from the Debt Security Statistics from the Bank for International Settlements (BIS).

Cheapest-to-deliver. We obtain the list of historical deliverable Gilts from the Intercontinental Exchange (ICE).

Financial Variables. We obtain the CBOE VIX Index from Center for Research in Security Prices (CRSP); the overnight indexed swap with 1Y residual maturity (BPSWS1 BGN Curncy) from Bloomberg; the benchmark 10Y (BMUK10Y) and 2Y yield (BMUK02Y) and S&P 500 total return (S&PCOMP) from Refinitiv/Datastream. We obtain the monthly hedge funds' return index from Barclay Hedge.

Macroeconomic News. We obtain the economic calendar from Bloomberg. This includes the day, hour, minute of the release, a survey median from professional forecasters and a Bloomberg relevance score. We drop monetary policy news that we know from Hanson and Stein (2015) have specific demand patterns. We compute the surprise as the difference between the actual realization and survey median. We use an approach similar to Boehm and Kroner (2023) for selecting the key news. We keep only news that have a Bloomberg score of at least 30/100. We then retain only news for which the survey median is available. On a given day, there may still be multiple macroeconomic news released. While not relevant for our baseline specification which includes just a dummy variable for a day with a macro news released, in exercises using the survey median we need to decide which news to use. In those cases, we keep the news that has the highest Bloomberg relevance score.

Secondary Market Trading. We use the MiFID II transaction data held by the Financial Conduct Authority (FCA). Jurkatis (2024) provides a comprehensive description of this data.

Economic News Calendar. We use the economic news calendar from Bloomberg (ECO function). This includes the date and time of the economic news, along with actual outturn and the survey median expectation that we use in computing surprises as in Boehm and Kroner (2023).

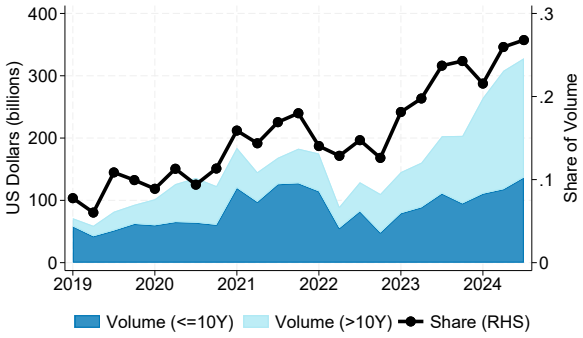
B.1 Hedge Funds Dominance in International Bond Markets

Hedge funds in our dataset cover a large fraction of global activity. I aggregate volume by UK-based hedge funds at the country-quarter level. I then compute the HF market shares dividing by the aggregate trading volume data obtained from different national sources. Specifically, we define the HF market share in market m and quarter t as

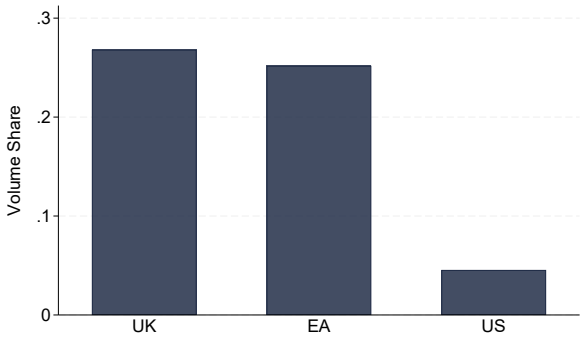
$$\text{Share}_t^{(m)} = \frac{\text{MiFID Volume}_t^{(m)}}{\text{Aggregate Volume}_t^{(m)}}.$$

Figure 2: Hedge Funds Across Government Bond Markets

(a) Time Series in U.K. Government Bonds



(b) Share in Major Markets



Note: Panel (a) shows the time series of the share (black line) and dollar amount split by maturity (blue-shaded areas) of total quarterly volume accounted by UK-based hedge funds in UK government bonds. Panel (b) shows the share of total quarterly volume accounted by UK-based hedge funds across UK, US and EA government bonds, as of 2024Q3.

C Additional Tables

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(Gross)	Log(Gross)	Log(|X|)	Log(|X|)	Log(N)	Log(N)
	b/se	b/se	b/se	b/se	b/se	b/se
$\log \sigma_t$	0.162***	1.014***	0.061	0.481**	0.299***	0.827***
	(0.037)	(0.126)	(0.055)	(0.170)	(0.020)	(0.065)
$\log \sigma_t \times$ VIX Q2		-0.265		-0.141		-0.173*
		(0.150)		(0.215)		(0.080)
$\log \sigma_t \times$ VIX Q3		-1.002***		-0.488*		-0.596***
		(0.145)		(0.199)		(0.074)
$\log \sigma_t \times$ VIX Q4		-1.129***		-0.561**		-0.721***
		(0.136)		(0.189)		(0.072)
VIX Q2		-0.768		-0.395		-0.520*
		(0.448)		(0.641)		(0.237)
VIX Q3		-3.231***		-1.543**		-1.913***
		(0.426)		(0.583)		(0.215)
VIX Q4		-3.658***		-1.779**		-2.338***
		(0.397)		(0.550)		(0.208)
R2	0.004	0.050	0.000	0.006	0.100	0.229
N	2,993	2,993	2,993	2,993	2,993	2,993

Table 8: Baseline Regression with Controls

	Dep var: $\log(\lvert X_t^{(\tau)}\rvert)$						Dep var: $\log(N_t^{(\tau)})$					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
$\log \sigma_t$	1.014***	0.548***	-0.285*	1.255***	0.971***	-0.079	0.827***	0.542***	0.002	0.898***	0.801***	0.111
	(0.126)	(0.149)	(0.142)	(0.135)	(0.127)	(0.150)	(0.065)	(0.075)	(0.072)	(0.070)	(0.064)	(0.073)
$\log \sigma_t \times$ VIX Q2	-0.265	-0.181	-0.067	-0.329*	-0.162	-0.054	-0.173*	-0.121	-0.047	-0.193*	-0.110	-0.040
	(0.150)	(0.147)	(0.139)	(0.147)	(0.151)	(0.137)	(0.080)	(0.078)	(0.075)	(0.079)	(0.080)	(0.073)
$\log \sigma_t \times$ VIX Q3	-1.002***	-0.785***	-0.401**	-1.007***	-0.799***	-0.183	-0.596***	-0.463***	-0.214**	-0.605***	-0.474***	-0.136
	(0.145)	(0.145)	(0.140)	(0.140)	(0.145)	(0.139)	(0.074)	(0.074)	(0.073)	(0.073)	(0.075)	(0.071)
$\log \sigma_t \times$ VIX Q4	-1.129***	-0.699***	-0.293*	-1.134***	-0.927***	-0.039	-0.721***	-0.457***	-0.190**	-0.724***	-0.599***	-0.112
	(0.136)	(0.154)	(0.136)	(0.132)	(0.139)	(0.148)	(0.072)	(0.079)	(0.071)	(0.071)	(0.073)	(0.076)
$y_t^{(10)} - y_t^{(2)}$		-0.232***				-0.028		-0.142***				0.014
		(0.047)				(0.040)		(0.022)				(0.022)
$y_t^{(2)}$			0.409***			0.434***			0.260***			0.275***
			(0.029)			(0.029)			(0.013)			(0.015)
Swap Spread$_t$				-0.123***		-0.202***				-0.035*		-0.080***
				(0.027)		(0.023)				(0.016)		(0.013)
R_{3m}^{HF}					0.113***	0.074***					0.068***	0.034***
					(0.024)	(0.019)					(0.011)	(0.010)
VIX Q2	-0.768	-0.450	-0.133	-0.966*	-0.481	-0.087	-0.520*	-0.325	-0.117	-0.584*	-0.347	-0.099
	(0.448)	(0.436)	(0.409)	(0.431)	(0.447)	(0.395)	(0.237)	(0.231)	(0.218)	(0.233)	(0.236)	(0.212)
VIX Q3	-3.231***	-2.456***	-1.179**	-3.229***	-2.639***	-0.456	-1.913***	-1.437***	-0.609**	-1.934***	-1.556***	-0.353
	(0.426)	(0.423)	(0.406)	(0.406)	(0.419)	(0.400)	(0.215)	(0.216)	(0.213)	(0.209)	(0.216)	(0.205)
VIX Q4	-3.658***	-2.247***	-0.745	-3.667***	-2.991***	0.126	-2.338***	-1.473***	-0.488*	-2.348***	-1.936***	-0.213
	(0.397)	(0.455)	(0.400)	(0.377)	(0.402)	(0.441)	(0.208)	(0.234)	(0.210)	(0.205)	(0.212)	(0.226)
R2	0.050	0.057	0.098	0.064	0.056	0.130	0.229	0.247	0.372	0.255	0.245	0.431
N	2,993	2,993	2,993	2,989	2,993	2,989	2,993	2,993	2,993	2,989	2,993	2,989

