

Bank of England

Hedging, market concentration and monetary policy: a joint analysis of gilt and derivatives exposures

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Gabor Pinter⁽¹⁾ and Danny Walker⁽²⁾

Abstract

We use granular data sets – merged across the UK government bond, interest rate swap, options and futures markets – to estimate exposures to interest rate risk at the sector level and for individual funds within the same sector. We focus on non-bank financial intermediaries (NBFIs) such as insurance companies, pension funds, asset managers and hedge funds. We find that NBFIs tend to use derivatives to amplify bond market exposures to interest rate risk, rather than to hedge them. Moreover, interest rate derivatives usage is highly concentrated among a few investors, which could increase the aggregate consequences of idiosyncratic shocks to these investors. We show that this market concentration impedes the monetary policy transmission to asset prices. We also find that monetary policy loosening (tightening) causes NBFIs to take on more (less) interest rate risk via derivatives, consistent with the risk-taking channel of monetary policy.

Key words: Interest rate risk, hedging, swaps, options, gilts, futures, NBFIs.

JEL classification: D40, E50, E52, G10, G20, G23.

(1) Bank of England. Email: gabor.pinter@bankofengland.co.uk

(2) Bank of England. Email: daniel.walker@bankofengland.co.uk

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Bank of England, Threadneedle Street, London, EC2R 8AH

Email: enquiries@bankofengland.co.uk

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1 Introduction

Over the last two decades there has been a steady increase in the size of interest rate markets globally. Government debt outstanding in advanced economies has grown from \$20 trillion to \$60 trillion over the past two decades.¹ Interest rate derivatives have grown from a total notional of \$100 trillion to \$500 trillion over the same period.² Following many years of very low interest rates, these markets have had to adjust to interest rate increases of up to 500 basis points in the space of 18 months, as central banks and market participants have responded to an increase in inflationary pressures around the world. There is limited evidence on who in the financial system holds interest rate risk and how they manage it, apart from for banks where some data is available.³ But non-bank financial intermediaries (NBFIs) – such as pension funds, insurance companies, asset managers and hedge funds – now hold a higher share of global financial assets (49%) than banks (38%) and are very active in interest rate markets. Policymakers are now turning their attention to understanding interest rate risk in NBFIs as well as banks.⁴

Which NBFI sectors are most exposed to interest rate risk? How does interest rate risk vary across firms within a sector? Are derivatives used to hedge or amplify government bond exposures? Is derivatives usage concentrated among a few investors? How do these factors affect the monetary policy transmission, and how does monetary policy affect hedging behaviour? Answering these questions is important given that volatility in interest rate markets can affect the real economy by influencing the monetary policy transmission, market functioning and financial stability, as shown during the recent crises in the UK government bond (gilt) market and in the US banking system.⁵

To answer these questions, we estimate interest rate exposures through fixed income trading activity using a granular, transaction-level dataset on the gilt, interest rate swap, interest rate futures and interest rate options markets.⁶ The identities of counterparties are observable in our datasets which allows us to estimate at the fund level how the profitability – defined as changes in the market value of positions – in the gilt and sterling interest rate derivatives (swap, futures and options) markets correlate with changes in interest rates. We classify each counterparty into three sectors – hedge funds, asset managers and a third group comprising liability-driven investors (LDI), pension funds and insurance companies, which we label LDI-PI. These sectors make up

¹See the IMF World Economic Outlook [database](#).

²See the BIS triennial [surveys](#) on derivatives.

³On the interest rate risk exposure of banks, see [Begenau, Piazzesi, and Schneider \(2015\)](#); [Hoffmann, Langfield, Pierobon, and Vuillemeys \(2019\)](#); [Gomez, Landier, Sraer, and Thesmar \(2021\)](#) among others.

⁴See the recent commentary by senior policy makers such as [Mervyn King](#) and [Tobias Adrian](#) among others.

⁵See [Cunliffe \(2022a\)](#); [Hauser \(2022\)](#); [Breden \(2022\)](#); [Pinter \(2023\)](#) among others for an analysis of the 2022 gilt market crisis and [McPhail, Schnabl, and Tuckman \(2023\)](#); [Jiang, Matvos, Piskorski, and Seru \(2023\)](#) among others for an analysis of the recent banking crisis in the US.

⁶The UK only accounts for around 5% of advanced economy government debt but it has a large financial system with total assets of more than \$25 trillion, roughly ten times national income. UK-based entities are involved in almost half of global interest rate derivatives trades, which makes it the largest financial centre in that market.

the bulk of fund-dealer activity in the gilt market, and they each have approximately equal sized gilt market trading activity. We then analyse in detail how interest rate exposures vary across the three sectors, across time for a given sector and across funds within a sector. We also estimate how concentrated derivatives usage is in each NBFi sector and quantify how this concentration affects the monetary policy transmission to swap rates.

The empirical analysis yields four sets of results. First, interest rate risk varies significantly across sectors, across firms within the sector and (to a lesser extent) over time. The LDI-PI sector is exposed to ample interest rate risk on aggregate through persistent long duration positions in both gilt and derivatives markets, consistent with the sector's need to hedge contractual pension liabilities. For example, the estimated combined gilt and derivatives profitability of an average LDI-PI fund has a correlation coefficient of about -0.4 with the first principal component of interest rates. Hedge funds take the opposite positions on aggregate: they are short duration and their returns increase with interest rates. The combined gilt and derivatives profitability of an average hedge fund has a correlation coefficient of about 0.16 with the interest rate factor. The majority of these exposures are driven by hedge funds' naked gilt exposures that are imperfectly hedged by interest rate swaps and options. Asset managers have similar positions to LDI-PI funds but are less exposed. Regarding time-variation in exposures, the exposure of the LDI-PI sector to interest rate risk has been persistent over time, but there is some evidence the average hedge fund has increased its short duration position as interest rates have increased.

Second, there is substantial heterogeneity in interest rate risk across funds within sectors. Funds in the LDI-PI sector tend to behave similarly to one another, with many maintaining persistent long duration positions (leaving their asset side negatively exposed to interest rates). The hedge fund sector exhibits more variation, although the largest and most active funds are typically short duration. Overall, based on our analysis of month-to-month variations in profitability, we find little evidence that the average NBFi investor uses interest rate derivatives to hedge gilt exposures. This is true at the aggregate sector level, for the average fund in each sector and for most individual funds within sectors. All in all, the evidence in our sample suggests that interest rate derivatives exposures tend to amplify gilt exposures, rather than to hedge them.

Third, we find that interest rate derivatives markets are highly concentrated, particularly among hedge funds. The top five hedge funds account for over 80% of sterling swap, options and futures markets in terms of gross notional. These funds have maintained large speculative short duration (receive floating, pay fixed) positions in interest rate swap markets during the hiking cycle. To a smaller extent, we observe significant concentration among LDI-PI firms and asset managers as well. We provide evidence that market concentration has implications for monetary policy, in so far as monetary policy transmission to swap rates is more muted when market concentration is higher.

Fourth, we show how new hedging activity by NBFi sectors responds to surprise changes in

monetary policy and how these effects are influenced by market concentration. We find that following a surprise increase in the interest rate the LDI-PI sector and hedge funds increase net notional in the interest rate swap market, i.e. they enter into new swap contracts whereby they receive the floating rate and pay the fixed rate on the swap. The response of hedge funds is more immediate, much larger in magnitude (based on the point estimates) but statistically less significant than the response of the LDI-PI sector. Importantly, the sector-level responses are generated entirely by the responses of the same selected investors that drive our market concentration result above.

To sum up, we find limited evidence of non-bank participants in interest rate derivatives markets hedging their gilt market exposures. We find that these markets are dominated on the one hand by preferred habitat investors, such as LDI-PI funds, taking persistent positions to hedge their contractual pension liabilities, and on the other hand a small number of hedge funds taking large speculative positions across both government bonds and interest rate derivatives.⁷

To arrive at these results, we first estimate, for each legal entity identifier (LEI) in our sample, monthly changes in the entity’s profit and loss (profitability) on their gilt and derivatives market activities separately as well as changes in the profitability in both markets combined. To measure the dynamics of profitability on derivatives positions, we track monthly changes in the mark-to-market values of all available floating-fixed swap contracts (including but not limited to overnight index swaps) as well as interest rate options and futures for each LEI. To measure the dynamics of profitability on gilt positions, we cumulate the observed transactions in our sample and estimate changes in mark-to-market values in the cumulated positions. Armed with our measures of derivatives and gilt market profitability, we estimate fund-level risk exposures by running time-series regressions of profitability on our interest-rate risk factor at the LEI-level.⁸ To estimate sector-level risk exposures, we run panel regressions separately for each of our three sectors. To quantify the role of monetary policy, we rely on high-frequency changes in asset prices around monetary policy announcements that are now standard in the monetary economics literature (Swanson, 2021; Braun, Miranda-Agrippino, and Saha, 2022).

Our results have a number of policy implications. First, some NBFIs – including LDI-PI, asset managers and hedge funds – are highly exposed to volatility in interest rates, which has implications for financial stability. Depending on their use of short-term funding and liquidity preparedness, this could lead to fire sales in core markets when there are sharp moves in interest

⁷LDI-PI funds in our analysis could be thought of preferred-habit investors with inelastic demand for long duration assets (Culbertson, 1957; Modigliani and Sutch, 1966; Greenwood and Vayanos, 2014; Gorodnichenko and Ray, 2017; Vayanos and Vila, 2021; Giese, Joyce, Meaning, and Worlidge, 2021).

⁸Our baseline risk factor is the first principal component of the UK term structure of interest rates, which explains around 99% of the variation in short-term interest rates during our sample period.

rates, such as during the 2022 gilt market crisis in the UK.⁹ Second, the degree of concentration in the interest rate derivatives markets could lead to greater risk of market disruptions. A small number of participants account for a large share of interest rate exposures, which could lead to dealer losses and infrastructure disruptions as they are hit with uninsurable idiosyncratic shocks. This echoes the recent findings of [Pinter \(2023\)](#) that during the 2022 gilt market crisis only a few investors were responsible for the majority of gilt liquidations. Third, our evidence suggests that this market concentration could impair the transmission of monetary policy to interest rates. It could also limit the signal that monetary policymakers should infer from these markets about macroeconomic developments and policy expectations.

Related Literature Our paper is connected to several strands of the literature. First, we relate to the expanding literature on the role of non-banks in the macroeconomy ([Adrian and Shin, 2010](#); [He, Khang, and Krishnamurthy, 2010](#); [Cappiello, Holm-Hadulla, Maddaloni, Mayordomo, Unger, Arts, Meme, Asimakopoulos, Migiakis, Behrens, and Moura, 2021](#); [Aramonte, Schrimpf, and Shin, 2021](#)). Our contribution to this literature is to use granular datasets on these entities' trading activity in gilt and derivatives markets, which allows us to quantify the distribution of interest rate risk both across different NBFIs sectors as well as across different firms within the same NBFIs sector.

Second, our paper is related to the literature on hedging with financial derivatives. Motivated by the large theoretical literature on the topic ([Smith and Stulz 1985](#); [Froot, Scharfstein, and Stein 1993](#); [Rampini and Viswanathan 2010](#); [Rampini, Sufi, and Viswanathan 2014](#)), increasing access to granular data on derivatives in recent years has helped the empirical literature make advances as well. This literature focused primarily on the interest rate risk exposure of banks ([Begenau, Piazzesi, and Schneider, 2015](#); [Hoffmann, Langfield, Pierobon, and Vuillemeys, 2019](#); [Gomez, Landier, Sraer, and Thesmar, 2021](#); [McPhail, Schnabl, and Tuckman, 2023](#); [Jiang, Matvos, Piskorski, and Seru, 2023](#)).¹⁰ We draw on this literature in terms of methodology to calculate risk exposures, and the analysis in our paper is complementary given our focus on the risk exposures of non-banks. Closest to our paper is a smaller set of literature that analyses the hedging behaviour of non-banks ([Koski and Pontiff, 1999](#); [Chen, 2011](#); [Aragon and Spencer Martin, 2012](#); [Baker, Haynes, Roberts, Sharma, and Tuckman, 2021](#); [Kaniel and Wang, 2022](#); [Khetan, Neamtu, and Sen, 2023](#)). The distinguishing feature of our paper is that we analyse all non-banks that are active in the market (i.e. not just mutual funds as in [Kaniel and Wang \(2022\)](#) or hedge funds

⁹Note that the Financial Policy Committee (FPC) of the Bank of England has taken policy action to build the resilience of LDI funds so that they are much better prepared to withstand further volatility in the interest rate markets without having to resort to fire sales.

¹⁰There is an increasing empirical literature in international finance that uses granular data on FX derivatives too (e.g. [Alfaro, Calani, and Varela \(2021\)](#); [Hau, Hoffmann, Langfield, and Timmer \(2021\)](#); [Adams and Verdelhan \(2022\)](#); [Du and Schreger \(2022\)](#))

as in [Chen \(2011\)](#)) and we jointly analyse their activities and exposures in various interest rate derivatives markets as well as the government bond market (i.e. not just in the interest rate swap market as in [Baker, Haynes, Roberts, Sharma, and Tuckman \(2021\)](#) or [Khetan, Neamtu, and Sen \(2023\)](#)).

Third, our results also relate to the large literature on monetary policy and the use of financial derivatives ([Fender, 2000](#)) as well as to the risk-taking channel of monetary policy more generally ([Maddaloni and Peydro, 2011](#); [Borio and Zhu, 2012](#); [Dell’Ariccia, Laeven, and Marquez, 2014](#); [Adrian, Estrella, and Shin, 2019](#); [Martinez-Miera and Repullo, 2019](#); [Bauer, Bernanke, and Milstein, 2023](#)). We add to this literature by presenting new results on the effects of monetary policy on the derivatives usage of NBFIs and how these effects are shaped by the concentration of derivatives markets. This also complements recent work on the effects of monetary policy on the term structure of interest rates ([Hanson, Lucca, and Wright, 2021](#); [Kekre, Lenel, and Mainardi, 2022](#); [Guimaraes, Pinter, and Wijnandts, 2023a,b](#)).

The remainder of the paper is organised as follows. [Section 2](#) provides some background on interest rate derivatives markets. [Section 3](#) describes the sources for our aggregate and transaction-level data. [Section 4](#) presents stylised facts on both the gilt and derivatives markets. [Section 5](#) presents the empirical results on interest rate exposures; [Section 6](#) studies the concentration of interest rate derivatives markets; [Section 7](#) analyses the effects of monetary policy on derivatives activity. [Section 8](#) concludes.

2 Background on Interest Rate Markets

We analyse exposure to sterling interest rate risk obtained via both cash bonds and interest rate derivatives in this paper. For cash bonds, we focus on the UK government bond market, which is known as the gilt market. We look at all available interest rate derivatives denominated in pounds sterling (GBP), which includes interest rate swaps, gilt and interest rate futures and interest rate options.

Mechanics of Interest Rate Derivatives Interest rate swaps are the largest interest rate derivatives market in the UK and globally. Swaps are typically structured as fixed-for-floating contracts, where one party agrees to exchange a fixed interest rate for a floating interest rate over a given term, where the amount exchanged is calculated on the basis of a notional amount of a given size. For example, an interest rate swap with a notional amount of £10 million, a fixed interest rate of 4% – known as the swap rate – and a term of 10 years, commits one party to pay £400,000 per year over a 10 year period. In return, the other party is committed to paying the prevailing short-term interest rate each year – typically SONIA in the UK, which has replaced

LIBOR – which moves around with the central bank policy rate and other short rates.¹¹ In practice these payments are netted, so that one party receives, and the other pays, the net of the fixed and floating payments at each point in time, and the notional amount is never transacted. That means that mechanically the party that is 'receiving fixed' will benefit from a reduction in interest rates, via an increase in the market value of their swap. On the other hand, they will lose out from an increase in interest rates. In our analysis we will show that many LDI-PI funds have receive fixed positions in interest rate swaps. In economic terms, the swap gives the LDI-PI fund an exposure that is equivalent to purchasing a long-term government bond funded by short-term borrowing.

Interest rate futures are contracts where one party commits to borrow or lend a notional amount of money at a fixed interest rate for a fixed period at some point in the future. For example, an interest rate future with a notional amount of £10 million, a fixed interest rate of 4%, a term of 90 days and an expiry in three months commits the buyer of the future to deposit £10 million at a rate of 4% for 90 days three months from when they buy it. If interest rates fall after the buyer has purchased the future, the market value of the future will increase and the seller will pay funds to the buyer. If interest rates rise, the market value of the future will fall and the buyer will pay the seller. The interest rate implied by the interest rate futures contract and the prevailing spot interest rate – the 90 day rate in the example – will converge as the futures contract approaches its expiry date, until they are equal on the date of expiry. Like for swaps, the notional amount – which is usually a standard contract size listed on an exchange in the UK market – is never actually transacted. In the sterling market there are futures contracts linked to gilts (longer-term government bond rates) and short-term interest rates (SONIA), both of which are included in our analysis.¹²

Interest rate options are more complex than swaps or futures. They give participants asymmetric exposure to interest rates in one direction – either up or down – as opposed to the symmetric exposure offered by swaps and futures. A party to an interest rate option contract has the opportunity to borrow or lend a notional amount of money at a fixed interest rate for a fixed period. But unlike for futures or swaps, if interest rates move in an adverse direction, the buyer of the option does not have to exercise the option and is therefore not exposed to losses beyond the amount they paid for the option. For example, consider a call option that has a notional amount of £10 million, a fixed interest rate of 4% and a term of three months. If interest rates rise above 4%, the option value falls to zero and the buyer is not committed to exercise the option to deposit the notional amount. If interest rates fall below 4%, the option rises in value and the seller has to pay the buyer. So the option gives the buyer and seller exposure to interest rates in one direction, meaning options can be used to place a cap or floor on interest rate exposures. The sterling options

¹¹Given the time period we study in this paper, we include swap contracts in our analysis that are linked to both LIBOR and SONIA. In practice LIBOR has been replaced by SONIA for new contracts that are taken out.

