The Market for Sharing Interest Rate Risk: Quantities and Asset Prices*

Umang Khetan† Jian Li‡ Ioana Neamțu§ Ishita Sen¶

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Abstract

We provide the first comprehensive characterization of end-user demand and its asset pricing implications for the interest rate swap market. Pension funds and insurers act as natural counterparties to banks and corporations, but their demand is highly segmented by maturity, exposing dealers to maturity-specific imbalances. We estimate demand elasticities using portfolio compression as an instrument, and calibrate a preferred-habitat model to quantify how demand imbalances interact with intermediary constraints to shape the term structure of swap spreads. In policy counterfactuals, we quantify the cross-sector implications of changing hedging mandates, e.g., showing that a decrease in pension funds' demand worsens banks' hedging outcomes.

Keywords: Interest rate risk, Pension funds, Insurers, Banks, Demand elasticities, Swap spreads

JEL classification: G11, G12, G15, G21, G22, G23, G24, G32

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†University of Iowa. Email: umang-khetan@uiowa.edu

‡Columbia Business School. Email: jl5964@columbia.edu

§Bank of England. Email: ioana.neamtu@bankofengland.co.uk

¶Harvard Business School. Email: isen@hbs.edu

The recent crises in the banking and pension sectors have raised questions about interest rate risk exposures across the financial system. One of the main ways financial institutions manage these risks is by trading interest rate swaps, a large over-the-counter market with daily trading volumes reaching trillions of dollars (BIS, 2022). Despite its scale and systemic relevance, beyond aggregate statistics there is a notable lack of data on the quantities-side of the market — particularly data that span multiple sectors and include a sufficiently broad set of participants. Yet, for many policy-relevant questions, it is essential to adopt a cross-sector perspective that considers how different segments of the economy interact and collectively shape outcomes in this market.

For example, one prominent strand of the literature focuses on asset pricing and the dynamics of swap spreads (e.g., Klingler and Sundaresan (2019), Hanson, Malkhozov, and Venter (2024)); however, lacking granular cross-sector data, it abstracts from the detailed composition of swap positions. Yet, it is precisely the interaction of demand across different participants that likely plays a central role in shaping asset prices. Another strand of the literature examines risk management within specific types of institutions, such as banks or the liability-driven strategies of insurers and pension funds. However, this work typically examines sectors in isolation, overlooking spillovers, i.e. how hedging decisions in one sector influence outcomes in others. For example, regulations requiring banks to hedge more could affect asset prices and hedging costs for pension funds and insurers, potentially prompting them to reduce hedging and amplifying their interest rate risk.

In this paper, we seek to answer these questions through the lens of a structural asset pricing model that jointly incorporates both demand- and supply-side forces, leveraging granular position-level data. We then evaluate policy counterfactuals to quantify the cross-sector implications of changing hedging mandates for any given sector — motivated by recent calls for banks to increase hedging following the SVB crisis, or for pension funds to reduce their use of swaps in light of liquidity risks exposed during the recent bond market turmoil (Jansen et al., 2025).

Our analysis addresses two challenges. The first is empirical: without granular, cross-sector data, it is difficult to assess the extent to which institutions offset each others' positions, and therefore how much residual exposure is absorbed by intermediaries. We obtain transaction-level data covering nearly the entire UK market, and for all institution types – banks, pension funds, insurers, asset managers, and corporations at an entity level – which allows us to characterize end-user demand and identify the sources of risk sharing and market segmentation. The second challenge is analytical: quantifying the cross-sector spillovers requires a structural framework that captures equilibrium interactions between demand and supply. This involves estimating key parameters that govern how quantities and prices co-move in response to shocks. For example, end-users' demand elasticities determine how hedging demand adjusts as cost changes, while the slope of intermediaries' supply curve dictates the extent to which demand shifts affect asset prices. We make progress by calibrating an asset pricing model in which heterogeneous end users interact with risk-averse arbitrageurs (dealers). Our framework allows us to map observed market behavior to underlying economic primitives, and trace the equilibrium effects of policy counterfactuals.

We make three contributions. First, we characterize the swap demand of all end users and show that pension funds and insurers (PF&I) are natural counterparties to banks and corporations with significant offsetting positions. While this cross-sector netting reduces the overall imbalance absorbed by dealers, end-user demand is highly segmented by maturity, exposing dealers to persistent maturity-specific imbalances. Second, we show that the distribution of demand imbalances across maturities plays a key role in shaping the term structure of swap spreads. To do so, we calibrate a preferred-habitat investor model (Vayanos and Vila, 2021), incorporating empirically estimated demand elasticities, and show that dealers' pricing of swap spreads reflects the risk arising from segmented end-user demand. Third, through a series of counterfactual experiments, we provide the first quantification of the extent to which demand shocks originating in one sector affect the hedging costs and positions of others. In particular, we show that regulations requiring PF&I to reduce (increase) hedging can substantially raise (lower) the hedging costs for banks.

Our analysis leverages granular transactions and positions data from the Bank of England, covering the near-universe of UK interest rate swaps. The data uniquely capture <u>all</u> end users of swaps at an individual entity level, which we categorize as: (a) pension, liability-driven investment funds, and insurers (PF&I); (b) end-user banks, which are distinct from dealers and considered separately; (c) corporations; (d) funds (including hedge funds and asset managers); and (e) official institutions. For each entity, we observe the stock of outstanding positions and the flow of new transactions, as well as detailed trade characteristics such as notional amounts, contracted fixed rate, direction, maturity, floating rate benchmark, and currencies. The sample spans December 2019 to June 2024, covering both low and rising interest rates, which enables us to calibrate the model across distinct rate environments.

Our paper proceeds in four parts. In the first part of the paper, we present two novel facts on end users' swap positions and trading, which determine the quantity and the nature of demand imbalances borne by the dealer sector. We use two key metrics of swap risk exposure: (i) net notional (receive fixed minus pay fixed) and (ii) dollar duration (i.e., the dollar value of a 1bp parallel shift in interest rates). First, we show that PF&I are natural counterparties to banks and corporations with large offsetting positions. As a sector, PF&I consistently receive fixed rates, adding duration to their portfolios with swaps. In contrast, banks and corporations consistently pay fixed rates, selling duration. This pattern also holds at the entity level, with most individual PF&I receiving fixed and banks and corporations paying fixed. Importantly, their trading behavior in response to interest rate changes further reinforces that the sectors are natural counterparties. As rates fall, PF&I buy duration, whereas banks and corporations sell duration, highlighting the sectors' opposite exposure to aggregate demand shocks. These results also hold when we consider unanticipated monetary policy shocks instead of overall yield changes.

Second, we show that end users' swap holdings are highly segmented by maturity, consistent with the presence of strong preferred habitats (Vayanos and Vila, 2021). We classify holdings into four maturity groups: below 3 months (ultra short), 3 months to 5 years (short), 5 to 10 years (intermediate), and 10 years & above (long). PF&I predominantly hold long maturity swaps, and do so consistently throughout the sample. In contrast, banks and corporations mainly hold short maturities. Notably, even at the entity level, most end users trade primarily within a single maturity group, e.g., 90% of bank trades occur in the short maturity group.

This preferred habitat behavior limits the extent of cross-sector netting we obtain from PF&I, banks, and corporations having offsetting positions. Dealers still have to absorb significant maturity-specific demand imbalances to clear the market. Specifically, dealers receive fixed (are long duration) in shorter maturities, opposite of banks and corporations, and pay fixed (are short duration) in long maturities, opposite of PF&I. These imbalances are substantial. For example, a 10 bps downward shift in rates would increase the value of dealers' position by about GBP 500 million in short-tenor swaps but reduce it by about GBP 1.4 billion in long-tenor swaps. Unexpected demand shifts in specific maturities (e.g., due to lower demand from banks) could expose dealers to non-parallel shifts in the swap spread curve, causing mark-to-market fluctuations in their positions. Dealers are therefore exposed to convergence risk, i.e. the risk that relative swap spreads diverge, impacting the value of their swap positions (Hanson et al., 2024).[1]

In the second part of the paper, we estimate end users' demand elasticities, which are important for determining how demand shocks in one sector propagate to others. When demand is inelastic, shocks are absorbed through price adjustments, affecting end users' hedging costs. Conversely, when demand is elastic, quantities adjust, altering their interest rate exposures. To address the simultaneity between prices and quantities, we exploit a novel feature of the derivatives market—portfolio compression—as an instrument. Under Basel III, dealers' leverage ratios are linked to the gross notional of their derivatives portfolios. Compression reduces this gross exposure by netting offsetting trades, thereby easing balance sheet constraints and allowing dealers to intermediate at lower cost (Duffie, 2018). Importantly, the design of the compression procedure makes it unlikely to be directly related to end users' demand shocks, supporting the exclusion restriction.

Following the literature, we use swap spreads as our measure of price as they capture the relative attractiveness of swaps versus comparable maturity bonds. Consistent with the expected balance sheet effects, we show that an increase in dealer-level compression significantly reduces swap spreads in the short maturities, where dealers receive fixed rates, and increases them in long maturities, where they pay fixed rates. We then use the instrumented swap spreads to estimate end users' demand elasticities. We find that end users in short maturities (e.g., banks) exhibit more elastic demand relative to those in long maturities (PF&I).

The key identifying assumption is that compression affects end-user demand only through its impact on swap spreads. One concern is that omitted variables, e.g., macro conditions, may

[1]Dealer imbalances also depend on the trading of funds, who hold substantial pay fixed positions briefly during our sample. However, these positions carry limited duration risk due to their ultra short maturities. Thus, while we account for fund positions throughout, our discussion focuses on banks and PF&I.

simultaneously affect both compression and end-user demand. For example, high volatility may prompt dealers to pursue more compression and end users to demand more swaps. However, several factors mitigate these concerns. First, compression requires exact matching of future cash flow dates, which individual dealers are less likely to control, making the volume of compressible trades less sensitive to macro or dealer-specific conditions. Second, compression is largely multilateral, limiting the influence of simultaneous changes in a dealer's own client demand. Third, compression occurs on fixed schedules set by central clearing, constraining dealers' ability to time or selectively influence which trades are compressed. Consistent with these features, we find that variables typically associated with shifts in end-user demand are uncorrelated with compression activity.

In the third part of the paper, we adapt the preferred-habitat framework of Vayanos and Vila (2021) to the swap market to examine how the interaction between end-user demand and dealer constraints shapes the term structure of swap spreads. The framework also sheds light on how sector-specific demand shifts generate spillovers across sectors. Motivated by the empirical facts, the model features end users having strongly segmented demand who trade in only one maturity group. There are three components to demand. First, it is a function of swap spreads, which captures the relative attractiveness of swaps over bonds. Second, we incorporate a demand pressure term, captured by an intercept, to reflect end users' underlying need for swaps driven by their balance sheet exposures. Third, demand varies over time in response to shifts in an aggregate demand factor (e.g., the level of interest rates). Building on the reduced-form evidence, we incorporate heterogeneity across end users by allowing demand elasticities, the direction and intensity of demand pressure, and sensitivity to the aggregate factor to vary.

While end users trade in specific maturities, dealers act as arbitrageurs and trade across maturities to exploit relative differences in swap spreads. Arbitrageurs are risk-averse and face time-varying funding costs for holding swaps on balance sheet (He, Nagel, and Song, 2022). Following the literature, we consider arbitrageurs as specialized intermediaries who hedge the interest rate risk of their swap positions in other markets, e.g., government bonds (Hanson et al., 2024), a behavior we also confirm empirically. While they bear minimal interest rate risk, they are exposed to convergence risk, i.e. mark-to-market fluctuations from movements in swap spreads. Funding costs reflect funding frictions and balance sheet constraints arising from the gap between the swap's floating rate and the dealer's funding rate, as well as certain regulatory costs of holding bonds for hedging (Bicu-Lieb et al., 2020, Du et al., 2023). We allow shocks to dealers' funding cost and the aggregate demand factor to be correlated to capture realistic market dynamics.

We first calibrate the model for the full sample. We match the means and variances of swap spreads and quantities across all maturity groups, using the reduced-form demand elasticities. The demand pressure coefficients from the calibration show that end users in the short maturity group prefer to pay fixed, while those in the long maturity group prefer to receive fixed. Moreover, they also have the opposite exposure to aggregate demand shocks. Overall, these estimated demand parameters, obtained without imposing any sign restrictions, align well with our reduced-form findings and the institutional composition across maturities, providing confidence that the model captures key economic patterns in the data. For arbitrageurs, our estimated parameters imply a relative risk aversion of approximately 13 and an average funding cost of 1%, closely matching the balance sheet cost of 81 bps reported in Fleckenstein and Longstaff (2020) and He et al. (2022). We then separately calibrate the model for two subsamples: 2019–21 (low-rate) and 2022–24 (high-rate). We find that both risk aversion and funding costs are higher in the high rate second subsample.

In the final part of the paper, we use the calibrated model to examine how the distribution of demand imbalances affects the term structure of swap spreads. We simulate counterfactual scenarios that vary the size and composition of demand imbalances across maturities, starting with two polar cases. The first scenario examines the role of banks' swap demand in explaining the term structure of swap spreads by shutting down the demand pressure of end users in the short maturity group, where the majority of bank positions are. We find that swap spreads turn more negative across maturities, particularly in long tenors. This outcome arises because banks' positions typically offset a part of PF&I positions, reducing dealers' aggregate risk exposure. In the absence of bank demand, dealers face larger imbalances and require greater compensation for holding long-term pay fixed positions, resulting in lower swap spreads. The second scenario assumes PF&I have no demand pressure for swaps, which we obtain by shutting down the demand intercept in the long maturity group. This results in the swap spread curve becoming upward-sloping, with positive spreads across maturities. Dealers demand higher fixed rates to supply swaps at shorter maturities and forego larger amounts to attract opposite receive-fixed positions at longer maturities.

A key takeaway is that demand shifts in one maturity generate spillover effects across maturities, altering swap spreads and, in turn, the hedging costs and swap demand of other end users. We quantify these cross-sector effects by simulating changes in demand pressure from banks and PF&I. When banks demand more, swap spreads rise in all maturities, implying that while hedging costs increase for banks, they decrease for PF&I. Conversely, increased PF&I demand lowers spreads across maturities, raising their own costs while lowering those for banks. Intuitively, since banks and PF&Is typically hold offsetting positions, greater activity by one alleviates the pricing burden on the other. Our estimates suggest that a 20% increase in banks' demand pressure would raise swap spreads by 13 bps, saving PF&I $\sim$ GBP 2 billion in hedging costs, while a similar increase in PF&I demand would reduce spreads for banks by 11 bps, yielding GBP 0.5 billion in savings. While part of the savings is offset as lower costs induce greater swap demand, this effect is modest: net quantities do not change meaningfully because demand is relatively inelastic.

Three extensions are worth noting. First, pricing effects are more pronounced in the high-rate subsample due to higher dealer risk aversion and balance sheet costs, highlighting how supply-side frictions amplify the pricing effects of demand imbalances. Second, price impact crucially depends on demand elasticities, with less elastic end users triggering larger price changes. For example, if end users were half as elastic as our estimates imply, then the same 20% increase in PF&I demand would lower banks' hedging costs by 60% more. Third, shifts in PF&I demand have a greater impact on spreads than those from banks. This is because demand imbalances in longer maturities expose dealers to more risks than in shorter maturities. These results show that both the magnitude and the source of demand imbalances shape the swap spread curve in distinct ways.

While we focus on how regulation in one sector affects others, our results also apply to cross-country settings where end users exhibit different swap demand. For example, economies with a smaller PF&I sector—e.g., those with pay-as-you-go pension systems or younger demographics—may have a different distribution of demand imbalances with short-tenor imbalances dominating long-tenor imbalances. Conversely, different mortgage contracts and regulatory frameworks could generate smaller hedging demand by banks (Hoffmann et al., 2019). For example, McPhail et al. (2023) show that US banks have limited hedging demand for swaps. Our counterfactual analyses shed light on the asset pricing consequences of different configurations of demand imbalances. Indeed, when we shut down the demand of UK banks, the counterfactual term structure of swap spreads appears closer to the observed spreads in the US. Our results underscore the broader implications of demand imbalances, and offer a framework to analyze how regulatory changes, demographic shifts, or market structures may affect asset prices and the distribution of risk.

Related literature. This paper contributes to the asset pricing literature on interest rate swaps. Our novel contribution is to show how the composition of cross-sector demand, originating from different institutional types, interacts with supply-side frictions to shape the term structure of swap spreads. The literature that studies the dynamics of swap spreads emphasizes both demand (Klingler and Sundaresan, 2019, Hanson et al., 2024) and supply (Boyarchenko et al., 2018, Jermann, 2020) factors.[2] However, it largely abstracts from the detailed characteristics of cross-sector positions data due to data limitations. Klingler and Sundaresan (2019) argue that persistent demand to receive fixed rates from underfunded pension funds drove swap spreads negative after the financial crisis, using pension underfunding as a proxy for this demand. Hanson et al. (2024) infer swap quantities from dealers' bond positions and jointly model supply frictions and demand factors to assess their relative contributions. Models without granular quantity data implicitly assume all end users operate in a single maturity, overlooking maturity segmentation and frictions faced by dealers when arbitraging across maturities. This limits their ability to quantify how sector-specific demand shocks affect pricing and positions across the term structure.[3]

We add to this literature in a number of ways. First, we identify large heterogeneity across end users in the direction, maturity choices, and exposure to aggregate demand shocks. This heterogeneity on the demand-side critically shapes the risks borne by the supply-side — effects that are masked in aggregated positions. To our knowledge, we are the first to provide such a detailed

[2]In addition, Augustin et al. (2021) consider fundamental factors such as sovereign default risks.

[3]Using similar regulatory data, Bahaj et al. (2023) examine the inflation swap market but impose desk-level separation for dealers, which rules out cross-maturity linkages and pricing spillovers.

characterization of the demand-side, and trace its asset pricing implications.[4] Second, we introduce a novel instrument to identify end users' demand elasticities, leveraging a unique institutional feature of the derivative market. Our instrument can potentially be applied more generally to other derivatives markets as well. Third, on the supply-side our framework allows dealers to optimize their swap positions across maturities, subject to balance sheet constraints. Specifically, dealers partially offset long-maturity positions with short-maturity positions, introducing additional convergence risk beyond what arises in models without segmented demand, such as Hanson et al. (2024). We show that accounting for segmented end-user demand and dealer arbitrage is crucial for explaining the shape of the swap spread curve and assessing the spillover effects of demand shifts.[5]

Our work also relates to the literature on interest rate risk management. Most existing studies examine different sectors in isolation—for example, Jansen (2021) and Jansen et al. (2025) study pension funds; Sen (2019) studies insurers; Begenau et al. (2015), Hoffmann et al. (2019), McPhail et al. (2023), and Jiang et al. (2023) examine banks; Bretscher et al. (2018) study corporations; Kaniel and Wang (2020) study mutual funds; and Pinter and Walker (2023) examine non-bank financial institutions. However, this literature largely overlooks cross-sector spillovers—specifically, how changes in one sector's hedging demand influence pricing and positions in others. In contrast, we take the sector-level hedging behavior as given and focus on the equilibrium consequences of those decisions. We jointly analyze the swap positions of all end-user sectors to study how their interactions shape market outcomes. This cross-sector perspective is critical for quantifying how localized demand shocks propagate across maturities and affect hedging costs and positions in other sectors. Our framework provides a unified approach that informs regulatory debates on interest rate risk management, which have traditionally considered financial sectors in isolation.

[4]Other studies using regulatory swaps data include Abad et al. (2016) who study the market structure and participants of EURIBOR interest rate swap market. Baker et al. (2021) use a one-day snapshot of US swap positions (as of March 15, 2019) to descriptively document the size and direction of end-user sector exposures. While our sector-level findings are broadly consistent, we focus on the asset pricing implications of cross-sector demand and find less within-sector heterogeneity—for example, most pension funds and insurers in our data hold receive fixed positions. Fontana et al. (2019) study swap trading networks and central clearing. Bolandnazar (2020) examines dealer competition and regulatory effects in the swap market.

[5]In a related application, Aldunate, Da, Larrain, and Sialm (2025) show that intermediaries (dealer banks) hedge the risks of pension funds' foreign currency demand, thereby transmitting end-user demand shifts to asset prices causing deviations from covered interest parity.

Finally, we build on the preferred habitat literature linking investor demand to asset prices (Vayanos and Vila, 2021), widely used to study how monetary policy and investor demand shape bond yield curves (e.g., Greenwood et al. 2016, Greenwood and Vissing-Jorgensen 2018). Recent extensions incorporate arbitrageurs' wealth effects and balance sheet constraints (He et al., 2022, Kekre et al., 2023), highlighting the role of intermediary frictions. Our work contributes to this evolving literature by applying the framework to interest rate swaps, an asset class where dealers are central. Our novel contribution is to non-parametrically estimate end-user demand by leveraging rich granular data on prices and quantities across maturities. To our knowledge, we are the first to use this framework to quantify the cross-maturity spillover effects and how hedging costs respond to system-wide shocks. Related applications of the preferred habitat framework to large financial markets include currency markets (Gourinchas et al., 2023, Greenwood et al., 2023). More recent work extends these applications to the US Treasury market (Jansen et al., 2024).

1. Regulatory Data from the Bank of England

We obtain granular position and transaction-level data on interest rate swaps, covering all sectors of the economy at the individual entity level from the Bank of England. Access to these data is enabled due to a key post-crisis reform, the European Market Infrastructure Regulation (EMIR), which seeks to enhance transparency in over-the-counter (OTC) markets by requiring derivatives to be reported to trade repositories. We source our data from two of the largest trade repositories, DTCC and UnaVista, that together constitute a 90% market share in interest rate derivatives (Abad et al., 2016). Our sample includes all trades where at least one counterparty is legally based in the UK, including UK-headquartered entities as well as UK branches and subsidiaries of foreign firms. Reporting obligation under EMIR began in February 2014, requiring all derivatives entered into by EU and UK counterparties since August 2012 (or outstanding at that time) to be reported. We focus on interest rate swaps as they comprise over 80% of outstanding OTC interest rate derivatives (BIS, 2023), and on a sample period from December 2019 to June 2024 due to a marked improvement in reporting quality starting in late 2019.

1.1. Data coverage

Our dataset provides the most comprehensive cross-sector coverage of the interest rate swap market, encompassing the universe of swaps executed in the UK. We benchmark the coverage of our data by comparing the turnover volume we observe with that of the triennial surveys conducted by the Bank for International Settlements (BIS). Table B1 shows that our data capture at least 60% of the global swaps turnover across all currencies, and over 84% of swaps denominated in GBP.[6] Our estimates are consistent with Abad et al. (2016), who find 70% coverage under EU EMIR in 2015, including the UK. Our vast coverage of this market is enabled by the fact that London serves as the center of global derivatives trading; BIS (2022) reports that close to 50% of all interest rate derivatives are traded in the UK. Our data cover nearly all of these trades, plus swaps executed outside the UK involving a UK entity. We focus our analysis on GBP swaps, where our coverage is most extensive and because we observe the entire swap portfolios of UK entities.

1.2. Outstanding Positions and Transactions

We source two types of complementary reports available from trade repositories: outstanding positions ("state files") and new transactions ("activity files") at an entity level. The stock of outstanding positions includes all trades contracted at any time in the past and open as on a given date, which helps us track the evolution of outstanding swap positions for each entity. The daily flow of new transactions includes trades contracted on a particular date and permits a more granular analysis of an entity's trading activity along dimensions of maturities and prices, in conjunction with current market conditions. These two reports jointly provide us with a complete picture of entity-level behavior in this market.

We extract 55 snapshots of outstanding positions from December 2019 to June 2024 at an entity level as of the beginning of each month. We also collect daily records of new transactions for the same period. To address well-known reporting issues with trade repositories' data, we

[6] Table B1 reports an average daily turnover of \$3.4 trillion in our data across currencies and \$287 billion in GBP swaps, which compares to about \$5 trillion of turnover for all swaps and \$341 billion of GBP swaps reported by the BIS.

perform extensive validation and cleaning procedures. Appendix A details the full methodology; a brief summary is below. First, we closely follow Abad et al. (2016) to exclude likely erroneously reported trades. Second, we remove duplicate trades which arise due to multiple reasons, e.g., the requirement that all counterparties separately report the position. Third, we concatenate information from multiple fields to construct the key features of each position, including the trade direction (receive or pay fixed), and the floating rate index (e.g., SONIA, LIBOR, SOFR).[7]

Our analysis focuses on single currency fixed-to-floating interest rate swaps and overnight indexed swaps referencing all floating rate benchmarks, across all tenors, and contracted by all types of counterparties. The trade-level variables we use from these reports include the outstanding notional, maturity date, identities of the counterparties, direction (receive or pay fixed), whether a trade is centrally cleared, and the underlying floating benchmark and currency. We use these variables to construct entity-level outstanding positions and maturity as of the report date. The variables describing new transactions closely resemble those in the outstanding position files, with the key addition of the trade's fixed rate, which we use to compute prices (swap spreads), as described below. We also use the transactions data to validate the preferred-habitat assumption, as maturities of outstanding positions naturally undergo a decay over time.