Note: The dependent variable is the logarithm of total traded amount in UK nominal Gilts of maturity bucket τ, above or below 15Y. Volatility is computed as an exponentially-weighted moving average of the FTSE UK Conventional Gilts 5-10Y. Data is winsorized at 1% level. r_{3m}^{HF} is the cumulative return over the previous 3 months over the Barclay Hedge Fund Return Index. Column (6) excludes Covid and the UK Gilts crisis. The table omits the individual coefficient on the VIX quartiles. The sample period is 2019-2024. Standard errors are clustered at the day level.

Table 9: Baseline Regression: By Maturity

$\log(Gross)$	(1)	(2)	(3)	(4)	(5)
	1-6Y	7-12Y	13-18Y	19-24Y	25Y+
	b/se	b/se	b/se	b/se	b/se
$\log \sigma_t^{(m)}$	1.131***	1.444***	1.465**	1.645*	0.692
	(0.247)	(0.309)	(0.516)	(0.767)	(0.609)
$\log \sigma_t^{(m)} \times$ VIX Q2	-0.240	-0.467	0.971	-0.230	-0.263
	(0.310)	(0.303)	(0.607)	(0.809)	(0.598)
$\log \sigma_t^{(m)} \times$ VIX Q3	-0.610*	-1.201**	-0.887	-1.422	-1.192
	(0.279)	(0.365)	(0.671)	(1.037)	(0.702)
$\log \sigma_t^{(m)} \times$ VIX Q4	-0.972***	-1.532***	-0.852	-2.362**	-1.398*
	(0.281)	(0.339)	(0.570)	(0.810)	(0.654)
$\log \sigma_t^{(m)} \times$ VIX Q5	-1.208***	-1.624***	-0.701	-1.890*	-0.927
	(0.273)	(0.336)	(0.676)	(0.810)	(0.625)
VIX Q2	-0.883	-1.402	2.646	-0.667	-0.601
	(1.263)	(0.918)	(1.504)	(1.795)	(1.042)
VIX Q3	-2.465*	-3.734***	-2.324	-3.682	-2.383
	(1.115)	(1.106)	(1.672)	(2.241)	(1.229)
VIX Q4	-4.281***	-4.800***	-2.424	-5.725**	-2.940*
	(1.126)	(1.024)	(1.388)	(1.745)	(1.144)
VIX Q5	-5.155***	-5.026***	-2.222	-4.847**	-2.010
	(1.093)	(1.012)	(1.686)	(1.738)	(1.080)
Constant	16.956***	16.998***	14.772***	14.026***	12.937***
	(0.966)	(0.926)	(1.233)	(1.645)	(1.056)
R2	0.084	0.093	0.087	0.060	0.073
N	1,495	1,495	1,438	1,380	1,494

Note:

Table 10: Difference in means across VIX Quintiles

VIX Q	diff	t-stat	p-value
1 vs 2	0.178	0.884	0.377
1 vs 3	0.921	4.718	0.000
1 vs 4	1.312	6.909	0.000
1 vs 5	1.338	7.306	0.000
2 vs 3	0.743	5.420	0.000
2 vs 4	1.134	8.765	0.000
2 vs 5	1.160	9.726	0.000
3 vs 4	0.391	3.271	0.001
3 vs 5	0.417	3.844	0.000
4 vs 5	0.026	0.266	0.790

Note: the table reports the ttest of difference in means between $\log \sigma_t \times \text{VIX} \in Q_j$ versus $\log \sigma_t \times \text{VIX} \in Q_i$, where i and j are specified in the first column.

	Volume	Open interest
Short (1.5 - 3Y)	0	0
Medium (4-6Y)	.011	.005
Long (8-13Y)	271.189	979.687
Ultra Long (28-37Y)	0	0

Note: the table reports the daily average volume and open interest by futures contract, in GBP thousands. Sample period due to availability: August 2024- August 2025. Source: Intercontinental Exchange (ICE).

D Motivating Evidence on Participation by Hedge Funds

In this section we present empirical evidences on the participation of hedge funds across government bond markets. We present aggregate time-series patterns and then proceed to decompose them.

We make three points: first, hedge funds are quantitatively important intermediaries, as measured by their market shares; third, while their rise has been documented in US markets (Barth and Kahn, 2025), there is a broader trend across countries; fourth, their participation has increased mostly at maturities below 10 years. The only exception is the United Kingdom, where participation in maturities above 10 year has also increased.

D.1 Aggregate Patterns in Participation

We aggregate volume by hedge funds at the country-quarter level.[51] We then obtain the HF market shares scaling it by the aggregate trading volume data obtained from different national sources. Figure 3 shows the results.[52] Hedge funds are important intermediaries in these markets, accounting for a substantial fraction of traded volume across many markets. As of 2024, they accounted for 26.7% of United Kingdom, 25.2% in the Euro-area, 7.7% of Canada and 4.5% in the United States. It is worth highlighting that while hedge funds appear smaller in the US Treasury market, this is due to the depth of the market. The dark and light blue areas in Figure 3 shows the volume in US Dollars. The United States is the second largest destination after the Euro-area, and the largest if we disaggregate the Euro-area at the country level.

Hedge funds have also been growing across many markets. This growth is particularly evident in the United Kingdom, United States, Japan and Canada.

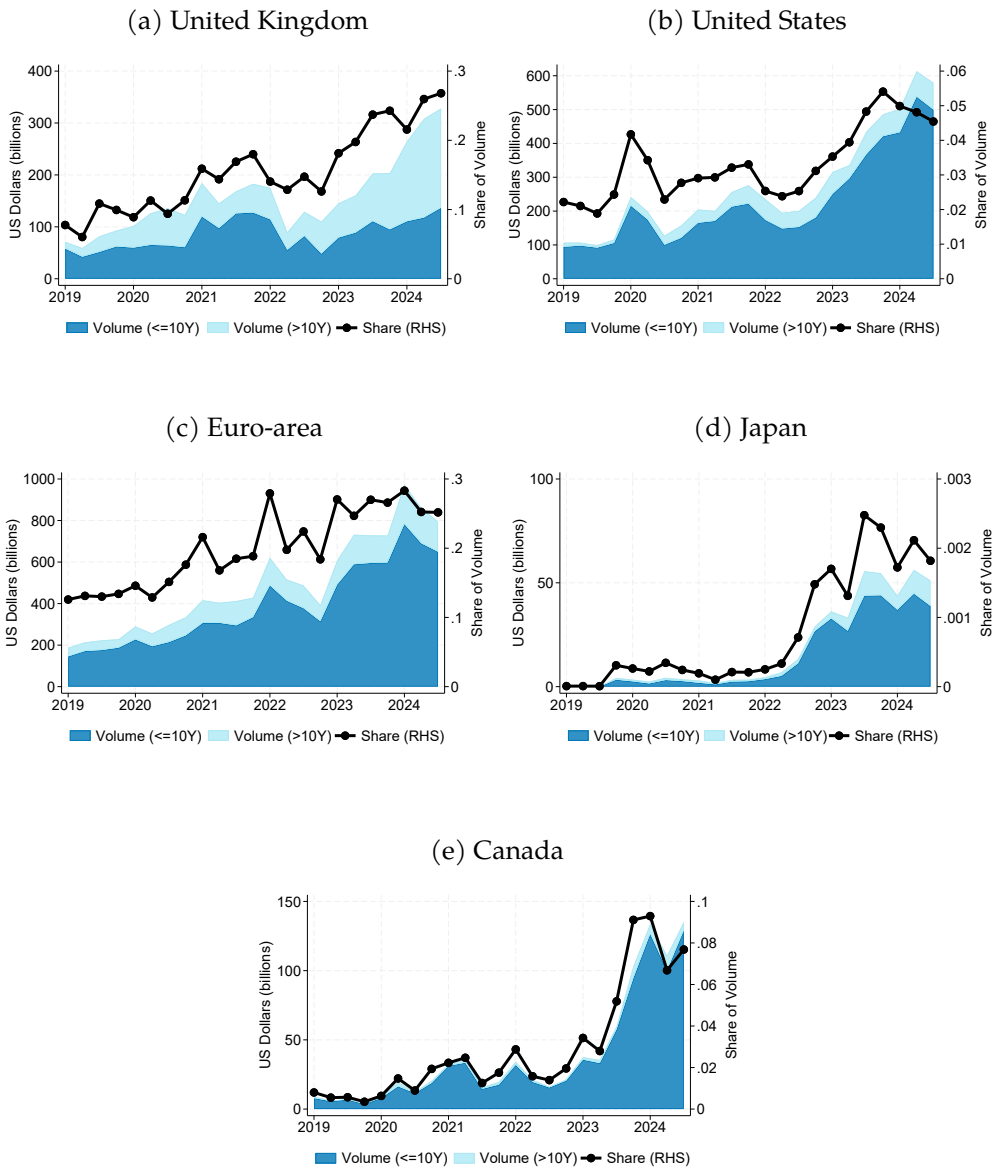
One further aspect concerns the maturity preference of hedge funds. The dark blue area shows the volume in maturity below 10 years. Except than in the UK, hedge funds concentrate their volume predominantly on maturities below 10 years.[53]