¹²In the case of gilt futures, sellers of the futures contract typically have to deliver a gilt to the buyer on expiry of the futures contract.

market is dominated by options on short-term interest rates (SONIA).

3 Data and Measurement

3.1 Data Sources

Our empirical analysis covers the period from November 2019 to February 2023, and uses both aggregate data and trade-level data on gilt market and derivatives transactions. Our baseline measure of interest rates is the first principal component of monthly zero coupon bond yields on UK government bonds, obtained from the Bank of England, which is a risk factor that captures shifts in the level of interest rates across the curve.¹³ To measure monetary policy shocks, we draw on recent developments in the monetary economics literature and use high-frequency movements in asset prices around Monetary Policy Committee meetings, as estimated by [Braun, Miranda-Agrippino, and Saha \(2022\)](#).¹⁴

To study the trading activity of NBFIs in the gilt market, we use the MIFID II database. This is a transaction-level dataset, maintained by the Financial Conduct Authority, which provides information for almost all secondary market transactions on execution time, transaction price and quantity, as well as the International Securities Identification Number (ISIN), the Legal Entity Identifier (LEI) of both counterparties, and buyer-seller flags among others.¹⁵

The identities of the participants involved in trades are denoted by the LEIs, which allows us to place funds into NBFIs sector classifications. We focus our analysis on LDI-PI, hedge funds and asset managers. Our definition of gilt market sectors builds on the Bank of England’s internal classification system, which allocates each LEI code to a sector. The LDI-PI sector comprises LEIs that are funds associated with pension funds, insurance companies and LDI, which are usually managed by asset managers. Our definition of hedge funds includes both discretionary and systemic funds featuring both macroeconomic and relative value strategies. Our definition of asset managers include both wealth and asset managers as well as other mutual funds.

The primary data source we use to study the trading activity of NBFIs in the interest rate derivatives market is the EMIR trade repository data.¹⁶ We use the state reports at the end of

¹³The data can be downloaded from the Bank of England’s [website](#).

¹⁴[Braun, Miranda-Agrippino, and Saha \(2022\)](#) in turn build on [Gurkaynak, Sack, and Swanson \(2005\)](#), [Gertler and Karadi \(2015\)](#), [Miranda-Agrippino \(2016\)](#), [Gerko and Rey \(2017\)](#), [Altavilla, Brugnolini, Gürkaynak, Motto, and Ragusa \(2019\)](#), [Cesa-Bianchi, Thwaites, and Vicendoa \(2020\)](#) and [Swanson \(2021\)](#) among other contributions in the rapidly expanding monetary economics literature.

¹⁵Further information on the MIFID II dataset can be found in the Reporting Guidelines: https://www.esma.europa.eu/sites/default/files/library/2016-1452_guidelines_mifid.ii_transaction_reporting.pdf. Recent applications of the datasets can be found in [Czech, Huang, Lou, and Wang \(2021\)](#); [Kondor and Pinter \(2022\)](#) among others.

¹⁶Further information can be found on the [website](#) of the Bank of England. See [Cenedese, Rinaldo, and Vasios \(2020\)](#) for a recent application of this dataset.

each month in our sample, which provide a snapshot of all outstanding interest rate swap, futures and options contracts at a point in time. Similar to MIFID II, each transaction report contains multiple fields that include information on trade characteristics such as LEIs, price, notional amount, maturity date, execution time and the value of contract among others. We use the LEIs to merge the trade information across the gilt and derivatives markets.

We use contract-level data on fixed-floating interest rate swaps, including overnight index swaps (OIS) with the floating legs linked to the Sterling Overnight Index Average (SONIA)¹⁷ as well as other interest rate swaps such as those remaining contracts still linked to LIBOR. In addition, we use all available listed and unlisted sterling interest rate options, including both call options and put options. We also use contract-level information on sterling interest rate futures. We use all available contracts in the trade repositories reported in sterling under the product classifications FF, HR, SRC and SRH in the [Classification of Financial Instruments](#).

3.2 Measuring the Profitability of Gilt and Derivatives Positions

To measure the dynamics of profitability on derivatives, we use the ‘value of contract’ variable in the state reports for interest rate swaps, options and futures, which measures the mark-to-market value of the each contract at the time of accessing the state reports. Each contract is assigned a unique identifier, which allows us to track the mark-to-market values of contracts through time. Formally, for contract c of fund i at the end of month t , we the approximate monthly changes in profit and loss (profitability) on interest rate derivatives positions, $P\&L_{c,i,t}^{derivatives}$, as follows:

$$\Delta_{t-1,t} \left(P\&L_{c,i,t}^{derivatives} \right) = \Delta_{t-1,t} \left(ValueOfContract_{c,i,t} \right), \quad (3.1)$$

where $ValueOfContract_{c,i,t}$ is the mark-to-market value of the contract (directly observable in the EMIR TR dataset) at end end of month t . For each fund i and in each month t , we sum the changes in contract values across all available contracts, which we use as a measure of profitability on interest rate derivatives positions:

$$\Delta_{t-1,t} \left(P\&L_{i,t}^{derivatives} \right) = \sum_c^{N_i} \left[\Delta_{t-1,t} \left(P\&L_{c,i,t}^{derivatives} \right) \right], \quad (3.2)$$

where N_i is the total number of derivatives contracts observed in our dataset for fund i .

To analyse interest rate risk in the gilt market over time, ideally we would use data on the market value of gilt holdings at the LEI level over time, which is not currently available. In the absence of that information we focus on cumulated gilt flows. We cumulate the observed signed transaction quantities (i.e. flows) of each LEI in a training sample (January 2018 to October 2019)

¹⁷Further information on SONIA can be found on the Bank of England’s [website](#).

to approximate holdings by the start of our baseline sample (November 2019 to February 2023). For the sector-level analysis, we extend the training sample all the way back to 2011 to further mitigate problems of ‘initial values’.

Keeping track of the transaction price of each historical transaction, we then use the evolution of market prices (measured by the median transaction price on a given trading day) as well as the evolution of approximated gilt holdings to estimate changes in mark-to-market values in gilt positions at the LEI level. Formally, we first compute cumulative sign transactions for each fund i in each bond j from the first observable date t_0 to the end of month t :

$$\mathbb{Q}_{i,j,t} = \sum_{s=t_0}^t Q_{i,j,s} \times \mathbf{1}_{i,j,s}^{B,S}, \quad (3.3)$$

where $\mathbb{Q}_{i,j,t}$ is the size of transaction s of fund i in bond j , and $\mathbf{1}_{i,j,s}^{B,S}$ is an indicator function equal to 1 when the transaction is a buy trade, and equal to -1 when it is a sell trade. We compute the cumulative sum of the nominal value of observed transactions:

$$\mathbb{V}_{i,j,t} = \sum_{s=t_0}^t Q_{i,j,s} \times P_{i,j,s} \times \mathbf{1}_{i,j,s}^{B,S}, \quad (3.4)$$

where $P_{i,j,s}$ is the transaction price for transaction s of fund i in bond j . Our proxy for the gilt-market profitability for fund i in bond j at the end of month t is then written as:

$$\Delta_{t-1,t} \left(P\&L_{i,j,t}^{gilt} \right) = \Delta_{t-1,t} \left(P_{j,t} \times \mathbb{Q}_{i,j,t} - \mathbb{V}_{i,j,t} \right), \quad (3.5)$$

where $P_{j,t}$ is the median transaction price in bond j on day t . We then sum across the bond-specific profitability as follows:

$$\Delta_{t-1,t} \left(P\&L_{i,t}^{gilt} \right) = \sum_j^{J_i} \left[\Delta_{t-1,t} \left(P\&L_{i,j,t}^{gilt} \right) \right], \quad (3.6)$$

where J_i is the total number of bonds traded by fund i . To highlight the working of the algorithm, Figure 15 in Appendix provides an illustration via a hypothetical example.

To summarise, the measures 3.2 and 3.6 will be our baseline measures of mark-to-market profitability in the derivatives and gilt markets, respectively, expressed in \mathcal{L} values. We do not have data on the total assets of market participants, so we focus on measures of profitability in \mathcal{L} values rather than percentages of assets. Our measure of total profitability is the sum of profitability in gilt and derivatives markets:

$$\Delta_{t-1,t} \left(P\&L_{i,t}^{total} \right) = \Delta_{t-1,t} \left(P\&L_{i,t}^{gilt} \right) + \Delta_{t-1,t} \left(P\&L_{i,t}^{derivatives} \right). \quad (3.7)$$

In the next section, we present a series of stylised facts for the gilt and interest rate derivatives markets, along with illustrating the time series behaviour of our profitability measures (3.2 and 3.6).

4 Stylised Facts

4.1 Gilt Market

Figure 1 shows the distribution of cumulative gilt purchases over the 2011 to 2023 period across the main sectors. The MIFID II transaction-level data that we focus on in the rest of this paper covers the 2018 to 2023 period only. To make sure that our aggregate time series analysis covers the longest period possible, we combine the MIFID II data with ZEN data covering the 2011 to 2017 period. This relies on matching across the two different datasets using BIC-LEI mappings.¹⁸ In this combined sample cumulative gilt purchases total more than £1 trillion. This implies that we can account for almost half of gilt holdings in the market, given that the total value of gilts outstanding is around £2 trillion in 2022.

NBFIs account for about half of total gilt purchases in this sample, which is consistent with their share in aggregate data sources. The group labelled 'Others' makes up the other half. Among other things it includes the Bank of England's gilt purchases conducted primarily for monetary policy purposes, commercial bank holdings and purchases by foreign government entities (for example foreign central banks), building societies and mortgage lenders. In terms of net (signed) volume, most of this category is made up of the Bank of England's purchases, which implies that in practice NBFIs hold a very large share of the 'free float' gilts available for purchase in the market. Hedge funds have negative positions on a cumulative basis, which is suggestive of them often taking short positions and of frequent trading in and out of the market i.e. they tend to have short investment horizons, consistent with Czech, Huang, Lou, and Wang (2021). LDI-PIs consistently make large purchases of gilts.

[Figure 1]

Table 6 presents summary statistics on gilt market activity for the main NBFIs sectors. In terms of average monthly trading volume, hedge funds generate a trading volume of around £168 billion which accounts for more than half (52.1%) of total NBFIs volume (£323 billion) in our sample. LDI-PIs and asset managers generate average monthly trading of around £96 billion and £59 billion. The ranking is different when we measure trading activity in terms of number of transactions. Asset managers are the most active sector in our sample by number of transactions,

¹⁸For further details on the Zen dataset, see the Transaction Reporting User Pack: <https://www.fca.org.uk/publication/finalised-guidance/fg15-03.pdf>.

with around 20,800 transactions a month, followed by LDI-PIs and hedge funds with around 16,600 and 8,400 transactions, respectively. This is consistent with hedge funds typically trading in larger trade sizes than other NBFIs.

[Table 6]

4.2 Interest Rate Derivatives

To get a sense of the positioning of NBFIs in the interest rate derivatives market, Figure 2 shows the total gross notional by sector in the sterling interest rate swap market. Total gross notional has been about £12 trillion over the last two years.¹⁹ Dealer banks²⁰ have the largest gross notional and show relatively little variation in their positions over time.

Panel B of Figure 2b shows the total signed net notional by sector.²¹ Hedge funds are the largest receivers of floating rates (payers of fixed rates), and dealer banks and LDI-PIs are the largest payers of floating rates (receivers of fixed rates). Hedge funds increased their positioning as large receivers of floating rates significantly in the fourth quarter of 2021 when the global hiking cycle started and interest rates began to increase significantly at both short and long maturities around the world. This is suggestive of hedge funds taking speculative positions related to expected future interest rate hikes (FT, 2022).

[Figure 2]

Figure 3 shows the maturity profiles of NBFIs exposures to interest rate swaps, before and after the start of the hiking cycle in the fourth quarter of 2021. LDI-PIs tend to take swap positions that are relatively evenly distributed across maturities. In relative terms this means they are much more exposed to longer duration via swap markets than other market participants, which is consistent with them managing their long-dated contractual liabilities. These positions are stable across time, consistent with contractual liabilities that evolve slowly over time (Cunliffe, 2022a,b). Hedge funds significantly increased their short-dated swap exposures as the hiking cycle began, which could be suggestive of speculation that there would be persistent rises in short interest

¹⁹Total gross notional is a crude measure of exposure that should not be directly compared to bond exposures. It does not net offsetting long and short positions in the same maturity, which are common given that it is often easier and cheaper to buy offsetting positions than to sell an existing position in an interest rate derivatives product. In our analysis in the rest of the paper we focus on other measures of interest rate risk.

²⁰Dealers are defined as those banks that are gilt-edged market makers (GEMMs). GEMMs are primary dealers in gilts that actively trade in either conventional gilts, index-linked gilts or both. Their number hovers around 18 during our sample, and they have number of obligations and enjoy certain privileges (see DMO (2011) for further details).

²¹This is the net of receive fixed and receive floating positions across all maturities. It does not adjust for the different level of interest rate risk implied by exposures at different maturities. In our analysis in the rest of the paper we focus on other measures of interest rate risk, such as the covariance between profitability and interest rates.

rates. Other participants (that include commercial banks, building societies and mortgage lenders) are large receivers of short-dated floating rates, which could be consistent with structural hedges designed to manage maturity transformation (Begenau, Piazzesi, and Schneider, 2015; Hoffmann, Langfield, Pierobon, and Vuillemeys, 2019; Gomez, Landier, Sraer, and Thesmar, 2021; McPhail, Schnabl, and Tuckman, 2023; Jiang, Matvos, Piskorski, and Seru, 2023).

[Figure 3]

Turning to the interest rate options market, Figure 5 shows the total notional of the main sectors on aggregate. We find that, in contrast to the swaps market, the LDI-PI sector is virtually absent in the interest rate options market. Hedge funds are very active in the market, taking large positions. Dealers also have large positions that are likely linked to their role as market makers.

[Figure 5]

In a similar spirit, Figure 4 shows the total notional of the main sectors in the sterling interest rate futures market. We find that the LDI-PI sector is virtually absent in the interest rate options market. Hedge funds are very active in the market, taking large positions. Dealers also have large positions that are likely linked to their role as market makers. Note that both in terms of gross notional and net notional, the futures market is substantially smaller than the swap market, consistent with recent evidence from the US markets (McPhail, Schnabl, and Tuckman 2023).

[Figure 4]

To give a sense of the extensive margin of interest rate swap, futures and options usage among our sample of gilt market investors, Table 1 shows the percentage of funds in each sector that use swaps, futures or options at least once in our sample period. The LDI-PI sector has the most active swap usage, with almost half of LEIs in the sample using swaps. We also find that around a third of the 122 hedge funds in our sample use swaps. The prevalence of interest rate swap usage is lowest (15%) among asset managers.

[Table 1]

The pattern is different when we consider the intensity of interest rate options usage in our sample of funds. Less than 7% of LDI-PI funds and around 5% of asset managers use options. In contrast, about 27% of hedge funds use options in our sample. In addition, we find that around 27% of funds across all three NBFIs sectors use interest rate futures.

4.3 *Dynamics of Profitability and Interest Rates*

Figure 6 plots a time series of the 10-year gilt yield against cumulative changes in aggregate profitability in derivatives (equation 3.2) and gilts (equation 3.6) for the main sectors. If the

sector as a whole was using interest rate derivatives to hedge the interest rate risk associated with its gilt exposures, we should observe that the profitability on gilts and derivatives move in opposite directions as interest rates change. However, we find that, with the exception of hedge funds in the second half of our period, none of the NBFIs were hedging their interest rate exposure on aggregate over the period.

The gilt and (to a lesser extent) derivatives profitability of hedge funds shows a positive correlation with interest rates, meaning that hedge funds on aggregate tend to be short duration. Profitability was stable while rates were close to zero and then increased rapidly from 2021 onwards as rates started to rise. The gilt and derivatives profitability of LDI-PI and asset managers move together, but show a negative correlation with interest rates, meaning that LDI-PI and asset managers on aggregate tend to be long duration. They have seen large losses during the hiking cycle when interest rates have risen steeply.