1.3. Measurement of Swap Quantities and Prices

To characterize the holding patterns, we construct two measures of swap risk exposure. First, we compute the net signed dollar exposures, $Q_{i,t}$, for end user i, defined as the total notional in receive fixed swaps minus the total notional in pay fixed swaps,

$$Q_{i,t} = \sum_{p} \text{Signed Notional}_{i,p,t}, \tag{1}$$

[7] After 2021, multiple indexes referencing the London Interbank Offered Rate (LIBOR) were discontinued from guaranteed publication, and GBP-denominated fixed income instruments transitioned to the Sterling Overnight Index Average (SONIA) benchmark (Klingler and Syrstad, 2021). During our sample period prior to this transition, the share of SONIA-denominated new GBP swap transactions steadily increased from about 75% in December 2019 to 90% in late 2021.

where Signed Notional$_{i,p,t}$ is the gross notional of trade p at time t, signed *positive* for receive fixed and *negative* for pay fixed swaps. Thus, positive values of $Q_{i,t}$ denote net receive fixed positions.

Second, we compute swaps' dollar duration, i.e. the dollar value of one basis point parallel shift in interest rates, which we label as DV01$_{i,t}$ and define as

$$\text{DV01}_{i,t} = \sum_p \text{Notional}_{i,p,t} \times \text{Duration}_p / 10,000, \tag{2}$$

where Duration$_p$ refers to the signed Macaulay duration of the fixed rate leg of the swap. We calculate swap durations using currency- and maturity-matched bond yields fixed at the start of our sample period to ensure that changes in DV01 reflect only active trading rather than mechanical valuation effects from interest rate movements.

Finally, we define the swap price faced by an end user as the difference between the swap fixed rate and the maturity-matched bond yield, and term it as *Swap Spread*:

$$\text{Swap Spread}_{i,p,t} = \text{Swap Fixed Rate}_{i,p,t} - \text{Bond Yield}_{p,t}. \tag{3}$$

We focus on swap spreads as they measure the relative attractiveness of swaps over comparable bonds, and allow us to net out the component of price associated with changes in bond yields. To closely match the maturity of the swap and the corresponding bond yield, we source daily bond yields at six-monthly maturity intervals from the Bureau van Dijk Bank of England database. Figure B1 shows the term structure of swap spreads for GBP swaps.

1.4. Sector Classification

We classify each entity into either a Dealer, a Central Counterparty Clearing House (CCP), or one of the five end-user sectors: (a) Banks; (b) Funds (including hedge funds and asset managers); (c) Pension, Liability-driven investment (LDI) funds, and Insurers (together referred to as PF&I);[8] (d) Corporate entities; and (e) Official institutions (sovereign funds or supra-national institutions).

[8] In the UK, some pension funds use liability-driven investment (LDI) funds to manage their funding risk, predominantly via increased exposure to gilts. Hence, we consider LDIs as part of the PF&I segment.

Although trade repositories include a field for counterparty sector, it is sparsely (and often erroneously) filled and not fully reliable. We leverage the non-anonymized unique identifier of each counterparty called the Legal Entity Identifier (LEI) to determine its sector using external sources, including the Global LEI Foundation, CapitalIQ, and Thomson Reuters databases. In total, we classify nearly 6,000 LEIs into one of seven distinct sectors. A step-by-step description of our sector classification methodology is provided in Appendix A.

A central feature of our classification is the ability to distinguish between end-user "banks" and market-making "dealers", allowing us to separate swap demand arising from banking activity and intermediation activity. We identify dealers using several criteria—including CCP membership, GSIB designation, and regulatory dealer lists. We combine this with a functional role-based assignment of LEIs to ensure that commercial banking and dealer arms of the same group are separated. We validate our classification using trading data. For entities classified as end user banks, we show their network of trading partners does not include other known end users at any point during the sample, confirming they are not dealers. For entities classified as dealers, we show their positions are consistent with two-sided intermediation rather than hedging. For example, Figure B2 shows dealers' net-to-gross positions are near zero, unlike other end users.

Columns (1)-(3) of Table 1 show the gross notional outstanding, the net notional, and DV01 for each end-user sector as of February 1, 2022. Funds held the largest gross notionals (GBP 1.2 trillion), followed by PF&I (GBP 1 trillion), banks (GBP 364 billion), the official sector (GBP 73 billion), and corporations (GBP 68 billion). Net notional in column (2) follow a similar pattern. However, DV01 in column (3) show that PF&I hold the largest positions, while funds are substantially smaller than what their gross positions suggest. Columns (4)–(5) show monthly trading volumes. Similar to outstanding positions, funds have the largest trading volume, followed by PF&I and banks. However, the net notional relative to gross notional is smallest for funds, indicating frequent two-way trading. Table B2 shows key statistics at the entity level. There were 365 funds, 576 PF&I, 105 banks, 258 corporations, and 16 official users that held outstanding positions as of February 1, 2022. Since we observe only a small number of official institutions, we omit discussing them in detail henceforth.

2. Key Facts on the Interest Rate Swaps Market

We begin by presenting two novel facts on the interest rate swap positions and trading of end users. These patterns help quantity and characterize the nature of demand imbalances being borne by the dealer sector, and motivate our focus on a preferred habitat investors model in which the supply-side (dealers) is exposed to fluctuations in demand.

2.1. Fact 1: PF&I, banks, and corporates have opposite risk exposures

2.1.1. Direction of exposures

We begin by examining the direction of net exposures. We find significant heterogeneity *across* end-user sectors. Figure 1 shows the net outstanding positions aggregated for all entities for a given sector at a monthly frequency. Throughout the sample period, PF&I on net consistently receive fixed rates, i.e. they add duration to their portfolios using swaps. In contrast, banks and corporations consistently pay fixed rates, i.e. they sell duration using swaps.[9] Figure 2 shows sector-level dollar duration exposures. Consistent with being long duration with swaps, a 10 bps parallel increase in interest rates would result in a decline of GBP 1.5 billion for the PF&I sector. In contrast, banks—who are short duration—would experience a gain of around GBP 0.4 billion.

We next examine how the direction of swap exposures varies across entities within each sector. Figure 3 plots the fraction of entities within a sector that receive fixed rates, depicted on the right-hand side axis. The left-hand side axis of Figure 3 maps this fraction to an "agreement score", where a value closer to +/-1 indicates perfect homogeneity in the direction of exposures, and a value closer to 0 indicates heterogeneity. We find that corporations, PF&I, and banks are largely homogeneous throughout the sample period: roughly 80% of PF&I receive fixed, while 70% of banks, and 80% of corporations pay fixed rates.[10]

[9] Figure B3 confirms that these directions are consistent for swaps denominated across all currencies.

[10] Since we observe only partial holdings of non-UK entities in our data (i.e., their trades booked with a UK counterparty), one may be concerned that the direction of exposures we document may not reflect the full portfolio of end users' swap holdings. However, we find consistent results when considering the net exposures of UK entities only for whom we observe all trades. Figure B4 shows that the exposures held by UK PF&I and UK banks are also in opposite direction and are of comparable magnitude.

These results suggest substantial position offsetting across sectors but relatively little within sectors. The consistently large and directionally opposing positions of PF&I relative to banks and corporations indicate that PF&I act as natural counterparties to the other two sectors in the interest rate swap market, enabling substantial risk transfer.

While our analysis largely focuses on banks, PF&I, and corporations, we also briefly discuss funds' swap positions, with additional detail provided in Appendix C. First, even though funds trade large notional amounts, their positions carry relatively small duration risk because they primarily hold short-maturity swaps (Figure 2). Second, unlike other end users, funds frequently flip trading directions: they hold substantial pay fixed positions at the start of the rate hiking cycle in 2021, but otherwise receive fixed at the beginning and the end of the sample (Figure 1). Moreover, there is significant within sector heterogeneity in trade direction for funds (Figure 3), unlike other sectors, which we trace to the contrasting trading strategies followed by different types of funds. Overall, despite large notionals, funds' positions are not the main source of duration risk and persistent imbalances for dealers.

2.1.2. Sensitivity to interest rates

Next, we examine the impact of changes in macroeconomic conditions on end users' swap exposures. Specifically, we consider movements in the level of interest rates, which could affect end-user demand or alter expectations of future swap returns. We estimate a model of the form:

$$\Delta q_{i,t} = \alpha_i + \beta \Delta Rate_{t-1} + \epsilon_{i,t}, \tag{4}$$

where $\Delta q_{i,t}$ is the change in the net outstanding position for entity i from month $t-1$ to t, scaled by the average absolute position held by the entity in the two months. This scaled variable approximates percentage changes and is bounded between +/-2, similar to the Davis and Haltiwanger (1992) growth rate measure, and addresses negative values and the effect of outliers. We also consider the change in DV01 as an alternate dependent variable to also account for swap durations. The independent variable, ΔRate_{t-1}, captures changes in interest rates. We consider a common interest rate factor, constructed as the monthly changes in the average value of the first principal component (PC) extracted from daily UK government bond (gilt) yields at maturities of 3 months, 5 years, 10 years, and 30 years. We also use the changes in yields at these four maturities directly as separate regressors. In both specifications, we use lagged changes to mitigate concerns about simultaneity. We also include entity fixed effects and cluster standard errors at the entity level.

Table 2 reports the results. We find striking heterogeneity in the positions' interest rate sensitivities across end-user sectors. β (i.e., the loading on rate changes) across specifications is negative for PF&I and positive for banks and corporations. This means that as rates fall, PF&I increase their net receive fixed exposures, i.e. buy duration. In contrast, banks and corporations increase their net pay fixed exposures, i.e. sell duration. Specifically, for a one percentage point decline in the first PC of yields, the average PF&I increases its net receive fixed exposure by 5%, and the average bank and corporation increases its net pay fixed exposure by 6% and 11%, respectively. The impact on DV01s is also of a comparable magnitude.

Responses to monetary policy shocks. To address potential endogeneity in the co-movement between yields and swap positions, we exploit unexpected yield movements driven by central bank policy announcements—monetary policy shocks (MPS). We obtain the MPS measure from Braun et al. (2024), which is constructed as the change in intraday gilt yields before and after Bank of England monetary policy announcements. Specifically, we use monetary policy shocks derived from gilt yields at three available maturities—2-year, 5-year, and 10-year—as separate regressors to estimate a model of the form:

$$\Delta q_{i,t} = \alpha_i + \beta MPS_{t-1} + \epsilon_{i,t}, \qquad (5)$$

with the rest of the specification analogous to Equation 4. Table 3 reports the results. Note that the number of observations is lower than in Table 2 because the MPS variable exists only when the Monetary Policy Committee meets (37 out of the 55 months in our sample period).

We find robust evidence that banks and PF&Is respond in the opposite direction to interest rate changes triggered by monetary policy announcements. For a one-standard-deviation positive monetary policy shock in 10Y gilt yield (3.8 bps), banks reduce their net pay fixed position by

2.6% and PF&I reduce their net receive fixed position by 1.4%. The opposite adjustments in swap demand by PF&Is and banks further reinforce that these institutions are natural counterparties in the swap market, with opposite exposure to aggregate demand shocks.

Discussion of end-users' swap demand: While the goal of our paper is not to quantify end-users' hedging activity, their net positions appear directionally consistent with the hedging of duration imbalances. Corporations often hedge interest rate risk arising from floating-rate debt issuance by paying fixed-rate swaps (Titman, 1992). PF&I typically hold long-term liabilities with fixed-rate guarantees and shorter-dated assets such as government and corporate bonds, creating a negative duration gap (EIOPA, 2014, Domanski et al., 2017, Sen, 2019, Jansen et al., 2025). To hedge this mismatch, they enter receive fixed swap positions. In contrast, banks generally face the opposite maturity mismatch: their longer-duration assets, such as fixed-rate mortgages, are funded by shorter-term deposit liabilities, resulting in a positive duration gap. To hedge this exposure, banks take pay fixed swap positions. Using aggregate balance sheet data, in Appendix D, we find that the swap holdings are not just directionally consistent but also quantitatively hedge a meaningful portion of UK banks' and PF&Is' duration mismatch.

Our finding that UK banks hold substantial amount of pay fixed swaps is consistent with recent evidence from other European countries (Velez et al., 2024), though it contrasts with US evidence showing more limited use of swaps to hedge interest rate risk (McPhail et al., 2023). We view these patterns as complementary, reflecting meaningful cross-country differences in regulation, bank business models, and asset compositions. Motivated by these cross-country differences, the counterfactual analysis in section 5 examines how shifts in banks' demand affect asset pricing dynamics in the swap market.

2.2. Fact 2: Strong maturity segmentation

While the different end-user sectors hold offsetting positions, we also find that swap holdings are highly segmented by maturity across end users. To illustrate the extent of segmentation, we classify holdings into four maturity groups: below 3 months (ultra short), 3 months to 5 years (short), 5 to 10 years (intermediate), and 10 years & above (long). For each group, we compute the net position as defined in Equation 1, which we denote as $Q^{<3M}$, Q^{3M-5Y}, Q^{5Y-10Y}, and $Q^{\geq 10Y}$.

Figure 4 panels (a) through (d) show the net positions for each maturity group. PF&Is' swap holdings are concentrated in the long-maturity group consistently throughout the sample. In contrast, banks' and corporations' positions are in the short maturity group. Funds predominantly hold ultra short and short maturity swaps. This maturity segmentation aligns with the distribution of duration risk (DV01s) across sectors. Reflecting their long-dated positions, PF&I have the largest DV01 exposures, as shown in Figure 2. In contrast, banks and corporations have smaller DV01 exposures, consistent with their shorter-duration holdings. Similarly, funds' ultra short and short maturities result in very small duration risk.

The extent of segmentation is even starker when we evaluate maturity distribution of new transactions. Panel A of Table 4 shows that about 90% of entities for any given end-user sector have a majority (more than 50%) of their new transactions in a single maturity group, which we define to be the end-user's *dominant* maturity group. The dominant maturity group is short for banks and corporations, ultra short for funds, and long for PF&I, consistent with their outstanding positions in Figure 4. Panel B of Table 4 shows that the average bank executes over 80% of trades in its own dominant maturity group, with the corresponding fraction for PF&I at 66% and corporate at 91%. Overall, the holdings and trading behavior of end users provide strong evidence of maturity segmentation, consistent with the presence of preferred habitat preferences.

2.3. Implications of End User Positions for Dealer (Im-)balances

We next examine the dynamics of aggregate net end-user demand and examine their implications for dealers' swap exposures. Since swaps are in zero net supply, dealers' net position is the opposite of the aggregate net end-user demand for each maturity group. Dealer balance is defined as

$$Dealer\ Balance_t^m = -\sum_s Q_{s,t}^m, \tag{6}$$

where s denotes all the five end-user sectors, including banks, funds, PF&I, corporations, and official institutions, and m denotes maturity group $< 3M$, $3M - 5Y$, $5Y - 10Y$, $\geq 10Y$. We also construct dealer balances in terms of DV01 analogously.

Figure 1 and Figure 4, which we discussed above, also overlay the dealer sector balances (in brown). There are two key points. (i) Figure 1 shows that a large portion of PF&Is' net receive fixed positions are offset by banks' and corporations' net pay fixed positions. This cross-sector netting reduces the net exposures borne by the dealer sector compared to what they would bear in the absence of these offsetting positions. (ii) However, despite the cross-sector netting, the strong maturity segmentation (and preferred habitat behavior) imply that dealers still have to absorb significant maturity-specific demand imbalances to clear the market. Specifically, Figure 4 shows that dealers consistently receive the fixed rate in short maturities, taking the opposite position of banks and corporations. In contrast, dealers pay the fixed rate in long maturities, taking the opposite position of PF&I.

Convergence risk. When receiving fixed in the short tenor and paying fixed in the long tenor, dealers face convergence risk- the risk that swap spreads diverge, resulting in mark-to-market fluctuations in the value of their swap positions. While aggregate net demand also exposes dealers to interest rate risk, prior research has suggested that dealers largely hedge this risk using cash instruments such as bonds (Hanson et al., 2024). We confirm this in our data: Table B3 shows a negative correlation between changes in dealers' swap and bond positions, consistent with dealers hedging the underlying interest rate risk of swaps.[11] Consistently, Wallen and Lu (2024) find that dealers' trading desk profits are relatively insensitive to changes in interest rates, implying that most of the interest rate risk is effectively hedged. We therefore argue that the primary risk dealers face is convergence risk arising from movements in swap spreads.

Maturity segmentation in demand amplifies this risk further by exposing dealers to non-parallel movements in the swap spread curve as well, which may arise due to demand shifts from specific end-user sectors. For example, a 10 bps increase in short-tenor swap spreads would lower the value

[11] Table B3 shows that as dealers' net notional in receive-fixed swaps increases, their net long bond positions tend to decline—a pattern consistent with interest rate hedging. However, the relationship is not one-to-one. This may reflect two factors. First, bond transactions are not available at the trading desk level, so our measure of bond activity may capture trades unrelated to hedging, such as those for client intermediation and regulatory requirements. Second, dealers may use other instruments, such as futures, to hedge their interest rate exposures.

of dealers' receive-fixed positions by approximately GBP 0.5 billion, while a simultaneous 10 bps decline in long-tenor spreads would reduce swap values by roughly GBP 1.4 billion.[12] Thus, dealers are significantly exposed to fluctuations in local (maturity-specific) demand and swap spreads.

3. Estimating Demand Elasticities of End Users

In this section, we exploit plausibly exogenous variation in swap spreads to estimate end-users' demand elasticities. These estimates form an important input to our model calibration, as they determine whether demand shocks are primarily absorbed through changes in hedging costs (if investors are inelastic) or through changes in quantities (if investors are elastic). Consistent with the literature, we focus on swap spreads as the relevant measure of price, rather than fixed rates, as they measure the relative attractiveness of swaps over comparable bonds and allow us to net out the component associated with bond yields.

3.1. Empirical Design

Estimating demand elasticities is challenging due to simultaneity bias, as prices and quantities are jointly determined in equilibrium. To address this challenge, we exploit a unique feature of the swap market known as "portfolio compression" as an instrument that shifts the supply curve independently of demand conditions by easing dealers' balance sheet constraints.

The main idea comes from the fact that under the Current Exposure Method of Basel III, dealers' leverage ratio requirements are based on the gross notional size of outstanding derivatives (Haynes and McPhail, 2021).[13] Portfolio compression is a common practice by which a central clearing house (LCH Ltd. in the UK) identifies and compresses offsetting trades among its member institutions (LCH Ltd, 2023). For dealers, this means consolidating offsetting derivatives into a

[12] As of February 1, 2022, dealers paid fixed on GBP 75 billion in long-tenor swaps with a duration of 18, resulting in an exposure of GBP 1.4 billion (75 billion $\times$ 18 $\times$ 10/10,000) for a 10 bps shift in the yield curve. On the same day, they received fixed on GBP 200 billion in short-tenor swaps with a duration of 2.5, resulting in an exposure of 0.5 billion (200 billion $\times$ 2.5 $\times$ 10/10,000) for a 10 bps shift in the yield curve.

[13] Exposure calculations rely on replacement costs and potential future exposure—both of which increase with gross notional (Haynes and McPhail, 2021). While gross notional of derivatives is considered under the Current Exposure Method, duration-adjusted effective notional is considered under the Standardized Approach for Counterparty Credit Risk calculations (Basel Committee on Banking Supervision, 2023).

single trade that preserves their net exposures while reducing gross notional outstanding. Compression, by lowering gross notionals, therefore helps ease dealers' regulatory capital requirements and allows them to intermediate at lower costs (Duffie, 2018, ISDA, 2012). The scale of compression activity has been large. For example, from January 2016 to December 2019, the LCH estimates compressing close to $2,700 trillion in gross notionals (LCH SwapClear, 2023).

Two features of compression are important for identification. First, only trades with matching cash flow dates are eligible for compression. This means that variation in changes in compression is driven by the random matching of cash flow dates of new swaps with the dealer's existing portfolio. This generates plausibly exogenous variation that is unrelated to contemporaneous shifts in end-user demand or macroeconomic shocks. Second, dealers opt in through a one-time sign-up, after which eligible trades are automatically compressed according to the LCH's preset schedule.[14] This limits dealers ability to directly influence the volume of compression activity.

Measurement of compression. We leverage our transaction-level data to estimate the number of compressed trades outstanding on a given date. We then construct a dealer-level weekly time series of the ratio of compressed trades relative to the total number of outstanding trades, which we refer to as "Compression ratio."[15] Table 5 provides summary statistics, as well as the characteristics of compressed trades. The average Compression ratio is about 19%, with a standard deviation of 15%. While it is possible that two entities bilaterally compress their trades without involving a clearing house, Table 5 shows that 99.8% of compressed trades face LCH Ltd, confirming that discretionary bilateral compression does not drive variation in our compression measure.

We construct our panel aggregating the net positions of a dealer across all its clients, separately for each maturity group, at a weekly frequency. We aggregate by maturity for two reasons. (i) From a dealer's perspective, asset prices are determined by aggregate demand imbalances within a maturity group, rather than individual client trades. Moreover, since end users within a given sector largely trade within specific maturity groups, estimating elasticities at the maturity group

[14] US and EU regulations require large dealers to compress trades periodically (Ehlers and Hardy, 2019).

[15] We observe whether a trade results out of compression activity, rather than the actual gross notional of trades that were compressed. We expect the resulting number of compressed trades to strongly correlate with the scale of compression activity.

level effectively captures sector-wide elasticities. This approach also aligns with the formulation in the model. (ii) Positions and trading behavior are relatively homogeneous *within* end-user sectors (Figure 3), so aggregating at the sector level does not overlook significant within-sector variation that would affect prices. We construct a weekly time series to exploit high-frequency variation in compression and prices, leveraging LCH Ltd.'s weekly compression runs to strengthen the instrument's explanatory power. A weekly frequency also reduces the likelihood of end users switching dealers within such short intervals. To focus on active market participants, we restrict the sample to dealers for whom we observe prices in at least 90% of the weeks.

Two-stage least squares regression. Using compression ratio as an instrument, we estimate the following two-stage least squares regression.

$$\text{First stage:} \quad \Delta\text{Swap Spread}^m_{i,t} = \gamma^m \Delta\text{Compression ratio}_{i,t} + \text{Controls} + \alpha_i + \alpha_t + v_{i,t}. \tag{7}$$

$$\text{Second stage:} \quad \Delta q^m_{i,t} = \beta^m \Delta\widehat{\text{Swap Spread}}^m_{i,t} + \text{Controls} + \alpha_i + \alpha_t + \varepsilon_{i,t}. \tag{8}$$

The first stage regresses the change in notional-weighted swap spreads offered by dealer i in week t on the change in dealer i's Compression ratio. We estimate this model separately for each maturity group, m, because the directional impact of compression on swap spreads, γ, depends on the dealer's net position in that maturity. We control for changes in the net position facing the dealer in the previous week, and include dealer and time fixed effects. In robustness checks, we control for the dealer's balance sheet characteristics, such as assets and capital ratios, as well as changes in the level and volatility of yields. In the second stage, we examine the extent to which (instrumented) swap spreads affect net client position facing the dealer in a given maturity group.

Since dealers *pay* fixed rates in long-dated swaps, opposite of PF&I, we expect more compression activity (i.e., a decrease in balance sheet costs) to *increase* swap spreads in the longest maturity group ($\gamma^m > 0$). This is because dealers would be willing to accept these positions at worse terms, i.e. pay a higher rate. Similarly, dealers *receive* fixed rates in shorter maturities, opposite of banks and corporations. An increase in compression activity should lead to *lower* swap spreads ($\gamma^m < 0$) as dealers would be willing to accept a lower rate. In other words, an increase in compression ratio “lowers” the price faced by end users.

Table 6 (Panel A) reports the results of estimating Equation 7 for the two primary maturity groups (short and long) which reflect the demand of the main end-user sectors (banks and corporations, and PF&I, respectively).[16] The first stage coefficient γ^m is statistically significant (at the 99% level) with a high F-statistic, showing that the relevance condition holds strongly. Moreover, the sign of γ^m is consistent with compression easing dealers' balance sheet constraints, as described above. An increase in compression significantly reduces swap spreads in the short maturities, where dealers receive fixed rates, and increases them in long maturities, where they pay fixed rates. For example, a 10 pp increase in Compression ratio is associated with 3.7 bps decrease in swap spreads for short maturities, and about 4 bps increase in swap spreads for long maturities.

3.2. Instrument Exogeneity

Our identifying assumption is that changes in the compression ratio affect swap demand solely through their impact on swap spreads. We discuss the validity of this assumption below.