[51] Note, we use sovereign bonds and hence each country has only an individual issuer, its respective government.

[52] We show results for the UK, US, EA, Japan and Canada which account for more than 90% of the traded volume by the funds in our sample. See Appendix **??** for details of other countries.

[53] Appendix Figure **??** further splits between 1-5Y and 5-10Y and 10Y+.

Figure 3: Participation by Hedge Funds in Government Bonds



Notes: The figures show the share of total quarterly volume accounted by UK-based hedge funds. Hedge funds volume is from MiFID data, excluding inflation-indexed bonds and bonds with remaining maturity less than one year. The data are winsorized at 1% level at the issuer level. Total volume for the Euroarea and United States is from Tradeweb, for the United Kingdom it is from the Debt Management Office (DMO), for Japan it is from the Japan Securities Dealers Associations (JSDA), for Canada is from the Canadian Investment Regulatory Organization (CIRO). The dark blue area shows the total quarterly volume, in billions of US Dollars, accounted for by bonds with maturity less than or equal to 10Y; the light blue area shows the same for bonds with remaining maturity >10Y. Figures are converted into US Dollars using the previous day spot exchange rate.

D.2 Decomposing the Participation

An advantage of our granular dataset is to observe the identity of the traders. We leverage this feature to decompose the growth in participation along two margins. In particular, we are interested in assessing how much of the change in volume was driven by increased activity by funds that were already present at the start of our sample relative to the arrival of funds that were not actively trading in the first year of our sample. If most of the volume growth is driven by increased activity by incumbents we will argue that this is due to growth; whereas if it is driven by other funds we attribute this is driven by net entry.

Consider a single country for which we omit subscript. We can decompose the market volume at time t as the sum of two components: the volume accounted for by incumbent funds ($V_{c,t}$) and the volume accounted for by newly active funds ($V_{e,t}$). More formally, we define incumbent funds as funds that had a non-zero volume in both time t and time $t-1$, while newly active funds as those that had zero volume in year $t-1$ but a non-zero volume at year t:

$$V_t = V_{c,t} + V_{e,t}, \tag{22}$$

Similarly, for time $t-1$ we can decompose the volume between that accounted for by the incumbent funds at time t ($V_{c,t-1}$) and that accounted for by funds that disappear at time t ($V_{x,t-1}$):

$$V_{t-1} = V_{c,t-1} + V_{x,t-1} \tag{23}$$

Subtracting (23) from (22) and dividing by the change in volume, ΔV_t, we obtain:

$$1 = \frac{\Delta V_{c,t}}{\Delta V_t} + \frac{(V_{e,t} - V_{x,t-1})}{\Delta V_t}. \tag{24}$$

We will use (24) to measure the quantitative importance of the two margins. We choose to perform the decomposition at the annual frequency.[54]

Table 11 shows the results. Panel A shows the average of the annual decomposition.[55] Take the US for example. On average, there are 97 funds trading across years, 21 funds left and 30 entered. The volume increases by $294.67 billions, of which $235.27 billions are accounted by the incumbent funds, and $59.41 billions are accounted by the net entry of funds. On average, incumbent funds account for 84.9% of the change in volume, while net entry accounts for 15%. While year-on-year,

[54] Higher frequency, such as daily or weekly, is likely to introduce substantial noise, and it is problematic for computing contributions to growth when changes in volume are negative which frequently happens at higher frequency.

[55] Appendix reports the year-on-year figure.

the contribution of entry is relatively small, when cumulated over longer horizons the pictures changes. Between the start of the sample in 2019 and the end in 2024, there were 61 funds that actively traded throughout, accounting for $589.7 billions of increase in volume. During the same period, 32 funds left and 81 were observed for the first time, accounting for $925.3 billions. While the entry occured more slowly across years, it cumulated over time accounting for 61.1% of the volume increase in the same period, whereas incumbents accounted for 38.9%. The picture is similar across countries.

Table 11: Decomposition

	No. of Funds			Volume (LC)			Contribution (%)			
	N_c	N_x	N_e	ΔV	ΔV_c	V_{e-x}	$\Delta V_c/\Delta V$	$V_{e-x}/\Delta V$	$V_e/\Delta V$	$V_x/\Delta V$
	Panel A: Year-on-Year Average									
Canada	27	9	11	137,340	77,716	59,624	0.864	0.136	0.169	-0.033
Euro-area	116	19	29	468,884	447,785	21,099	0.959	0.041	0.060	-0.018
Japan	24	5	8	56,326	45,108	11,217	0.931	0.069	0.074	-0.005
UK	89	17	26	139,696	122,672	17,024	0.912	0.088	0.090	-0.002
US	97	21	30	294,677	235,271	59,407	0.849	0.151	0.166	-0.014
	Panel B: Cumulative changes between 2019 and 2024									
Canada	22	8	21	688,846	330,290	358,555	0.479	0.521	0.535	-0.014
Euro-area	71	47	90	2,496,150	1,284,557	1,211,593	0.515	0.485	0.530	-0.045
Japan	15	5	12	211,095	155,103	55,992	0.735	0.265	0.265	0.000
UK	55	25	65	740,233	208,925	531,309	0.282	0.718	0.725	-0.007
US	62	32	81	1,515,031	589,701	925,329	0.389	0.611	0.643	-0.032

Notes: Panel A reports the annual averages over 2019-2024. Panel B reports the changes between 2019 and 2024. V_c denotes the volume accounted for by the continuing funds, V_n by the new funds, V_x by the inactive funds. The volume for Canada, United Kingdom, United States and Euro-area is in million of local currency (LC), while for Japan it is in 100 million of local currency.