[Figure 6]

Derivatives in our analysis consist of interest rate swaps, futures and options. A natural question, motivated by Figure 6, is what the relative contributions of interest rate options vs swaps are to profitability. To address that, Figure 7 decomposes the time-series of derivatives return into the time-series of the three components. Figure 7a shows that some of the decline in hedge fund profitability after 2022 is driven by loss on their interest rate options positions which is more than offset by the gains on their swap and futures positions. Figure 7b shows that virtually the whole variation in LDI-PI derivatives profitability in our sample is driven by interest rate swaps, consistent with the lack of options or futures usage by the sector in liability management. In case of asset managers, as shown by Figure 7c, all three assets contributed negatively to the sector's profitability on these derivatives.

[Figure 7]

In the next section, we use regression analysis to estimate interest rate risk exposures at the sector and fund levels.

5 Interest Rate Exposures

5.1 Empirical Methodology

To measure interest rate risk, we draw on the large literature on the risk exposures of banks, hedge funds, mutual funds among others.²² To quantify interest rate risk exposures at the aggregate

²²See Fung and Hsieh (2001); Ferson and Lin (2014); Huang, Sialm, and Zhang (2011); Patton and Ramadorai (2013); Begenau, Piazzesi, and Schneider (2015); Agarwal, Mullally, and Naik (2015) among many others.

sector-level, we estimate the following time-series regression separately for each sector s :

$$\Delta_{t-1,t}\Pi_{s,t,k} = c_s + \beta_{s,k} \times \Delta_{t-1,t}f_t + \varepsilon_{s,t,k}, \quad (5.1)$$

where $\Delta_{t-1,t}\Pi_{s,t,k}$ is the monthly change in the cumulative profitability, $\Pi_{i,t,k}$, of sector s ; c_s is a constant and $\Delta_{t-1,t}f_t$ is the monthly change in our baseline interest rate factor, which is the first principal component of gilt yields. We keep the units of $\Pi_{i,t,k}$ and f in \mathcal{L} values and basis points, respectively, so that our estimated coefficients can be interpreted as the average DV01 (dollar value of a basis point) over time.

To measure interest rate risk exposures of the average fund in a sector, we estimate the following panel regression separately for each sector s :

$$\Delta_{t-1,t}\Pi_{i,t,k,s} = \alpha_i + \beta_{k,s} \times \Delta_{t-1,t}f_t + \varepsilon_{i,t,k,s}, \quad (5.2)$$

where $\Delta_{t-1,t}\Pi_{i,t,k,s}$ is the monthly change in cumulative profitability, $\Pi_{i,t,k,s}$, of fund i in sector s in market $k \in \{Total, Gilt, Swap\}$; α_i is a fund fixed effect; $\Delta_{t-1,t}f_t$ is the monthly change in our baseline interest rate factor, which is the first principal component of yields; and the estimated coefficient $\beta_{k,s}$ is assumed to be common across funds within sector s and profit definition k .

To measure interest rate risk exposures at the fund-level, we estimate the following time-series regression separately for each fund i :

$$\Delta_{t-1,t}\Pi_{i,t,k} = c_i + \beta_{i,k} \times \Delta_{t-1,t}f_t + \varepsilon_{i,t,k}, \quad (5.3)$$

where $\Delta_{t-1,t}\Pi_{i,t,k}$ is the monthly change in cumulative profitability, $\Pi_{i,t,k}$, of fund i in market $k \in \{Total, Gilt, Swap\}$.

We estimate both unweighted and weighted regressions where we use the average monthly trading volume in gilt and the total notional in derivatives as proxies for size. Throughout the analysis, we use two-way clustering (at the month and fund level) to estimate standard errors. We standardise both the dependent and independent variables in regressions 5.3-5.2 so that our regression coefficients can be interpreted as correlation coefficients.

5.2 Aggregate Risk Exposures by Sector

To estimate interest rate risk for sectors on aggregate (corresponding to Figure 6), we estimate time series regressions (based on 5.3) separately for each of the main sectors, for gilts and derivatives. The results should be interpreted as average DV01s over the time period specified for the sectors on aggregate. When estimating the regression for gilts, the ideal experiment would be to use data on gilt holdings directly, which is not currently available as mentioned above. We use cumulated

flows in the same way we constructed Figure 1, combining information from the MIFID II (2018 to 2023) and ZEN datasets (2011 to 2017), which reduces the measurement error associated with approximating gilt holdings. We present the results for the shorter (MIFID II only, 2018 to 2023) and longer sample periods (MIFID II plus ZEN, 2011 to 2023) separately.

Table 2 presents the results of these separate time series regressions. Panels A and B present the estimates for gilts and derivatives, respectively. The results show that LDI-PIs have the largest negative exposures to interest rates, with an aggregate DV01 of £-200 to £-600 million in gilts and £-400 million in derivatives over the period (mainly driven by the sector’s swap positions). These investors tend to exhibit consistent risk exposure over time, driven by preferred habitat behaviour linked to their long-dated contractual liabilities (Klingler and Sundaresan, 2019; Pinter, 2023). The analysis in the rest of the paper, which focuses on the MIFID II data, is likely to reflect a lower bound on the absolute interest rate exposure of funds in the LDI-PI sector, which is evident from the relative magnitudes of the estimates using the shorter and longer sample periods in Table 2.

[Table 2]

As shown by Panel B of Table 2, hedge funds have positive exposures to interest rates in gilt markets, with a DV01 of around £27.3 million.²³ However, hedge funds’ overall exposures in derivatives markets seem limited, as their positive swap exposures (with a DV01 of around £5 million) and futures exposures (with a DV01 of around £2.6 million) more than offset the negative exposures in interest rate options (with a DV01 of around £4.6 million). As shown by Panel C of Table 2, asset managers are qualitatively the same as the LDI-PI sector with both gilt and derivatives positions being negatively exposed to interest rates.

5.3 Average fund Exposures by Sector

Table 3 presents the results of separate fund-level panel regressions for each of the main sectors, for gilts and derivatives (regression 5.2). In these specifications the dependent and independent variables are standardised so that the coefficient estimates are interpreted as correlations between profitability and interest rates (the first principal component) for the average fund in a sector over the 2019 to 2023 period.

Inspecting the results in columns (1)-(3) reveals that the average fund in LDI-PI sector has significant negative exposures to interest rates. An increase in interest rates is associated with a significant reduction in profitability across gilt and derivatives exposures. We find that the total profitability of an average LDI-PI fund across gilts and derivatives combined has a correlation of

²³Note we could not find evidence on any material gilt holdings by the hedge fund sector in the ZEN dataset, consistent with recent evidence on hedge funds’ short investment horizons in this market (Czech, Huang, Lou, and Wang, 2021). Hence we did not make adjustments to our estimates based on MIFID II.

-0.39 with the interest rate risk factor, and this effect is stronger (-0.49) when we look at volume-weighted exposures, suggestive of larger LDI-PI funds having larger risk exposures than smaller funders in the sector.

[Table 3]

Importantly, risk exposures on gilt and derivatives exposures have the same sign, implying that derivatives positions of the LDI-PI sector amplify – rather than hedge – its gilt market exposures. This can be explained by the fact that funds in the sector tend to use interest rate exposures in these markets to hedge their long-dated contractual liabilities (Greenwood and Vayanos, 2010; Blake, Sarno, and Zinna, 2017; Douglas and Roberts-Sklar, 2018; Klingler and Sundaresan, 2019; Jansen, Klingler, Ranaldo, and Duijm, 2023). They use both gilts and interest rate derivatives to hedge against falls in interest rates (which would increase the present value of their liabilities) to ensure that their net worth is stable over time and to minimise the variance of top-up contributions to the funds required by their corporate sponsors.

Inspecting columns (4)-(6) of Table 3 reveals that the average hedge fund has a positive exposure to the interest rate factor, with unweighted and weighted regressions yielding a correlation coefficient of 0.16 and 0.36, respectively. Interestingly, average unweighted derivatives exposures in hedge funds are negative (-0.09) and statistically insignificant, whereas size-weighted exposures are large and significant (0.47). This suggests that some large hedge funds take sizeable derivatives positions, which also increase the size-weighted total exposures (0.36) compared the unweighted total exposures (0.16). We analyse this issue further in Section 6 which looks at the concentration of derivatives usage among investors.

Columns (7)-(9) report the estimates for asset managers. The unweighted regression results show that the average asset manager has a negative exposure (-0.18) to interest rate risk that is somewhat smaller in magnitude than for the average LDI-PI fund. Similar to LDI-PIs, asset managers' exposures in gilt and derivatives markets have the same sign, providing further evidence against the use of interest rate derivatives to hedge gilt market exposures.

Given the size of the LDI-PI sector's exposure, we decompose the sector into a group of LDI managers and a group of pension funds and insurance companies (PI). LDI managers tend to act as agents for pension funds who are aiming to manage the interest rate risk associated with long-term contractual liabilities (Pinter, Siriwardane, and Walker, 2023). Pension funds pay capital into LDI funds and LDI managers often employ leverage to increase exposure to interest rates at multiples of the capital. This leverage is obtained through the use of repurchase agreements (repo) as borrowing secured against gilt holdings, or interest rate derivatives that act as synthetic leverage with direct interest rate exposure (Hauser, 2022; Breeden, 2022; Pinter, 2023). Outside of LDI funds, pension funds tend to employ a wider range of strategies and do not always seek to take on as much interest rate risk. Therefore, one would expect interest rate exposures to be

more pronounced among LDI managers than among PI entities.

To test this hypothesis, we re-estimate our panel regression 5.2 separately for LDI funds and for PI entities, with the results presented in Table 4. We find that total risk exposures are about twice as large for the average LDI fund as for the average PI entity. Specifically, the correlation coefficients among LDI funds are -0.36 and -0.45 using unweighted and weighted regressions, respectively. The estimates for the average PI entity are -0.28 and -0.25 using unweighted and weighted regressions, respectively. In terms of the gilt and derivatives mix, the unweighted regressions imply that the average LDI fund has about five times larger derivatives exposure to interest rates (-0.53) than PI entities (-0.27), whereas gilt exposures across the two sub-sectors are similar. The weighted regressions show a different picture: once we assign larger weights to larger funds, the average LDI fund has a much larger gilt (-0.64 vs 0.05) and derivatives exposure (-0.80 vs -0.37) than the average PI entity.

[Table 4]

As a robustness check, we explore how much our baseline results change when we include as an additional regressor, the second principal component of the yield curve – the slope factor (Litterman, 1991). This slope factor has a correlation coefficient of -0.47 with the term spread (computed as the difference between the 20-year and 1-year yields) in our sample period. Table 10 in the Appendix shows the results. We find that the average LDI-PI fund has little sensitivity to the slope factor and the level factor continues to be dominant. The profitability of the average hedge fund tends to load positively on the slope factor, i.e. an inversion of the yield curve is associated with a positive change in the profitability, which is primarily driven by the sector’s positioning in gilts. In contrast, we find some evidence that asset managers’ total profits tend to load negatively on the slope factor, though the effect becomes insignificant once we run weighted regressions.

Moreover, we also check how the results change when we replace the level factor with the 1-year (Table 11) and 10-year (Table 12) yields. Overall, we find that the effects are similar to our baseline, and there is some evidence that LDI-PI exposures to long-term interest rates are larger than short-term interest rates, consistent with the sector’s preference for long-term duration.

5.4 *Time Variation in Average fund Exposures by Sector*

Given the rapid increase in interest rates that came with the start of the hiking cycle at the end of 2021, a natural question to explore is whether there has been time-variation in interest rate risk exposures. To that end, we perform a rolling window estimation of regression 5.2 with the first (last) estimation window covering the period November 2019 to November 2021 (February 2021 to February 2023).

Figure 8 shows the time variation in risk exposures across the three NBFIs sectors along with 90% confidence bands based on two-way (month and fund level) clustering of standard errors. We use the results from weighted regressions so that we can proxy for changes in the aggregate exposures of the sectors (i.e. taking into account that larger firms’ exposures are more important in determining aggregate exposures).

[Figure 8]

The results show that, as one would expect, the exposure of the average LDI-PI fund is stable over time. This is consistent with their strategy to hedge slow-moving long-dated contractual liabilities. Asset managers exhibit a similar pattern, which is consistent with stable investment strategies. However, the picture for hedge funds stands out. The average hedge fund has steadily increased its exposure to interest rates as interest rates have risen. This is suggestive of speculative behaviour where hedge funds have responded to the hiking cycle by increasing their short duration exposure over time to position for higher rates – this is a strategy that has proven very profitable ex post. This might indicate some informational advantage over other investors, or an ability to adapt positioning more quickly in response to changing information sets (Kondor and Pinter, 2022). We show later in the paper that this behaviour has been concentrated in a small number of hedge funds.

5.5 Average Sector-Level Monetary Policy Exposures

So far in the paper, our definition of interest rate risk exposures has been based on the co-movement between fund profitability and changes in interest rates. A natural question to explore is whether the nature of risk exposures remains the same when we look at variation in interest rates caused by monetary policy surprises – interest rate changes that are, by definition, unexpected by financial markets. To that end, we draw on recent developments in the monetary economics literature and use high-frequency movements in yields around the Monetary Policy Committee of the Bank of England’s meetings.

[Table 5]

Table 5 presents the results from variants of regression 5.2 where we instrument the monthly change in the interest rate factor with the ‘target shock’ of Swanson (2021), obtained from Braun, Miranda-Agrippino, and Saha (2022), which is interpreted as shocks to conventional monetary policy, i.e. surprise changes in the Bank rate. Overall, the results are similar to the baseline: the average fund in the LDI-PI sector and (to a lesser extent) in the asset manager sector has a large negative exposure, whereas hedge fund exposures tend to be positive. Importantly, we continue to find evidence that derivatives exposures have the same sign as gilt exposures, underlining the role

of derivatives as amplifier of gilt exposures in our sample. According to these findings, our baseline results can be interpreted as the causal impact of interest rates on NBF1 profitability in interest rate markets. Another words, it is unlikely that the results are driven by reverse causality (e.g. developments in the NBF1 sector affecting monetary policy), anticipation effects (e.g. hedging behaviour changes in anticipation future monetary policy) or omitted factors (e.g. fiscal policy) rather than the other way around.

As robustness, we use alternative measures of monetary policy shocks Table 13 in the Appendix paints a qualitatively similar picture to our baseline, though the statistical significance of the results is somewhat lower.

5.6 Fund-level Variation in Exposures within Sectors

Looking at average estimates for exposures at the sector level may mask the potentially large heterogeneity across funds within the same sector. To study this heterogeneity, we now analyse fund-level exposures, obtained by estimating individual time series regressions for each fund separately (5.3). We explore the distribution of fund-level exposures across the three NBF1 sectors. Given that one of our main research questions is whether or not participants in interest rate markets hedge their interest rate risk, we do not distinguish between negative and positive exposures for this analysis. That is, we plot the distribution of the absolute value of exposures to the interest rate factor. We focus on exposures based on total profitability (as in 3.7) so we account for the possible neutralising effect of derivatives exposures on gilt positions. An entity that was using derivatives to hedge its gilt exposures, or holding fully hedged derivatives portfolios, would have zero exposure to interest rates.

[Figure 9]

Figure 9 presents a histogram of the absolute value of interest rate exposures (measured as correlation coefficients) for the main sectors. An obvious take-away is that there is very little clustering around zero, i.e. there is little hedging within these markets. In fact, most of the fund-level exposures across all three sectors concentrate at the right tail of the distribution. In other words, most funds in the NBF1 sector have large interest rate exposures. As discussed above, the explanation for this clearly varies across sectors: LDI-PI funds typically hedge their contractual liabilities using interest rate markets, but both hedge funds and asset managers appear to be taking more speculative positions. We do not find evidence for many arbitrageurs in the data.

As a robustness check, we construct versions of these histogram, using size as frequency weights. As shown by Figure 16 in the appendix, these weighted histograms present even more extreme pictures. However, when we look at the data through this alternative lense there is some tentative evidence of a number of larger hedge funds with very low interest rate exposures overall, which could be indicative of arbitrageur behaviour (Vayanos and Vila, 2021).

5.7 Determinants of Fund-level Exposures

We now turn to investigating the determinants of fund-level interest rate risk exposures. What type of market participants are more likely to take directional positions in the interest rate markets and less likely to hedge their exposures? A natural trader characteristic to explore is trader size, i.e. are larger funds most likely to take larger positions in the interest rate markets?

The scatter in Figure 10 shows the relationship between fund size and interest rate exposure, taking into account gilt and swap exposures, across the three main sectors. This analysis reveals a positive and statistically significant relationship between fund size and interest rate exposure for hedge funds, consistent with previous results on the concentration in that sector. This relationship is not evident for other sectors.