Concern 1: Demand shifts. One potential threat to identification arises when demand shifts lead to increased compression. To understand the nature of such shifts, consider a dealer with an existing imbalance. Notice first that one-sided demand affect compression only when they offset the dealer's existing positions within the same maturity group. Since dealers are net pay-fixed in the long maturity group, then additional PF&I pay-fixed demand (receive-fixed for the dealer) would increase compression, whereas more receive-fixed trading would not. If PF&I indeed increase pay-fixed trading, we would observe both higher compression and increasing swap spreads, resulting in a positive γ^m in the long maturity group. However, this may violate the exclusion restriction as the correlation reflects demand pressures rather than supply. Note that we also estimate a negative γ^m for the short maturity group. For a demand-driven explanation for both patterns, banks would need to simultaneously increase offsetting receive-fixed positions in short maturities. In sum, our

[16] We focus attention on maturity groups 2 and 4 because they reflect the demand of the main end users we are interested in. Further, dealers' net positions are not consistently in one direction in the first maturity group (Figure 4), implying that it is not entirely obvious how to sign the first-stage coefficient. Finally, end-user positions in the third maturity group mainly reflect long-tenor swaps whose maturity has decayed over time and Table 4 confirms that the third maturity group is not a preferred habitat for any sector.

identification is threatened only if demand shifts across maturity groups are both concurrent and offsetting, as might occur during episodes of elevated market volatility.

However, several institutional features mitigate this concern. First, to be compressed the settlement dates of cash flows on new trades must match those of existing trades. Even if there are aggregate shifts in end-user demand, the matching of cash flow dates at the dealer level is likely to be largely random, thus creating plausibly exogenous cross-dealer variation in changes in compression activity. Second, end-user demand would pose a threat to identification only if a dealer's compression activity were primarily driven by trades with their own clients. In practice, however, compression is largely driven by inter-dealer transactions and executed through multilateral netting across many counterparties (Table 5). This structure introduces variation in a dealer's compression ratio that is largely independent of their own clients' behavior.

Consistent with these features, Table B4 shows that variables typically associated with shifts in end-user demand are uncorrelated with compression activity. (i) Compression ratio cannot be predicted by past net imbalance in any maturity group. (ii) Macroeconomic factors (e.g., level or volatility of interest rates) could also affect end user demand. However, these factors also do not predict Compression ratio. Nevertheless, our empirical specifications control for dealers' past net imbalances, as well as time fixed effects to account for market-wide macro factors.

Concern 2: Dealer strategic behavior. Another threat to identification could be that dealers strategically use *non-price* incentives (e.g., lower collateral requirements on bilaterally cleared trades) to attract offsetting trades that increase compression, overstating demand elasticities.[17] However, the institutional arrangement underlying the compression process weakens dealers' ability to influence the extent of compression. For example, even if dealers elicit trades that offset their existing positions directionally, they have little control over the cash flow settlement dates which ultimately influences the eligibility of trades to compress. Second, compression occurs on fixed schedules set by central clearing, constraining dealers' ability to time or selectively influence which trades are compressed. For example, LCH SwapClear platform automatically identifies trades el-

[17] It is important to note that if a dealer improves *prices* to attract offsetting trades, thereby enabling greater compression, our elasticity estimates remain unbiased.

igible for compression and runs multiple weekly cycles to cancel gross positions of each member institution across a range of counterparties. Importantly, Table B4 shows that the compression ratio is not explained by standard measures of dealers' past balance sheet constraints, such as changes in total assets or regulatory capital ratios.

Concern 3: End-user switching. Our estimates could also be affected if end users switch dealers in response to price changes. For example, if a dealer improves prices as a result of compression and end users quickly switch dealers, then we will over-estimate the elasticities. This is because the new quantities facing the dealer will be higher, arising from both existing as well as new clients. However, Table 7 shows that even at a monthly frequency, the vast majority of end-user trading occurs with a single dealer. Since we estimate elasticities at a weekly frequency, this further reduces the likelihood of dealer switching over such short intervals.

3.3. Demand Elasticity Estimates

Panel B of Table 6 reports the estimated elasticities. We find that $\beta^m > 0 \; \forall m$. A positive β coefficient implies a downward-sloping demand curve, indicating that as swap spreads rise, end users reduce their net pay fixed positions (or equivalently, increase their net received fixed positions). Importantly, there is significant heterogeneity in the estimated elasticities across maturity groups. For example, end users in short maturities (banks, funds, and corporations) increase their net receive fixed position by about 8%, in response to a 10 bps increase in swap spreads. However, end users in long maturities (PF&I) are significantly less elastic: they increase their net receive fixed position by 3.5 times less for a similar 10 bps increase in swap spreads, with wider confidence intervals. The lower elasticity of PF&I could potentially be explained by their stronger preference for swaps over bonds due to funding ratio constraints (Klingler and Sundaresan, 2019) as well as a shortage of long-dated government bonds in European countries (Du et al., 2023).

Table B5 provides several robustness of these results. We obtain similar estimates when we add controls for yield changes, volatility of rates, and dealers' balance sheet characteristics. We also provide estimates for the period excluding significant bond market volatility, such as March 2020 (COVID-19 crisis) and September 2022 (UK gilt crisis). The estimates are highly similar to the ones we obtain for the full sample period.

While the second stage estimates for end users in the second maturity group are strongly statistically significant, we note that our elasticity estimates for PF&I are somewhat imprecise. Notwithstanding the imprecision, this exercise allows us to anchor the elasticities to empirical estimates obtained from the data. In the model calibration detailed below, we account for the wider confidence intervals by drawing demand elasticities from the entire *distribution* of our full sample estimates in Table 6 rather than using just the point estimates.

4. Model and Calibration

In this section, we calibrate a structural model of the interest rate swap market. The model has two objectives. First, it helps quantify how demand imbalances, arising from different end-user sectors, interact with dealers' constraints to determine the term structure of swap spreads. Second, the model allows us to conduct a series of counterfactual policy experiments to study the impact of demand shifts on end users' hedging costs. We begin by outlining the model setup and parameter calibration, followed by a decomposition of the resulting equilibrium prices. Section 5 discusses the role of the distribution of demand imbalances and our counterfactual experiments.

4.1. A Preferred Habitat Model for Interest Rate Swaps

Motivated by the fact that end-users exhibit strongly segmented demand and trade in only one maturity group, we adapt the preferred-habitat framework of Vayanos and Vila (2021) to the swap market. Time is continuous $t \in [0, \infty)$. The maturities of swaps lie in $(0, \infty)$.

Preferred-habitat investors. End users are modeled as preferred-habitat investors, who demand swaps of a specific maturity and only trade swaps of that maturity.[18] We empirically verify this is true for most end users, including PF&Is, corporations, and banks. Following Vayanos and

[18] It is possible that some funds, following specific trading strategies, specialize in a specific maturity group. We consider such funds to be preferred-habitat as well.

Vila (2021), we specify end-users' demand in maturity τ as:

$$Q_t(\tau) = -\alpha(\tau) log(P_t(\tau)) - \theta_0(\tau) - \sum_{k=1}^{K} \theta_k(\tau)\beta_{k,t}. \tag{9}$$

There are three components of demand. First, demand is a function of swap spreads, $P_t(\tau)$, which represent the relative price of swaps compared to bonds, with $\alpha(\tau)$ denoting the corresponding demand elasticities.[19] We specify the demand for swaps as a function of swap spreads for two reasons. (i) End users can choose to hedge their interest rate risk either in the cash or the swap market, and swap spreads capture the relative attractiveness of swaps over bonds. For example, demand for swaps would be weaker if they are more expensive relative to bonds of similar maturity. (ii) Swap spreads help net out the direct impact of interest rate changes on end users' demand. We denote by $s_t(\tau)$ the swap spread of swaps with maturity τ at time t. The corresponding price $P_t(\tau) \equiv \exp(-\tau s_t(\tau))$ captures the value of a fixed stream of payments in the swap contract *relative to* the value of a government bond with the same maturity.[20]

Second, we incorporate a demand pressure term, captured by the intercept $\theta_0(\tau)$, to reflect end-users' underlying need for swaps. Third, demand varies over time in response to shifts in an aggregate demand factor $\beta_{k,t}$. End users in different maturity groups may be exposed to similar demand shocks, such as the level of interest rates, but the extent to which they are affected could be different, as captured by the sensitivity of their demand to the aggregate factor $\theta_k(\tau)$. For example, Table 2 suggests that banks and PF&Is react to interest rate changes in opposite directions. Finally, if $Q_t(\tau) > 0$, end users are receiving fixed; otherwise, they are paying fixed.

We do not explicitly model end-users' joint demand for both swaps and government bonds due to the absence of comprehensive data on their bond holdings. Instead, we focus on modeling end-users' demand for swaps as a function of swap spreads. This approach is equivalent to assuming that the own-price elasticity of swap demand is equal in magnitude to the cross-price elasticity with

[19]Factors such as convenience yield may affect the pricing of government bonds. However, given that the government bonds are the most relevant substitutes for interest rate swaps, it is still the relative price, i.e, swap spreads, that matters for investors' demand for swaps.

[20]To see this, denote the fixed rate in the swap contract by $y_F(\tau)$; the present value of this fixed stream of payments is $P_F = \exp(-\tau y_F(\tau))$. Similarly, denote the yield of a zero-coupon government bond by $y_T(\tau)$; its price is then $P_T = \exp(-\tau y_T(\tau))$. Under $P \equiv P_F/P_T$, $P = \exp(-\tau(y_F(\tau) - y_T(\tau))) = \exp(-\tau s(\tau)))$.

respect to bond prices — that is, a decrease in swap prices or an increase in bond prices would both lead to higher demand for swaps. We find this the most natural and tractable assumption absent detailed bond position data. Under this formulation, any determinants of swap demand beyond the swap spread itself are captured by the residual demand shifters $\theta_k(\tau)\beta_{k,t}$.

Arbitrageurs. Arbitrageurs are risk-averse agents who trade *across* maturities without a preference for specific maturities. Arbitrageurs can include dealers as well as certain funds who engage in cross-maturity arbitrage strategies. Following the literature, and the empirical evidence in Table B3, we assume that arbitrageurs are specialized intermediaries who hedge the interest rate risk exposure of their swap positions using other instruments, e.g., government bonds (Du et al., 2023, Hanson et al., 2024). This is also consistent with recent findings that dealer desks bear little market risk (Wallen and Lu, 2024). As a result, the primary risk that arbitrageurs face is the convergence risk of swap spreads. Specifically, when receiving fixed in short maturities and paying fixed in long maturities, arbitrageurs face the risk that relative swap spreads may diverge, negatively impacting the value of their swap positions.

We assume that arbitrageurs face a cost c_t at time t for each unit of swap held. The cost captures funding market frictions and balance sheet costs associated with holding swaps, and may arise from multiple sources. Most importantly, c_t captures the difference between the short-term floating rate referenced by the swap and the short-term financing rate available to dealers to fund the bond positions required to hedge their interest rate risk. This funding cost is linear in the net notional amount of swaps held and is maturity-independent. Second, c_t also partially captures the balance sheet costs of holding government bonds (Bicu-Lieb et al., 2020, He et al., 2022, Du et al., 2023). Third, a sizable share of client-facing swaps are not centrally cleared (Cenedese et al., 2020), requiring dealers to hold costly capital against counterparty risk. Finally, these costs would also apply to situations where hedge funds, and not dealers themselves, act as arbitrageurs. Since hedge funds often obtain funding from dealers, dealers' balance sheet costs would get passed on to hedge funds in the form of higher funding costs. Depending on the specific regulatory framework, it is possible that the funding cost may apply to absolute notional amounts or may vary with contract maturity. While real-world frictions are more complex, our specification offers a tractable first-order approximation to the marginal cost dealers face in expanding intermediation.

Arbitrageurs maximize a mean-variance objective over instantaneous changes in wealth dW_t. We denote the arbitrageurs' swap positions in maturity group τ as $X_t(\tau)$. Thus, dW_t can be expressed as

$$dW_t = \int_0^{\infty} X_t(\tau) \left(\frac{dP_t(\tau)}{P_t(\tau)} - c_t \right) d\tau + W_t r_t dt \tag{10}$$

where $\frac{dP_t(\tau)}{P_t(\tau)}$ is the return from holding swaps of maturity τ and r_t is the return from the arbitrageurs' outside option. Arbitrageurs face two sources of risk. On the demand side, shifts in swap demand from end users can turn the mark-to-market value of existing positions negative. For example, if PF&Is increase receive fixed demand, long maturity swap spreads may decline and, without a corresponding change in the short maturity swap spreads, arbitrageurs would face a loss. This relative change in the term structure of swap spreads can impact arbitrageurs' wealth even when the underlying interest rate risk in each maturity τ is hedged. On the supply side, arbitrageurs are exposed to time-varying shocks in funding costs, which introduce additional unforeseen costs to holding swaps. The arbitrageur's problem is

$$\max_{\{X_t(\tau)\}_{\tau=0}^{\infty}} \left[\mathbb{E}_t(dW_t) - \frac{a}{2} Var\left(dW_t\right) \right] \tag{11}$$

where $a \geq 0$ is the arbitrageur's risk aversion coefficient, reflecting regulatory constraints or internal risk limits that restrict risk-taking. Arbitrageurs benefit from differences in swap spreads in different maturities, but face both demand and supply-side risks that get reflected in equilibrium prices.

Dynamics and market clearing. The state variables can be represented by a $(K+1)\times 1$ vector $g_t \equiv (c_t, \beta_{1,t}, ..., \beta_{K,t})^{\top}$. We assume that g_t is stationary and follows the process

$$dg_t = -\Gamma(g_t - \bar{g})dt + \Sigma dB_t \tag{12}$$

$$\bar{g} \equiv \left(\bar{c}, 0, ..., 0 \right)^{\top} \tag{13}$$

where Γ and Σ are constant $(K+1) \times (K+1)$ matrices; dB_t is a $(K+1) \times 1$ independent Brownian motion.[21] Γ governs the speed of mean-reversion and Σ governs the variance and covariance of shocks. Furthermore, $\bar{c}$ denotes the average funding cost for arbitrageurs. Note that arbitrageurs can hold either positive or negative amount of swaps; we verify in our estimation that the net funding cost for arbitrageurs is indeed positive.

Finally, swaps of any given maturity are in zero-net supply. The market clearing condition is

$$X_t(\tau) + Q_t(\tau) = 0, \qquad \forall \tau > 0. \tag{14}$$

Equilibrium characterization. We first guess that the relative price of swaps with maturity τ takes the form

$$P_t(\tau) = \exp[-(A(\tau)^\top g_t + C(\tau))] \tag{15}$$

where $A(\tau)$ is a $(K+1) \times 1$ matrix, and $C(\tau)$ is simply a constant. The first element of $A(\tau)$ captures the price's sensitivity to the supply factor c_t, and the other elements of $A(\tau)$ capture the price's sensitivity to the K demand factors.

Using the arbitrageur's first order conditions and setting $K = 1$, we can characterize $A(\tau)$ and $C(\tau)$ in a set of differential equations, as presented below.

$$\Gamma^\top A(\tau) + A'(\tau) - \begin{pmatrix} 1 \\ 0 \end{pmatrix} - a \left[\int_0^\infty \left(\theta(\tilde{\tau}) \begin{pmatrix} 0 \\ 1 \end{pmatrix} A(\tilde{\tau})^\top - \alpha(\tilde{\tau}) A(\tilde{\tau}) A(\tilde{\tau})^\top \right) d\tilde{\tau} \right] \Sigma\Sigma^\top A(\tau) = 0 \tag{16}$$

$$A(\tau)^\top \Gamma \begin{pmatrix} -\bar{c} \\ 0 \end{pmatrix} + \frac{1}{2} A(\tau)^\top \Sigma\Sigma^\top A(\tau) + C'(\tau) - a A(\tau)^\top \Sigma\Sigma' \int_0^\infty \left(-\alpha C(\tilde{\tau}) + \theta_0(\tilde{\tau})\right) A(\tilde{\tau}) d\tilde{\tau} = 0 \tag{17}$$

The boundary conditions are $A(0) = 0$ and $C(0) = 0$. We provide derivations in Appendix E.

[21]It is without loss of generality to assume that the demand factors, $\beta_{k,t}$, have mean zero.

4.2. Calibration Methodology

Discretization. To bring the model to the data, we discretize the maturity space into M maturity groups, separated by a sequence of break-points $m(0) \equiv 0 < m(1) < m(2) < ... < m(M-1) < m(M) \equiv \infty$. With a slight abuse of notation, we use τ to denote the maturity group, $\tau \in \{0, 1, ..., M-1\}$. A swap belongs to maturity group τ if its maturity is in $[m(\tau), m(\tau+1))$. We denote the average maturity of swaps in group τ by $\bar{m}(\tau)$.

We consider a discretized term structure for two reasons. First, it allows us to estimate end-users' demand in each maturity group non-parametrically. We do not impose any parametric assumptions on demand side parameters $\theta_0(\tau)$ and $\theta_k(\tau)$. We allow the calibration exercise to uncover the underlying demand parameters, and find that the signs are consistent with the direction of demand given the types of end users trading in each maturity group and the empirical counterparts reported in Section 2. Second, the preferred-habitat investor assumption is more likely to hold for a given maturity group than for a specific maturity point.

Denote $s_t(\tau)$ as the average swap spread in maturity group τ, and $X_t(\tau)$ as the total swap holdings by the arbitrageurs in maturity group τ. Furthermore, the relative price of the swap can be written as $P_t(\tau) = \exp(-\bar{m}(\tau)s_t(\tau))$. Finally, we define $\delta(\tau) \equiv \frac{1}{\bar{m}(\tau)-\bar{m}(\tau-1)}$, which is the probability that a swap in maturity group τ transitions to maturity group $\tau - 1$ in the next period. The discrete versions of Equation 16 and Equation 17 become

$$\Gamma^\top A(\tau) + [A(\tau) - A(\tau-1)]\delta(\tau) - \begin{pmatrix} 1 \\ 0 \end{pmatrix} = a\left[\sum_{\tilde{\tau}} \left(\theta(\tilde{\tau}) \begin{pmatrix} 0 \\ 1 \end{pmatrix} A(\tilde{\tau})^\top - \alpha(\tilde{\tau})A(\tilde{\tau})A(\tilde{\tau})^\top\right)\right]\Sigma\Sigma^\top A(\tau)$$

$$A(\tau)^\top\Gamma \begin{pmatrix} -\bar{c} \\ 0 \end{pmatrix} + \frac{1}{2}A(\tau)^\top\Sigma\Sigma^\top A(\tau) + [C(\tau) - C(\tau-1)]\delta(\tau) = aA(\tau)^\top\Sigma\Sigma'\sum_{\tilde{\tau}}\left(-\alpha C(\tilde{\tau}) + \theta_0(\tilde{\tau})\right)A(\tilde{\tau})$$

for all $\tau \geq 1$. Furthermore, the boundary conditions translate to $A(0) = C(0) = 0$.

Maturity groups. We specify the number of maturity groups $M = 5$, with $m(1) = 0.05$, $m(2) = 0.25$, $m(3) = 5$ and $m(4) = 10$.[22] Under this definition, the preferred-habitat assumption holds

[22] We need a near-zero maturity group for the boundary conditions. We take $m(1) = 0.05$ as an approximation for this near-zero tenor.

for most end users, who primarily trade within a single maturity group, as shown in Table 4. Specifically, funds dominate the "ultra short" maturity group one (below 3 months), while "short" maturity group two (3 months to 5 years) includes banks, corporations, and funds.[23] In contrast, the dominant end users in the "long" maturity group (10 years & above) are PF&I. For the first four maturity groups, we set $\bar{m}(\tau)$ to be the mid-maturity in the interval. For the last maturity group, we set $\bar{m}(\tau)$ to be 25, which is the empirically observed notional-weighted average maturity of swaps in that group. The parameters for the maturity groups are summarized in Table 8.

Demand factor. We consider one aggregate demand factor, i.e., $K = 1$. This implies that we have two aggregate shocks in total, one for the supply side and one for the demand side. We refer to the shocks to arbitrageurs' funding cost c_t as supply shocks, and shocks to the demand factor, $\beta_{1,t}$, as demand shocks. We do not take a stance on exactly what the demand factor is. The reduced form evidence in Table 2 suggests the demand factor is related to the level of the interest rate. Importantly, we do not impose any assumptions on Σ, which means that we allow contemporaneous supply and demand shocks to be potentially correlated.

Demand elasticities. We leverage the estimated distributions of the coefficients from Table 6 to pin down the demand elasticities for the end users in different maturity groups. Specifically, for each maturity group τ ($\tau = \{1, 2, 3, 4\}$), we draw an estimate from the empirical distribution in Table 6 and compute the demand elasticity $\alpha(\tau)$ accordingly.[24] For each set of coefficients drawn, we calibrate the other parameters by targeting the moment conditions, and then compute the counterfactual effects described in the next section. Since we have a distribution of counterfactual effects, we report the mean and the 90% confidence interval. Although we primarily focus on maturity groups two and four, where most of the end users are, for completeness, we also estimate and input the elasticities of maturity groups one and three using the same instrument as before.

[23] It is possible that ultra short-tenor swap spreads (below 3 months) may be primarily driven by policy rates, more than by demand-supply imbalances (Klingler and Sundaresan, 2023). We include ultra short-tenor swaps in our analysis for completeness, as excluding this maturity group would exclude a vast majority of funds' positions (Table 4). Nonetheless, Figure B5 confirms that re-defining the maturity groups to drop ultra short-tenor swaps does not materially affect the observed swap spread patterns.

[24] The empirical distribution of the coefficient has mean equal to the point estimate, and standard deviation equal to the standard error in Table 6. We truncate the coefficients at zero.

Parameter estimation using method of moments. We calibrate a total of 16 parameters in the model by matching a set of model-generated moments with the corresponding empirical moments. We estimate $2 \times (M-1) = 8$ demand side parameters (θ_0 and θ_1 for maturity groups 1-4). We set the demand side parameters for group 0 to 0. We do not impose any assumptions on the demand parameters of the other groups. On the supply side, we need to calibrate the average funding cost $\bar{c}$ and the risk aversion coefficient a. Next, we calibrate the speed of mean reversion of the two state variables, captured in the Γ matrix. We assume that Γ is a diagonal matrix, i.e., the predictable components of the change in the demand factor and dealers' funding cost depend only on their own lag. Finally, we estimate 4 parameters in the Σ matrix, which includes the loadings on the Brownian shocks to the two state variables.

We construct the empirical moments using monthly data on swap holdings and daily flow of new transactions. We calculate swap spreads for each maturity group using the actual fixed rate observed in our data for new transactions between end users and dealers, and subtract from it the bond (gilt) yield of equivalent maturity. Then, we aggregate the swap spreads to a monthly frequency using a notional-weighted average.[25] We define quantities, Q_t, as in Equation 1.[26] We define changes in quantity, as in Equation 4, as

$$\Delta q_t = \frac{Q_t - Q_{t-1}}{(|Q_t|+|Q_{t-1}|)/2}. \tag{18}$$

To calibrate the parameters, we first target the volume-weighted average swap spreads and the average net notional held by end users in our sample period. These moments are informative about the level of the hedging needs $\theta_0(\tau)$. We then target a set of second moments related to price and quantity changes. We target the variances of swap spreads changes ($\Delta s_t(\tau)$) and the variances of scaled quantity changes ($\Delta q_t(\tau)$) for maturity groups 1-4. The dynamics of spreads and quantities

[25]Some trades erroneously report the fixed rate in terms of basis points instead of percentage points. We benchmark the fixed rate in our data with the maturity-matched daily market overnight indexed swap (OIS) fixed rate sourced from the Bank of England yield curve database. We retain trades where the difference between our fixed rate and the market OIS rate falls within 2.5% to 97.5% of its distribution.

[26]To capture each end user's behavior within its preferred habitat, we include only the quantities and prices corresponding to its dominant maturity group. Some large pension funds operate in-house investment management arms; for these entities, we include only their positions in the long maturity group.

are informative about the law of motion of the supply and demand factors, as well as different sectors' exposure to the demand shock. We summarize the empirical moments in Table 9. The exact expressions for the model counterparts are presented in Appendix E.

Sample splits. We calibrate the model for the full sample, and also separately for two subsamples using the same set of moment conditions described above. The Bank of England began raising interest rates sharply in early 2022, followed by periods of quantitative tightening. These shifts in the macroeconomic environment could influence both end-user demand and dealers' supply-side constraints. Concurrently, the shape of the swap spread curve also evolved significantly over time. Motivated by these patterns, we split the sample into two periods: Dec 2019–Dec 2021 (low-rate environment) and Jan 2022–Jun 2024 (high-rate environment).

Simulated vs. empirical moments. Figure 5 shows the fit between the empirical and the model-implied price and quantity moments. The model captures the average spreads and quantities across maturity groups well. In the full sample, the swap spreads have a downward-sloping pattern: they decrease from 10 bps in the first maturity group to negative 78 bps in the fourth maturity group. In contrast, in the first subsample, swap spreads have a hump-shaped pattern. We find that the model implied spreads closely align with these patterns. In terms of quantities, both in the model and in the data, on average, end users in groups one and four receive fixed, and end users in group two pay fixed. Note that group three has little outstanding amount because it is not a preferred habitat for any of the end user sectors. Table 9 reports the remaining empirical moments, which are also broadly consistent with the model implied moments.