Table 12: Scheduled Macroeconomic Releases in the UK

Event	N	Time	S	Mean	Min	P25	P50	P75	Max
BRC Sales Like-For-Like YoY	27	00:01	33.72	0.36	-0.92	-0.05	-0.00	0.01	5.51
BRC Shop Price Index YoY	9	00:01	31.40	1.09	-1.46	-0.02	-0.02	0.00	9.24
Bank of England Bank Rate	49	12:00	98.84	-0.04	-3.53	0.00	0.00	0.00	2.55
CBI Retailing Reported Sales	53	11:00	34.88	0.05	-15.40	-2.24	0.07	2.02	31.62
CBI Trends Total Orders	42	11:00	36.05	-0.52	-20.55	-2.58	-0.49	2.08	7.53
CPI	73	07:00	97.67	0.14	-5.20	-0.75	0.00	1.32	2.90
GDP	49	07:00	95.35	1.09	-7.21	-0.02	0.00	0.03	14.15
GfK Consumer Confidence	21	00:01	63.95	-0.34	-4.85	-1.17	0.00	1.30	2.84
ILO Unemployment Rate 3Mths	70	07:00	89.53	-0.26	-4.79	-1.74	0.00	0.00	5.06
Industrial Production	49	07:00	90.70	-0.03	-1.95	-0.03	-0.01	0.01	0.73
Mortgage Approvals	51	09:30	83.72	0.54	-3.43	-0.60	0.55	1.56	5.09
Nationwide House PX MoM	42	07:00	87.21	0.45	-2.16	-0.02	0.02	0.05	4.76
PSNB ex Banking Groups	45	07:00	65.12	0.50	-3.64	-0.54	0.15	1.51	4.25
RICS House Price Balance	57	00:01	60.47	0.35	-4.43	-0.02	0.01	0.36	5.05
Retail Sales	67	07:00	82.56	0.14	-0.05	-0.01	0.00	0.02	4.51
S&P Global UK Construction PMI	33	09:30	77.91	0.96	-8.36	-1.23	0.85	2.88	9.11
S&P Global UK Manufacturing PMI	34	09:30	90.00	2.77	-12.03	-0.99	1.23	4.38	52.39
S&P Global UK Services PMI	31	09:30	80.23	1.83	-9.11	-2.11	1.57	5.30	18.96

E Model Proofs

E.1 Model Proofs

Proof of Lemma 1. Define

$$g(\sigma) = \gamma z_t \, \sigma^2 - \phi(\sigma).$$

By $\lim_{\sigma \to 0} \phi(\sigma)/\sigma^2 = 0$,

$$\lim_{\sigma \to 0} \frac{g(\sigma)}{\sigma^2} = \gamma z_t > 0,$$

so $g(\sigma) > 0$ for all sufficiently small $\sigma > 0$, and hence (9) holds near zero volatility. By $\lim_{\sigma \to \infty} \phi(\sigma)/\sigma^2 = +\infty$ we have $g(\sigma) \to -\infty$ as $\sigma \to \infty$, so (9) fails for large σ. Since $\phi(\sigma)/\sigma^2$ is increasing, then the cutoff is unique. □

Proof of Proposition 1. To prove the proposition use the demand for type-A arbitrageurs (8) into the market clearing condition (6).

Suppose $\mathbb{E}_t \, r_{t+1}^{(\ell)} - r_t < \phi(\sigma)$, then type-A does not participate, type-B absorb the preferred-habitat demand shock $b_t = z_t$ and the term premium is

$$\mathbb{E}_t \, r_{t+1}^{(\ell)} - r_t = \gamma \sigma^2 z_t,$$

which implies the price of the long-term bond is

$$\log P_t^{(\ell)} = -\kappa \bar{r} - (2 - \kappa) r_t - \gamma \sigma^2 z_t. \tag{25}$$

Suppose $\mathbb{E}_t \, r_{t+1}^{(\ell)} - r_t \geq \phi(\sigma)$, then type-A and type-B share the preferred-habitat demand shock. The term premium is given by

$$\mathbb{E}_t \, r_{t+1}^{(\ell)} - r_t = \frac{\gamma \sigma^2}{2} z_t + \frac{\phi(\sigma)}{2},$$

and the long-term bond price is

$$\log P_t^{(\ell)} = -\kappa \bar{r} - (2 - \kappa) r_t - (\frac{\gamma \sigma^2}{2} z_t + \frac{\phi(\sigma)}{2}). \tag{26}$$

Type-A and type-B arbitrageurs share the preferred-habitat demand shock according to

$$b_t = \frac{z_t}{2} + \frac{\phi(\sigma)}{2\gamma\sigma^2}, \qquad a_t = \frac{z_t}{2} - \frac{\phi(\sigma)}{2\gamma\sigma^2}. \tag{27}$$

□

Proof of Proposition 1. Long-term bond prices in the two regimes are

$$\log P_t^{(\ell)} = -\kappa\bar{r} - (2-\kappa)r_t - \gamma\sigma^2 z_t \qquad \text{(B-only)}$$
$$\log P_t^{(\ell)} = -\kappa\bar{r} - (2-\kappa)r_t - \left(\tfrac{\gamma\sigma^2}{2} z_t + \tfrac{\phi(\sigma)}{2}\right) \qquad \text{(AB)}$$

so, with $y_t^{(\ell)} = -\frac{1}{2}\log P_t^{(\ell)}$ and $S_t \equiv y_t^{(\ell)} - r_t$,

$$S_t^{B\text{-only}} - S_t^{AB} = \frac{\gamma\sigma^2 z_t - \phi(\sigma)}{4}. \tag{28}$$

In the AB regime, arbitrageurs' participation condition implies

$$\gamma\sigma^2 z_t \geq \phi(\sigma). \tag{29}$$

Combining (35) and (29) gives $S_t^{B\text{-only}} \geq S_t^{AB}$, with strict inequality whenever $\gamma\sigma^2 z_t > \phi(\sigma)$. □

E.2 Estimating the Nonlinear Participation

We start from

$$\frac{\partial a_t}{\partial \sigma} = \frac{1}{\gamma\sigma^2}\left(\frac{\phi(\sigma)}{\sigma} - \frac{1}{2}\frac{\partial\phi(\sigma)}{\partial\sigma}\right).$$

Noting that a log-elasticity implies a regression coefficient β_t

$$\begin{aligned}\beta_t &\equiv \frac{\partial \ln(a_t)}{\partial \ln(\sigma)} \\ &= \frac{1}{a_t\gamma\sigma}\left(\frac{\phi(\sigma)}{\sigma} - \frac{1}{2}\frac{\partial\phi(\sigma)}{\partial\sigma}\right).\end{aligned}$$

Finally recall that $\phi(\sigma) = \lambda_t(\phi_0 + \phi_1\sigma^\alpha)$.

E.3 Asset Prices

The expected value of the short rate next period is:

$$\mathbb{E}_t(r_{t+1}) = r_t + \kappa_r(\bar{r} - r_t). \tag{30}$$

This follows by taking conditional expectations of (1).

The holding-period return of the long-term bond is:

$$\begin{aligned} r_{t+1}^{(\ell)} &= \log(\frac{e^{-r_{t+1}}}{P_t^{(\ell)}}) \\ &= -r_{t+1} - \log P_t^{(\ell)}, \end{aligned}$$

taking expectations conditional on time t information

$$\mathbb{E}_t(r_{t+1}^{(\ell)}) = -\mathbb{E}_t(r_{t+1}) - \log P_t^{(\ell)}, \tag{31}$$

$$= -\kappa\bar{r} - (1-\kappa)r_t - \log P_t^{(\ell)}, \tag{32}$$

where the second step follows from (30).

E.4 Equilibrium Prices

Type-B Equilibrium. Suppose we are in the Banks-only equilibrium. Then using the banks' demand (7) into market clearing (6) we obtain the equilibrium term premium:

$$\mathbb{E}_t\, r_{t+1}^{(\ell)} - r_t = \gamma\sigma^2 z_t.$$

Using (31) to substitute out the expected return, we find the market clearing price of the long-term bond in terms of model primitives

$$\log P_t^{(\ell)} = -\kappa\bar{r} - (2-\kappa)r_t - \gamma\sigma^2 z_t.$$

The first two terms are the expectations hypothesis. The final term is a 'liquidity' discount to compensate risk-averse investors for holding positive supply z_t.

Type-AB Equilibrium. Suppose both banks and arbitrageurs participate. Then using the arbitrageurs and banks' demand (8), (7) into market clearing (6) we obtain the equilibrium term premium:

$$\mathbb{E}_t\, r_{t+1}^{(\ell)} - r_t = \frac{\gamma\sigma^2}{2} z_t + \frac{\phi(\sigma)}{2}, \tag{33}$$

Using (31), we can find the market clearing price of the long-term bond in terms of model primitives

$$\log P_t^{(\ell)} = -\kappa\bar{r} - (2-\kappa)r_t - (\frac{\gamma\sigma^2}{2} z_t + \frac{\phi(\sigma)}{2}). \tag{34}$$

We complete the model solution by plugging equilibrium prices (34) into the demand (7) and (8) to derive the allocations to the long-term bond.