[Figure 10]

What other characteristics determine interest rate risk? Do funds with larger interest rate exposures trade more frequently, trade in certain parts of the curve or tend to trade assets with longer maturities? To answer these questions, we estimate a cross-sectional regression of the following form:

$$\begin{aligned} Exposure_i = & c + \beta_1 \times TradeVolume_i + \beta_2 \times TradeFrequency_i \\ & + \beta_3 \times AverageMaturity_i + \beta_4 \times MaturityDisperion_i \\ & + \beta_5 \times BuySellDispersion_i + \varepsilon_i, \end{aligned} \quad (5.4)$$

where the $Exposure_i$ is the absolute value of the total exposure of fund i and the definitions of the regressors are as follows. The variable $TradeVolume_i$ is the average monthly trading volume, which is a proxy for the size of the gilt market investor. The variable $TradeFrequency_i$ is the average number of monthly transactions, which proxies how active the fund is (O'Hara, Wang, and Zhou, 2018); $AverageMaturity_i$ is the average maturity of all gilt market transactions (weighted by trade size) of a fund. The variable $MaturityDisperion_i$ is the average daily dispersion of the maturity of the given fund, which captures how concentrated the given fund's activity along the yield curve. Lastly, the variable $BuySellDispersion_i$ is the average dispersion of the buy indicator, which takes value 1 (-1) if a trade is a buy (sell) trade. This dispersion variable would be one if the fund sells as many times as it buys, and therefore a low value could be interpreted as a directional strategy.

[Table 7]

The regression results are presented in Table 7. Looking at column (1) reveals that those LDI-PI funds that trade more frequently, in larger maturities and follow a directional strategy tend to have larger exposures. Column (2) of Table 7 shows that hedge funds that are larger, trade in

longer maturities and concentrate their trading activity in a narrower segment of the yield curve. This former result is consistent with the notion that systematic hedge funds (that aim to trade away mispricings and have lower level exposure compared to discretionary hedge funds) tend to trade multiple maturities simultaneously. Finally, column (3) of Table 7 shows that asset managers that trade longer maturities and have larger maturity dispersion tend to have larger interest rate exposures.

Overall, the results indicate that average maturity is the only variable that have a positive (negative) association with interest rate exposures (hedging) across all three NBFBI sectors (though note that the marginal effect is much larger among hedge funds (0.28) than in the other two sectors). All other variables considered in this analysis have a differential effect on the sector’s average hedging behaviour, which highlights the heterogeneous nature of NBFBI activities.

6 Concentration in Interest Rate Derivatives Markets

6.1 Stylised Facts

In our estimates of the average fund exposures by sector, there is a striking result for the hedge fund sector (Table 3): the estimated interest rate exposure of the average hedge fund in the derivatives market is close to zero (-0.09) on an unweighted basis, but very large (0.47) and statistically significant when we weight by size. This could be because the within-sector derivatives exposures are concentrated among a few particularly large hedge funds. To explore this possibility, we decompose the total gross positions of hedge funds (shown in Figure 2b) into the top five hedge funds by size, and compare them to the rest of the hedge fund sector. (At the request of the data owner, we do not present the units on the vertical axis of any of these charts.)

Panel B of Figure 11 presents this concentration analysis for the hedge fund sector. The results show a remarkable level of concentration in this market over the sample period. Just five hedge funds, with very large short duration positions (receive floating, pay fixed), account for a very large share of the total derivatives positions of the hedge fund sector. They account for almost all of the variance in the sector’s aggregate derivatives notional over time during the sample period.²⁴

[Figure 11]

Figure 11 also presents the decomposition for the LDI-PI (panel A) and asset manager sectors (panel B). We find substantial concentration in the LDI-PI sector: the five LDI-PI firms with

²⁴Given the quantitative importance of a few hedge funds in interest rate swap markets, we revisit the stylised facts on profitability (Figure 6) to explore their concentration: we find that the increase in the aggregate profitability in the sector over the sample period has been entirely driven by the top five largest hedge funds. This analysis suggests that the speculative behaviour we discussed above can be explained by the idiosyncratic behaviour of relatively few investors that have taken on large short duration positions that have resulted in very high profitability during the hiking cycle ex post.

the largest gross positions explain around half of the sector’s total gross position, and this concentration is even larger in interest rate options. The concentration in swap positioning among asset managers is also sizeable, with five funds explaining around 20-30% of total gross notional; concentration in options is even larger with five funds explaining 80-90% of total options notionals.

Overall, our results suggest that there is substantial concentration in derivatives usage across NBFIs sectors. In our knowledge, these results are novel and have not been documented in the literature yet.

6.2 Implications for Monetary Policy

To illustrate the aggregate implications of derivatives market concentration, we estimate how concentration affects the propagation of monetary policy shocks to asset prices. As an application, we focus on the interest rate swap market, given the importance of this market in analysing short-term interest rates in the UK.²⁵ To measure market concentration, we use our fund-level data on the outstanding notional of clients $i = 1, 2, \dots, N$ from all three NBFIs sectors, and construct a Herfindahl index at the end of each month t as follows:

$$HI_t = \sum_{i=1}^{N_t} s_{i,t}^2, \quad (6.1)$$

where $s_{i,t} = \text{notional}_{i,t} / \sum_{i=1}^{N_t} \text{notional}_{i,t}$. The obtained time-series are plotted in Figure 12, indicating substantial cyclical variation during our sample. To explore the implications for the monetary policy transmission, we first sort trading days into two groups based on whether the previous end-of-month value of the concentration measure is below or above its median (0.12). Given these two groups of days $g = \{g_1, g_2\}$, we estimate the following daily time-series regression:

$$\Delta OISRate_t^m = \sum_{c=1}^2 \eta_c \times \mathbf{1}[t \in g_c] \times MPShock_t + \varepsilon_t, \quad (6.2)$$

where $\mathbf{1}[t \in g_c]$ is an indicator function equal to 1 if trading day t belongs to group g , and 0 otherwise. As a measure of monetary policy shocks, we use target shock (Swanson, 2021; Braun, Miranda-Agrippino, and Saha, 2022) as in section 5.5.

[Table 8]

Table 8 presents the results for five separate versions of regression 6.2, corresponding to maturities $m = 1\text{year}, \dots, 5\text{year}$. Panel A presents the estimated linear effects of the monetary policy shocks, indicating a fairly fast decay of the effect along the maturity spectrum in our sample

²⁵Unlike in the US, there are few outstanding government bonds at short-maturities in the UK, which makes it difficult to use bond prices to estimate short-term interest rates in the UK.

(2019m11-2022m11) and finding a statistically significant effect only at one-year maturity. Panel B shows the estimates when the effect of monetary policy shocks is conditioned on the level of market concentration. We find that when the monetary policy shock arrives at the swap market when concentration is low, then the effect on swap rates is close to one-to-one and statistically significant across the 1-5 year maturities. In contrast, we find virtually no effect on the swap curve when market concentration is high.²⁶

In addition, we explore the dynamic effects of monetary policy by estimating the following regression:

$$OISRate_{t+T}^{1Y} - OISRate_{t-1}^{1Y} = \sum_{c=1}^2 \eta_c \times \mathbf{1}[t \in g_c] \times MPShock_t + \varepsilon_t, \quad (6.3)$$

where the left-hand-side variable is the cumulative change in the one-year swap rate over different horizons, $T = \{0, 1, 5, 10\}$, measured in trading days. Table 9 shows that the dynamic effects are close to one-to-one, statistically significant and persistent when market concentration is low. In contrast, when market concentration is high, we find significant estimates only for the contemporaneous effect, implying a more transitory propagation of the monetary policy shock over time.²⁷

[Table 9]

One possible interpretation of these results is that market concentration affects monetary policy propagation via changing market liquidity. Based on our conversations with market practitioners, the activity of ‘text-book arbitrageurs’ (e.g. relative value hedge funds) to smooth the sterling swap curve in response to shocks tends to be limited when the market is dominated by either preferred habitat-investors (e.g. LDI-PI firms) or a few speculators who take directional bets regarding the future developments of monetary policy (e.g. discretionary hedge funds who started shorting interest rates when the hiking cycle began during 2021Q4 – Figures 2-3). When market concentration is driven by these investors and if ‘text-book’ arbitrage activity is limited, then the market can be thought of as more illiquid.²⁸ The validity of this mechanism of course depends on whether arbitrageurs are unable or unwilling to participate in the swap market, when certain LDI-PI clients demand more liability hedging or when certain discretionary hedge funds make larger bets on future macroeconomic developments. A possible avenue for future research is to test this

²⁶To show that these estimates are not driven by the chosen proxy for monetary policy shock, Table 14 in Appendix re-estimates the regressions after we replace the target shock with changes in the 3-month OIS rate (as an alternative proxy for short-term interest rates) in the same 30-minute window around MPC announcements. The results remain quantitatively similar to our baseline.

²⁷As shown by Table 15 in Appendix, the dynamic effects are similar when we replace the target shock with shocks to the 3-month OIS rate around MPC events.

²⁸Recent empirical evidence indeed shows that the monetary policy transmission to the yield curve is enhanced when market liquidity is higher (Guimaraes, Pinter, and Wijnandts, 2023b).

mechanism rigorously by disentangling arbitrageurs’ ability and willingness to participate in the given market. This would likely requires a structural modelling approach in place of reduced-form regression analysis.

7 The Effects of Monetary Policy on Hedging Behaviour

A main result of our paper is related to how mark-to-market values in NBFIs’ derivatives positions co-move with interest rates. However, month-to-month changes in derivatives positions can be driven by valuation changes in existing derivatives contracts (i.e. ‘via stocks’) or valuation changes in contracts that have been recently entered into (i.e. ‘via new flows’). To study this issue further, this section estimates how new hedging activity by NBFIs at higher (i.e. daily) frequency responds to surprise changes in monetary policy and how these effects are influenced by market concentration as defined in Section 6. Note that this question is also interesting in its own right, as there is relatively little empirical evidence on how interest rate policy impacts NBFIs’ derivatives usage.

We estimate the following daily time-series regression:

$$NetNotional_{t,t+T}^s = \beta \times MPShock_t + \varepsilon_t, \tag{7.1}$$

where $NetNotional_{t,t+T}^s$ is the total net notional (measured in £ billions) in sterling interest rate swaps taken out by sector $s \in \{LDI - PI, Hedge Funds, Asset Managers\}$ up to T days following the realisation of the shock on day t ; $MPShock_t$ is target shock (Swanson, 2021; Braum, Miranda-Agrippino, and Saha, 2022) used in the previous sections. We estimate regression 7.1 separately for each sector s , with the results presented in Figure 13.

[Figure 13]

We find that following surprise increases in the interest rate the LDI-PI sector increases net notional (top-left panel), i.e. enters into new swap contracts whereby it receives the floating rate and pays the fixed rate on the swap. Recall that the LDI-PI sector tends to have large negative net positions that are fairly stable over time (Figure 2), consistent with these firms using swaps to hedge against discount rate risk in their management of long-term pension liabilities (Blake 2003; BMO 2018; Pinter 2023; Jansen, Klingler, Ranaldo, and Duijm 2023). The results in Figure 13 imply that the LDI-PI sector reduces its large negative net positions (in absolute value), by receiving the floating rate on new swap contracts, which amounts to an increase of around \$20 billion 3-4 days after a 1% surprise increase in the target rate.

We find that the response of hedge funds is more immediate and an order of magnitude larger than the LDI-PI sector (though the 90% confidence bands include zeros as well); whereas we

find the weakest evidence for asset managers who do not seem to react to the monetary policy shock. Regarding the large response of the hedge funds, our discussions with market practitioners suggest that the observed hedge fund behaviour could be interpreted as certain funds extrapolating unexpected interest rate hikes (starting in 2021Q4) into expected further hikes in the future, receiving the floating rate on large new swap positions. While this is consistent with the stylised facts regarding the sharp changes in hedge fund positioning around this period (Figures 2–3), a rigorous identification of this mechanism could be subject to future research.

A further interpretation of the results is that the estimated dynamic effects are consistent with the risk-taking channel of monetary policy (Maddaloni and Peydro, 2011; Borio and Zhu, 2012; Dell’Ariccia, Laeven, and Marquez, 2014; Adrian, Estrella, and Shin, 2019; Martinez-Miera and Repullo, 2019; Bauer, Bernanke, and Milstein, 2023). Given the linearity of regression 7.1, one could interpret Figure 13 as an unexpected loosening of monetary policy leading to the LDI-PI and hedge fund sectors taking on more interest rate risk. In other words, these sectors would now pay the floating rate on new swap positions, thereby exposing them to larger mark-to-market losses should interest rates unexpectedly rise from that point on. However, we acknowledge that this interpretation is suggestive given that our sample period (2019-2022) is dominated by an interest rate hiking cycle.

Moreover, we connect these results with the findings of the previous section by decomposing the sectoral responses in Figure 13 into those driven by the five largest firms in each sector (in terms of total notional) and the rest. That is, we compute the dynamics of total signed notional on new swap contracts (left-hand-side variable of regression 7.1) separately for the two sets of investors in each of the three NBFIs sectors.

[Figure 14]

As shown by Figure 14, virtually the entire baseline effect (presented in Figure 13) is driven by those selected firms in each sector where most of the sector’s swap notional is concentrated.²⁹ This further corroborates the point presented in Section 6 that a few, systemically important firms in derivatives markets have sizeable effects on the monetary policy propagation.

8 Conclusion

A rapidly expanding literature in economics and finance has studied the interest rate exposures of banks. However, empirical evidence on the interest rate exposures of non-banks (NBFIs) has been rather scant, mainly due to data limitations. Our paper fills this gap in the literature by using

²⁹As shown by Figure 17 in Appendix, the dynamic effects are similar when we replace the target shock with shocks to the 3-month OIS rate around MPC events.

transaction-level data to analyse the distribution of interest rate risk across a range of market participants in the UK government bond and interest rate derivatives markets.

Overall, we find little evidence that the average participant in interest rate derivatives markets hedges its gilt market exposure. We find that these markets are dominated on the one hand by large numbers of preferred habitat investors, such as LDI-PI, taking persistent positions to hedge their contractual pension liabilities, and on the other hand a small number of hedge funds taking large speculative positions. Importantly, we find that interest rate derivatives markets are highly concentrated in the NBFIs sectors, which could lead to greater risk of market disruptions. A small number of participants account for a large share of interest rate exposures, which could lead to dealer losses and infrastructure disruptions as they are hit with uninsurable idiosyncratic shocks. We also find evidence that this market concentration could impair the transmission of monetary policy to asset prices, which could also limit the signal that monetary policymakers should infer from these markets about macroeconomic developments and policy expectations.

References

- ADAMS, P., AND A. VERDELHAN (2022): “Exchange Rate Risk in Public Firms,” mimeo, MIT. [10](#)
- ADRIAN, T., A. ESTRELLA, AND H. S. SHIN (2019): “Risk-taking channel of monetary policy,” *Financial Management*, 48(3), 725–738. [1](#), [7](#)
- ADRIAN, T., AND H. S. SHIN (2010): “Financial Intermediaries and Monetary Economics,” in *Handbook of Monetary Economics*, ed. by B. M. Friedman, and M. Woodford, vol. 3, chap. 12, pp. 601–650. Elsevier, 1 edn. [1](#)
- AGARWAL, V., K. A. MULLALLY, AND N. Y. NAIK (2015): “The Economics and Finance of Hedge Funds: A Review of the Academic Literature,” *Foundations and Trends(R) in Finance*, 10(1), 1–111. [22](#)
- ALFARO, L., M. CALANI, AND L. VARELA (2021): “Granular Corporate Hedging Under Dominant Currency,” Working Paper 28910, National Bureau of Economic Research. [10](#)
- ALTAVILLA, C., L. BRUGNOLINI, R. GÜRKAYNAK, R. MOTTO, AND G. RAGUSA (2019): “Measuring euro area monetary policy,” *Journal of Monetary Economics*, 108(C), 162–179. [14](#)
- ARAGON, G. O., AND J. SPENCER MARTIN (2012): “A unique view of hedge fund derivatives usage: Safeguard or speculation?,” *Journal of Financial Economics*, 105(2), 436–456. [1](#)
- ARAMONTE, S., A. SCHRIMPF, AND H. S. SHIN (2021): “Non-bank financial intermediaries and financial stability,” BIS Working Papers 972, Bank for International Settlements. [1](#)
- BAKER, L., R. HAYNES, J. ROBERTS, R. SHARMA, AND B. TUCKMAN (2021): “Risk Transfer with Interest Rate Swaps,” *Financial Markets, Institutions & Instruments*, 30(1), 3–28. [1](#)
- BAUER, M. D., B. S. BERNANKE, AND E. MILSTEIN (2023): “Risk Appetite and the Risk-Taking Channel of Monetary Policy,” *Journal of Economic Perspectives*, 37(1), 77–100. [1](#), [7](#)
- BEGENAU, J., M. PIAZZESI, AND M. SCHNEIDER (2015): “Banks’ Risk Exposures,” NBER Working Papers 21334, National Bureau of Economic Research, Inc. [3](#), [1](#), [4.2](#), [22](#)
- BLAKE, D. (2003): *Pension Schemes and Pension Funds in the United Kingdom*. Oxford University Press. [7](#)
- BLAKE, D., L. SARNO, AND G. ZINNA (2017): “The market for lemmings: The herding behavior of pension funds,” *Journal of Financial Markets*, 36(C), 17–39. [5.3](#)
- BMO (2018): “Liability Driven Investment Explained,” Technical report, BMO Global Asset Management. [7](#)
- BORIO, C., AND H. ZHU (2012): “Capital regulation, risk-taking and monetary policy: A missing link in the transmission mechanism?,” *Journal of Financial Stability*, 8(4), 236–251. [1](#), [7](#)
- BRAUN, R., S. MIRANDA-AGRIPPINO, AND T. SAHA (2022): “A new dataset of High-Frequency Monetary Policy Surprises for the UK,” mimeo, Bank of England. [1](#), [3.1](#), [14](#), [5.5](#), [6.2](#), [7](#), [13](#), [14](#), [??](#), [??](#), [??](#), [??](#), [??](#), [??](#), [17](#)
- BREEDEN, S. (2022): “Risks from leverage: how did a small corner of the pensions industry threaten financial stability?,” Speech, Bank of England. [5](#), [5.3](#)