4.3. Calibrated Parameters

4.3.1. Full Sample

Table 10 column (1) shows the calibrated parameters for the full sample. First, we estimate that $\theta_0(4) < 0$ and $\theta_0(2) > 0$, indicating that end users in the long maturity group (PF&Is), demand receive fixed swaps. In contrast, end users in the short maturity group (e.g., banks, corporations), demand pay fixed swaps. This is consistent with the reduced-form evidence in Section 2. Importantly, these estimates are derived without imposing any parameter restrictions during the calibration process. Second, we also find that the average $\theta_1(2)$ and $\theta_1(4)$ have opposite signs, which means that end users in the short and long maturities have opposite exposure to demand shocks. These sensitivity estimates are also qualitatively consistent with the findings in Section 2 under the interpretation that the level of interest rates is part of the demand factor. When interest rates increase, long maturity and short maturity swap users adjust their demand in opposite directions. The opposite signs of the demand intercept and the exposure to the demand factor confirm that end users trading in short maturities are natural counterparties to end users trading in long maturities. However, demand segmentation and intermediation frictions prevent them from perfectly sharing risks with each other.

On the supply side, we estimate the risk aversion parameter to be 201.29 in the full sample, which can be interpreted as risk aversion per ten billion pounds of net position. To contextualize this estimate, we benchmark it against the net equity of dealers regulated in the UK using the Common Equity Tier 1 Capital (CET1) as a proxy for capital. UK dealers on aggregate held a CET1 of about GBP 150 billion in 2023. At these capital levels, our estimated parameter translates to a relative risk aversion of about 13 (201.29×10 / 150). The arbitrageurs' average returns implied by the risk aversion estimate range from 50 bps to 1.1%, depending on the maturity group. We also estimate the average funding cost parameter for the full sample to be 1%, which closely aligns with the balance sheet cost of 81 bps in Fleckenstein and Longstaff (2020) and He et al. (2022).

4.3.2. Subsample Comparison

Table 10 columns (2) and (3) present the calibrated parameters for each subsample. Comparing the supply-side coefficients, we find that the arbitrageurs' risk aversion and balance sheet costs are significantly higher in the second subsample as compared to the first. This suggests that supply-side constraints are more binding in a monetary policy tightening environment. Our results are consistent with early evidence that intermediation constraints have tightened in the recent high rate environment (Li et al., 2024, Cochran et al., 2024).[27] As we will see in the next section, differences in supply-side frictions matter in how demand shifts affect swap spreads across the two subsamples.

[27] Industry reports from the UK also suggest increased funding cost pressures for dealers.

4.4. Decomposing the Swap Spread Curve

We next examine how different supply and demand side factors affect the level and the shape of the swap spread curve, using the full sample calibration. We isolate the effect of individual parameter estimates by setting each calibrated parameter value to zero, one at a time, and assess how the model-implied swap spreads change. Panel (a) of Figure 6 presents our results.

Funding cost. We start by removing the average funding cost for arbitrageurs by setting $\bar{c} = 0$. During our sample period, on net, arbitrageurs hold positive amount of swaps in aggregate across all maturity groups. Arbitrageurs therefore demand positive swap spreads to compensate for the funding cost incurred. Hence, setting the average funding cost $\bar{c}$ to 0 leads to an almost parallel downward shift, reducing fixed rates across all maturities by approximately 13 bps. We note that this change in the swap spreads is relatively small, compared to the average swap spreads in the data, which range from negative 80 bps to 10 bps. As a result, eliminating the average funding cost still leaves swap spreads to be significantly different from zero, because risk averse dealers continue to demand compensation for bearing demand imbalances.

Demand pressure parameters. We next shut down the demand pressure parameters by setting the intercepts of all the end users' demand to 0, i.e., $\theta_0(\tau) = 0$ for all τ. Panel (a) of Figure 6 shows that removing demand pressure essentially brings swap spreads to zero for all maturity groups. This shows that demand pressure plays a quantitatively significant role in driving the level and the shape of the swap spread curve.

Demand and supply shocks. Similarly, setting the demand shocks to 0, i.e., $\beta_{1,t} = 0$, reduces the swap spreads for all the maturities because it reduces the risks borne by the dealer sector. Finally, shutting down the supply-side risks (i.e., unexpected changes in funding costs), collapse swap spreads to zero, which is the frictionless equilibrium case.

Arbitrageurs' risk aversion. We note that the pronounced effect of demand pressure on swap spreads hinges on dealers being risk averse, which amplifies the price impact of demand imbalances. Our calibration implies a relatively high risk aversion coefficient, implying that local demand shocks in specific maturity groups lead to substantial spread adjustments. Conversely, when a approaches zero, this amplification effect is reduced and demand pressure has limited impact on spreads. To illustrate the role of dealers' risk aversion, we simulate a scenario where a is reduced by half. As shown in panel (b) of Figure 6, this leads to a material compression in spreads: +5 bps at short maturities and +35 bps at long maturities. These results demonstrate that less risk-averse arbitrageurs are willing to intermediate demand imbalances at lower cost, reinforcing the idea that swap spread dynamics emerge from the interaction between end-user demand and dealers' risk-bearing capacity.

5. Demand Imbalances and the Term Structure of Swap Spreads

We now turn to a more detailed analysis of how the distribution of demand imbalances across maturities affects the shape of the swap spread curve. This question is inherently challenging, as demand imbalances are endogenously determined in equilibrium, making it difficult to isolate their impact. To address this issue, we use our calibrated equilibrium framework to simulate counterfactual scenarios that vary the size and the composition of imbalances across maturities.

We proceed in three steps, combining qualitative intuition with quantitative analysis. First, we examine two polar cases to illustrate that the distribution of demand imbalances is a key determinant of the shape of the swap spread curve. This provides intuition for how the positions of different end-user sectors influence pricing across maturities. Second, we turn to a quantitative analysis, estimating how changes in one sector's demand, which alters the overall distribution of imbalances, affect the hedging costs faced by other sectors. In particular, we quantify how increased PF&I demand impacts banks' hedging costs, and vice versa, highlighting the potential cross-sector externalities of sector-specific regulation. Finally, to assess the impact of market segmentation, we explore a counterfactual scenario in which PF&Is reallocate part of their demand toward shorter maturities, and analyze how this shift alters the term structure of swap spreads.

5.1. Does the Distribution of Demand Imbalances Matter?

To assess the impact of changes in the distribution of demand imbalances, we alter the demand of specific end-user sectors, and examine the resulting effects on swap spreads. Specifically, we simulate counterfactual scenarios that vary the size and the composition of imbalances in two key maturity groups (short and long). To do so, we set the demand pressure term, θ_0, to zero for each maturity group one at a time, keeping all the other parameters unchanged. This yields two polar scenarios. In the first scenario, we set $\theta_0(2) = 0$, i.e. we shut down the demand pressure term for end users in the second maturity group (e.g., banks).[28] In the second scenario, we set $\theta_0(4) = 0$, i.e. we assume that end users in the fourth maturity group (PF&I), have no demand pressure. For each scenario, we compute the counterfactual swap spreads for all maturity groups. Figure 7 shows the counterfactual swap spreads compared to the actual swap spreads.

When banks' demand pressure is zero. Our first result highlights the role of banks' demand in explaining the term structure of swap spreads. When banks' demand pressure is zero, swap spreads turn more negative across maturities, with the most pronounced effect occurring in the long maturity group. Intuitively, banks' swap demand offsets a part of PF&I positions because banks trade in the opposite direction. This reduces the aggregate net risk borne by dealers. However, in the absence of bank demand (i.e., zero demand pressure in maturity group two), dealers are exposed to a larger demand imbalance, which increases the risk of holding long-term pay fixed positions arising from PF&I demand in the opposite direction. As a result, dealers require greater compensation for holding long-term pay fixed positions in the form of lower swap spreads. The same channel also reduces swap spreads in short-tenor swaps, albeit with a smaller magnitude due to lower riskiness of short-tenor positions.

One interpretation of these results is that they provide a benchmark for comparing UK swap spreads with those of other countries where, unlike the UK, the banking sector exhibits limited hedging demand in swaps. For example, McPhail et al. (2023) show that US banks do not hedge

[28] While maturity group two also includes funds and corporations, in addition to banks, corporate positions are small and funds hold large positions only briefly during our sample period (Figure 4). Hence, we refer to changes in maturity group two as changes in bank demand.

interest rate risk using swaps in a meaningful way. By setting the demand intercept of banks to zero, our analysis shows the counterfactual swap spreads in the absence of demand from banks. Consistent with the empirically observed negative swap spreads in shorter maturity groups in the US, as shown in Figure B1, we find that the UK swap spreads also become negative in shorter maturity groups. In other words, when we shut down the demand of UK banks, the counterfactual term structure of swap spreads start to appear closer to the observed spreads in the US. This highlights the importance of the distribution of demand imbalances in potentially explaining the relative differences in the swap spread curves across countries.

When PF&Is' demand pressure is zero. We next consider the role of PF&I demand in explaining the shape of the swap curve. When PF&I have no demand pressure for swaps, the swap spread curve becomes upward sloping with spreads turning positive across maturities. At shorter maturities, dealers now demand a higher fixed rate to supply swaps. Long-term swap spreads also rise substantially, indicating that dealers are willing to forego larger amounts to attract opposite receive fixed positions at longer maturities.

A key implication of this result is that a lower pension sector demand worsens the hedging outcomes for banks, increasing their hedging costs and lowering demand. A lower PF&I demand pressure could arise due to several factors. First, the PF&I sector in many countries may be substantially smaller relative to banks. For example, economies that are more bank-based than capital-market-based, economies with pay-as-you-go (PAYGO) pension systems, developing or younger economies could all have a smaller pension sector. Second, even in economies with a large pension and insurance sector, the availability of substitute assets (e.g., long-term bonds) could result in lower PF&I demand for swaps.[29] Finally, recent bond market turmoil has sparked discussions about reducing pension funds' use of swaps due to heightened liquidity risks (Jansen et al., 2025). These factors could affect the size of PF&I demand relative to that of banks, and as our results highlight, swap spread dynamics across maturities.

[29] For example, the UK gilt market is much smaller at \$3 trillion relative to the size of its pension sector at \$4.2 trillion (UK Debt Management Office). In contrast, the US Treasury market is valued at \$28 trillion relative to the size of its pension sector at \$24.5 trillion (Investment Company Institute, 2025).

5.2. Quantifying the Cross-Sector Spillovers

A central insight is that demand shifts in one maturity create spillovers across maturities, influencing swap spreads and thereby affecting the hedging costs (and potentially swap demand) of end users in other sectors. Building on this qualitative insight, we next quantify how demand shifts in one sector affect hedging costs and quantities for other sectors. To do so, we increase the magnitude of the demand pressure term for banks and PF&I by 20%.[30] The magnitude of the demand shock is motivated by estimates in Appendix D, which show that these sectors hedge a large but incomplete portion of their balance sheet exposures with swaps, making the exogenous demand shift considered in our analysis plausible. Figure 8 and Figure 9 plot the difference between the counterfactual and the actual swap spreads for the two subsamples. We have the following results.

Cross-sector spillovers. First, when banks demand more swaps, swap spreads rise in all maturity groups, as seen in panel (a). This means that the hedging costs *increase* for banks, since they pay fixed, but *decrease* for PF&I, since they receive fixed. Similarly, when PF&I demand more swaps, swap spreads fall in all maturity groups, as seen in panel (b). That is, the hedging costs *increase* for PF&I but *decrease* for banks. In both cases, given that banks and PF&Is have offsetting positions, an increase in one sector's demand *reduces* the hedging costs for the other.

Time-series heterogeneity. Second, comparing the magnitudes across the two subsamples, we see that the swap spread changes are much more pronounced in the second (high rate) subsample. This makes sense given the substantially higher balance sheet costs and risk aversion we estimate for the dealer sector in the second subsample. This implies that the same demand shock leads to higher swap spreads in the second subsample relative to the first subsample, highlighting how supply-side frictions amplify the pricing effects of demand imbalances.

Heterogeneity by demand elasticities. Third, we examine how demand elasticities shape the impact of demand shifts on swap spreads. Specifically, we evaluate the case where end users become 50% less elastic. We plot the changes in the swap spreads in panels (c) and (d) for the two cases: when banks' demand increase and when PF&Is' demand increase. We do so for each

[30] Note that a higher demand for banks implies a smaller $\theta_0(2)$ i.e. more pay fixed positions, while a higher demand for PF&I means a larger $\theta_0(4)$, i.e. more receive fixed positions.

subsample in Figure 8 and Figure 9. We find that a demand shift of the same magnitude has a greater impact on swap spreads when end users are more inelastic. Intuitively, when end users are less responsive to price changes, quantities adjust less, causing the demand shock to be absorbed primarily through larger adjustments in swap spreads.

Origin of demand shifts. Fourth, we evaluate whether the effect of the demand shift differs depending on where the shocks originate. Comparing panel (c) and panel (d) in Figure 8 and Figure 9, we find that the effect on swap spreads is 3-4 times larger when the demand shift occurs among PF&Is rather than banks, even though the absolute magnitude of the demand shift in maturity group four is smaller (because of lower average net positions compared to group two). Intuitively, demand imbalances in longer maturity groups expose the dealer sector to more risks, hence each unit of long-maturity demand has a larger impact on asset prices compared to the demand in short maturity swaps. Furthermore, regardless of where the demand shift originates, its impact on spreads is monotonically increasing in swaps' maturities. In both cases, the change in swap spreads in the longest maturity group is much larger than the change in the second maturity group. We conclude that the shape of the swap spreads curve reacts differently to changes in both the magnitude and the specific source of demand imbalances.

Magnitudes of the cross-sector spillovers. To illustrate the economic magnitudes, we next present a back-of-the-envelope estimate of the effect of the demand shifts on hedging costs of the various end user sectors. Panel (a) of Figure 8 and Figure 9 show that a 20% increase in banks' demand would raise swap spreads by 10 bps in the long maturity group in the first subsample and by 13 bps in the second subsample. This implies substantial savings for the PF&I sector, the primary end users in this maturity group. For example, in the second subsample, the increase in swap spreads translates to approximately GBP 2 billion ($\approx 0.13\% \times 63$ billion $\times$ 25 years) lower hedging costs over the typical life of swaps traded by this sector. In theory, part of the savings is offset because PF&I demand more swaps as hedging costs decline. However, we note that because PF&I demand is relatively inelastic, this effect is muted and the net notional exposure does not change meaningfully. The demand shock also raises swap spreads in the short maturity group by about 4 bps, thereby increasing the hedging costs for banks themselves by approximately GBP 0.16

billion ($\approx 0.04\% \times 151$ billion $\times$ 2.75 years) over the typical life of swaps traded.

On the other hand, a 20% increase in PF&I demand would reduce the swap spread faced by banks by about 11 bps and the swap spread faced by the PF&I sector by 43 bps in the second subsample. This leads to an estimated GBP 0.5 billion ($\approx 0.11\% \times 151$ billion$\times 2.75$years) reduction in hedging costs for banks. In contrast, the demand shock also reduces the swap spreads for the PF&I sector itself, increasing their hedging costs by an estimated GBP 6.8 billion ($\approx 0.43\% \times$ 63 billion $\times$ 25 years). The effects are even larger when we consider end users with more inelastic demand. For example, if end users were half as elastic as our empirical estimates suggest, then the same 20% increase in PF&I demand would lead to a GBP 0.8 billion (or 60% more) reduction in hedging costs for banks and a GBP 10.2 billion increase in hedging costs for PF&I.

5.3. Market Integration

A key friction shaping the distribution of imbalances is the mismatch in the maturities of PF&I and bank trades, which leads dealers to absorb imbalances at different maturity points along the curve. We consider a scenario where the market is less segmented, such that dealers are able to offset a larger fraction of end-user demand *within* a given maturity group. To make the swap market more integrated on the demand-side, we shift a part of the long maturity receive fixed demand to the short maturity group, and study its impact on the term structure of swap spreads. We conduct this exercise separately for both subsamples.

We consider a case where $\gamma = 20\%$ of the demand from maturity group four is moved to maturity group two. We adjust the demand parameters as follows:

$$\theta_0'(2) = \theta_0(2) + \gamma \times \theta_0(4) \qquad \theta_0'(4) = (1-\gamma) \times \theta_0(4) \tag{19}$$

$$\theta_1'(2) = \theta_1(2) + \gamma \times \theta_1(4) \qquad \theta_1'(4) = (1-\gamma) \times \theta_1(4) \tag{20}$$

$$\alpha'(2) = \alpha(2) + \gamma \times \alpha(4) \qquad \alpha'(4) = (1-\gamma)\alpha(4) \tag{21}$$

The remaining demand parameters $\theta_1'(\tau)$, $\theta_0'(\tau)$ and $\alpha'(\tau)$ for $\tau = 0, 1, 3$ are same as the baseline estimates.

Figure 10 shows that moving a part of PF&I demand to the maturity group of banks shifts the swap spread curve upwards in both the subsamples. There are two channels behind this equilibrium pricing effect. First, there is a local effect where moving part of the PF&I demand to the same group as banks reduces the demand imbalance *within* each maturity group. This leads to a narrowing of swap spreads in both the maturity groups. Second, there is a "global" effect where dealers' overall position reduces in magnitude because of a reduction in long-tenor pay fixed positions that carry much higher risk relative to an increase in the short-tenor position of equal size. This leads to an upward shift in the entire swap spread curve, reinforcing the positive impact on maturity group four but offsetting the decline in swap spreads in maturity group two. We find that the global effect dominates such that for group two, swap spreads turn slightly more positive. The effects are particularly more pronounced in the second subsample given that supply-side frictions are higher. In the second subsample, the changes in swap spreads increase the hedging cost for the banking sector by GBP 0.11 billion per year, while they decrease the hedging cost for the PF&I sector by GBP 0.27 billion per year.

Market integration can be motivated by situations where PF&I strategically shorten the maturity of their swaps to capture higher swap spreads. Another source of integration would arise from banks and PF&Is operating within the same entity. This would enable internal positions to offset, allowing the entity to manage interest rate risk on a smaller net position basis, thereby reducing overall hedging costs. As our results show, a more integrated market would substantially reduce the hedging costs borne by PF&Is, with a slightly higher hedging costs for banks. At the same time, PF&I would be exposed to rollover risk - the uncertainty about the prices that will prevail when renewing their swaps - which may be large when interest rates are volatile. The extent of market integration and cost savings would therefore depend on several factors, including the regulatory treatment of intra-group exposures, the relative balance sheet sizes of banks and PF&I, and the degree to which end users are willing to bear rollover risk.

6. Conclusion

We provide the first comprehensive cross-sector analysis of interest rate risk sharing across the financial system, using granular transaction-level data covering the near-universe of the UK interest rate swaps market. We document that PF&Is are natural counterparties to banks and corporations, with consistently offsetting swap positions. PF&I buy duration, whereas banks and corporations sell duration, which reduces the risks borne by the dealer sector. We show, however, that these end users have strong preferred habitats along the maturity dimension, which leave dealers to absorb persistent, maturity-specific demand imbalances.

To quantify the asset pricing implications of these demand imbalances, we calibrate a preferred-habitat investor model with risk-averse arbitrageurs and embed empirically estimated demand elasticities identified through a novel instrument based on portfolio compression. We show that the distribution of demand imbalances are a first-order determinant of the shape of the swap spread curve. Moreover, we find that demand shifts in one sector, potentially induced by regulatory changes such as increased hedging requirements for banks, generate economically significant spillovers on other sectors' hedging costs as local demand changes affect swap spreads across the entire curve. These spillovers are amplified further when end users are more inelastic and when dealer balance sheet constraints are more binding.

Our results can be useful in several settings. A key application of our framework is to evaluate how changes in interest rate risk regulation in one sector can spill over to other sectors by altering hedging costs and, consequently, demand. The framework also lends itself to cross-country comparisons where institutional demand for swaps may differ. For instance, demand imbalances are likely to concentrate in short maturities in countries with smaller PF&I sector, such as those with pay-as-you-go pension systems or younger populations. Conversely, differences in mortgage design or regulatory regimes may lead to lower hedging demand from banks. Our analysis reveals how the structure of demand imbalances shapes asset prices and highlights their broader significance for market functioning. The framework provides a lens to examine how sector-specific regulations, demographic forces, or institutional design influence the pricing and allocation of financial risk.

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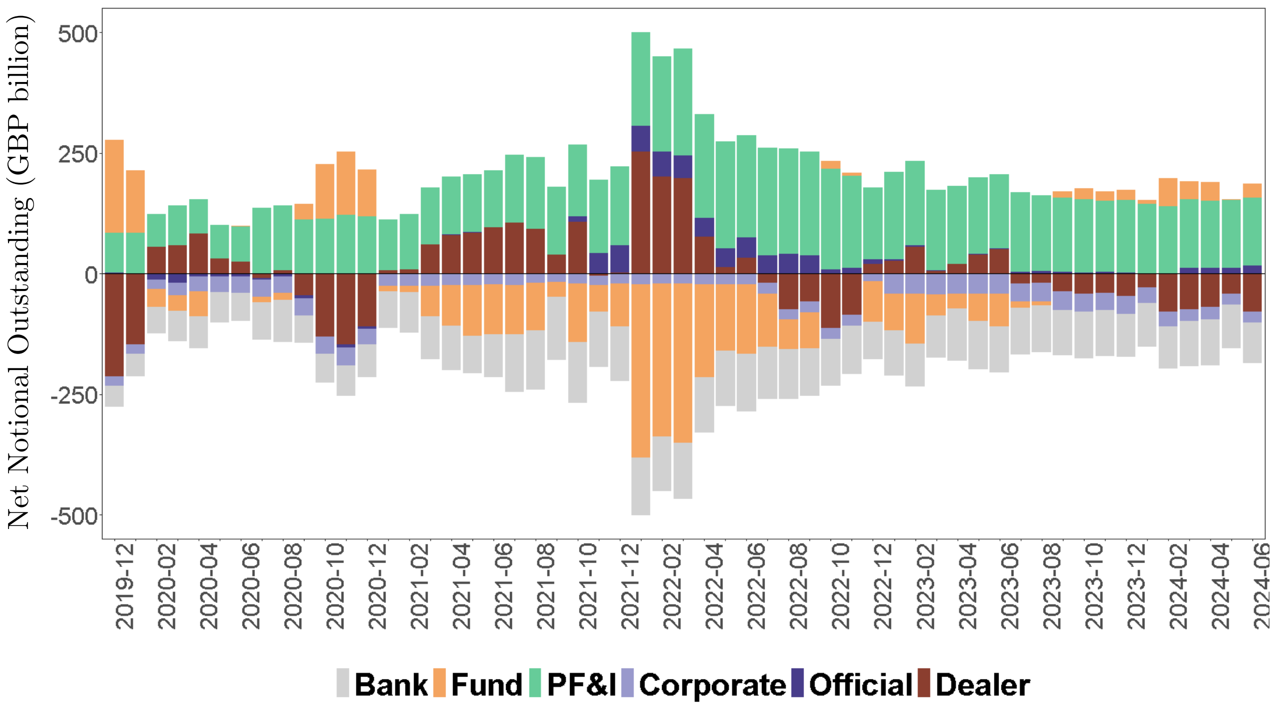
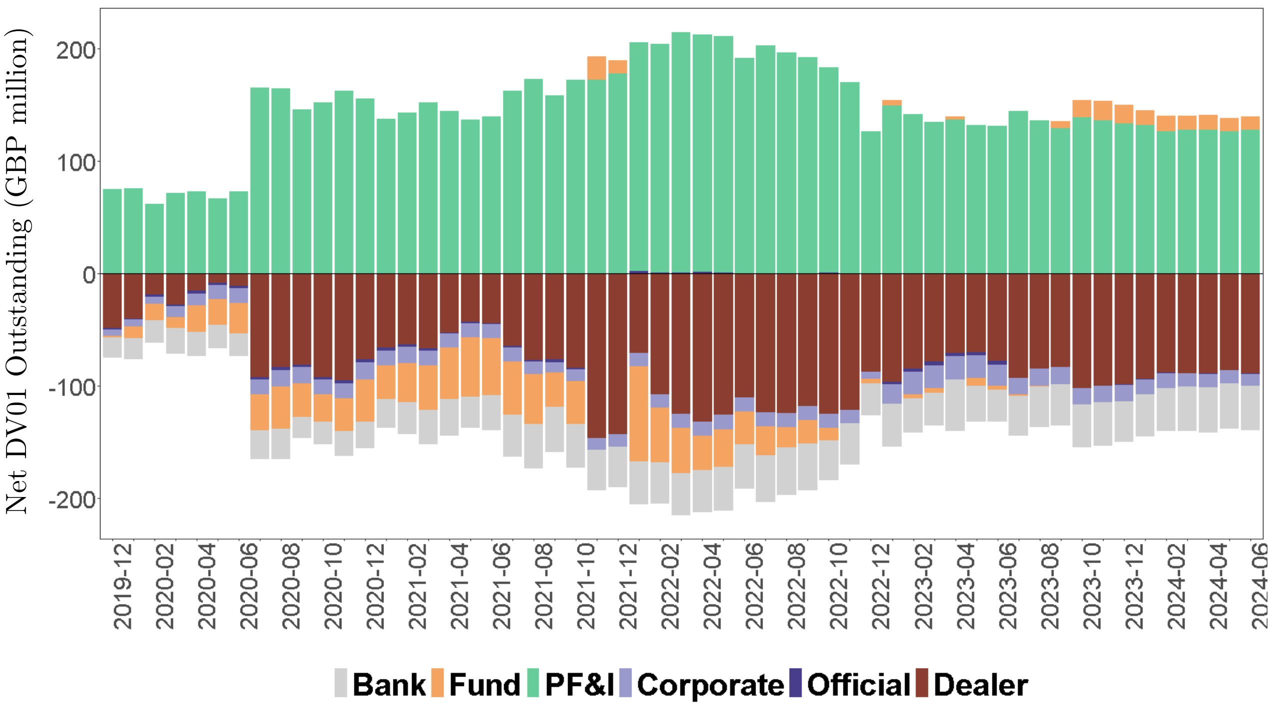
Figure 1: Net Notional Outstanding