E.5 The Slope of the Yield Curve

Proposition 1 (The Slope of the Yield Curve in the Two Regimes)**.** *Suppose $z_t > 0$. When arbitrageurs participate, the slope of the yield curve is (weakly) lower than when they are absent.*

$$Slope_t^B - Slope_t^{AB} = \frac{\gamma\sigma^2 z_t - \phi(\sigma)}{4} \geq 0. \tag{35}$$

The participation of arbitrageurs increases the risk-bearing capacity in long-term bonds. The difference in term premium between the two regimes is positive because of the "liquidity" compensation that arbitrageurs require to participate in the market.

E.6 Sharpe Ratio in the Model

Consider the type-AB equilibrium. The Sharpe ratio (SR_t) is defined as:

$$\begin{aligned}\text{SR}_t &\equiv \frac{\mathbb{E}_t\left(r_{t+1}^{(\ell)}\right) - r_t}{\sigma} \\ &= \frac{\gamma\sigma}{2} z_t + \frac{\phi(\sigma)}{2\sigma},\end{aligned}$$

where we used the equilibrium term premium, (33). Then

$$\begin{aligned}\frac{\partial \text{SR}_t}{\partial \sigma} &= \frac{\gamma}{2} z_t - \frac{1}{\sigma}\left(\frac{\phi(\sigma)}{\sigma} - \frac{\phi'(\sigma)}{2}\right) \\ &= \frac{\gamma}{2} z_t + \gamma\sigma \frac{\partial a_t}{\partial \sigma} \\ &= \frac{\gamma}{2} z_t + \frac{\gamma}{a_t} \frac{\partial \ln(a_t)}{\partial \ln(\sigma)}\end{aligned}$$

As volatility increases, the Sharpe ratio changes because of two effects. First, because the agent is risk averse, an increase in asset volatility requires compensation. Second, because of the friction demand also changes and the Sharpe ratio adjusts to ensure market clearing. In particular, an increase in volatility generates additional demand from the frictional agent. This effect counterintuitively depresses the Sharpe ratio. Second, an increase in volatility tightens the financial friction and reduces demand. This effect instead increases the Sharpe ratio to induce participation by the now more constrained agent.

E.7 Microfoundation using a Value-at-Risk Constraint

In this section we show that a standard value-at-risk constraint can generate a constraint that is increasing in volatility and, in the context of the term structure, increasing in maturity.

Recall that the short rate is given by $\Delta r_{t+1} = (1-\kappa_r)(\bar{r} - r_t) + \sigma_r \varepsilon_{r,t+1}$.

There is a financier in the background that sets the margin requirement on each security separately so that the maximum probability of a loss exceeding ϕ is π using $\Delta \ln P_t^{(\tau)} \approx \Delta P_t^{(\tau)} / P_t^{(\tau)}$.

$$\pi = \mathbb{P}\Big(-\Delta \ln P_t^{(\tau)} > \phi\Big).$$

In an equilibrium where yields are affine in the short rate: $(\tau^{-1}) \ln P_t^{(\tau)} = (-A(\tau) r_t + C(\tau))$. Using $\Delta \ln P_{t+1}^{(\tau)} \equiv \ln P_{t+1}^{(\tau)} - \ln P_t^{(\tau)} = -A(\tau)\Delta r_{t+1}$ we get

$$\begin{aligned}
\pi &= \mathbb{P}\big(\Delta r_{t+1} > A^{-1}(\tau)\phi\big), \\
&= \mathbb{P}\big((1-\kappa_r)(\bar{r} - r_t) + \sigma_r \varepsilon_{r,t+1} > A^{-1}(\tau)\phi\big), \\
&= \mathbb{P}\left(\varepsilon_{r,t+1} > \frac{(1-\kappa_r)(r_t - \bar{r}) + A^{-1}(\tau)\phi}{\sigma_r}\right), \\
&= 1 - \Phi\big(\frac{(1-\kappa_r)(r_t - \bar{r}) + A^{-1}(\tau)\phi}{\sigma_r}\big).
\end{aligned}$$

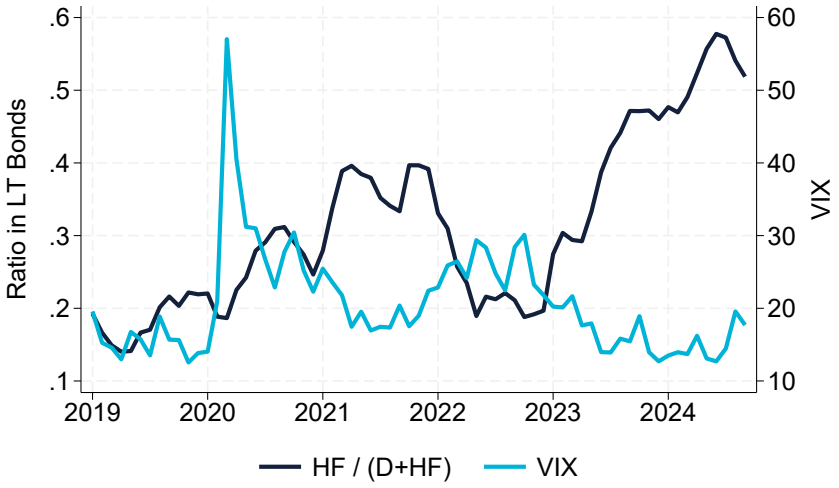
Equivalently

$$\phi(\tau) = \phi_0^{(\tau)} + \phi_1^{(\tau)} \sigma,$$

where $\phi_0^{(\tau)} \equiv A(\tau)(1-\kappa_r)(\bar{r} - r_t)$ and $\phi_1^{(\tau)} = A(\tau)\Phi^{-1}(1-\pi)$. The first component is independent of volatility and reflects the expected gain/loss originating from the mean reversion of monetary policy. The second component represents risk management. The tighter the risk management is, the lower the tolerance level set by the financier, π. The more volatile the asset is the tighter the constraint will be. Note that this is specific to the asset via duration $A(\tau)$ which is increasing in maturity. Both $\phi_1^{(\tau)}$ as well as $\phi_0^{(\tau)}$ are increasing in maturity.

F Additional Figures

Figure 4: The Relative Activity of Dealers and Hedge Funds



Note: The figure shows the ratio of total monthly traded amount in bonds with maturity more than 19Y by hedge funds and the VIX index. The ratio is the 3-month moving average. The VIX is the average monthly level. Sample period is 2019/01-2024/09.