- CAPPIELLO, L., F. HOLM-HADULLA, A. MADDALONI, S. MAYORDOMO, R. UNGER, L. ARTS, N. MEME, I. AS-
IMAKOPOULOS, P. MIGIAKIS, C. BEHRENS, AND MOURA (2021): “Non-bank financial intermediation in the
euro area: implications for monetary policy transmission and key vulnerabilities,” Occasional Paper Series 270,
European Central Bank. [1](#)
- CENEDESE, G., A. RANALDO, AND M. VASIOS (2020): “OTC premia,” *Journal of Financial Economics*, 136(1),
86–105. [16](#)
- CESA-BIANCHI, A., G. THWAITES, AND A. VICONDOA (2020): “Monetary policy transmission in the United
Kingdom: A high frequency identification approach,” *European Economic Review*, 123(C). [14](#)
- CHEN, Y. (2011): “Derivatives Use and Risk Taking: Evidence from the Hedge Fund Industry,” *Journal of Financial
and Quantitative Analysis*, 46(4), 1073–1106. [1](#)
- CULBERTSON, J. M. (1957): “The Term Structure of Interest Rates,” *The Quarterly Journal of Economics*, 71(4),
485–517. [7](#)
- CUNLIFFE, S. J. (2022a): “Letter to Treasury Committee, 18 Oct,” letter, Bank of England. [5](#), [4.2](#)
- (2022b): “Letter to Treasury Committee, 5 Oct,” letter, Bank of England. [4.2](#)
- CZECH, R., S. HUANG, D. LOU, AND T. WANG (2021): “Informed trading in government bond markets,” *Journal
of Financial Economics*, 142(3), 1253–1274. [15](#), [4.1](#), [23](#)
- DELL’ARICCIA, G., L. LAEVEN, AND R. MARQUEZ (2014): “Real interest rates, leverage, and bank risk-taking,”
Journal of Economic Theory, 149(C), 65–99. [1](#), [7](#)
- DMO (2011): “A guide to the roles of the DMO and Primary Dealers in the UK government bond market,”
Discussion paper, Debt Management Office. [20](#)
- DOUGLAS, G., AND M. ROBERTS-SKLAR (2018): “What drives UK defined benefit pension funds’ investment
behaviour?,” Bank of England working papers 757, Bank of England. [5.3](#)
- DU, W., AND J. SCHREGER (2022): “Chapter 4 - CIP deviations, the dollar, and frictions in international
capital markets,” in *Handbook of International Economics: International Macroeconomics, Volume 6*, ed. by
G. Gopinath, E. Helpman, and K. Rogoff, vol. 6 of *Handbook of International Economics*, pp. 147–197. Elsevier.
[10](#)
- FENDER, I. (2000): “Corporate hedging: the impact of financial derivatives on the broad credit channel of monetary
policy,” BIS Working Papers 94, Bank for International Settlements. [1](#)
- FERSON, W., AND J. LIN (2014): “Alpha and Performance Measurement: The Effects of Investor Disagreement
and Heterogeneity,” *Journal of Finance*, 69(4), 1565–1596. [22](#)
- FROOT, K., D. SCHARFSTEIN, AND J. STEIN (1993): “Risk Management: Coordinating Corporate Investment
and Financing Policies,” *Journal of Finance*, 48(5), 1629–58. [1](#)
- FT (2022): “Investors bet against UK government bonds on rising inflation fears,” *Financial Times*. [4.2](#)

- FUNG, W., AND D. A. HSIEH (2001): “The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers,” *Review of Financial Studies*, 14(2), 313–341. 22
- GERKO, E., AND H. REY (2017): “Monetary Policy in the Capitals of Capital,” *Journal of the European Economic Association*, 15(4), 721–745. 14
- GERTLER, M., AND P. KARADI (2015): “Monetary Policy Surprises, Credit Costs, and Economic Activity,” *American Economic Journal: Macroeconomics*, 7(1), 44–76. 14
- GIESE, J., M. JOYCE, J. MEANING, AND J. WORLIDGE (2021): “Preferred habitat investors in the UK government bond market,” Bank of England working papers 939, Bank of England. 7
- GOMEZ, M., A. LANDIER, D. SRAER, AND D. THESMAR (2021): “Banksâ exposure to interest rate risk and the transmission of monetary policy,” *Journal of Monetary Economics*, 117(C), 543–570. 3, 1, 4.2
- GORODNICHENKO, Y., AND W. RAY (2017): “The Effects of Quantitative Easing: Taking a Cue from Treasury Auctions,” NBER Working Papers 24122, National Bureau of Economic Research, Inc. 7
- GREENWOOD, R., AND D. VAYANOS (2010): “Price Pressure in the Government Bond Market,” *American Economic Review*, 100(2), 585–90. 5.3
- (2014): “Bond Supply and Excess Bond Returns,” *The Review of Financial Studies*, 27(3), 663. 7
- GUIMARAES, R., G. PINTER, AND J.-C. WIJNANDTS (2023a): “An Anatomy of Monetary Policy Transmission through the Gilt Market,” mimeo, Bank of England. 1
- (2023b): “Market Liquidity and the Monetary Policy Transmission,” mimeo, Bank of England. 1, 28
- GURKAYNAK, R. S., B. SACK, AND E. SWANSON (2005): “Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements,” *International Journal of Central Banking*, 1(1). 14
- HANSON, S. G., D. O. LUCCA, AND J. H. WRIGHT (2021): “Rate-Amplifying Demand and the Excess Sensitivity of Long-Term Rates,” *The Quarterly Journal of Economics*, 136(3), 1719–1781. 1
- HAU, H., P. HOFFMANN, S. LANGFIELD, AND Y. TIMMER (2021): “Discriminatory Pricing of Over-the-Counter Derivatives,” *Management Science*, 67(11), 6660–6677. 10
- HAUSER, A. (2022): “Thirteen days in October: how central bank balance sheets can support monetary and financial stability,” Speech, Bank of England. 5, 5.3
- HE, Z., I. G. KHANG, AND A. KRISHNAMURTHY (2010): “Balance Sheet Adjustments during the 2008 Crisis,” *IMF Economic Review*, 58(1), 118–156. 1
- HOFFMANN, P., S. LANGFIELD, F. PIEROBON, AND G. VUILLEMEY (2019): “Who Bears Interest Rate Risk?,” *Review of Financial Studies*, 32(8), 2921–2954. 3, 1, 4.2
- HUANG, J., C. SIALM, AND H. ZHANG (2011): “Risk Shifting and Mutual Fund Performance,” *Review of Financial Studies*, 24(8), 2575–2616. 22
- JANSEN, K., S. KLINGLER, A. RANALDO, AND P. DUIJM (2023): “Pension Liquidity Risk,” Working paper, Dutch National Bank. 5.3, 7

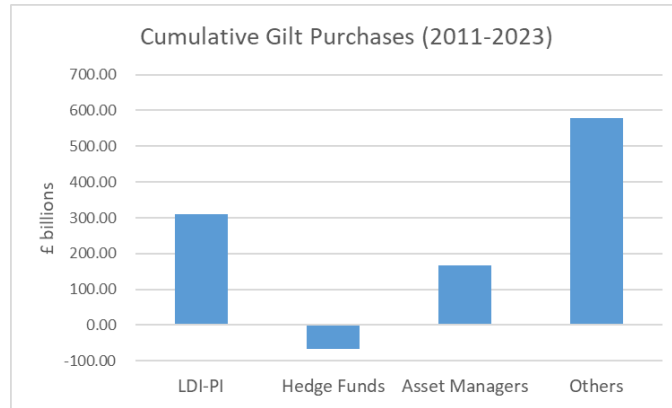
- JIANG, E. X., G. MATVOS, T. PISKORSKI, AND A. SERU (2023): “Monetary Tightening and U.S. Bank Fragility in 2023: Mark-to-Market Losses and Uninsured Depositor Runs?,” *Ssrn*. 5, 1, 4.2
- KANIEL, R., AND P. WANG (2022): “Unmasking Mutual Fund Derivative Use,” *Ssrn*, University of Texas at Dallas. 1
- KEKRE, R., M. LENEL, AND F. MAINARDI (2022): “Monetary Policy, Segmentation, and the Term Structure,” mimeo, Univeristy of Chicago. 1
- KHETAN, U., I. NEAMTU, AND I. SEN (2023): “The Market for Sharing Interest Rate Risk: Quantities behind Prices,” mimeo, Bank of England. 1
- KLINGLER, S., AND S. SUNDARESAN (2019): “An Explanation of Negative Swap Spreads: Demand for Duration from Underfunded Pension Plans,” *Journal of Finance*, 74(2), 675–710. 5.2, 5.3
- KONDOR, P., AND G. PINTER (2022): “Clients’ Connections: Measuring the Role of Private Information in Decentralized Markets,” *The Journal of Finance*, 77(1), 505–544. 15, 5.4
- KOSKI, J. L., AND J. PONTIFF (1999): “How Are Derivatives Used? Evidence from the Mutual Fund Industry,” *Journal of Finance*, 54(2), 791–816. 1
- LITTERMAN, ROBERT B, S. J. (1991): “Common Factors Affecting Bond Returns,” *The Journal of Fixed Income*, 1(1), 54–61. 5.3
- MADDALONI, A., AND J.-L. PEYDRO (2011): “Bank Risk-taking, Securitization, Supervision, and Low Interest Rates: Evidence from the Euro-area and the U.S. Lending Standards,” *The Review of Financial Studies*, 24(6), 2121–2165. 1, 7
- MARTINEZ-MIERA, D., AND R. REPULLO (2019): “Monetary Policy, Macroprudential Policy, and Financial Stability,” *Annual Review of Economics*, 11(1), 809–832. 1, 7
- MCPHAIL, L., P. SCHNABL, AND B. TUCKMAN (2023): “Do Banks Hedge Using Interest Rate Swaps?,” Working Paper 31166, National Bureau of Economic Research. 5, 1, 4.2
- MIRANDA-AGRIPPINO, S. (2016): “Unsurprising shocks: information, premia, and the monetary transmission,” Bank of England working papers 626, Bank of England. 14
- MODIGLIANI, F., AND R. SUTCH (1966): “Innovations in Interest Rate Policy,” *The American Economic Review*, 56(1/2), 178–197. 7
- O’HARA, M., Y. WANG, AND X. ZHOU (2018): “The execution quality of corporate bonds,” *Journal of Financial Economics*, 130(2), 308–326. 5.7
- PATTON, A., AND T. RAMADORAI (2013): “On the High-Frequency Dynamics of Hedge Fund Risk Exposures,” *Journal of Finance*, 68(2), 597–635. 22
- PINTER, G. (2023): “An anatomy of the 2022 gilt market crisis,” Bank of England working papers 1019, Bank of England. 5, 1, 5.2, 5.3, 7

- PINTER, G., E. SIRIWARDANE, AND D. WALKER (2023): “The 2022 Gilt Market Crisis: Causes and Consequences,” . 5.3
- RAMPINI, A., A. SUFI, AND S. VISWANATHAN (2014): “Dynamic risk management,” *Journal of Financial Economics*, 111(2), 271–296. 1
- RAMPINI, A. A., AND S. VISWANATHAN (2010): “Collateral, Risk Management, and the Distribution of Debt Capacity,” *Journal of Finance*, 65(6), 2293–2322. 1
- SMITH, C. W., AND R. STULZ (1985): “The Determinants of Firms’ Hedging Policies,” *Journal of Financial and Quantitative Analysis*, 20(4), 391–405. 1
- SWANSON, E. (2021): “Measuring the effects of federal reserve forward guidance and asset purchases on financial markets,” *Journal of Monetary Economics*, 118(C), 32–53. 1, 14, 5.5, 6.2, 7, 13, 14, ??, ??, ??
- VAYANOS, D., AND J.-L. VILA (2021): “A Preferred-Habitat Model of the Term Structure of Interest Rates,” *Econometrica*, 89(1), 77–112. 7, 5.6

Figures and Tables

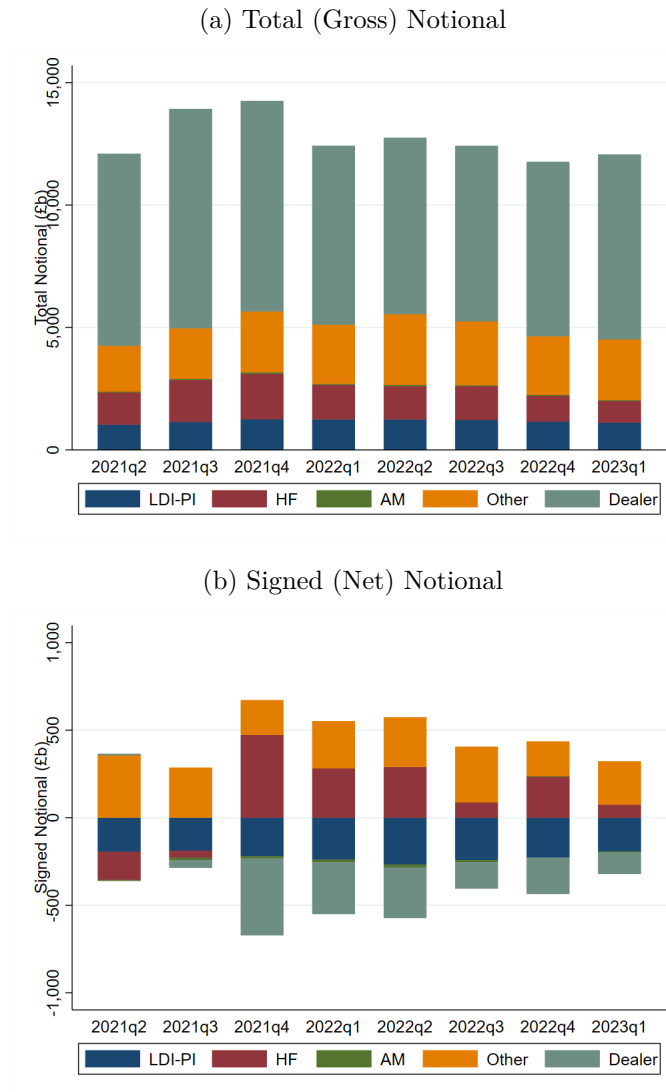
8.1 Figures

Figure 1: Distribution of Gilt Cumulative Purchases Across Sectors



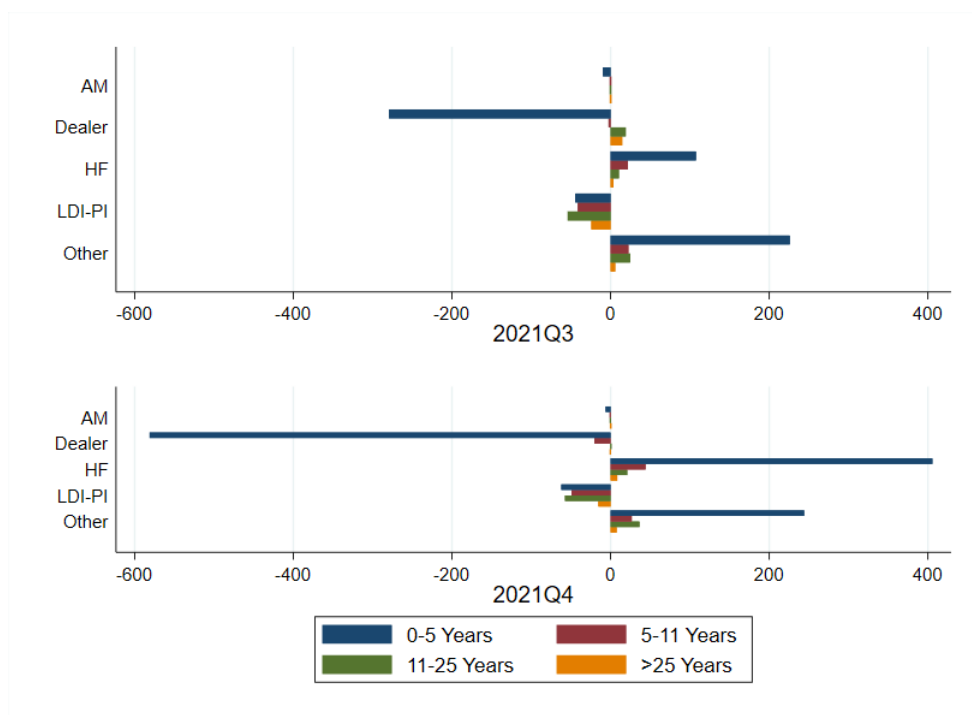
Notes: this figure shows the cumulative gilt purchases across the three NBFIs sectors as well as others. The LDI-PI sector includes pension funds, insurance companies and asset managers with an LDI remit. Other includes the purchases of the Bank of England as well as the trades by commercial banks, building societies, foreign government entities (such as foreign central banks) among others. To construct this chart we pool trades between the ZEN (2011-2017) and MIFID2 (2018-2023) datasets.