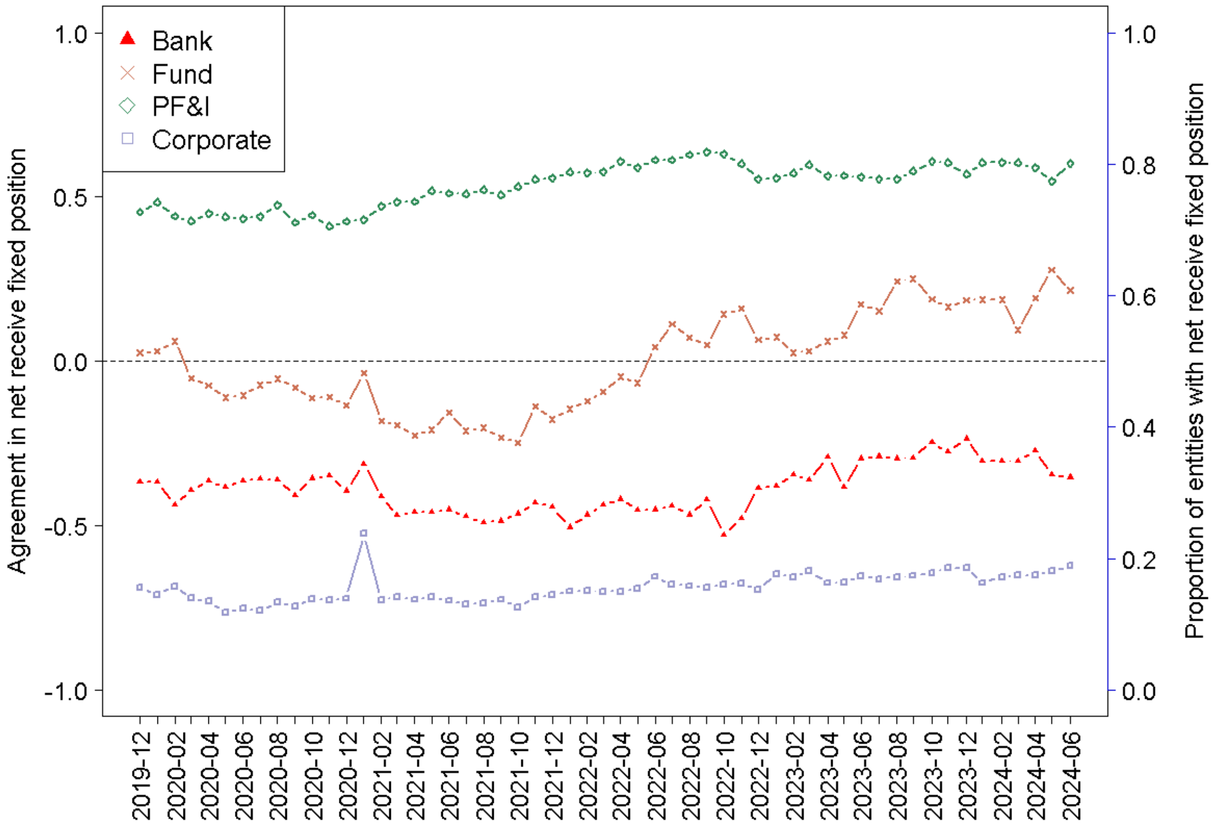
Notes: This figure shows the net notional outstanding positions in GBP billion at the start of every month for the different end-user sectors and the dealer sector. Net notional outstanding is calculated as outstanding notional values of receive fixed rate positions minus the pay fixed rate positions for each entity as specified in Equation 1, and then aggregated for the five end-user sectors: Bank, Fund, PF&I, Corporate, and Official. A positive value on the y-axis indicates net receive fixed positions while a negative value indicates net pay fixed positions. The net notional outstanding for the dealer sector is the opposite of the aggregate end-user positions such that the market clears. This figure considers swaps denominated in British pound sterling (GBP), while Figure B3 considers swaps denominated across all currencies in our sample.

Figure 2: Net DV01 Outstanding



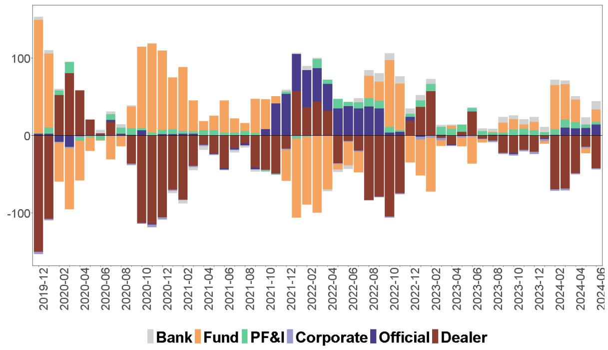
Notes: This figure shows the net DV01 outstanding in GBP million at the start of every month for the different end-user sectors and the dealer sector. DV01 refers to the change in the dollar value of swaps for a one basis point parallel shift in the interest rate curve. A positive value on the y-axis indicates a net positive DV01 (i.e., the value of swap increases with a decrease in interest rates) while a negative value indicates a net negative DV01. The net outstanding DV01 for the dealer sector is the opposite of the aggregate end-user positions such that the market clears. This figure considers swaps denominated in British pound sterling (GBP), while Figure B3 considers swaps denominated across all currencies in our sample.

Figure 3: Exposure Heterogeneity within End User Sectors

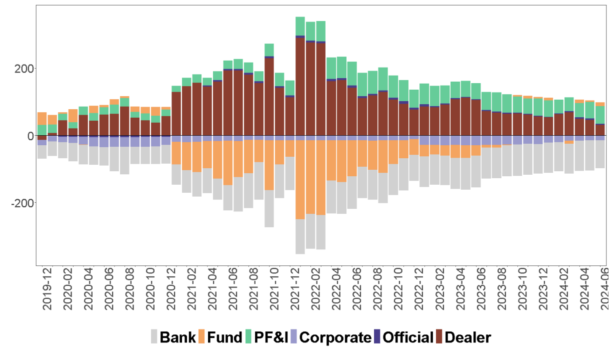


Notes: This figure depicts within-sector heterogeneity in the direction of exposures using entity-level net positions at the start of every month. We use two measures of exposure heterogeneity. The left axis represents an agreement score, where each entity gets a score of +1 if it has a net receive fixed outstanding position, or -1 if it has a net pay fixed outstanding position. We then plot the monthly time series of an average score across all entities within each sector. A score closer to zero indicates large disagreement within the sector, while a score closer to +1 (-1) indicates that most entities hold net receive (pay) fixed position. The second measure is depicted on the right axis which shows the proportion of entities within each sector that held a net receive fixed position.

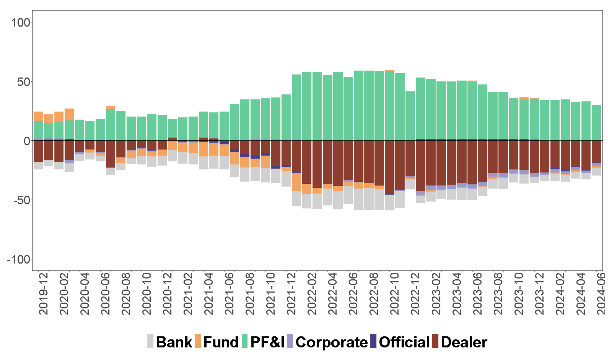
Figure 4: Net Notional Outstanding by Maturity Groups



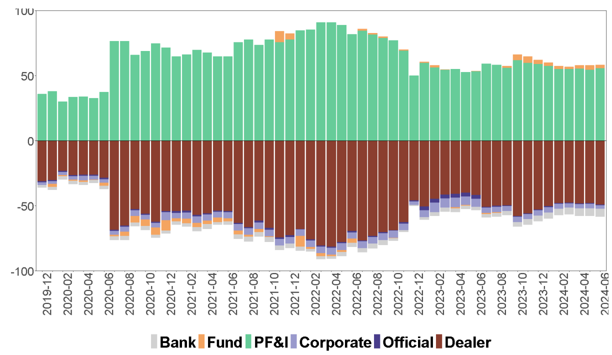
(a) Below 3 months



(b) 3 months to 5 years



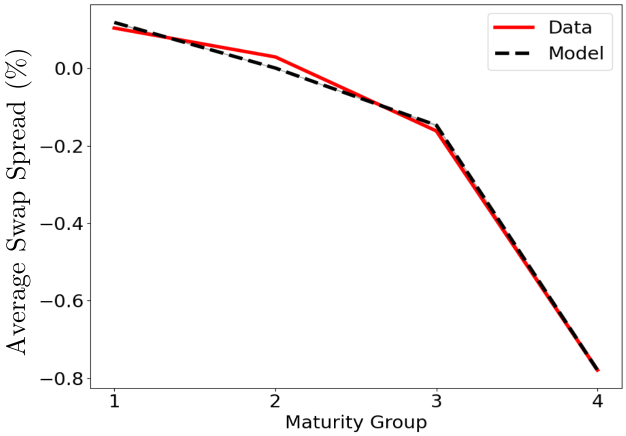
(c) 5 years to 10 years



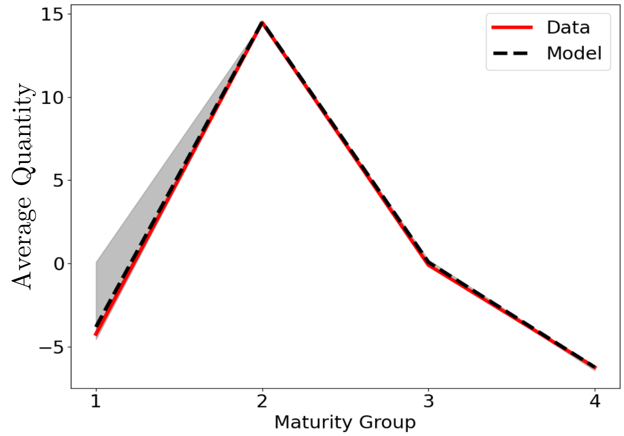
(d) 10 years & above

Notes: This figure shows the net outstanding positions in GBP billion at the start of every month for for the different end-user sectors and the dealer sector, split by four maturity groups: below 3 months in panel (a), 3 months to 5 years in panel (b), 5 years to 10 years in panel (c), and 10 years & above in panel (d). Net notional outstanding is calculated as outstanding notional values of receive fixed rate positions minus the pay fixed rate positions for each entity as specified in Equation 1, and then aggregated for the five end-user sectors: Bank, Fund, PF&I, Corporate, and Official. A positive value on the y-axis indicates net receive fixed positions while a negative value indicates net pay fixed positions. The net notional outstanding for the dealer sector is the opposite of the aggregate end-user positions such that the market clears.

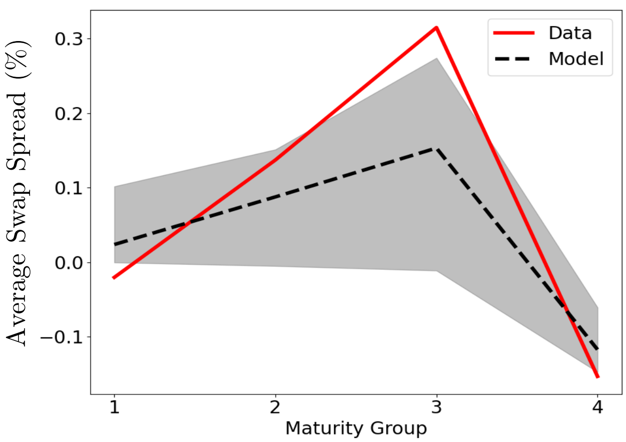
Figure 5: Comparing Model Simulated Moments with Empirical Moments



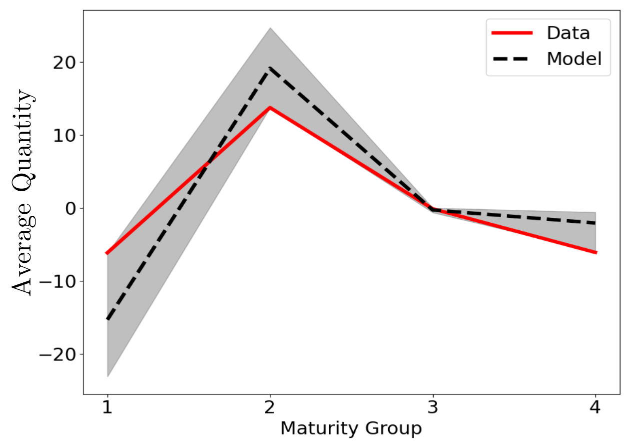
(a) Full Sample: Spread



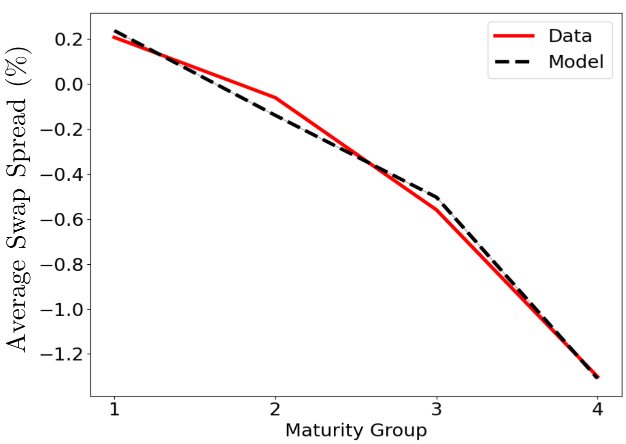
(b) Full Sample: Quantity



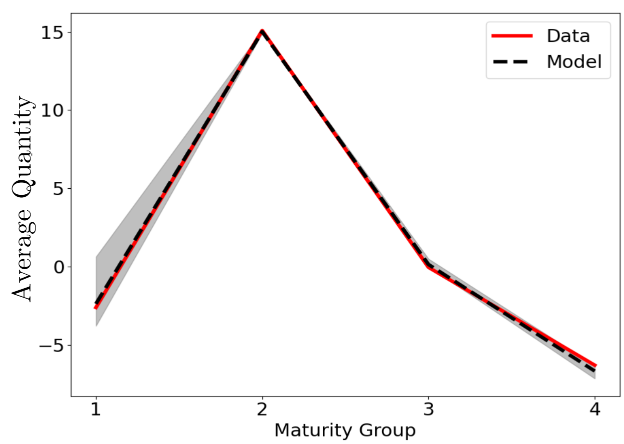
(c) First Subsample: Spread



(d) First Subsample: Quantity



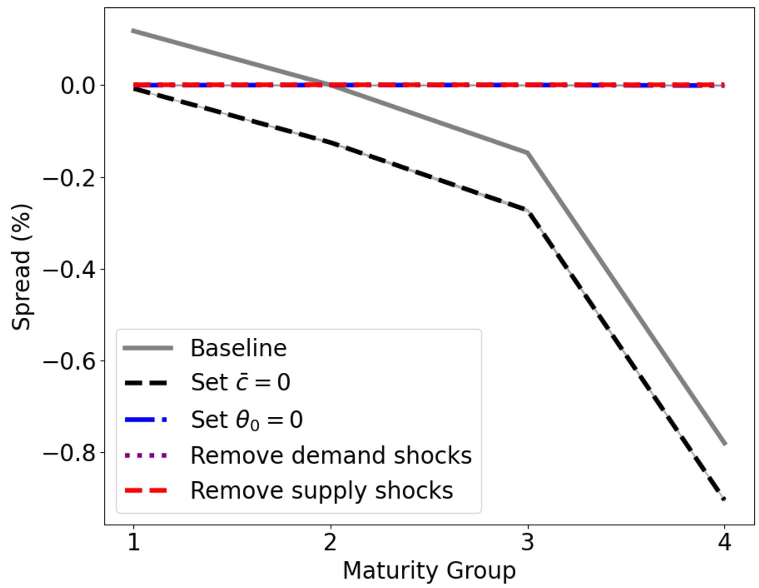
(e) Second Subsample: Spread



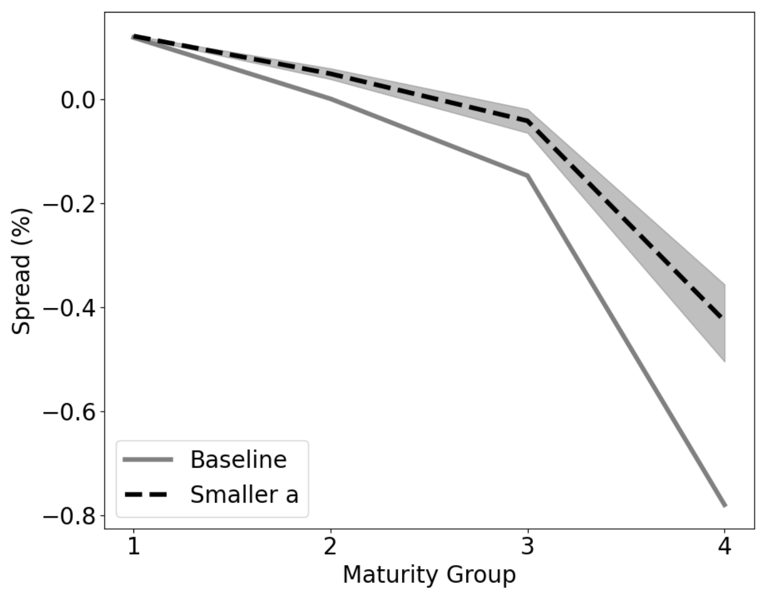
(f) Second Subsample: Quantity

Notes: This figure compares the model simulated moments with the corresponding empirical moments from the data. The shaded region indicates the 90th percentile confidence interval. All the spreads are quoted in percentage terms and quantities are in GBP tens of billion.

Figure 6: Decomposing the Swap Spread Curve



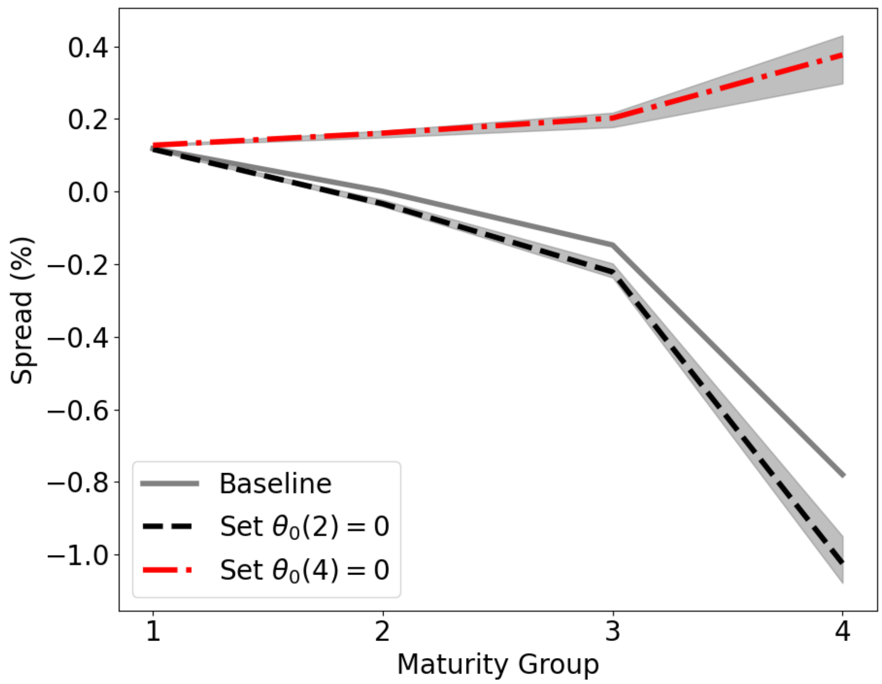
(a) Shut down supply and demand parameters



(b) Reduce arbitrageurs' risk aversion by 50%

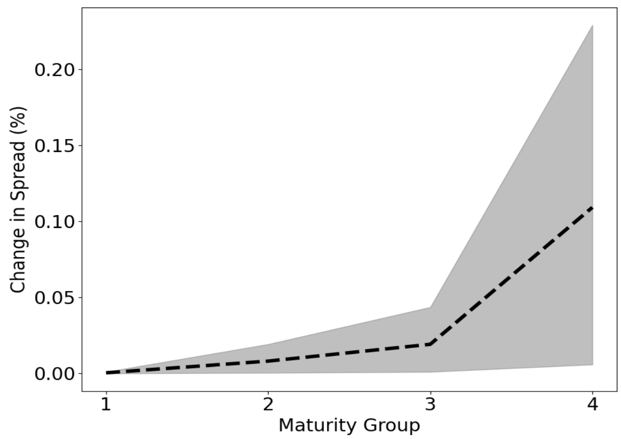
Notes: This figure plots the average swap spreads for different scenarios. In panel (a), we start with the baseline swap spreads (in grey), then we set $\bar{c} = 0$ and recalculate the swap spreads in equilibrium. Next, we set $\theta_0(\tau) = 0$ for all τ. We then remove demand side shocks, i.e. $d\beta_{1,t} = 0$ and finally remove all supply side shocks $dc_t = 0$. Spreads are quoted in percentage terms. In panel (b), we consider a scenario where the arbitrageurs become half as risk averse as in the baseline case, and recalculate the equilibrium swap spreads. The shaded area indicates 90th percentile confidence interval.

Figure 7: Distribution of Demand Imbalances and Swap Spreads

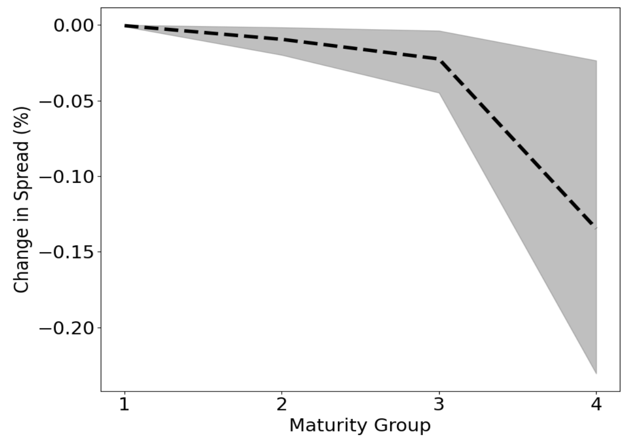


Notes: This figure plots the average swap spreads when demand pressure is set to zero for different maturity groups one at a time. In the first scenario, we set $\theta_0(2) = 0$, i.e. the demand pressure term is shut down for end users in the second maturity group (e.g., banks). In the second scenario, we set $\theta_0(4) = 0$, i.e. the demand pressure term is shut down for end users in the fourth maturity group (PF&I). For each scenario, we recalculate the equilibrium swap spreads for all maturity groups. Spreads are quoted in percentage terms. The shaded area indicates the 90th percentile confidence interval.