Figure 5: Quarterly Share of Volume by Currency

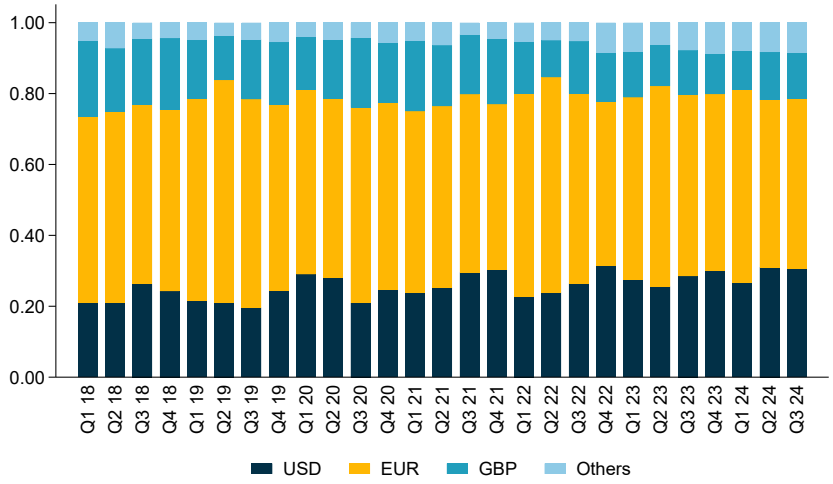


Figure 6: Alternative Sorting Variable

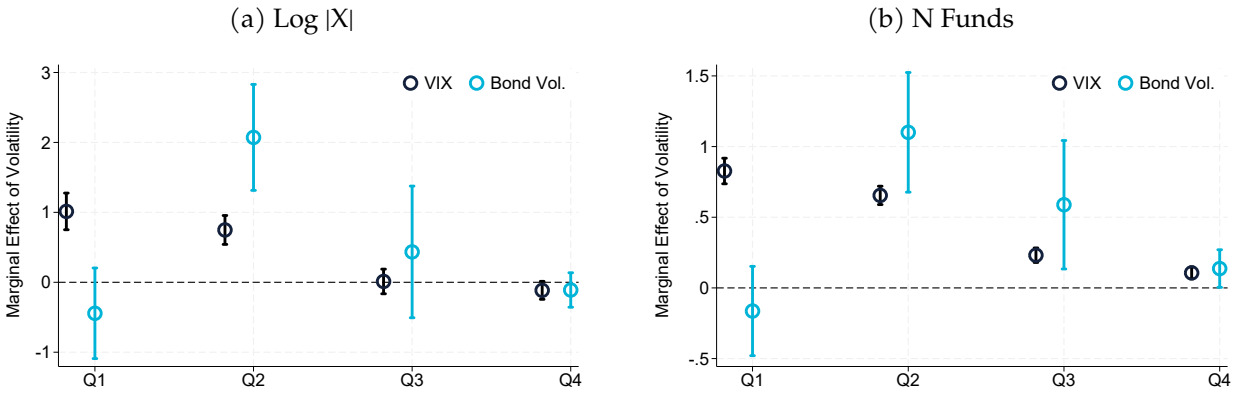
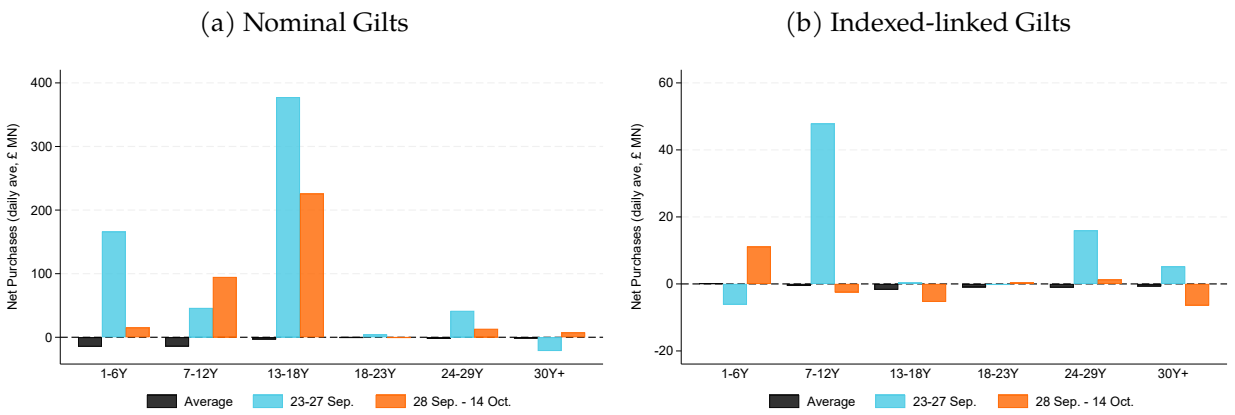


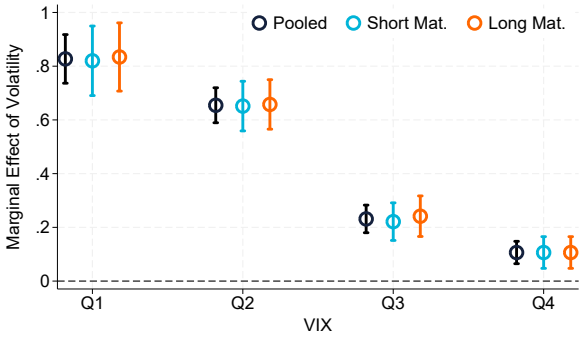
Figure 7: Hedge Funds Purchases – Split Pre- and Post-BOE Intervention



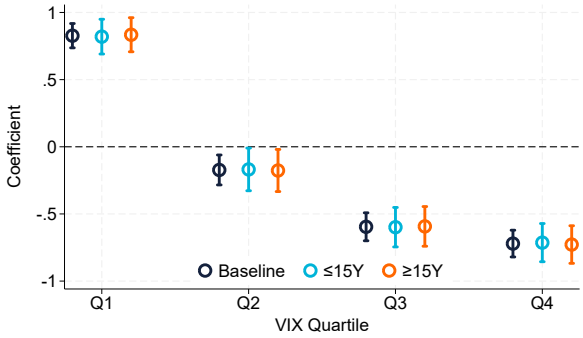
Notes: The figure shows cumulative hedge funds purchases, in daily average space, across nominal and inflation-linked bonds. The periods are split between (i) pre-BOE intervention (23-27 September); (ii) post-BOE intervention (28 September - 14 October); (iii) average outside of these two periods.

Figure 8: Arbitrageurs' Trading, Bond Volatility and the VIX

(a) Marginal Effect of Volatility ($\beta + \gamma_k$)



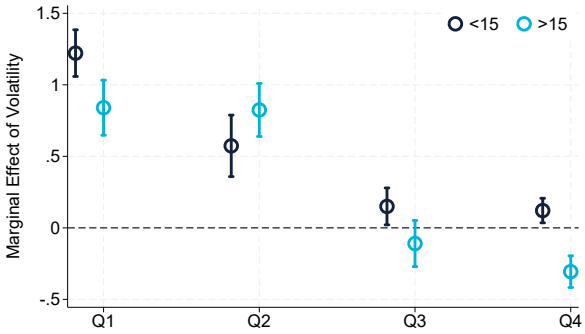
(b) Two Forces Shaping Participation (γ_k)



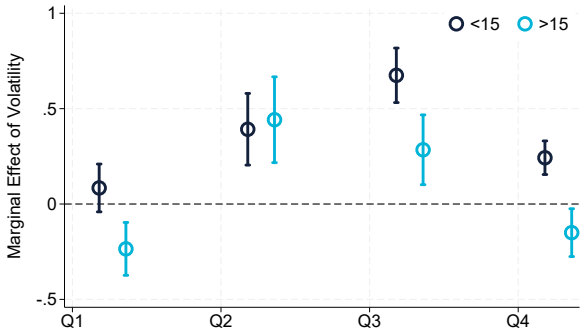
Note: The figure reports the OLS coefficients estimated from the regression $\ln(N_t^{(\tau)}) = \alpha + \beta \ln(\sigma_t) + \sum_{k=2}^{4} \gamma_k (\ln(\sigma_t) \times \mathbb{1}\{Q_{VIX_t}^{(k)}\}) + \sum_{k=2}^{4} \delta_k \mathbb{1}\{Q_{VIX_t}^{(k)}\} + \varepsilon_t$. Specifically it reports $\beta + \gamma_k$ for $k = \{2, 3, 4\}$. The dependent variable is the number of unique funds trading UK Gilts traded on day t. The sample period is 2019-2024. Panel (b) reports the same coefficients this time estimated separately on short ($\leq$15Y) and long (>15Y) maturity bonds. Standard errors are clustered at the day level.