Figure 2: Sectoral Aggregates in the Sterling Interest Rate Swap Market



Notes: these bar charts summarise the positioning of different sectors in the sterling interest rate swap market where the reference rate is SONIA or GBP LIBOR. The top panel shows the total (gross) notional for each sector. The bottom panel shows the signed (net) notional. The LDI-PI sector includes pension funds, insurance companies and asset managers with an LDI remit. Other includes commercial banks, foreign government entities (such as foreign central banks) among others. Dealers are those dealer banks that act as gilt-edged market makers (GEMM) in the gilt market.

Figure 3: Sectoral Aggregates in the Sterling Interest Rate Swap Market: Maturity Breakdown



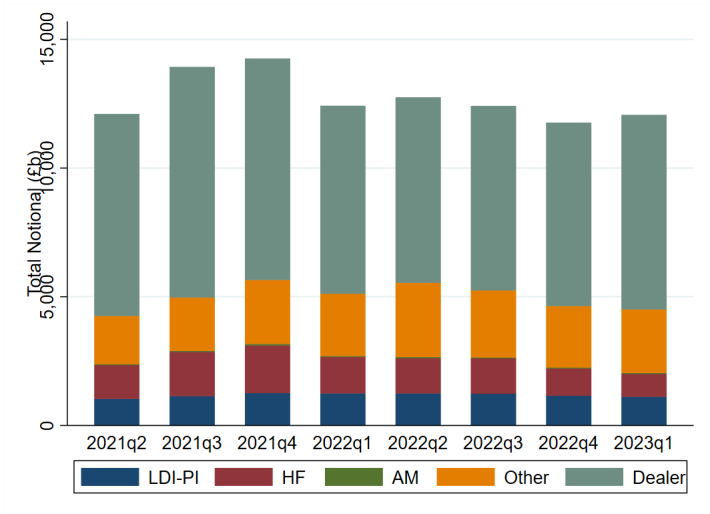
Notes: these bar charts summarise the positioning of different sectors in the interest rate swap markets at the end of 2021Q3 (upper panel) and 2021Q4 (lower panel). Positive (negative) values indicate receiving (paying) the floating rate on the swap. The LDI-PI sector includes pension funds, insurance companies and asset managers with an LDI remit. Other includes commercial banks, foreign government entities (such as foreign central banks) among others. Dealers are those dealer banks that act as gilt-edged market makers (GEMM) in the gilt market.

Figure 4: Sectoral Aggregates in the Sterling Futures Market



Notes: these bar charts summarise the positioning of different sectors in the sterling futures market. The top panel shows the total (gross) notional for each sector. The bottom panel shows the signed (net) notional. The LDI-PI sector includes pension funds, insurance companies and asset managers with an LDI remit. Other includes commercial banks, foreign government entities (such as foreign central banks) among others. Dealers are those dealer banks that act as gilt-edged market makers (GEMM) in the gilt market.

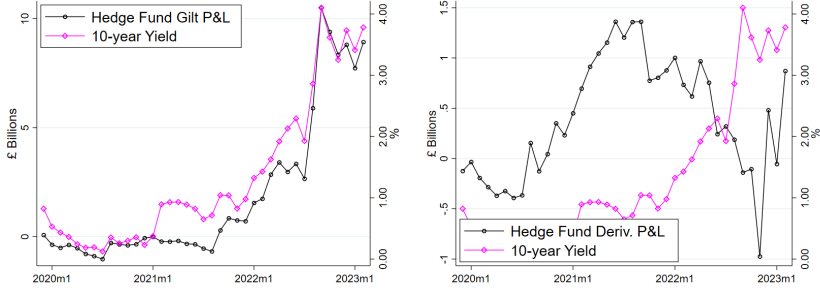
Figure 5: Sectoral Aggregates in the Sterling Interest Rate Options Market: Total (Gross) Notional



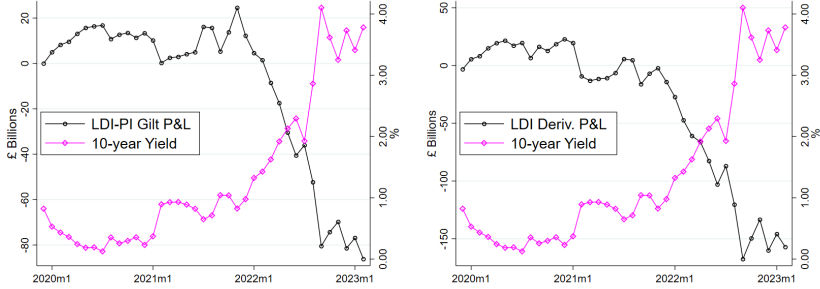
Notes: this bar chart summarise the total notional (in £ billions) of different sectors in the sterling interest rate options market. The LDI-PI sector includes pension funds, insurance companies and asset managers with an LDI remit. Other includes commercial banks, foreign government entities (such as foreign central banks) among others. Dealers are those dealer banks that act as gilt-edged market markers (GEMM) in the gilt market.

Figure 6: Dynamics of NBFI Profitability and Interest Rates

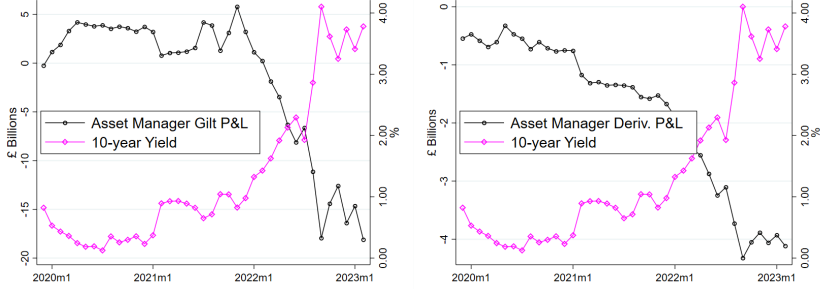
(a) Hedge Funds



(b) LDI-PI

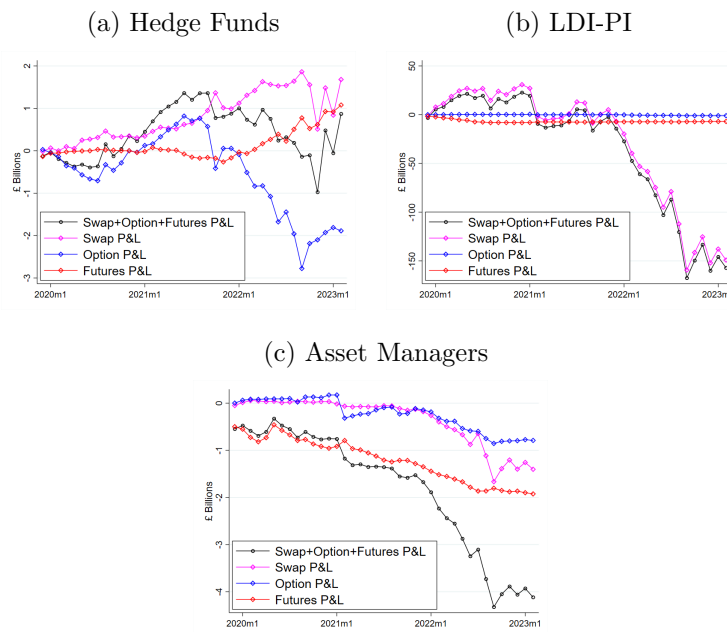


(c) Asset Managers



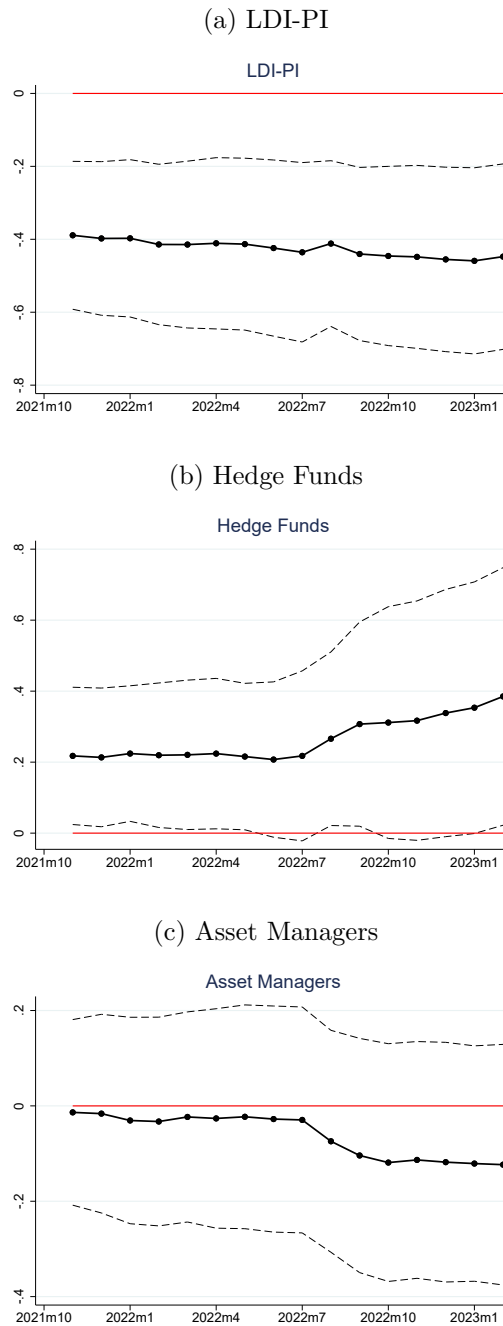
Notes: the figures show the cumulative changes in P&L along with the 10-year yields over the 2021m11-2023m2 period.

Figure 7: Decomposing Profitability on Interest Rate Derivatives: Swaps vs Options vs Futures



Notes: the figures show the cumulative changes in P&L on interest rate swaps, options and futures (separately and combined) over the 2021m11-2023m2 period.

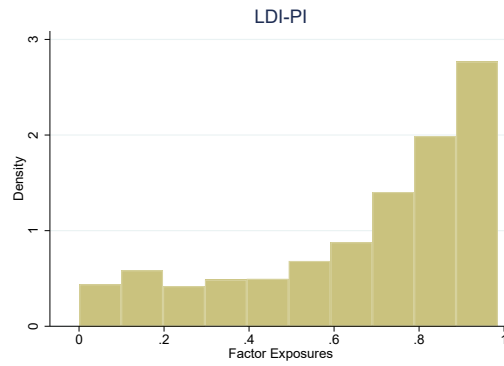
Figure 8: Time-Variation in Interest Rate Exposures



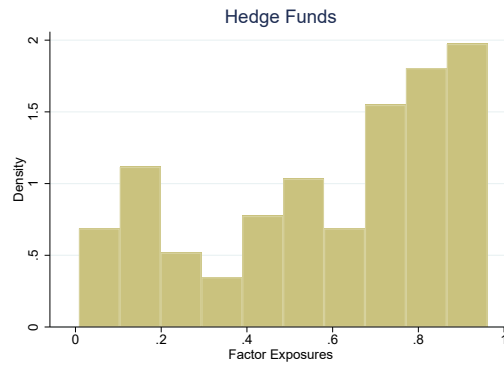
Notes: this figure plots the estimated β coefficients from variants of regression 5.2 using rolling estimation windows. The first (last) estimation window cover the period 2019m11-2021m11 (2021m2-2023m2). To reduce noise, we winsorise the profitability measures the 1%-level. The shaded area denotes the 90% confidence band associated with the estimated β coefficients, It is based on robust standard errors, using two-way clustering at the day and the fund level.

Figure 9: Within-Sector Variation in Interest Rate Exposures

(a) Exposures of LDI-PI



(b) Exposures of Hedge Funds

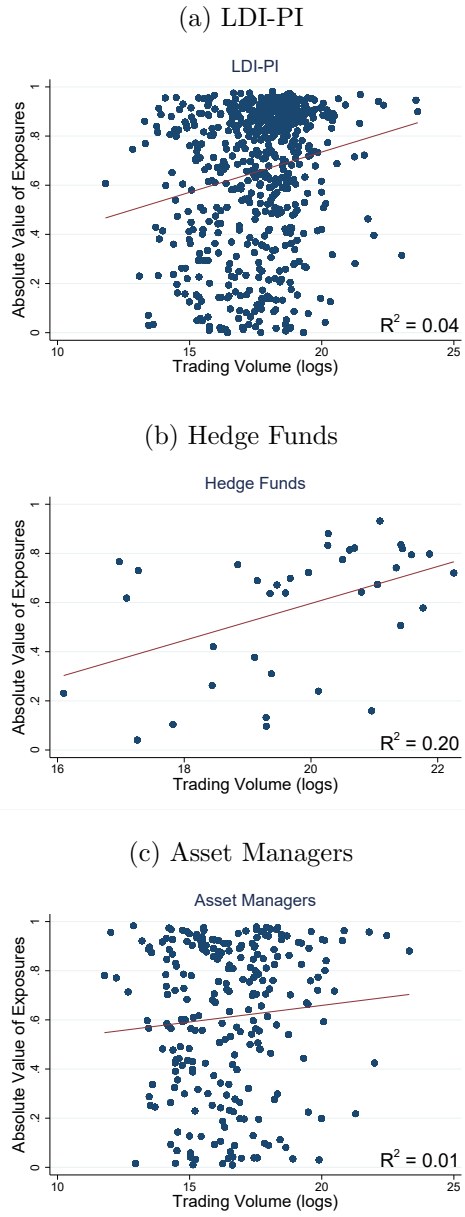


(c) Exposures of Asset Managers



Notes: this figure plots the distribution of β coefficients obtained from regressions 5.3. We group fund-level exposures by NBFBI sectors, shown by the three histograms. The left-hand panels show equal weighted histograms, whereas the right-hand-panels show histograms where the frequency weights are the average monthly trading volume of the given fund.

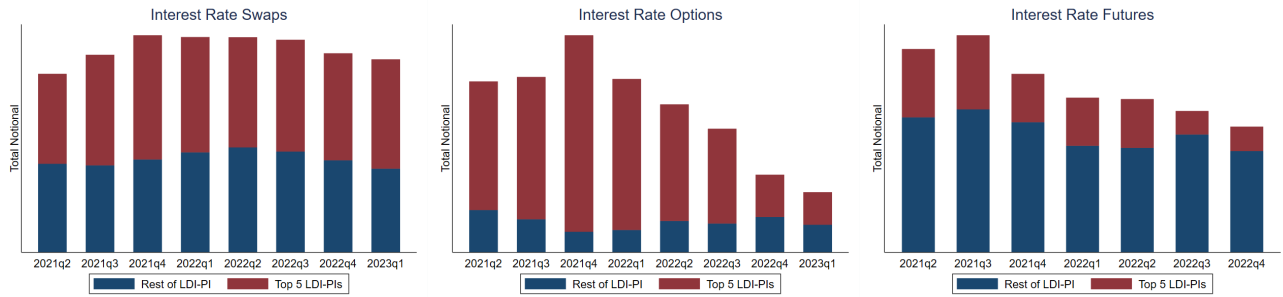
Figure 10: The Relationship Between Risk Exposure and Size



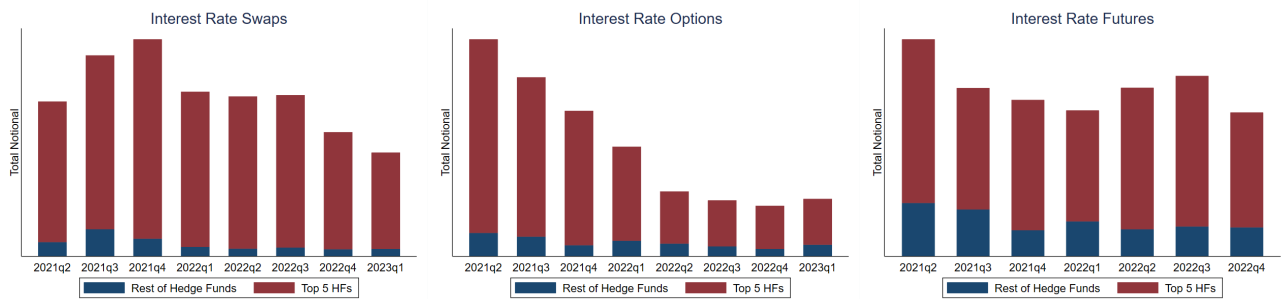
Notes: the scatter plots show the relationship between the absolute value of fund-level interest rate exposures and size (measured by the average monthly trading volume in logs).