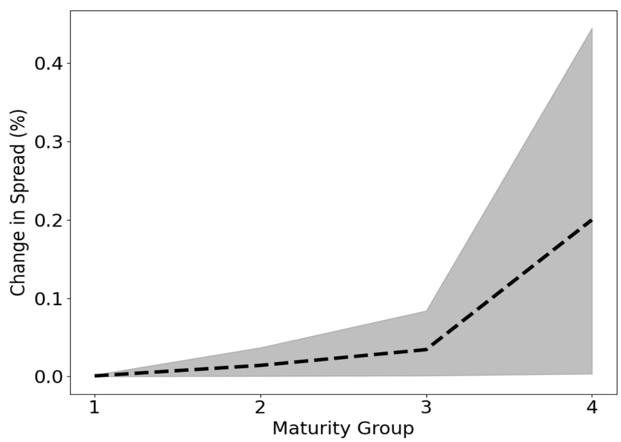
Figure 8: Counterfactual Analysis on Demand Pressure — First Subsample



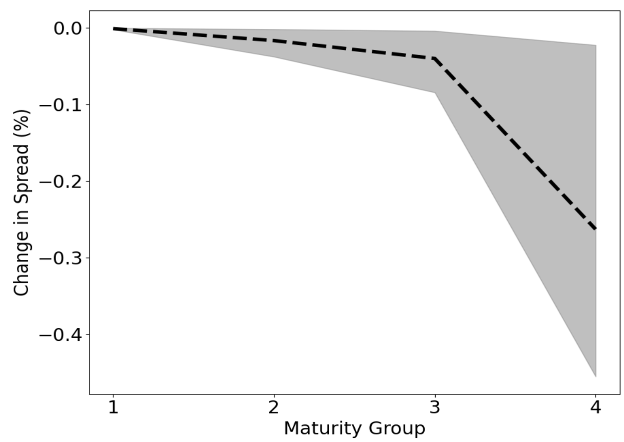
(a) Bank Demand Rises



(b) PF&I Demand Rises



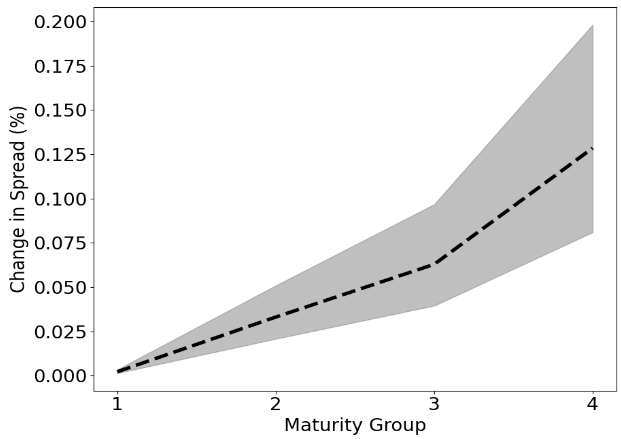
(c) Bank Demand Rises (Inelastic Demand)



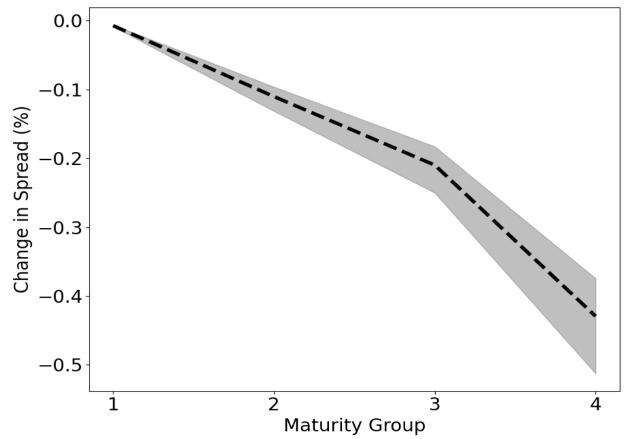
(d) PF&I Demand Rises (Inelastic Demand)

Notes: Panels (a) and (b) plot the counterfactual changes in swap spreads when the magnitude of $\theta_0(2)$ (banks) and $\theta_0(4)$ (PF&I) increases by 20% respectively. Panels (c) and (d) plot the changes in swap spreads for the same shift in demand pressure but when the demand elasticities for all end users decrease by a half. The sample period for this analysis is December 2019 through December 2021 (low rate).

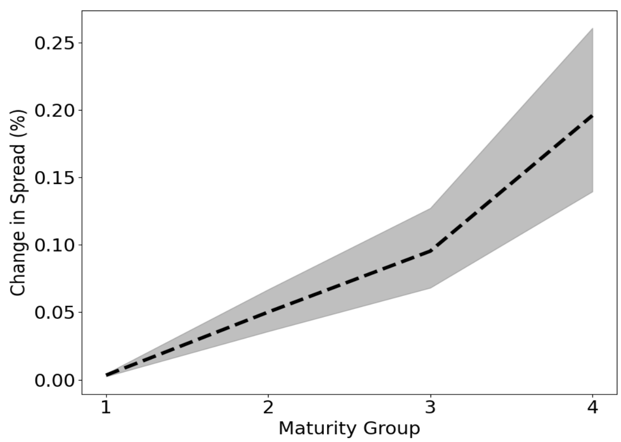
Figure 9: Counterfactual Analysis on Demand Pressure — Second Subsample



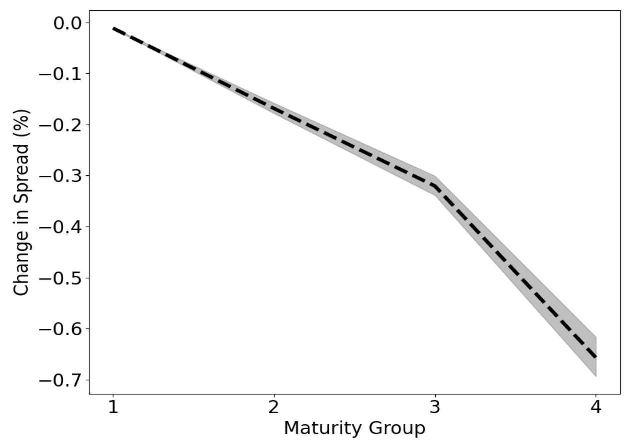
(a) Bank Demand Rises



(b) PF&I Demand Rises



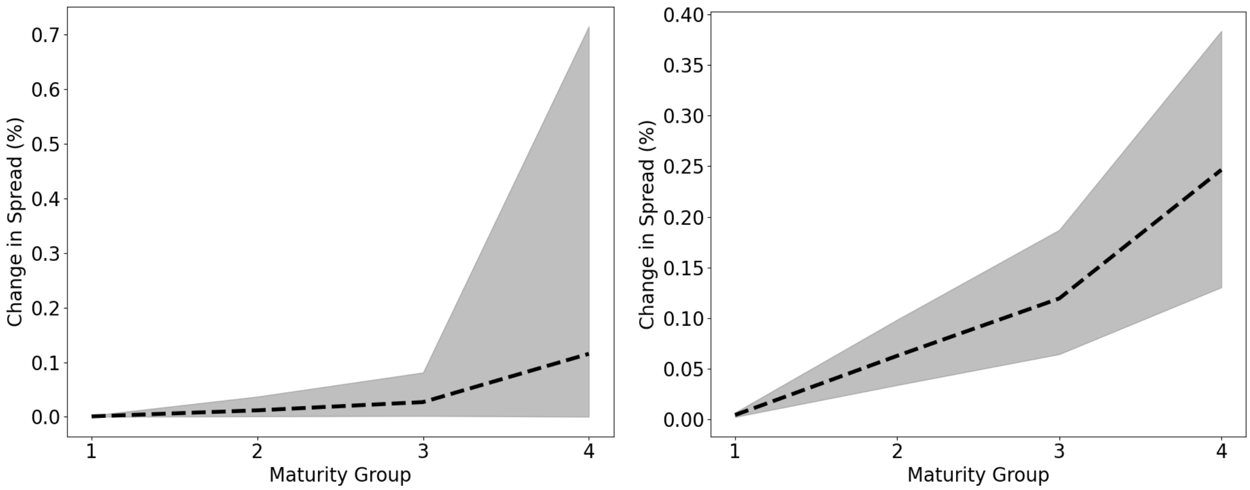
(c) Bank Demand Rises (Inelastic Demand)



(d) PF&I Demand Rises (Inelastic Demand)

Notes: Panels (a) and (b) plot the counterfactual changes in swap spreads when the magnitude of $\theta_0(2)$ (banks) and $\theta_0(4)$ (PF&I) increases by 20% respectively. Panels (c) and (d) plot the changes in swap spreads for the same shift in demand pressure but when the demand elasticities for all end users decrease by a half. The sample period for this analysis is January 2022 through June 2024 (high rate).

Figure 10: Counterfactual Analysis on Market Integration



(a) First Subsample (b) Second Subsample

Notes: This figure plots the counterfactual changes in swap spreads for the scenario where we shift 20% of the demand in maturity group four to maturity group two. The demand parameters are adjusted according to Equation 19 through Equation 21. We do not change the demand parameters for the remaining maturity groups. Panel (a) shows the sample period December 2019 through December 2021 (low rate), and panel (b) shows the sample period January 2022 through June 2024 (high rate).

Table 1: Outstanding Positions and Transaction Volume

	Outstanding Positions (as on Feb 1, 2022)			Transaction Volume (monthly average)	
	Gross notional (GBP billion) (1)	Net notional (GBP billion) (2)	Net DV01 (GBP million) (3)	Gross notional (GBP billion) (4)	Net notional (GBP billion) (5)
Bank	364	-112	-37	41	-2
Fund	1,187	-317	-48	1,322	9
PF&I	1,007	197	203	73	9
Corporate	68	-21	-12	3	-1
Official	73	53	1	13	0

Notes: This table reports the outstanding positions and new transaction volumes for the different end-user sectors: Bank, Fund, PF&I, Corporate, and Official. Column (1) reports the gross outstanding notional, column (2) reports the net outstanding notional, and column (3) reports the net DV01. Outstanding positions data are as on February 1, 2022. Column (4) reports the average monthly gross notional traded by each sector throughout our sample period, and column (5) reports the average monthly net notional traded. Net notional outstanding is calculated as outstanding notional values of receive fixed rate positions minus the pay fixed rate positions. A positive value indicates a net receive fixed position while a negative value indicates a net pay fixed position. DV01 refers to the change in the dollar value of swaps for a one basis point parallel shift in the interest rate curve. A positive value indicates a net positive DV01 (i.e., the value of swap increases with a decrease in interest rates) while a negative value indicates a net negative DV01. All values are for swaps denominated in British pound sterling (GBP).

Table 2: Interest Rate Changes and Evolution of Swap Exposures

Panel A	Δ Quantity (scaled)			
	Bank	Fund	PF&I	Corporate
Δ Rate (PC1, t-1)	0.063***	0.011	-0.050***	0.114***
	(0.024)	(0.019)	(0.011)	(0.014)
Δ Rate (30Y yield, t-1)	0.135***	-0.032	-0.084***	0.213***
	(0.047)	(0.035)	(0.021)	(0.026)
Δ Rate (10Y yield, t-1)	0.099**	0.004	-0.083***	0.190***
	(0.043)	(0.033)	(0.019)	(0.025)
Δ Rate (5Y yield, t-1)	0.065*	0.026	-0.074***	0.161***
	(0.037)	(0.030)	(0.017)	(0.022)
Δ Rate (3M yield, t-1)	0.093**	0.072**	-0.060***	0.114***
	(0.036)	(0.032)	(0.018)	(0.022)
N	6,264	22,536	29,901	13,965
Entity FE	Yes	Yes	Yes	Yes
Panel B	**Δ DV01 (scaled)**			
	Bank	Fund	PF&I	Corporate
Δ Rate (PC1, t-1)	0.041*	0.030	-0.042***	0.116***
	(0.024)	(0.019)	(0.012)	(0.015)
N	6,244	22,456	29,879	13,824
Entity FE	Yes	Yes	Yes	Yes

Notes: This table reports the results of estimating Equation 4. In Panel A, the dependent variable is the change in the monthly outstanding net notional held by an entity within an end-user sector, while in panel B it is the net DV01 of these positions. Panel A presents separate estimation results using 5 regressors: the first principal component (PC1) of 3 month, 5 year, 10 year, and 30 year GBP bond (gilt) yields, and then each of these yields individually. For brevity, panel B shows estimates using PC1 only. All regressors are expressed as monthly changes and lagged by one period. All columns include entity fixed effects. Standard errors clustered by entity are reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 3: Monetary Policy Shocks and Evolution of Swap Exposures

Panel A	Δ Quantity (scaled)			
	Bank	Fund	PF&I	Corporate
MPS (10Y yield, t-1)	0.677**	-1.01***	-0.366**	0.067
	(0.277)	(0.237)	(0.144)	(0.165)
MPS (5Y yield, t-1)	0.755***	-0.725***	-0.257**	0.338**
	(0.247)	(0.202)	(0.121)	(0.157)
MPS (2Y yield, t-1)	0.605***	-0.634***	-0.105	0.150
	(0.219)	(0.183)	(0.108)	(0.140)
N	4,055	14,489	19,353	8,989
Entity FE	Yes	Yes	Yes	Yes
Panel B	**Δ DV01 (scaled)**			
	Bank	Fund	PF&I	Corporate
MPS (10Y yield, t-1)	0.584**	-1.03***	-0.405***	0.029
	(0.269)	(0.242)	(0.141)	(0.173)
MPS (5Y yield, t-1)	0.634**	-0.784***	-0.285**	0.280*
	(0.245)	(0.200)	(0.121)	(0.165)
MPS (2Y yield, t-1)	0.500**	-0.725***	-0.142	0.100
	(0.221)	(0.178)	(0.109)	(0.145)
N	4,039	14,438	19,339	8,898
Entity FE	Yes	Yes	Yes	Yes

Notes: This table reports the results of estimating Equation 5. In Panel A, the dependent variable is the change in the monthly outstanding net notional held by an entity within an end-user sector, while in panel B it is the net DV01 of these positions. We present separate estimation results using monetary policy shocks (MPS) reflected in gilt yields of tenors 2 year, 5 year, and 10 year, respectively. All regressors are lagged by one period. All columns include entity fixed effects. Standard errors clustered by entity are reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 4: Preferred Habitat Behavior: Maturity Preference

Panel A	End users trading in single maturity group (%)		Dominant
	Equal-weighted	Notional-weighted	maturity group
Bank	0.94	0.92	3M to 5Y
Fund	0.91	0.92	Below 3M
PF&I	0.74	0.79	10Y & Above
Corporate	0.97	0.94	3M to 5Y

Panel B	Trades in the dominant maturity group (%)				
	Mean	SD	p25	p50	p75
Bank	0.82	0.18	0.70	0.86	1.00
Fund	0.80	0.20	0.62	0.85	1.00
PF&I	0.66	0.20	0.50	0.63	0.82
Corporate	0.91	0.17	0.90	1.00	1.00

Notes: This table shows the degree to which end users exhibit preferred habitat behavior in the interest rate swaps market. Panel A reports the (equal-weighted and notional-weighted) fraction of end users within each sector that trade at least 50% of their total transaction volume in a single maturity group, which we define to be the entity's "dominant maturity group." The last column in Panel A identifies the dominant maturity group of each end-user sector, based on the total (gross) trading volume. Panel B reports the distribution of the proportion of (notional-weighted) trades that belong to each entity's dominant maturity group. We then report the distribution of this variable for all entities within an end-user sector.

Table 5: Descriptive Statistics on Portfolio Compression

	Compression					
	Mean	SD	p25	p50	p75	Fraction of trades
Compression ratio (dealer-week)	0.19	0.15	0.08	0.15	0.24	
Centrally cleared						0.998
Inter-dealer (estimated lower bound)						0.830

Notes: This table reports the distribution of compression ratio, defined as the ratio of compressed trades relative to the total number of outstanding trades constructed at the dealer-week level. It also shows the fraction of compressed trades that are centrally cleared and originating from inter-dealer trading. All statistics are for trades outstanding as of February 1, 2022. We estimate the share of inter-dealer trades in overall compression as follows. On February 1, 2022, about 74,000 net trades resulting out of compression exercise were outstanding and centrally cleared. Under the assumption that two gross trades are netted into one single compressed trade, the actual number of centrally cleared trades that were compressed would be 74,000 $\times$ 2 = 148,000. On the same day, there were 25,000 outstanding centrally cleared *client-facing* trades and 282,000 inter-dealer trades. Even if we assume that every client-facing trade underwent compression, such trades would have accounted for at most 25,000/148,000 = 17% of overall compression. The rest (83%) forms the estimated lower bound for inter-dealer compression trades.

Table 6: Estimated Demand Elasticities

Panel A: First stage	Δ Swap spread			
	3M to 5Y		10Y & above	
Δ Compression ratio	-0.378***	-0.381***	0.400***	0.410***
	(0.082)	(0.081)	(0.109)	(0.119)
N	2,501	2,387	2,436	2,322
Controls	Yes	Yes	Yes	Yes
Dealer FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Drop Mar. 2020 and Sep. 2022	No	Yes	No	Yes
Instrument F-statistic	21.74	22.12	13.46	11.87

Panel B: Second stage	Δ Quantity (scaled)			
	3M to 5Y		10Y & above	
$\Delta\widehat{\text{Swap spread}}$	0.812***	0.630**	0.242	0.268
	(0.224)	(0.250)	(0.435)	(0.429)
N	2,501	2,387	2,436	2,322
Controls	Yes	Yes	Yes	Yes
Dealer FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Drop Mar. 2020 and Sep. 2022	No	Yes	No	Yes

Notes: This table reports the estimates of the instrumental variable regression in Equation 7 (first stage) and Equation 8 (second stage). Panel A reports the first stage where the dependent variable is the change in notional-weighted swap spreads offered by dealer i in week t in maturity group m. The instrument is Compression ratio, defined as the ratio of compressed trades relative to the total number of outstanding trades constructed at the dealer-week level. In Panel B, the dependent variable is the scaled change in the weekly outstanding net position facing a dealer and the regressor of interest is the instrumented change in swap spreads for the respective maturity group. We control for the changes in the past week's quantities and include dealer and time fixed effects. The second and the fourth columns drop the months of March 2020 and September 2022 when the UK gilt market witnessed extreme volatility. Standard errors clustered by dealer and time are reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 7: Dealer-Client Stickiness

	Share of trades with their top dealer				
	Mean	SD	p25	p50	p75
Bank	0.77	0.22	0.56	0.79	1
Fund	0.87	0.20	0.73	1	1
PF&I	0.87	0.20	0.76	1	1
Corporate	0.79	0.24	0.56	1	1

Notes: This table measures the degree of dealer-client stickiness, i.e. the extent to which an end user trades with the same dealer in a given month. We compute this measure for each end user, and report the distribution at a sector level. For an end user with at least two trades in a given month, we compute the fraction of trades (by count) that it executes with the dealer it most frequently trades with. For example, if end user i executes 3 trades with dealer A and 2 trades with dealer B, then its stickiness equals $3/5 = 0.6$. We exclude cases where the end user executes only one trade in a month because the stickiness will mechanically equal 1 in such cases.

Table 8: Maturity Groups and Relevant Parameters

	Values
Maturity groups $\tau = 0, 1, ..., 4$	$\{(0, 0.05), [0.05, 0.25), [0.25, 5), [5, 10), [10, \infty)\}$
Average maturity $\bar{m}(\tau)$	$\{0.025, 0.15, 2.75, 7.5, 25\}$
Transition prob. $\delta(\tau)$	$\{20, 6.67, 0.38, 0.21, 0.06\}$

Notes: This table defines the maturity groups, and the relevant parameters, including average maturity and the transition probabilities we use for each maturity group in the calibration.

Table 9: Targeted Moments

	Maturity Group			
Panel A: Full Sample (Dec 2019 - Jun 2024)	Below 3M	3M to 5Y	5Y to 10Y	10Y & Above
Average swap spreads (%)	0.104	0.029	-0.162	-0.779
Average net quantity (GBP tens of billion)	-4.236	14.466	-0.095	-6.224
Variances of swap spread changes	0.038	0.091	0.399	0.145
Variances of scaled quantity changes	0.058	0.003	0.087	0.001
Panel B: First Subsample (Dec 2019 - Dec 2021)	Below 3M	3M to 5Y	5Y to 10Y	10Y & Above
Average swap spreads (%)	-0.02	0.137	0.315	-0.153
Average net quantity (GBP tens of billion)	-6.172	13.719	-0.146	-6.123
Variances of swap spread changes	0.002	0.043	0.039	0.045
Variances of scaled quantity changes	0.02	0.003	0.084	0.002
Panel C: Second Subsample (Jan 2022 - Jun 2024)	Below 3M	3M to 5Y	5Y to 10Y	10Y & Above
Average swap spreads (%)	0.207	-0.061	-0.56	-1.30
Average net quantity (GBP tens of billion)	-2.623	15.088	-0.053	-6.31
Variances of swap spread changes	0.067	0.132	0.698	0.285
Variances of scaled quantity changes	0.089	0.002	0.091	3.6×10^{-4}

Notes: This table summarizes the empirical moments that we target in our calibration. Panel A uses monthly data from Dec 2019 through Jun 2024. Panel B uses data from Dec 2019 to Dec 2021, and Panel C uses data from Jan 2022 to Jun 2024. Swap spreads are in percentages and are calculated as the volume weighted average swap spreads for a given maturity group. Quantities are in GBP tens of billion and changes in quantities are calculated according to Equation 18.

Table 10: Calibrated Parameters

Parameters	Value (median)		
	(1) Full Sample	(2) First subsample	(3) Second subsample
Demand intercepts θ_0	$[4.17, 14.47, 0, -8.08]$	$[-13.42, 20.31, 0.06, -1.80]$	$[7.3, 13.26, 0.02, -9.93]$
Demand sensitivities to aggregate demand factor θ_1	$[0.1, 1.22, 0, -0.9]$	$[-10.55, -27.25, -2.98, -0.30]$	$[0, -0.84, 0, 0.18]$
Arbitrageur risk aversion coeff. a	201.29	24.81	786.78
Arbitrageur funding cost $\bar{c}$	0.01	0.001	0.02
Speed of mean reversion Γ	$(9.58 \times 10^{-4}, 9.63 \times 10^{-4})$	$(2.81 \times 10^{-4}, 2.35 \times 10^{-4})$	$(6.66 \times 10^{-2}, 6.66 \times 10^{-2})$
Matrix for supply and demand shocks Σ	$\begin{pmatrix} 1.78 & -0.81 \\ 0.24 & -0.11 \end{pmatrix}$	$\begin{pmatrix} -1.29 & 1.67 \\ 0.002 & 0.003 \end{pmatrix}$	$\begin{pmatrix} 1.78 & -0.8 \\ 0.24 & -0.11 \end{pmatrix}$

Notes: This table summarizes the calibrated parameter values in the model, for the full sample and each subsample.

Internet Appendix
"The Market for Sharing Interest Rate Risk: Quantities and Asset Prices"

Umang Khetan Jian Li Ioana Neamțu Ishita Sen

August 2025

A. Data Processing and Sample Construction

A.1. Data Processing Steps

In this appendix, we detail the data processing steps and the construction of our sample. Our starting point is the monthly outstanding positions and daily new transactions reports from the two largest trade repositories in the interest rate swaps market - DTCC and UnaVista. Our sample includes all trades where at least one of the counterparties is based in the UK.[31] Since trade repositories' data suffer from some well-known reporting issues, we dedicate a significant amount of time to accurately capture quantities and prices, which entails three major steps.[32]

First, we exclude likely erroneously reported trades. Closely following Abad et al. (2016), we drop trades below notional values of $1,000 and above $10 billion, filter out trades whose maturity date lies before the effective date or whose reporting date precedes the execution date,[33] and drop intra-group trades which, while not erroneous, may indicate risk transfers within a group and not necessarily trading in response to changes in economic conditions.

Second, we remove duplicate trades. The most common cause of duplicates is the "dual reporting" requirement under EMIR, where each of the two counterparties needs to report a trade if they both fall under the reporting obligation. Following Cenedese et al. (2020), we retain one copy of these trades using the unique trade identifier field. The second reason for duplicates is that, for centrally cleared trades, we observe the original trade contracted between the dealer and its client, and a "novation" trade that is a leg facing the centralized clearing house and a clearing member (usually the same or another dealer), both with different trade identifiers. Since we focus on end-user exposures, this duplication does not affect our assessment of *client* level positions but it does lead to double counting of centrally cleared trades in the estimation of total turnover. Therefore, when estimating our data coverage, we halve the notional of centrally cleared trades. A third reason for duplicates is trade compression. Compression entails netting trades with similar economic characteristics at a counterparty level and re-booking a single entry of the net exposure to reduce the size of trading books. The raw positions data include both the original trades and the net trade arising out of compression exercise, which can lead to a miscalculation of outstanding positions. Therefore, we drop all trades tagged as compression when calculating exposures, but

[31] Note that trades starting January 2021 are reported under UK EMIR, while trades prior to 2021 are reported under EU EMIR. For the period under EU EMIR, we additionally observe trades between EU-domiciled banks and non-UK counterparties. However, as part of the post-EU-exit arrangements of the UK, trades between those entities are not covered starting 2021. For consistency, therefore, we exclude such trades from the earlier part of our sample. More details on the UK EMIR reporting obligation are available at: www.bankofengland.co.uk/financial-stability/trade-repository-data

[32] European Securities and Markets Authority (2021) provides a recent report on EU EMIR data quality.

[33] Execution date refers to the trade date, reporting date refers to when the counterparty reports the trade (usually within 2 business days of execution date), and effective date refers to when the swap gets active.

separately use these trades to construct a supply shifter when estimating demand elasticities.