Figure 9: Decomposing the VIX

(a) Sorting on Conditional Variance

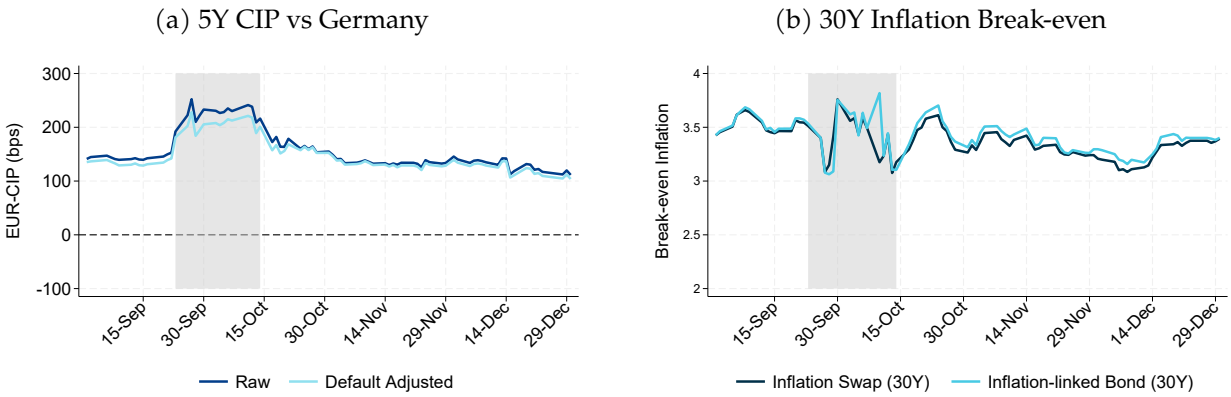


(b) Sorting on Variance Risk Premium



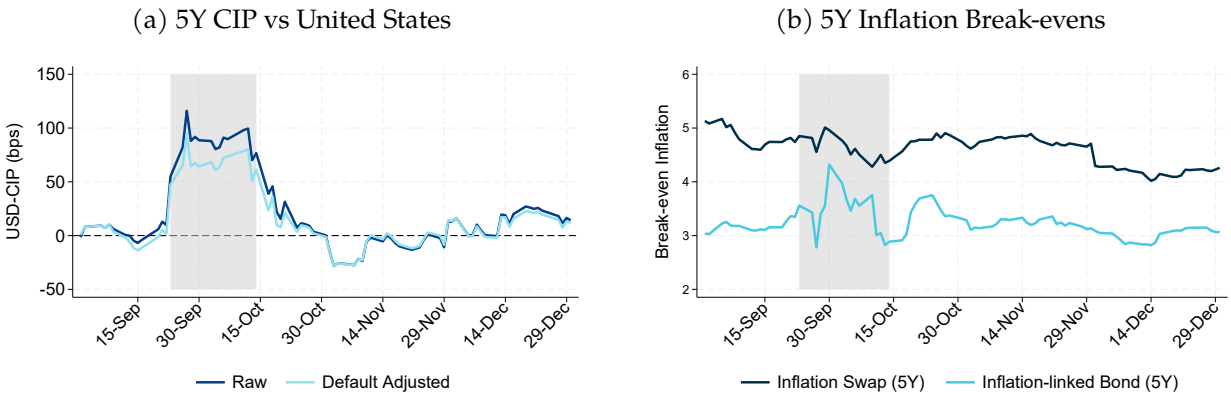
Note: The figure decomposes the VIX into its risk premium and conditional expectations using the methodology of (Bekaert et al., 2013).

Figure 10: Sizing Default Risk



Note: Panel (a) shows deviation from covered interest rate parity between the UK and the US. Panel (b) shows inflation break-even from inflation-linked bonds and inflation swaps with 30Y to maturity. The CIP deviation between the UK and country c at maturity τ is $CIP_{ct}^{(\tau)} = (\text{Swap Rate}_{UK,t}^{(\tau)} - \text{Swap Rate}_{c,t}^{(\tau)}) - \text{XCCY Basis}_{c,t}^{(\tau)}$. For panel (a) The interest rate swaps are on SONIA, SOFR and ESTR. Default adjusted include an adjustment for CDS spreads $(\text{CDS}_{UK,t}^{(\tau)} - \text{CDS}_{c,t}^{(\tau)})$.

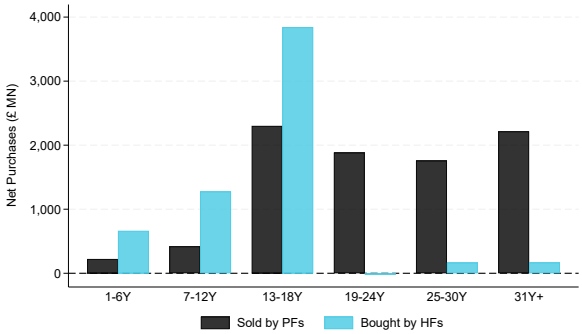
Figure 11: Sizing Default Risk



Note: Panel (a) shows deviation from covered interest rate parity between the UK and the US. Panel (b) shows CIP deviations between the UK and Germany. The CIP deviation between the UK and country c at maturity τ is $CIP_{ct}^{(\tau)} = (\text{Swap Rate}_{UK,t}^{(\tau)} - \text{Swap Rate}_{c,t}^{(\tau)}) - \text{XCCY Basis}_{c,t}^{(\tau)}$. The interest rate swaps are on SONIA, SOFR and ESTR. Default adjusted include an adjustment for CDS spreads $(\text{CDS}_{UK,t}^{(\tau)} - \text{CDS}_{c,t}^{(\tau)})$. Panel (b) shows 5Y UK inflation break-evens and inflation swap rates.

Figure 12: Arbitrageurs Purchases by Maturity

(a) Nominal Gilts



(b) Indexed-linked Gilts

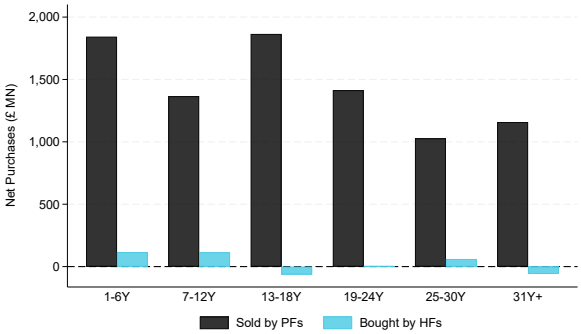
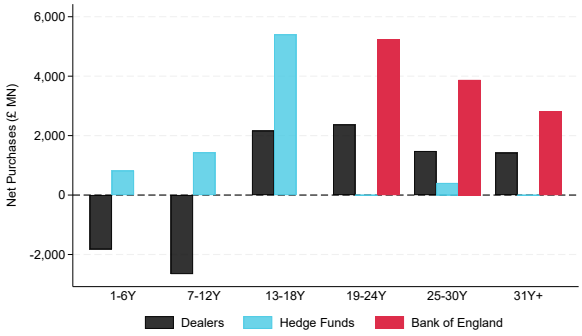