Figure 11: Concentration in UK Interest Rate Derivatives Markets: Top 5 Notional vs Rest

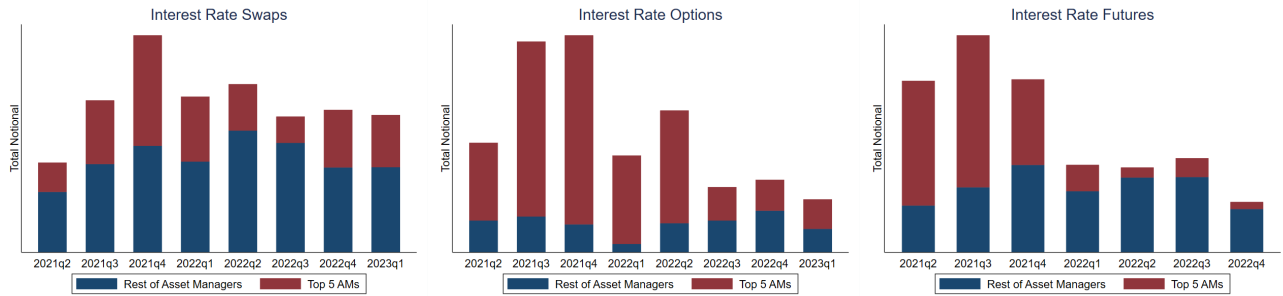
(a) LDI-PI



(b) Hedge Funds

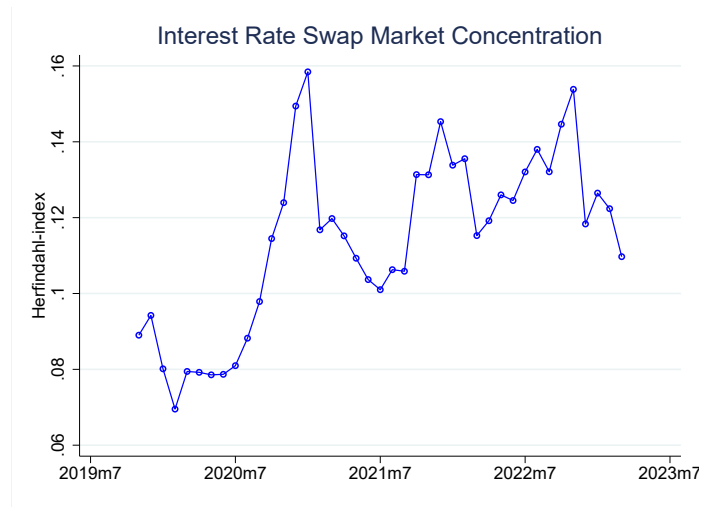


(c) Asset Managers



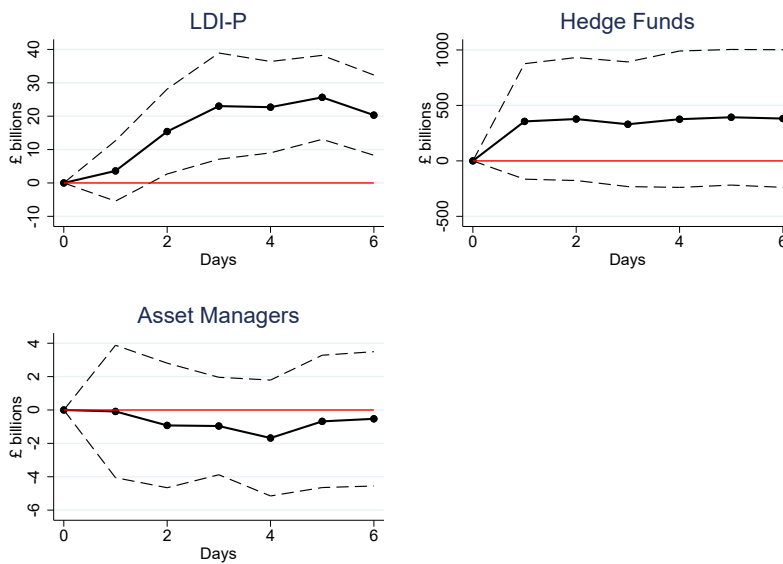
Notes: the bar chart shows the total gross notional in the three NBFIs sectors in the sterling interest rate swap market (left column), options market (middle column) and futures market (right column). The red bars correspond to the positions of the five funds with the largest notional in the given market and sector, and blue charts correspond to the total positions of all other funds that are active in our sample of interest rate swap, futures and options contracts. (At the request of the data owner, we do not present the units on the vertical axis of any of the charts.)

Figure 12: Concentration in the UK Interest Rate Swap Markets over Time: Monthly Time-series of the Herfindahl Index



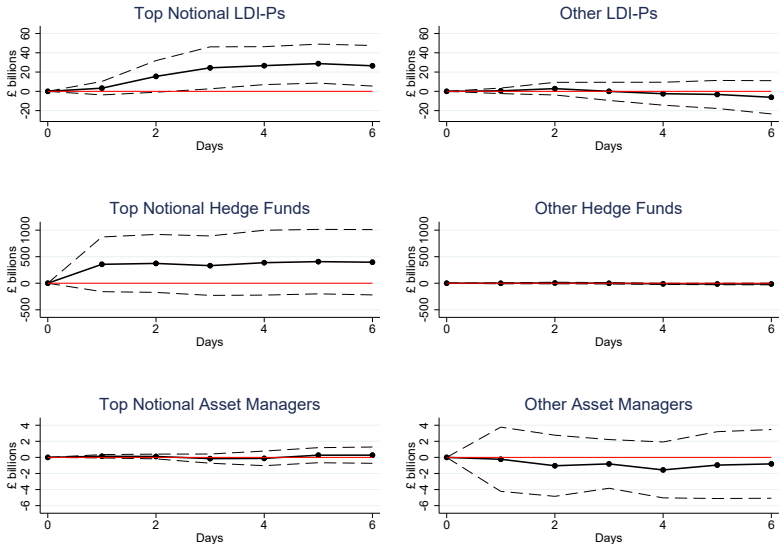
Notes: the figure shows the monthly time-series of the Herfindahl index in the UK interest rate swap market. To construct the index, we apply formulæ 6.1 to all available swap transactions for clients in the NBFIs sectors (hedge funds, LDI-PI, asset managers) as in Figure 11.

Figure 13: The Effect of Monetary Policy Shocks on NBFIs Swap Activity



Notes: this figure plots the estimated β coefficients from variants of regression 7.1, where we use the target shock (Swanson, 2021; Brau, Miranda-Agrippino, and Saha, 2022) as a proxy for monetary policy surprises. The estimation uses daily data covering the period 2019m11-2022m11. The shaded area denotes the 90% confidence band associated with the estimated β coefficients, based on Newey-West standard errors.

Figure 14: The Effect of Monetary Policy Shocks on NBFI Swap Activity: Top Notional Firms vs Rest of the Firms



Notes: this figure plots the estimated β coefficients from variants of regression 7.1, where we use the target shock (Swanson, 2021; Braun, Miranda-Agrippino, and Saha, 2022) as proxy a for monetary policy surprises. The left panel shows the responses of the top five firms (in terms of total notional) in each sector, and the right panel shows the responses of all other firms in each sector. The estimation uses daily data covering the period 2019m11-2022m11. The shaded area denotes the 90% confidence band associated with the estimated β coefficients, based on Newey-West standard errors.

8.2 Tables

Table 1: Extensive Margin of Derivatives Usage among Gilt Investors

	Swap Usage	Options Usage	Futures Usage	N
LDI-PI	44.7%	6.6%	27.2%	1520
Hedge Funds	32.8%	27.0%	27.8%	122
Asset Managers	14.6%	4.5%	27.7%	1747
Total	28.7%	6.3%	27.6%	3389

Note: this table presents summary statistics on the use of interest rate swaps, options and futures among our sample of gilt market investors, comprising 3389 funds over the sample 2019m11-2023m2.

Table 2: Sector-level Risk Exposures to Interest Rates

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: LDI-PI						
	MIFID	MIFID+ZEN	Sw.+Opt.+Fut.	Swap	Options	Futures
DV01 (\pounds m)	-218.50*** (-14.60)	-565.27*** (-13.11)	-413.19*** (-17.73)	-414.57*** (-17.81)	-2.62*** (-3.75)	4.01*** (2.89)
<i>N</i>	39	39	39	39	39	39
<i>R</i> ²	0.794	0.770	0.861	0.864	0.342	0.066
Panel B: Hedge Funds						
DV01 (\pounds m)	27.30*** (6.36)	27.30*** (6.36)	2.90 (1.05)	4.98** (2.52)	-4.65*** (-4.17)	2.57*** (6.15)
<i>N</i>	39	39	39	39	39	39
<i>R</i> ²	0.771	0.771	0.035	0.251	0.219	0.582
Panel C: Asset Managers						
DV01 (\pounds m)	-59.50*** (-15.75)	-198.08*** (-11.57)	-5.23*** (-11.95)	-4.09*** (-12.00)	-1.72*** (-3.02)	0.57** (2.32)
<i>N</i>	39	39	39	39	39	39
<i>R</i> ²	0.857	0.787	0.744	0.838	0.306	0.030

Note: this table shows the estimation results for regression 5.2. We estimate the regressions for the LDI-PI (Panel A) sector, hedge funds (Panel B) and asset managers (Panel C) separately. T-statistics in parentheses are based on robust standard errors. Column (1) shows the results for gilt market returns using the MIFID II data (2018-2023) only and column (2) shows the results for gilt market return where the ZEN dataset (2011-2017) was additionally used to estimate gilt holdings by cumulating observed flows. This adjustment is not applied to the hedge fund sector, because its cumulative flows result in non-positive values by the end of the ZEN dataset. Column (3) shows the returns for swaps, options and futures combined, and columns (4)-(5)-(6) show the results separately for swaps, options and futures, respectively. Asterisks denote significance levels (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table 3: Average Interest Rate Risk Exposures

	LDI-PI			Hedge Funds			Asset Managers		
	Total	Gilts	Derivatives	Total	Gilts	Derivatives	Total	Gilts	Derivatives
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Equal-weighted Exposures									
β_{F1}	-0.39***	-0.27***	-0.35***	0.16*	0.30***	-0.09	-0.18***	-0.19***	-0.12***
	(-13.09)	(-8.36)	(-12.62)	(1.91)	(3.23)	(-1.08)	(-3.96)	(-4.08)	(-3.61)
N	24806	24806	24377	1695	1695	1500	9988	9988	9636
R^2	0.183	0.107	0.147	0.047	0.114	0.034	0.064	0.071	0.035
Size-weighted Exposures									
β_{F1}	-0.49***	-0.38***	-0.49**	0.36*	0.21	0.47*	-0.24	-0.26	-0.12
	(-3.14)	(-2.72)	(-2.68)	(1.74)	(1.58)	(1.78)	(-1.29)	(-1.12)	(-1.65)
N	24806	24806	24338	1695	1695	1461	9988	9988	9319
R^2	0.268	0.184	0.273	0.146	0.067	0.233	0.083	0.093	0.022

Note: this table shows the estimation results for regression 5.2. We estimate the regressions for the LDI-PI (columns 1-3) sector, hedge funds (columns 4-6) and asset managers (columns 7-9) separately. We employ three return definitions: on gilt and derivatives positions combined ('total'), and on gilt and derivatives (including swaps, options and futures) positions separately. To reduce noise, we winsorise the profitability measures at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and fund level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 4: Decomposing the Exposure of the LDI-PI Sector

	PI			LDI		
	Total	Gilts	Derivatives	Total	Gilts	Derivatives
	(1)	(2)	(3)	(4)	(5)	(6)
Equal-weighted Exposures						
β_{F1}	-0.36***	-0.28***	-0.27***	-0.45***	-0.25***	-0.53***
	(-10.81)	(-7.56)	(-8.45)	(-9.87)	(-5.12)	(-12.51)
N	16934	16934	16661	7872	7872	7716
R^2	0.162	0.114	0.089	0.231	0.093	0.317
Size-weighted Exposures						
β_{F1}	-0.34	0.05	-0.37*	-0.74***	-0.64***	-0.80***
	(-1.67)	(0.48)	(-1.71)	(-8.42)	(-4.40)	(-10.44)
N	16934	16934	16622	7872	7872	7716
R^2	0.153	0.048	0.172	0.567	0.434	0.663

Note: this table shows the estimation results for regression 5.2. We estimate the regressions for pension funds and insurance companies (columns 1-3) and LDI managers (columns 4-6) separately. We employ three return definitions: on gilt and derivatives (including swaps, options and futures) positions combined ('total'), and on gilt and derivatives positions separately. To reduce noise, we winsorise the profitability measures at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and fund level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 5: Average Exposures to Monetary Policy Shocks

	LDI-PI			Hedge Funds			Asset Managers		
	Total	Gilts	Derivatives	Total	Gilts	Derivatives	Total	Gilts	Derivatives
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Equal-weighted Exposures									
β_{F1}	-0.53*** (-3.93)	-0.37*** (-4.53)	-0.50*** (-2.91)	0.37* (1.94)	0.68** (2.08)	-0.37* (-1.72)	-0.32** (-2.60)	-0.21*** (-2.85)	-0.29* (-1.79)
N	22907	22907	22511	1543	1543	1363	9220	9220	8895
R^2	0.149	0.069	0.130	-0.029	-0.069	-0.073	0.014	0.033	-0.006
Volume-weighted Exposures									
β_{F1}	-0.70*** (-2.97)	-0.52*** (-4.19)	-0.68*** (-2.88)	0.49** (2.70)	0.49 (1.68)	0.51*** (2.78)	-0.31** (-2.61)	-0.23 (-1.38)	-0.37* (-1.84)
N	22907	22907	22475	1543	1543	1327	9220	9220	8602
R^2	0.212	0.149	0.225	0.061	-0.063	0.169	0.062	0.070	-0.025

Note: this table shows the estimation results for variants of regression 5.2 where the interest rate factor is instrumented by the total monthly monetary policy surprise based on the high-frequency measure of the target shock (Swanson, 2021) obtained from Braun, Miranda-Agrippino, and Saha (2022). We estimate the regressions for the LDI-PI (columns 1-3) sector, hedge funds (columns 4-6) and asset managers (columns 7-9) separately. We employ three return definitions: on gilt and derivatives (including swaps, options and futures) positions combined ('total'), and on gilt and derivatives positions separately. To reduce noise, we winsorise the profitability measures at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and fund level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 6: Average Monthly Gilt Market Activity of NBFIs: Volume And Number of Transactions

	Trading Volume		Transactions	
	£ billion	%	Number	%
	(1)	(2)	(3)	(4)
LDI-PI	96.2	29.8%	16,597	36.3%
Hedge Funds	168.4	52.1%	8,351	18.2%
Asset Managers	58.7	18.2%	20,818	45.5%
Total	323.3	100.0%	45,766	100.0%

Note: this table presents summary statistics on monthly gilt trading activity of the three NBFIs sectors in our sample, covering the period 2019m11-2023m2. Columns (1) and (2) report average trading volumes in billions and as %-shares, respectively. Columns (3) and (4) report average number of transactions.