In the final step, we construct the key features of swap contracts, including the currency of denomination, the direction of trade as receive or pay fixed from the perspective of the reporting counterparty, and the floating rate index (e.g., SONIA, LIBOR, SOFR). As floating rate benchmarks are typically not directly available under a single field, we construct them by concatenating information from multiple fields, such as the underlying index name and reset frequency. Note that in 2021, several benchmark indices underwent a transition from LIBOR to overnight benchmarks that exclude bank credit risk, such as SOFR for USD swaps and SONIA for GBP swaps (Klingler and Syrstad, 2021). We verify that in our sample, a majority of GBP swaps were already SONIA-benchmarked before the transition.

Our final sample consists of single currency fixed-to-floating interest rate swaps and overnight indexed swaps referencing all floating rate benchmarks, across all tenors, and contracted by all types of counterparties. We restrict attention to swaps denominated in the British pound sterling (GBP) because of our largest coverage of these swaps and our ability to observe the entire swaps portfolio of UK-based entities.

A.2. Sector Classification

A key step in our sample construction is assigning sectors to individual entities that we observe in the data. Even though trade repositories have a reporting field for the sector of the counterparty, it is either sparsely or erroneously filled, so it cannot be used reliably. We leverage the non-anonymized version of our data to assign a sector type to all the end users, dealers, and central clearing houses present in our data. To do so, we focus on the legal entity identifier (LEI) and the entity name.[34]

We start by filling in the missing names and jurisdictions of the LEIs using the Global Legal Entity Identifier Foundation (GLEIF) public database. Then, we use CapitalIQ and Thomson Reuters to populate the sectors associated with the individual LEIs. This method works well for larger entities. However, a substantial number of LEIs also need to be manually classified using their names and details of incorporation. Manual classification is particularly helpful for funds, where a main fund family often has several separate legal entities that trade derivatives but are too small to be reported in standardized data sources. If an entity falls into multiple sectors - for example, a pension fund that may also have an in-house investment management fund - then we assign to it the sector that most closely reflects the primary nature of its business.

An important part of our sector classification is to make an economically meaningful distinction between end-user "banks" and market-making "dealers". This distinction helps us capture hedging

[34]LEI is a unique identifier for each legally distinct entity that engages in a financial transaction. Multiple LEIs may roll up into the same firm or fund family. Financial Stability Board (2019) provides institutional details on LEI implementation.

of interest rate risk arising out of banking activities separately from intermediation services. To make this distinction as accurately as possible, we follow a two-step procedure.

First, from the list of all the entities classified as banks, we carve out dealers, defined as entities that meet any of the following four criteria: (i) members of a clearing house such as the LCH Ltd. (formerly London Clearing House) or the Chicago Mercantile Exchange (CME), (ii) globally systemically important banks (GSIBs), (iii) participating dealers defined by the Federal Reserve Bank of New York, or (iv) broker-dealers and non-bank liquidity providers that facilitate order-matching. We retrieve the list of clearing members directly from the LCH Ltd. website.[35] The corresponding list for CME is also available on its website.[36] We source the list of GSIBs from the Financial Stability Board website,[37] and the list of participating dealers from the Federal Reserve Bank of New York website.[38]

Membership of clearing houses provides the sharpest identification of dealers because end users are not allowed to directly clear trades with CCPs but large financial institutions and broker-dealers that meet certain minimum capital thresholds are. For instance, the membership criteria of LCH Ltd. states "major financial groups (including the majority of the major investment banks), broker-dealers and specialist commodity houses" (see www.lch.com/membership). As of August 2023, there were 124 unique LEIs that qualified as LCH Ltd. clearing members for interest rate derivatives. Moreover, the list of CCP members is available both by product (e.g., interest rate swaps) and LEI, which enables a direct matching with our database.

Then, we take additional steps to ensure the validity of our separation of dealers from end user banks. First, to the extent identifiable, we assign entities based on their functional role rather than corporate affiliation. For instance, we classify "Global Dealer" as a dealer if it meets the relevant criteria described above, but we classify its affiliated entities such as "Global Dealer Commercial Bank" and "Global Dealer Asset Management" as a bank and a fund, respectively. Second, we verify that the entities we classify as end-user banks do not trade with other known end-users and do not directly face clearing houses, which are features that apply to dealers rather than end-user banks. For example, the entities we refer to as dealers trade with pension funds or corporations, but the entities we refer to as banks do not trade with other end users. Third, while some dealers' positions may also reflect the trading of their affiliate banking arms, we show that this behavior is limited. Figure B2 shows that, in contrast to other end users, dealers' net-to-gross positions are near zero, which is consistent with two-sided intermediation rather than their positions being primarily driven by their affiliated banking arms.

[35] www.lch.com/system/files/media_root/swapclear--esma-template-list-of-clearing-members-lch-ltd-Aug-2023.xlsx

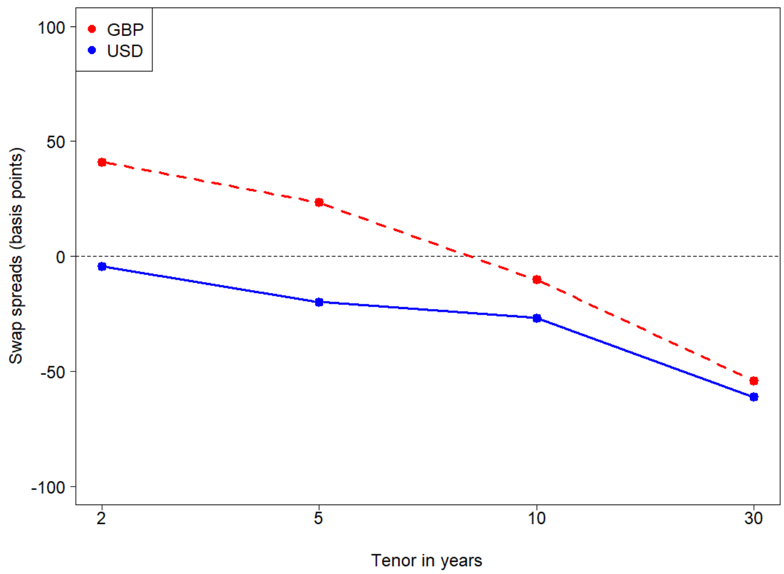
[36] www.cmegroup.com/clearing/financial-and-regulatory-surveillance/clearing-firms.html

[37] www.fsb.org/2022/11/2022-list-of-global-systemically-important-banks-g-sibs/

[38] www.newyorkfed.org/markets/otc_derivatives_supervisors_group.html

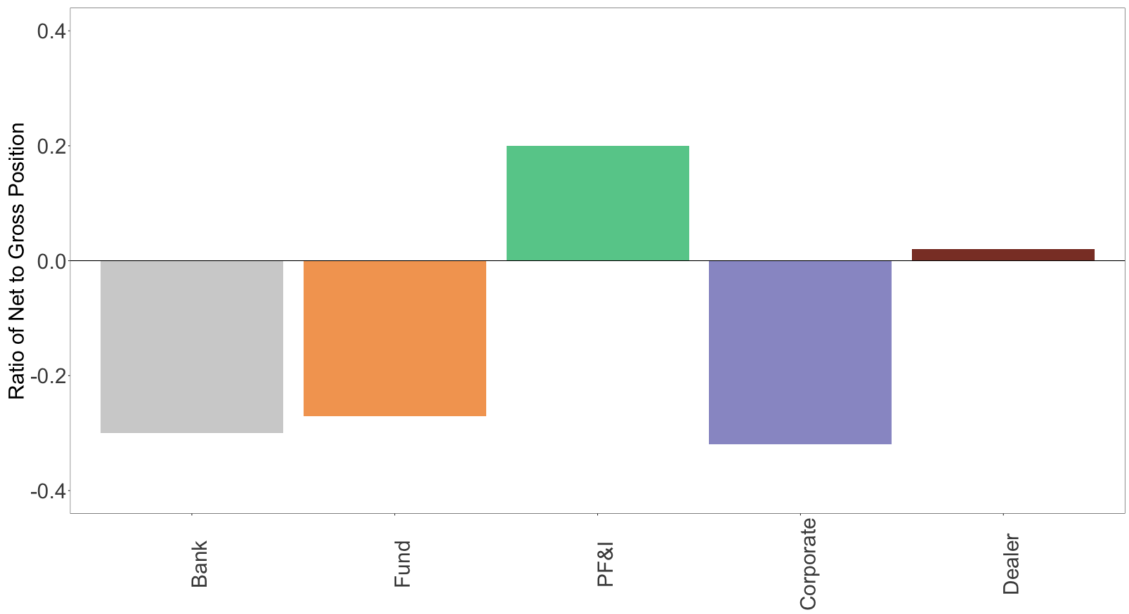
B. Additional Figures and Tables

Figure B1: Swap Spreads



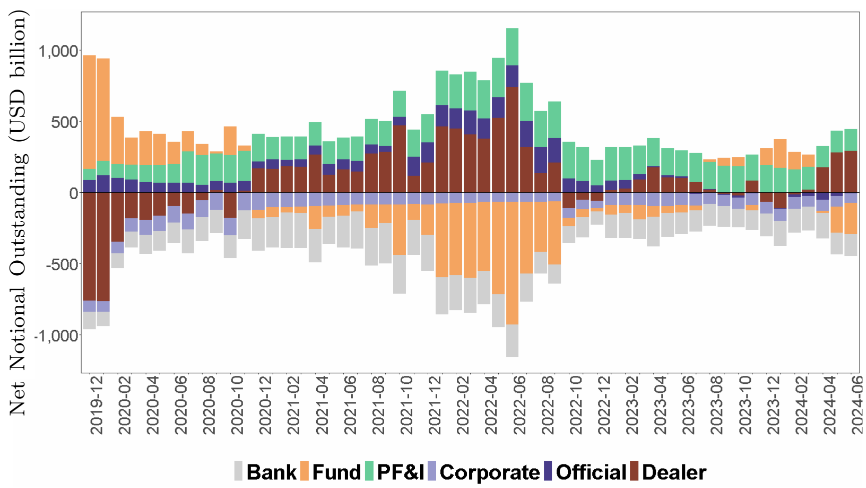
Notes: This figure plots the term structure of GBP swap spreads (red dashed line) and USD swap spreads (blue solid line) for swaps of tenors 2 year, 5 year, 10 year and 30 year. Swap spread is defined as the difference between swap fixed rate and the maturity matched bond yield. The underlying data for these plots is sourced from the Bureau van Dijk Bank of England bond and overnight indexed swap (OIS) database for GBP swaps, and Bloomberg for USD swaps.

Figure B2: Sector-level Net-to-Gross Positions

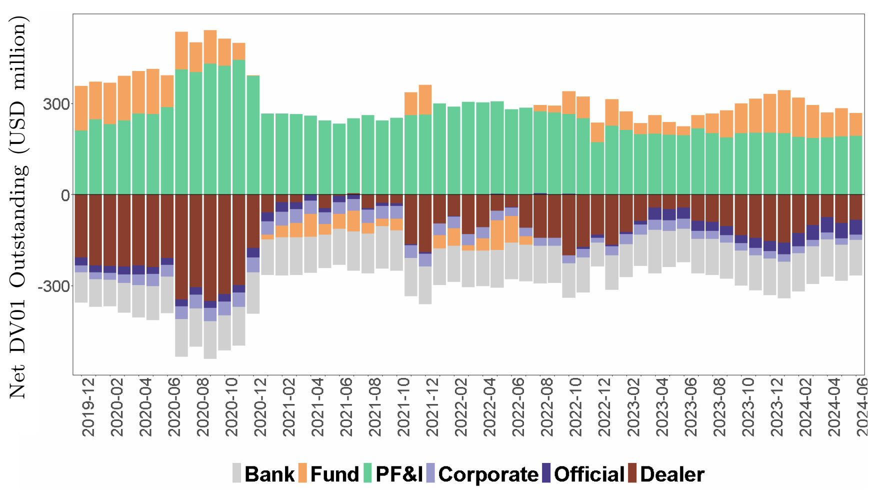


Notes: This figure plots the ratio of net-to-gross outstanding notional at a sector level as on February 1, 2022. A positive ratio indicates excess of receive fixed notional over pay fixed notional, and a negative ratio indicates an excess of pay fixed notional over receive fixed notional. Values close to zero indicate two-sided positions.

Figure B3: Net Notional and DV01 Outstanding (All Currencies)



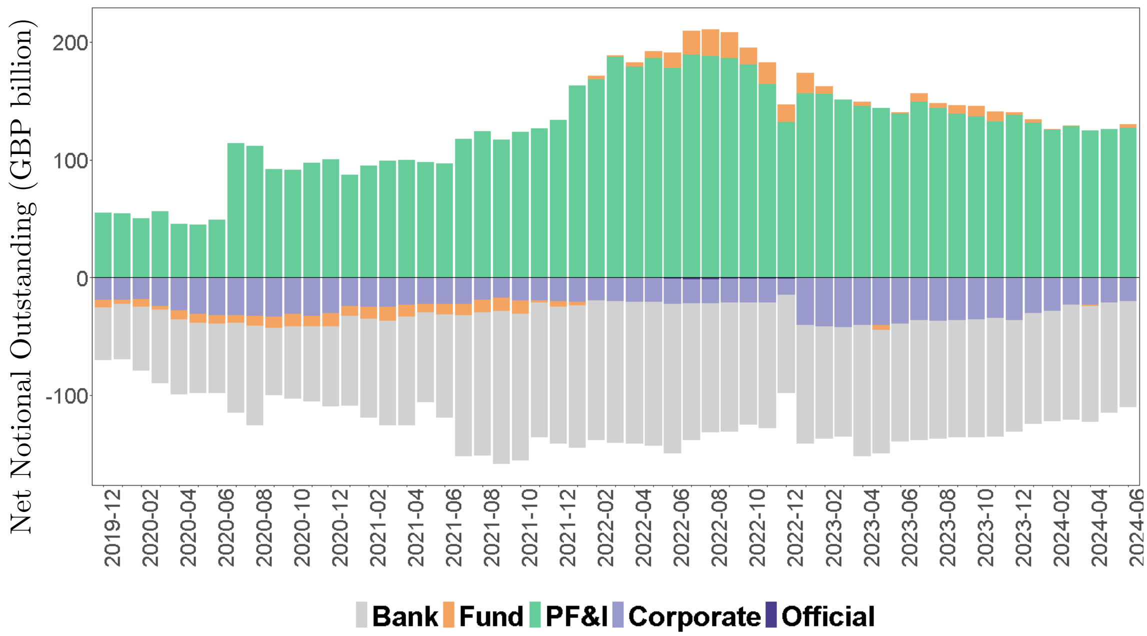
(a) Notional



(b) DV01

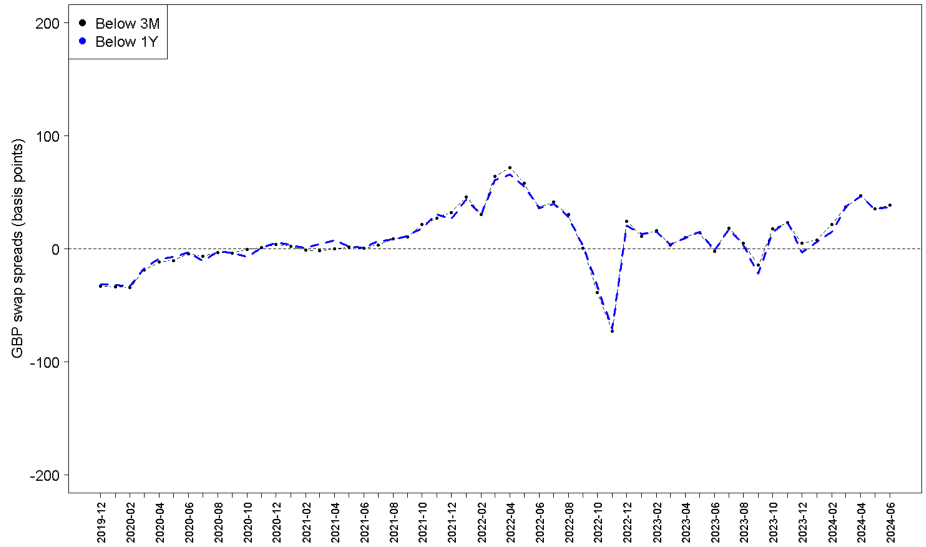
Notes: Panel (a) shows the net notional outstanding positions in USD billion at the start of every month for the different end-user sectors and the dealer sector, and panel (b) shows the corresponding DV01. A positive value on the y-axis indicates a net receive fixed position (or positive duration) while a negative value indicates a net pay fixed position (or negative duration). This figure considers swaps denominated in all currencies present in our sample, while Figure 1 plots the net notional of GBP swaps and Figure 2 plots the DV01 of GBP swaps.

Figure B4: Net Notional Outstanding (UK Entities)

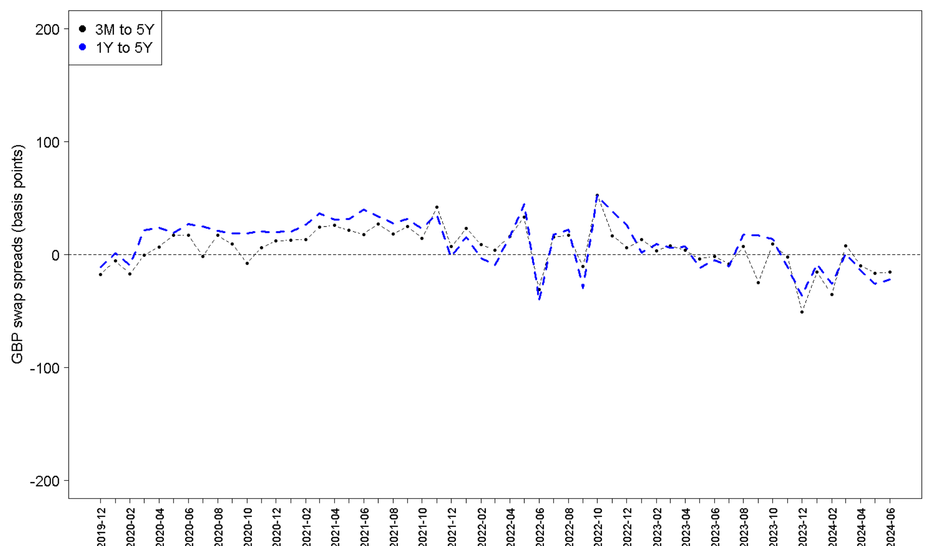


Notes: This figure shows the net notional outstanding positions in GBP billion at the start of every month for the different end-user sectors, where each entity is located in the United Kingdom (UK). Net notional outstanding is calculated as outstanding notional values of receive fixed rate positions minus the pay fixed rate positions for each entity as specified in Equation 1, and then aggregated for the five end-user sectors: Bank, Fund, PF&I, Corporate, and Official. A positive value on the y-axis indicates net receive fixed positions while a negative value indicates net pay fixed positions. This figure considers swaps denominated in British pound sterling (GBP).

Figure B5: Swap Spreads for Alternative Maturity Group Definitions



(a) Ultra Short Maturity Group



(b) Short Maturity Group

Notes: This figure plots the time series of volume-weighted GBP swap spreads in our data for the baseline and alternative definitions of ultra short and short maturity groups. Panel (a) shows the swap spreads by changing the definition of the ultra short maturity group from "below 3 months" to "below 1 year". Panel (b) shows the swap spreads by changing the definition of the short maturity group from "3 months to 5 year" to "1 year to 5 year".

Table B1: Estimated Coverage of Transactions Activity

	Average daily turnover in April 2022		
	Our data ($ billion)	BIS benchmark ($ billion)	Coverage
All currencies	3,425	4,987	69%
Pound sterling (GBP)	287	341	84%
Euro (EUR)	1,328	1,688	79%
US dollar (USD)	1,460	2,209	66%
Australian dollar (AUD)	141	279	51%
Other currencies	209	470	44%

Notes: This table reports the estimated coverage of swap transactions observed in our data using the April 2022 Bank for International Settlements (BIS) over-the-counter interest rate derivatives turnover survey as the benchmark. Our sample includes all single currency fixed-to-floating interest rate swaps and overnight indexed swaps where at least one of the counterparties is a UK entity. We adjust for double counting arising out of the dual reporting of trades with same unique identifier, as well as for duplication on account of centralized clearing of trades with different unique trade identifiers. We calculate the adjusted turnover in the month of April 2022 and divide it by 19, the number of trading days in that month. We compare our average daily turnover to the BIS benchmark that includes all interest rate derivatives except options and complex derivatives, and report the estimated share for all currencies put together and for some of the major currency pairs separately. BIS data can be accessed here.

Table B2: Descriptive Statistics for Entity-level Outstanding Positions

	Entity-level net absolute position (GBP million)					
	N	Mean	SD	p25	p50	p75
Bank	105	1,411	4,119	34	163	755
Fund	365	1,328	17,699	5	30	142
PF&I	576	435	1,573	21	61	217
Corporate	258	165	403	14	40	106
Official	16	3,446	12,798	28	166	405

Notes: This table reports the distribution of net (absolute) outstanding positions at an entity-level within an end-user sector as on February 1, 2022. Units are in GBP million except the count of entities. We calculate the net exposure at the entity-level as the difference between the notional values of receive fixed and pay fixed swaps outstanding on a date, and report the distribution of its absolute value within the sector. "N" refers to the number of unique entities that had any outstanding exposure in GBP swaps as on February 1, 2022 in our sample. All sectors in general and funds in particular display the presence of a few large entities as evidenced by the large difference in the mean and median positions.

Table B3: Dealers' Swap and Bond Positions

	Δ Bond (Net notional)			
	(1)	(2)	(3)	(4)
Δ Swap (Net notional)	-0.065**	-0.074**	-0.043***	-0.040***
	(0.026)	(0.032)	(0.016)	(0.003)
Δ Rate (10Y)		0.601		0.074
		(0.417)		(0.064)
	Size-weighted		Equal-weighted	
N	2,079	2,079	2,081	2,081
Dealer FE	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	No

Notes: This table reports the results of estimating the below equation:

$$\Delta \text{Bond}_{i,t} = \Delta \text{Swap}_{i,t} + \alpha_i + \alpha_t + \varepsilon_{i,t},$$

where $\Delta\text{Bond}_{i,t}$ refers to the net purchase or sale of UK government bonds (gilts) by dealer i in month t, and $\Delta\text{Swap}_{i,t}$ refers to changes in the net client-facing swap position held by dealer i in month t. Columns (1) and (2) weight the observations by the size of the dealer, while columns (3) and (4) equally weight all observations. The specification considers the net notional for maturities of 10 years & above. We focus on the notional of long-term swaps and bonds because they carry the largest interest rate risk and because shorter-tenor bond holdings may reflect regulatory requirements as well as intermediation in other markets such as repo, where shorter-tenor bonds are commonly used as collateral (Julliard et al., 2022). We source data on dealer-level bond transactions available to the Bank of England through the Markets in Financial Instruments Directive (MiFID) II regulatory reporting. Columns (2) and (4) control for changes in 10Y gilt yields, while columns (1) and (3) include time (month) fixed effects. All columns include dealer fixed effects. Standard errors clustered by dealer and time are reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table B4: Determinants of Compression

	Δ Compression ratio				
	(1)	(2)	(3)	(4)	(5)
Δ Quantity (Below 3M, t-1)	-0.001	-0.001	-0.001	-0.002	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Δ Quantity (3M - 5Y, t-1)	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)
Δ Quantity (5Y - 10Y, t-1)	0.002	0.002	0.002	0.0006	0.0008
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Δ Quantity (10Y & Above, t-1)	-0.0004	-0.0003	-0.0003	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.005)
Δ Rate (10Y, t-1)		0.006	0.006		
		(0.004)	(0.004)		
Δ Rate volatility (10Y, t-1)		-0.018	-0.019		
		(0.015)	(0.015)		
Δ Assets (log)					-0.008
					(0.026)
Δ CET1/RWA					0.060
					(0.073)
N	2,609	2,573	2,573	2,573	1,929
Dealer FE	No	No	Yes	Yes	Yes
Time FE	No	No	No	Yes	Yes

Notes: This table correlates the weekly change in dealer-level compression ratio with variables that may independently move end-users' swap demand. The regressors include changes in maturity-specific net quantities facing the dealer in the previous week. Columns (2) and (3) additionally include lagged changes in the 10Y gilt yield and its squared term that represents interest rate volatility. Columns (4) and (5) include time (week) fixed effects. Finally, column (5) includes the quarterly changes in dealers' (log) assets and common equity tier 1 (CET1) capital scaled by risk-weighted assets (RWA). Standard errors clustered by dealer and time are reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table B5: Demand Elasticities (Alternative Specifications)

Panel A	Δ Quantity (scaled)			
	3M to 5Y		10Y & above	
$\Delta\widehat{\text{Swap spread}}$	0.664*	0.480	0.008	0.022
	(0.374)	(0.359)	(0.373)	(0.363)
Δ Quantity (scaled, t-1)	-0.227***	-0.228***	-0.189***	-0.195***
	(0.068)	(0.066)	(0.046)	(0.043)
N	2,537	2,423	2,466	2,352
Dealer FE	Yes	Yes	Yes	Yes
Drop Mar. 2020 and Sep. 2022	No	Yes	No	Yes

Panel B	Δ Quantity (scaled)			
	3M to 5Y		10Y & above	
$\Delta\widehat{\text{Swap spread}}$	0.839**	0.660**	-0.096	-0.072
	(0.289)	(0.276)	(0.416)	(0.399)
Δ Quantity (scaled, t-1)	-0.310***	-0.309***	-0.200**	-0.192**
	(0.079)	(0.079)	(0.076)	(0.075)
Δ Rate (10Y, t-1)	0.055	0.032	0.001	0.012
	(0.079)	(0.069)	(0.093)	(0.092)
Δ Rate volatility (10Y, t-1)	-0.570	-0.442	-0.024	-0.020
	(0.368)	(0.387)	(0.151)	(0.141)
Δ Assets (log)	-0.042	-0.043	-0.057	-0.073
	(0.101)	(0.078)	(0.069)	(0.079)
Δ CET1/RWA	-0.493	-0.579	-0.339	-0.459
	(0.824)	(0.761)	(0.518)	(0.494)
N	1,891	1,802	1,862	1,772
Dealer FE	Yes	Yes	Yes	Yes
Drop Mar. 2020 and Sep. 2022	No	Yes	No	Yes

Notes: This table reports the estimates of the instrumental variable regression in Equation 8 (second stage). In both panels, the dependent variable is the scaled change in the weekly outstanding net position facing a dealer. The regressor of interest is the change in notional-weighted swap spreads offered by dealer i in week t in maturity group m, instrumented using portfolio compression. Panel A controls for changes in lagged quantities. Panel B additionally controls for changes in 10 year gilt yield, interest rate volatility, (log) assets of dealers, and their common equity tier 1 (CET1) scaled by risk-weighted assets (RWA). The dealer-level controls pertain to the respective quarter for which the data are available. All columns include dealer fixed effects. Standard errors clustered by dealer and time are reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

C. Additional Facts on the Swap Positions of the Fund Sector

In this appendix, we discuss the swap positions and the trading behavior of funds and relate it to the strategies that they appear to follow. In the aggregate, funds trade orders of magnitude more swaps than any other end-user sector: Table 1 shows that the average monthly gross transaction volume executed by funds is GBP 1.3 trillion, followed by PF&I at GBP 73 billion. Despite this, funds do not represent a significant and persistent source of risky demand imbalances for dealers due to large intra-sector netting and ultra short maturity of their swap holdings. We discuss three key features of funds' swap holdings below.