Figure 13: Arbitrageurs, Banks and the Bank of England

(a) Nominal Gilts



(b) Indexed-linked Gilts

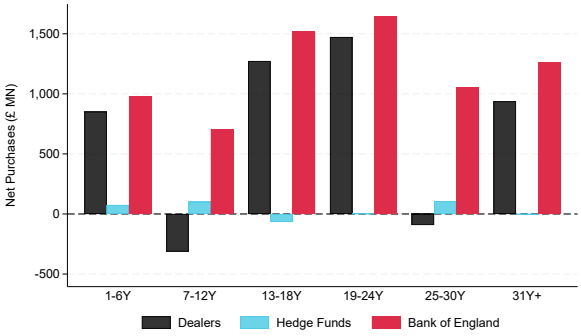
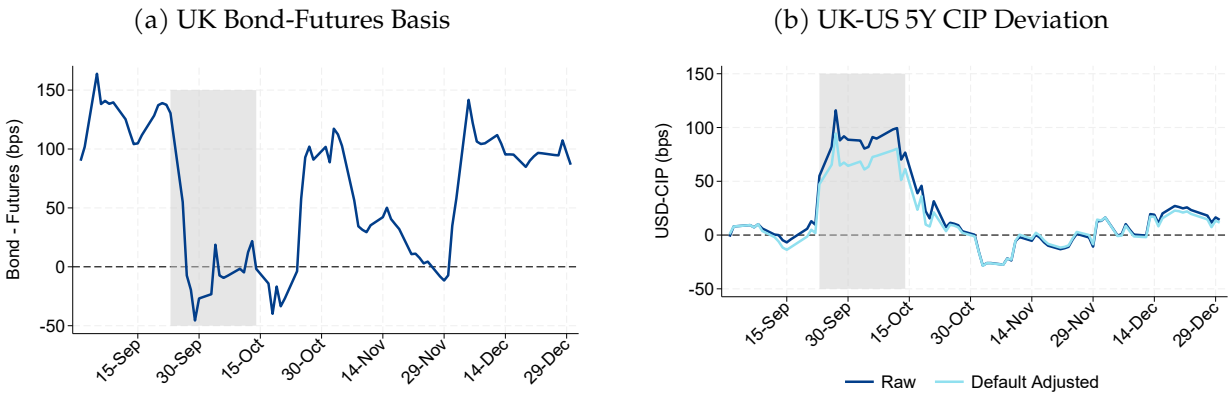
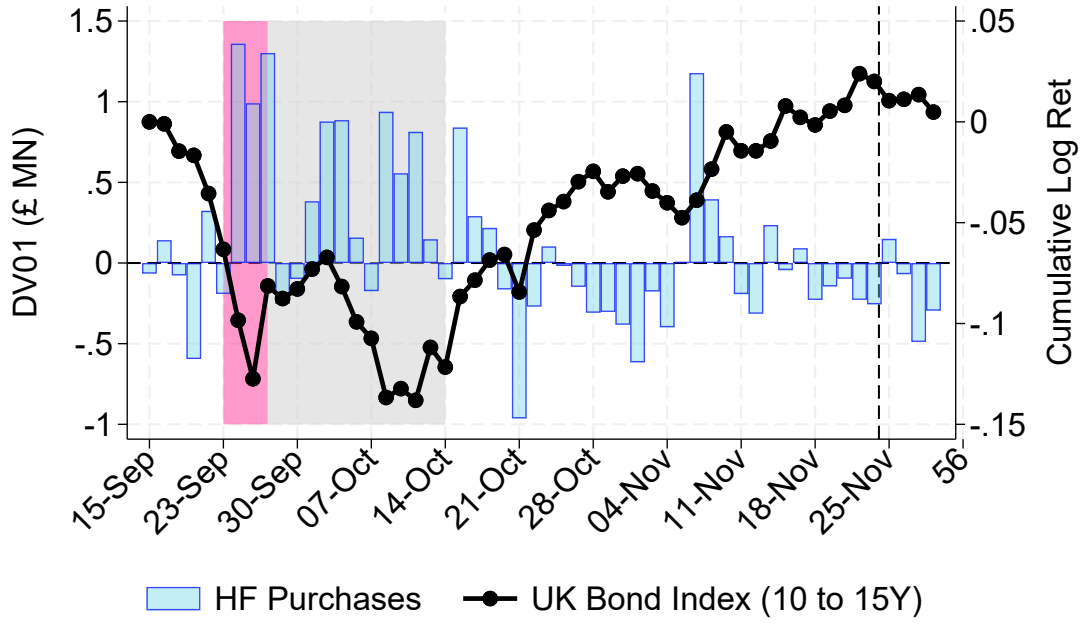


Figure 14: Arbitrage Spreads



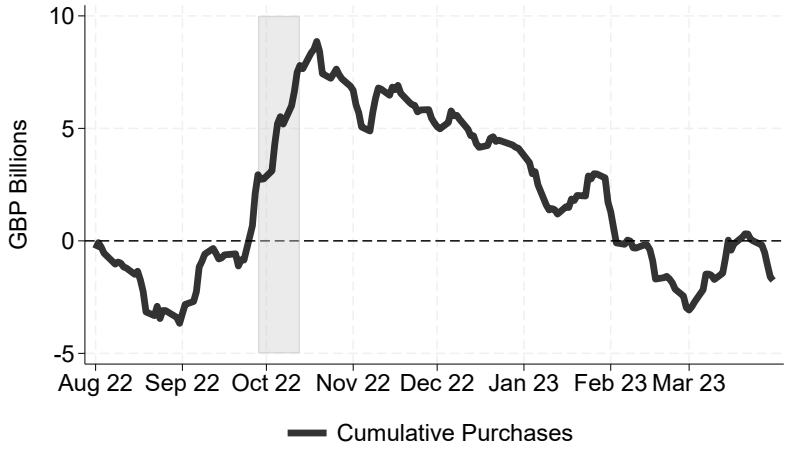
Note: Panel (a) shows the 3-day moving average of UK bond-futures basis, defined as the price of the Long Gilt futures minus the cheapest-to-deliver bond price. A positive basis means that the bond is expensive and the futures is cheap. Panel (b) shows the 5Y CIP deviation, computed with the methodology of Du and Schreger (2022) using the 5Y cross-currency basis swap and SONIA and SOFR interest rate swaps. The default adjusted CIP uses the difference in credit-default swap premium between UK and US. The gray shaded area is the UK Gilts market meltdown 23/09-14/10.

Figure 15: Time Series of Hedge Funds Purchases

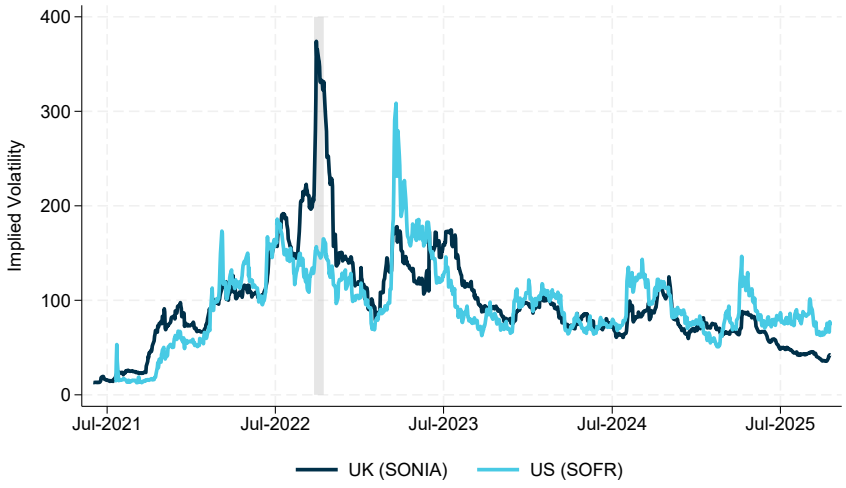


G Appendix Meltdown

(a) Hedge Funds' Cumulative Purchases (Longer)



(a) Implied Volatility



Note: The figure shows the implied volatility of SONIA (UK) and SOFR (US) interest rates derived from 1m1y swaptions. Source is Bloomberg.

G.0.1 Default and Inflation Risk

A natural explanation is a flight to safety. However, the evidence is inconsistent with this explanation. Following an increase in default risk we expect to see a shortening of traded maturities (Aguiar and Amador, 2014). Two observations cast doubt on default risk as a complete expla-

nation. First, if default risk increases monotonically with maturity, arbitrageurs' positions should decline monotonically across maturities.[56] Instead, positions increase with maturity up to 19Y and then they drop to (near) zero, with purchases heavily concentrated at intermediate maturities. Second, default risk cannot explain why arbitrageurs bought no inflation-linked bonds of *any* maturity. Those instruments hedge inflation risk emanating from "bad fiscal news", and are thus strictly safer than nominal bonds.

It is not straightforward to quantify default risk. One approach is to compute covered interest rate parity (CIP) deviations and adjust for the default risk via credit default swaps (CDS).[57] Figure 11 indicates some default risk, as evidenced by the difference between the default-adjusted and raw series, but it accounts for only about 18.2% of the UK-US yield spike.

In Panel (b), weshow that inflation swaps did not move during the crisis. According to Bahaj et al. (2023), short-term inflation swaps reflect more accurately hedge funds expectations, hence wereport the 5Y.[58] The 5Y rate, if anything, falls during the crisis.

[56] Note that they had limited pre-existing exposure in bonds, see Figure 16a. Pinter (2023) reports that, if anything, hedge funds had a short position in UK interest rate swaps.

[57] wefollow the methodology of Du et al. (2018) applied to the United Kingdom and use the most liquid tenor, the 5Y.

[58] In Appendix Figure 10, wereport the CIP relative to Euro and the 30Y inflation break-evens.