Table 7: The Determinants of Interest Rate Exposures

	LDI-PI	Hedge Funds	Asset Managers
	(1)	(2)	(3)
Size (Trade Volume)	0.01 (0.72)	0.17*** (3.65)	-0.01 (-1.05)
Trade Frequency	0.04** (2.06)	-0.03 (-0.56)	0.03 (1.29)
Average Maturity	0.14*** (4.61)	0.28*** (3.04)	0.06*** (3.07)
Maturity Dispersion	-0.03 (-1.15)	-0.33*** (-2.95)	0.05*** (5.04)
Buy-Sell Dispersion	-0.08*** (-2.68)	-0.01 (-0.06)	-0.01 (-0.28)
<i>N</i>	620	37	232
<i>r</i> ²	0.091	0.478	0.184

Note: this table presents the estimation results for regression 5.4. T-statistics in parentheses are based on robust standard errors. Asterisks denote significance levels (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table 8: Monetary Policy Transmission and Market Concentration in the UK Interest Rate Swap Market

	(1)	(2)	(3)	(4)	(5)
	1Y-OIS	2Y-OIS	3Y-OIS	4Y-OIS	5Y-OIS
Panel A: Linear Effects of Monetary Policy Shocks					
Target Shock	0.77** (2.10)	0.55 (1.22)	0.39 (0.82)	0.27 (0.59)	0.19 (0.43)
<i>N</i>	777	777	777	777	777
<i>R</i> ²	0.020	0.007	0.003	0.002	0.001
Panel B: Heterogeneous Effects of Monetary Policy Shocks					
Target Shock # Low Concentration	1.09*** (4.51)	0.95*** (3.90)	0.89*** (2.81)	0.87** (2.38)	0.83** (2.19)
Target Shock # High Concentration	0.71* (1.71)	0.48 (0.94)	0.31 (0.58)	0.18 (0.35)	0.09 (0.19)
<i>N</i>	757	757	757	757	757
<i>R</i> ²	0.020	0.007	0.004	0.003	0.002

Notes: this table regresses the daily change in OIS rates (obtained from the Bank of England yield curve [database](#)) on monetary policy shocks interacted with dummy variables indicating whether the previous month-end market concentration in the sterling interest rate swap market was above or below the median value, as in 6.2. The monetary policy shock is measured as the target shock (Swanson, 2021) obtained from Braun, Miranda-Agrippino, and Saha (2022). T-statistics in parentheses are based on robust standard errors. Asterisks denote significance levels (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table 9: Monetary Policy Transmission and Market Concentration in 1-year OIS Rates: Dynamic Effects

	(1)	(2)	(3)	(4)
	0-day	1-day	5-day	10-day
Target Shock # Low Concentration	1.09***	0.87***	1.00***	0.92***
	(4.51)	(4.85)	(4.08)	(2.61)
Target Shock # High Concentration	0.71*	-0.86	-1.56	-0.95
	(1.71)	(-0.63)	(-0.80)	(-0.49)
N	757	756	752	747
R^2	0.020	0.010	0.009	0.002

Notes: this table regresses the daily change in the one-year OIS rate (obtained from the Bank of England yield curve [database](#)) over different horizons on monetary policy shocks interacted with dummy variables indicating whether the previous month-end market concentration in the sterling interest rate swap market was above or below the median value, as in [6.3](#). The monetary policy shock is measured as the target shock ([Swanson, 2021](#)) obtained from [Braun, Miranda-Agrippino, and Saha \(2022\)](#). T-statistics in parentheses are based on Newey-West standard errors. Asterisks denote significance levels (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

A Appendix

A.1 Tables

Table 10: Average Interest Rate Risk Exposures – Including the Slope Factor

	LDI-PI			Hedge Funds			Asset Managers		
	Total	Gilts	Derivatives	Total	Gilts	Derivatives	Total	Gilts	Derivatives
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Equal-weighted Exposures									
β_{F1}	-0.39*** (-13.38)	-0.27*** (-8.65)	-0.35*** (-12.21)	0.15* (1.86)	0.27*** (3.49)	-0.06 (-0.96)	-0.16*** (-4.48)	-0.18*** (-4.00)	-0.11*** (-4.01)
β_{F2}	-0.01 (-0.41)	-0.02 (-0.97)	-0.02 (-1.25)	0.09*** (2.75)	0.18*** (4.73)	-0.15*** (-5.19)	-0.10*** (-9.20)	-0.08*** (-4.36)	-0.06*** (-3.81)
N	24806	24806	24377	1695	1695	1500	9988	9988	9636
R^2	0.183	0.108	0.148	0.055	0.147	0.058	0.076	0.077	0.039
Size-weighted Exposures									
β_{F1}	-0.48*** (-3.18)	-0.38** (-2.66)	-0.49*** (-2.80)	0.34* (1.75)	0.19 (1.57)	0.45* (1.80)	-0.23 (-1.22)	-0.25 (-1.06)	-0.10 (-1.64)
β_{F2}	-0.02 (-1.34)	-0.00 (-0.15)	-0.01 (-0.13)	0.10 (1.44)	0.12 (1.42)	0.11 (1.07)	-0.09*** (-6.93)	-0.09*** (-5.73)	-0.10** (-2.64)
N	24806	24806	24338	1695	1695	1461	9988	9988	9319
R^2	0.269	0.184	0.273	0.155	0.082	0.245	0.092	0.102	0.033

Note: this table shows the estimation results for regression 5.2, where we include as an additional regressor the second principal component of the yield curve. We estimate the regressions for the LDI-PI (columns 1-3) sector, hedge funds (columns 4-6) and asset managers (columns 7-9) separately. We employ three return definitions: on gilt and derivatives (including swaps, options and futures) positions combined ('total'), and on gilt and derivatives positions separately. To reduce noise, we winsorise the profitability measures at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and fund level. Asterisks denote significance levels (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

Table 11: Average Interest Rate Risk Exposures – Exposure to 1-year Yields

	LDI-PI			Hedge Funds			Asset Managers		
	Total (1)	Gilts (2)	Derivatives (3)	Total (4)	Gilts (5)	Derivatives (6)	Total (7)	Gilts (8)	Derivatives (9)
Equal-weighted Exposures									
β_{1Y}	-0.29*** (-6.65)	-0.22*** (-5.47)	-0.27*** (-8.30)	0.17** (2.22)	0.32*** (3.98)	-0.14* (-1.77)	-0.19*** (-5.94)	-0.18*** (-5.08)	-0.12*** (-4.32)
N	24806	24806	24377	1695	1695	1500	9988	9988	9636
R^2	0.108	0.077	0.085	0.049	0.123	0.046	0.068	0.069	0.035
Volume-weighted Exposures									
β_{1Y}	-0.36*** (-2.80)	-0.29** (-2.68)	-0.35** (-2.24)	0.31* (1.69)	0.24* (1.92)	0.38 (1.53)	-0.24 (-1.56)	-0.26 (-1.35)	-0.14** (-2.09)
N	24806	24806	24338	1695	1695	1461	9988	9988	9319
R^2	0.150	0.118	0.146	0.114	0.081	0.158	0.080	0.089	0.029

Note: this table shows the estimation results for regression 5.2, where we replace the first principal component of yields (as regressor) with the time-series of one-year yields in first differences. We estimate the regressions for the LDI-PI (columns 1-3) sector, hedge funds (columns 4-6) and asset managers (columns 7-9) separately. We employ three return definitions: on gilt and derivatives (including swaps, options and futures) positions combined ('total'), and on gilt and derivatives positions separately. To reduce noise, we winsorise the profitability measures at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and fund level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 12: Average Interest Rate Risk Exposures – Exposure to 10-year Yields

	LDI-PI			Hedge Funds			Asset Managers		
	Total (1)	Gilts (2)	Derivatives (3)	Total (4)	Gilts (5)	Derivatives (6)	Total (7)	Gilts (8)	Derivatives (9)
Equal-weighted Exposures									
β_{10Y}	-0.38*** (-13.22)	-0.27*** (-9.74)	-0.35*** (-12.01)	0.18** (2.10)	0.34*** (3.91)	-0.12 (-1.49)	-0.20*** (-5.26)	-0.20*** (-4.75)	-0.13*** (-4.62)
N	24806	24806	24377	1695	1695	1500	9988	9988	9636
R^2	0.173	0.103	0.144	0.053	0.135	0.042	0.072	0.076	0.038
Size-weighted Exposures									
β_{10Y}	-0.48*** (-3.16)	-0.37*** (-2.86)	-0.48** (-2.55)	0.37* (1.70)	0.23 (1.65)	0.48* (1.71)	-0.25 (-1.40)	-0.27 (-1.20)	-0.14* (-1.90)
N	24806	24806	24338	1695	1695	1461	9988	9988	9319
R^2	0.259	0.172	0.261	0.153	0.073	0.247	0.089	0.099	0.029

Note: this table shows the estimation results for regression 5.2, where we replace the first principal component of yields (as regressor) with the time-series of ten-year yields in first differences. We estimate the regressions for the LDI-PI (columns 1-3) sector, hedge funds (columns 4-6) and asset managers (columns 7-9) separately. We employ three return definitions: on gilt and derivatives (including swaps, options and futures) positions combined ('total'), and on gilt and derivatives positions separately. To reduce noise, we winsorise the profitability measures at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and fund level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 13: Average Exposures to Monetary Policy Shocks (3-month OIS rates)

	LDI-PI			Hedge Funds			Asset Managers		
	Total (1)	Gilts (2)	Derivatives (3)	Total (4)	Gilts (5)	Derivatives (6)	Total (7)	Gilts (8)	Derivatives (9)
Equal-weighted Exposures									
β_{F1}	-0.52*** (-3.42)	-0.36*** (-3.84)	-0.50** (-2.27)	0.37 (1.44)	0.64* (1.75)	-0.34 (-1.39)	-0.31* (-1.91)	-0.17 (-1.56)	-0.31 (-1.38)
N	22907	22907	22511	1543	1543	1363	9220	9220	8895
R^2	0.151	0.071	0.129	-0.029	-0.040	-0.054	0.016	0.034	-0.013
Volume-weighted Exposures									
β_{F1}	-0.66** (-2.30)	-0.51*** (-3.43)	-0.64** (-2.19)	0.46** (2.08)	0.44 (1.48)	0.42 (1.63)	-0.21 (-0.92)	-0.10 (-0.29)	-0.37 (-1.42)
N	22907	22907	22475	1543	1543	1327	9220	9220	8602
R^2	0.227	0.150	0.238	0.075	-0.033	0.179	0.065	0.044	-0.026

Note: this table shows the estimation results for variants of regression 5.2 where the interest rate factor is instrumented by the total monthly monetary policy surprise based on the high-frequency changes in the 3-month sterling OIS rate obtained from [Braun, Miranda-Agrippino, and Saha \(2022\)](#). We estimate the regressions for the LDI-PI (columns 1-3) sector, hedge funds (columns 4-6) and asset managers (columns 7-9) separately. We employ three return definitions: on gilt and derivatives (including swaps, options and futures) positions combined ('total'), and on gilt and derivatives positions separately. To reduce noise, we winsorise the profitability measures at the 1%-level. T-statistics in parentheses are based on robust standard errors, using two-way clustering at the month and fund level. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 14: Monetary Policy Transmission and Market Concentration in the UK Interest Rate Swap Market: Alternative Shock Series

	(1) 1Y-OIS	(2) 2Y-OIS	(3) 3Y-OIS	(4) 4Y-OIS	(5) 5Y-OIS
Panel A: Linear Effects of Monetary Policy Shocks					
3M-OIS Shock	0.88*** (2.87)	0.70* (1.83)	0.56 (1.38)	0.44 (1.13)	0.36 (0.95)
N	777	777	777	777	777
R^2	0.037	0.016	0.009	0.006	0.004
Panel B: Heterogeneous Effects of Monetary Policy Shocks					
3M-OIS Shock # Low Concentration	0.90*** (4.02)	0.72*** (4.01)	0.70*** (2.64)	0.71** (2.16)	0.70** (1.97)
3M-OIS Shock # High Concentration	0.87** (2.32)	0.70 (1.48)	0.52 (1.06)	0.38 (0.81)	0.28 (0.62)
N	757	757	757	757	757
R^2	0.037	0.016	0.009	0.007	0.005

Notes: this table regresses the daily change in OIS rates (obtained from the Bank of England yield curve [database](#)) on monetary policy shocks interacted with dummy variables indicating whether the previous month-end market concentration in the sterling interest rate swap market was above or below the median value, as in 6.2. The monetary policy shock is measured as high-frequency changes in the 3-month OIS rate, obtained from [Braun, Miranda-Agrippino, and Saha \(2022\)](#). T-statistics in parentheses are based on robust standard errors. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

Table 15: Monetary Policy Transmission and Market Concentration in 1-year OIS Rates: Dynamic Effects

	(1)	(2)	(3)	(4)
	0-day	1-day	5-day	10-day
3M-OIS Shock # Low Concentration	0.90***	0.67***	0.86***	0.90***
	(4.02)	(5.26)	(4.14)	(2.77)
3M-OIS Shock # High Concentration	0.87**	-0.19	-0.58	-0.25
	(2.33)	(-0.15)	(-0.32)	(-0.15)
N	757	756	752	747
R ²	0.037	0.002	0.002	0.001

Notes: this table regresses the daily change in the one-year OIS rate (obtained from the Bank of England yield curve [database](#)) over different horizons on monetary policy shocks interacted with dummy variables indicating whether the previous month-end market concentration in the sterling interest rate swap market was above or below the median value, as in [6.3](#). The monetary policy shock is measured as high-frequency changes in the 3-month OIS rate, obtained from [Braun, Miranda-Agrippino, and Saha \(2022\)](#). T-statistics in parentheses are based on Newey-West standard errors. Asterisks denote significance levels (* p<0.1, ** p<0.05, *** p<0.01).

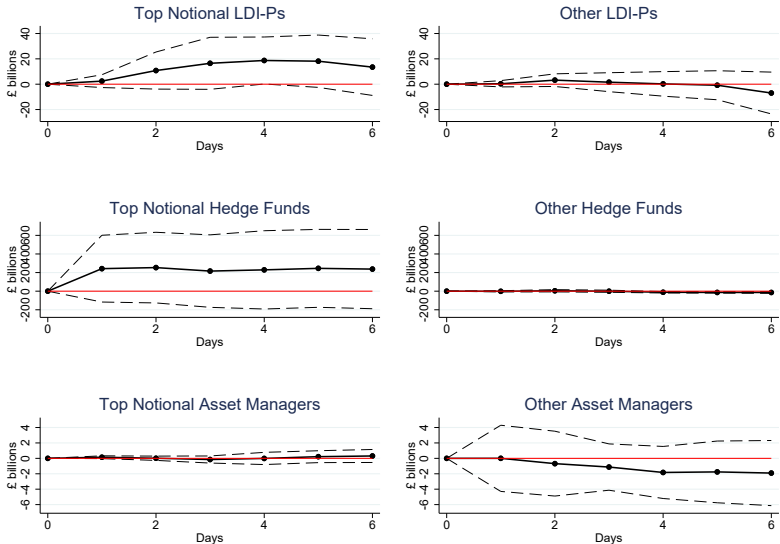
A.2 Figures

Figure 15: Illustrating the Gilt P&L Computation

	Day 1	Day 2	Day 3
Market price (P)	100	99	98
Transactions	-1	+3	-1
Cumulative transactions (Q)	-1	2	1
Cumulative transaction value (V)	-100	197	99
Cumulative stock value (P x Q)	-100	198	98
Cumulative P&L	0	+1	-1

Notes: this figure illustrates the computation of the gilt P&L (equations [3.3-3.6](#)), using a hypothetical example.

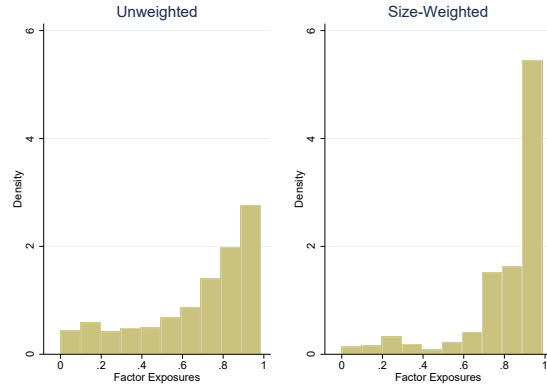
Figure 17: The Effect of Monetary Policy Shocks on NBFI Swap Activity: Top Notional Firms vs Rest of the Firms



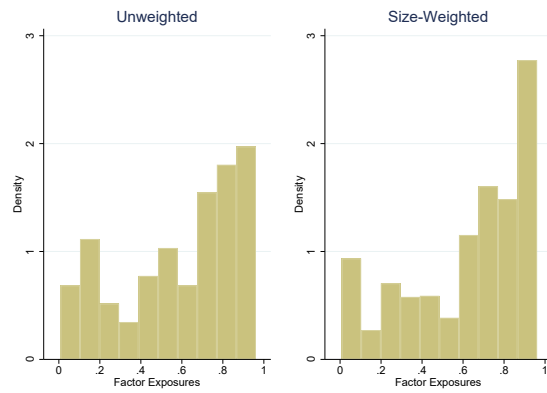
Notes: this figure plots the estimated β coefficients from variants of regression 7.1, where high-frequency changes in the 3-month OIS rates are used as monetary policy shocks (Braun, Miranda-Agrippino, and Saha, 2022). The left panel shows the responses of the top five firms (in terms of total notional) in each sector, and the right panel shows the responses of all other firms in each sector. The estimation uses daily data covering the period 2019m11-2022m11. The shaded area denotes the 90% confidence band associated with the estimated β coefficients, based on Newey-West standard errors.

Figure 16: Within-Sector Variation in Interest Rate Exposures

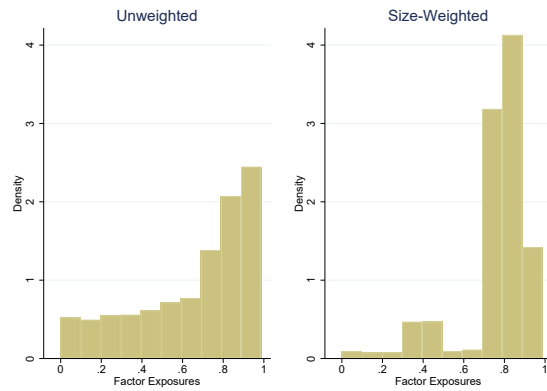
(a) LDI-PI



(b) Hedge Funds



(c) Asset Managers



Notes: this figure plots the distribution of β coefficients obtained from regressions 5.3. We group fund-level exposures by NBFY sectors, shown by the three histograms. The left-hand panels show equal weighted histograms, whereas the right-hand-panels show histograms where the frequency weights are the average monthly trading volume of the given fund.