C.1. Fund Exposures

Large intra-sector netting: First, Table 1 shows that the *net* notional of funds' transactions is much smaller than their overall trading (at GBP 9 billion), reflecting substantial offsetting between receive and pay fixed swaps. Similarly, their net outstanding notional is GBP 317 billion, with a net DV01 of GBP 48 million, significantly lower than the DV01 of PF&I. At an individual entity level, Figure 3 highlights considerable heterogeneity within the fund sector: in any given month, roughly half of fund entities are net receivers and half are net payers of fixed rate. Within this distribution, exposures are highly concentrated in a few large entities. Figure C1 shows that the ten largest funds accounted for over 80% of the sector's net outstanding exposure as of February 2022. Altogether, these facts show that many funds offset each other's flows and that sector-level positions are driven primarily by a small number of very large funds.

Inconsistent direction of exposure: Second, unlike PF&Is, banks, and corporations, funds frequently flip the direction of their net exposures. Figure 1 shows that funds held substantial pay fixed positions at the start of the interest rate hiking cycle in late 2021, consistent with market timing, but otherwise held receive fixed positions at the beginning and end of our sample.

Short maturity and low duration risk: Third, Figure 4 shows that fund exposures are concentrated in ultra short (under 3 months) and short (3 months to 5 years) maturities. As a result, funds' net interest rate risk, as measured by DV01, is considerably lower than that of PF&I and, in many cases, even lower than that of banks (Figure 2).

C.2. Fund Trading Strategies

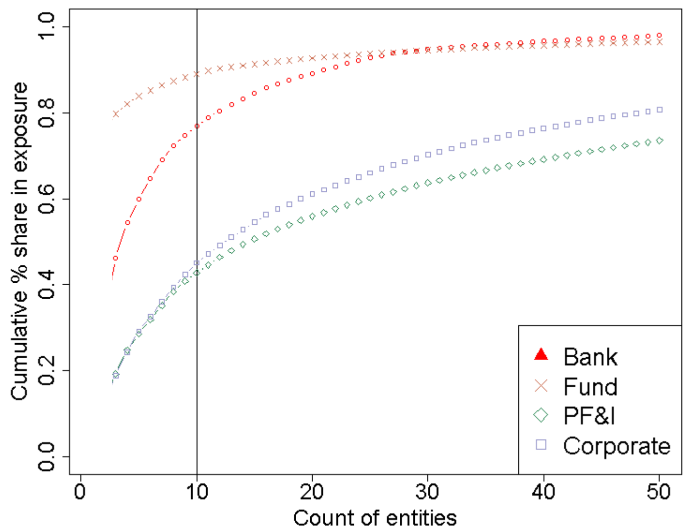
To better understand the sources of heterogeneity within the fund sector, we classify all the individual fund entities into granular categories that reflect common trading strategies. To do so, we scan the names of these entities in our non-anonymized data and also leverage publicly available information on major funds to group them into four types: (i) Fixed Income or Bond funds, (ii)

Macro funds, (iii) Quant or Relative Value funds, and (iv) Other Asset Managers.

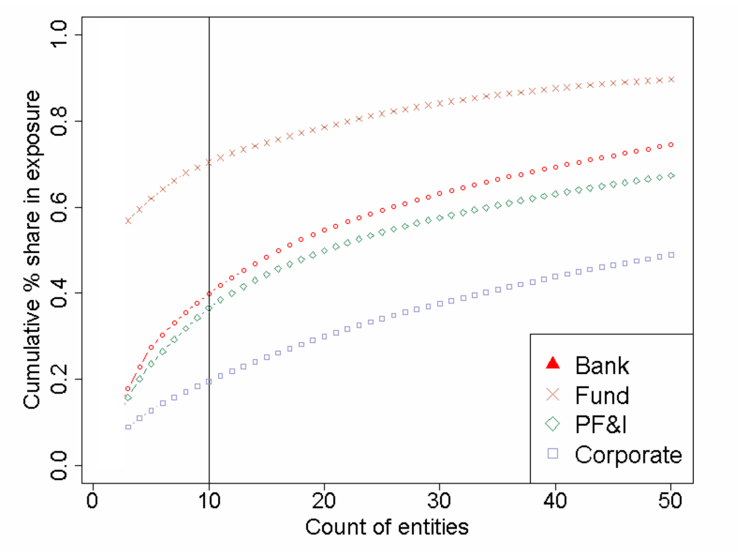
We find that the heterogeneity in funds' swap exposures is closely linked to the trading strategies they follow. Table C1 summarizes their gross and net positions. Macro funds are the largest and, similar to banks and corporations, primarily pay fixed. They hold 45% of the fund sector's gross notional, but with a net-to-gross position ratio of 0.6, they account for 85% of *net* (absolute) exposures. This also holds quite consistently over time, as evident in panel (a) of Figure C2. In contrast, Other Asset Managers primarily receive fixed rates. Strikingly, the net-to-gross position ratio of Quant or Relative Value funds is only 0.03, implying that they hold two-way positions that mostly net out, consistent with their perceived role of exploiting relative value. Overall, some funds behave like end-user hedgers (e.g., Macro), while others like tactical traders (e.g., Quant or Relative Value). While our discussion focuses more on banks, corporations, and PF&I, who are a larger source of persistent directional imbalance for dealers, we account for fund positions throughout.

Finally, panel (b) of Figure C2 shows that all fund types display large volatility in their net swap exposures, that is orders of magnitude more than other sectors. For example, panel (a) of Figure C2 shows that at the start of the interest rate hiking cycle in 2022, macro funds substantially increased their pay fixed position, and quickly reversed it towards the end of the year. One key driver of such fluctuations is unexpected monetary policy shocks. Table 3 shows that funds strongly react to monetary policy shocks in a pro-cyclical direction similar to PF&Is.

Figure C1: Concentration in Exposures



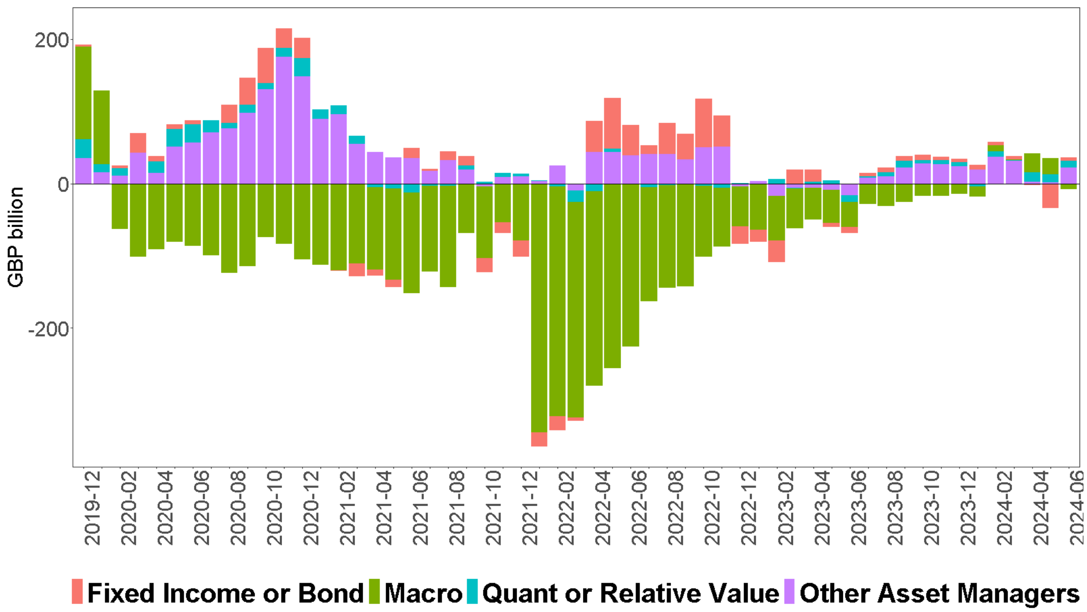
(a) GBP



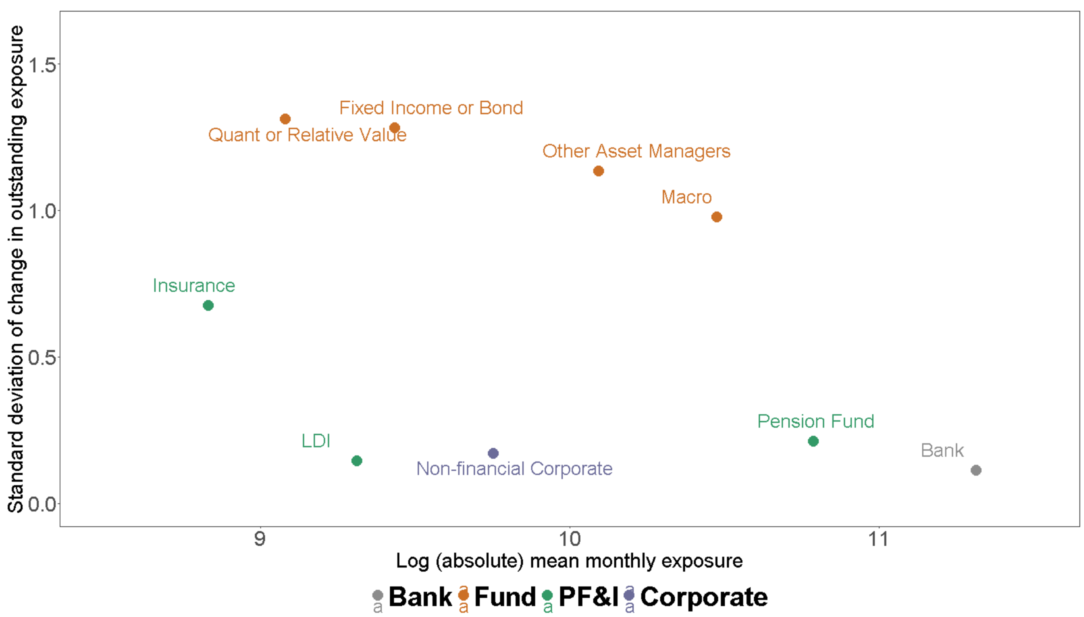
(b) All currencies

Notes: This figure shows that net exposures are concentrated within a few entities, particularly in the fund sector. The figure plots the cumulative share of net (absolute) position held by top 50 entities within each sector as on February 1, 2022, for GBP swaps in panel (a) and swaps across all currencies in panel (b). Vertical line in black shows the top 10 entities in each sector with their corresponding cumulative share on the y-axis. The first point in both plots shows the share of top 3 entities put together in each sector.

Figure C2: Swap Positions of the Fund Sector



(a) Net Notional Outstanding



(b) Entity Size and Exposure Volatility

Notes: This figure zooms in on the fund sector. Panel (a) shows the net notional outstanding positions in GBP billion at the start of every month for four fund types: Fixed Income or Bond, Macro, Quantitative or Relative Value, and Other Asset Managers. Panel (b) plots the relationship between the size of sub-sectors, measured as the log of mean (absolute) net monthly exposure observed during our sample period, and the volatility in their outstanding positions, measured as standard deviation of the change in monthly outstanding positions within that sector's dominant maturity group.

Table C1: Gross and Net Notional Outstanding by Fund Type

Panel A	Gross notional (GBP billion)					
	Below 3M	3M to 5Y	5Y to 10Y	10Y & above	Total	Share
Fixed Income or Bond	121	77	11	4	213	0.18
Macro	254	268	7	3	532	0.45
Quant or Relative Value	108	28	6	3	145	0.12
Other Asset Managers	147	109	17	23	297	0.25
Panel B	**Net notional (GBP billion)**					
	Below 3M	3M to 5Y	5Y to 10Y	10Y & above	Net-to-gross	Share
Fixed Income or Bond	-17	-1	0	0	0.08	0.05
Macro	-80	-232	-5	-2	0.60	0.85
Quant or Relative Value	-4	0	-1	0	0.03	0.01
Other Asset Managers	14	13	-3	1	0.08	0.08

Notes: This table reports the gross outstanding notional (panel A) and net outstanding notional (panel B) as on February 1, 2022, held within each of the four maturity groups by four fund types: Fixed Income or Bond, Macro, Quantitative or Relative Value, and Other Asset Managers. We identify fund types at a legal entity level using string matching on their names with common investment strategies. The second-to-last column in panel A reports the total position of the fund type across all maturities, and the last column reports the share of each fund type in the overall outstanding gross positions. The second-to-last column in panel B reports the ratio of net position to gross notional for each fund type using positions aggregated across maturity groups, and indicates the extent of two-sided exposures held by each fund type. The last column in panel B reports the share of each fund type in the net (absolute) positions in aggregate across all maturity groups.

D. Quantifying the Extent of Hedging with Swaps for UK Banks and PF&I

While quantifying swap usage across end users is not the primary goal of this paper, we provide back-of-the-envelope estimates for UK pension funds and banks to illustrate that (i) swap usage is economically meaningful, and (ii) the magnitude of the demand shocks considered in our counterfactuals is plausible. We summarize our calculations and the underlying assumptions below.

UK PF&I: PF&I have long-dated liabilities that embed fixed rate guarantees. However, their assets, consisting of government and corporate bonds, typically have shorter maturities than liabilities (EIOPA, 2014, Domanski, Shin, and Sushko, 2017). As a result, the sector has a negative duration gap (duration of assets is shorter than that of liabilities) and is therefore exposed to declines in interest rates. A pension fund or an insurer wanting to close the duration gap with swaps would need to receive the fixed rate. Consistent with this, we observe that the PF&I sector holds receive fixed swaps in our data, implying their positions are directionally consistent with the hedging needs arising out of their balance sheet duration mismatch.

To estimate the extent to which PF&Is hedge their duration gap using swaps, we compile aggregate balance sheet data from two sources. First, we use the maturity profile of UK pension fund liabilities from The Pensions Regulator (2023), which covers the universe of defined benefit schemes. These funds hold total liabilities of approximately GBP 1.9 trillion, with a weighted-average duration of 19 years. With a funding ratio (assets/liabilities) of 111%, aggregate assets amounting to GBP 2.1 trillion and equity amounting to roughly GBP 200 billion as of March 2022. Second, for asset duration, we turn to Pension Protection Fund (2022), which reports that 70% of pension fund assets are allocated to UK gilts and other fixed income instruments. The reported sensitivity of equity to gilt yields implies an asset duration of 10. However, this estimate does not fully capture the leveraged exposure of Liability-Driven Investment (LDI) strategies widely used by UK pension funds. Pinter et al. (2024) document that LDI funds predominantly invest in long-dated gilts (20+ years) and finance these positions through repo markets. Incorporating the exposures of LDI funds, we estimate the effective asset duration to be around 15 years.

We next benchmark the balance sheet duration gap against the duration of PF&Is' swap positions, which we obtain from our data. Table 1 shows that the PF&I DV01 is GBP 203 million, which scales to a total dollar duration of 2,030 billion. Comparing this to the estimated duration gap of GBP 4,600 billion suggests that approximately 44% is hedged using swaps.[39]

[39]Some of these swap positions may belong to non-defined benefit pension schemes, however, we assume their allocation of swaps to be relatively small.

	Pension Funds			Banks		
	Amount (GBP bn)	Years	Duration (GBP bn)	Amount (GBP bn)	Years	Duration (GBP bn)
Liabilities	1,900	19	36,100	424	1	424
Assets	2,100	15	31,500	500	4.5	2,250
Duration gap			-4,600			1,826
Swap duration			2,030			-370
Hedged using swaps			44%			20%
Equity	200			76		
Swap DV100	20.3			3.7		
Impact on equity	10.2%			4.9%		

UK Banks: In contrast to PF&I, we expect banks to have a positive duration gap because their assets, which include fixed rate mortgages, have longer duration than their liabilities, which are mainly short-term deposits. If so, a bank wanting to close the mismatch between assets and liabilities with swaps would need to pay the fixed rate. Consistent with this, we observe that banks in our sample pay the fixed rate using swaps.

We source data on UK banks' assets and liabilities from CapitalIQ. As of February 2022, non-dealer banks in our sample that held swaps had total assets of about GBP 500 billion, with liabilities totaling GBP 424 billion. Direct estimates of UK banks' asset and liability durations are unavailable, so we draw on evidence from other countries. Velez et al. (2024) report an asset duration of 4.8 years for Italian banks' bond holdings, while Hanson (2014) estimates a 3.3 year duration for US banks' mortgage portfolios, reflecting prepayment risk. Since UK mortgages have lower prepayment risk due to prepayment penalties, we set asset duration at 4.5 years. On the liability side, UK bank funding is largely deposit-based, so we assume a liability duration of 1 year. This implies a duration gap of GBP 1,826 billion.

Table 1 shows that the net DV01 of banks' swap positions is GBP 37 million, which scales to a total dollar duration of GBP 370 billion. Thus, these estimates suggest that roughly 20% of the estimated duration gap of GBP 1,826 billion is hedged using swaps.

We stress that these estimates rely on a combination of industry data and estimates from other countries, and are subject to the assumptions outlined above. Nonetheless, they highlight the economic relevance of swaps as a key instrument for interest rate risk management and suggest that the magnitude of the demand shocks considered in our counterfactuals is plausible.

Impact on equity: We also estimate the impact of a 100 bps parallel shift in the yield curve on the aggregate equity of each sector, focusing only on derivative positions. This exercise abstracts from estimating the effects of interest rate changes on assets and liabilities, focusing instead on equity directly. Our goal is to highlight the role of swaps in mitigating equity losses from rate changes. We find that such an upward (downward) shift increases the value of banks' (PF&Is') swaps by 4.9% (10.2%) of equity. For comparison, Velez et al. (2024) report that, for Italian banks, a 100 bps increase in rates raises the value of swaps by 3.65% of Common Equity Tier 1 (CET1). This is similar to the estimate we obtain for UK banks.

While these results are consistent with the broader literature and the basic business model of these sectors, we note that our results on UK banks stand in contrast to the literature on US banks, who do not seem to meaningfully hedge their interest rate risks with swaps (McPhail et al., 2023). We highlight several institutional differences between the US and the UK banking sector that may help reconcile these findings. First, UK (and European) banks face higher regulatory pressure to hedge their interest rate risk (Wilkes, 2023a,b), compared to US banks. Second, US banks face high prepayment risk from mortgages and to hedge that risk they need to *receive* the fixed rate instead (Hanson, 2014). This is less applicable to UK banks as mortgage prepayment is often associated with a penalty (Benetton, 2021).

E. Equilibrium Derivation

To solve the equilibrium, apply Ito's lemma to the equilibrium price Equation 15 and plug in the expression of dg_t in Equation 18, we get the expected return,

$$\begin{aligned} dP_t(\tau) =& - A(\tau)^\top P_t(\tau) \left(-\Gamma(g_t - \bar{g})dt + \Sigma dB_t\right) + \frac{1}{2} A(\tau)^\top \Sigma\Sigma^\top A(\tau) P_t(\tau) dt \\ & (A'(\tau) g_t + C'(\tau)) P_t(\tau) dt \\ \frac{dP_t(\tau)}{P_t(\tau)} =& - A(\tau)^\top \left(-\Gamma(g_t - \bar{g})dt + \Sigma dB_t\right) + \frac{1}{2} A(\tau)^\top \Sigma\Sigma^\top A(\tau) dt \\ & A'(\tau) g_t dt + C'(\tau) dt \end{aligned}$$

Collecting the terms in front of dt, we get

$$\mu_t(\tau) = A(\tau)^\top \Gamma(g_t - \bar{g}) + \frac{1}{2} A(\tau)^\top \Sigma\Sigma^\top A(\tau) + A'(\tau) g_t + C'(\tau) \tag{22}$$

Dealer's problem is

$$\max_{X_t(\tau)} \left[\int_0^\infty X_t(\tau)(\mu_t(\tau) - c_t) d\tau - \frac{a}{2} Var\left(\int_0^\infty X_t(\tau) A(\tau)^\top \Sigma d\tau dB_t \right) \right]$$

Take first order condition with respect to $X_t(\tau)$, we get

$$\mu_t(\tau) - c_t = aA(\tau)^\top \Sigma\Sigma' \left[\int_0^\infty X_t(\tau) A(\tau) d\tau \right] \tag{23}$$

Plug in the expression for $X_t(\tau)$ from the market clearing condition (assuming $K = 1$)

$$\begin{aligned} X_t(\tau) &= -Q_t(\tau) = \alpha(\tau) log(P_t(\tau)) + \beta_t(\tau) \\ &= -\alpha(\tau)[A(\tau) g_t + C(\tau)] + \theta_0(\tau) + \theta_1(\tau)\beta_{1,t} \end{aligned}$$

Furthermore, plug in the expression for $\mu_t(\tau)$ from Equation 22 into Equation 23. Matching the coefficients in front of g_t, we get Equation 16. Matching the coefficients in front of the constant terms, we get Equation 17.

To get the moments, the average spread for maturity group τ is

$$E[s_t(\tau)] = \left[A(\tau)^\top \begin{pmatrix} \bar{c} \\ 0 \end{pmatrix} + C(\tau) \right] / \tau \tag{24}$$

The average quantity from the client's perspective for maturity group τ is

$$E[Q_t(\tau)] = \alpha(\tau)[A(\tau)^\top \begin{pmatrix} \bar{c} \\ 0 \end{pmatrix} + C(\tau)] - \theta_0(\tau) \tag{25}$$

The change in spread is

$$ds_t(\tau) = \frac{A(\tau)}{\tau} dg_t \tag{26}$$

Hence the variance is

$$Var(ds_t(\tau)) = \frac{A(\tau)^\top}{\tau} Var(dg_t) \frac{A(\tau)}{\tau} \tag{27}$$

We define $\tilde{A}$ to be a $T \times 2$ matrix, where the τth row is $\frac{A(\tau)}{\tau}$.

Plug in

$$dg_t = -\Gamma g_t + \Sigma dB_t \tag{28}$$

$$Var(dg_t) = \Gamma Var(g_t) \Gamma^\top + \Sigma\Sigma^\top \tag{29}$$

$$Var(g_t) = \rho \tag{30}$$

where ρ is the solution to

$$-\Gamma\rho - \rho^\top \Gamma^\top + \Sigma\Sigma^\top = 0 \tag{31}$$

we get the formula for variance of spread changes.

Furthermore, to match the empirical counterpart, we define the change in quantities as the change in Q_t scaled by the absolute average quantity, i.e.,

$$\frac{dQ_t(\tau)}{|E[Q_t(\tau)]|} = \frac{\alpha(\tau)A(\tau)^\top dg_t - (0, \theta(\tau))dg_t}{|E[Q_t(\tau)]|} = \frac{[\alpha(\tau)A(\tau)^\top - (0, \theta(\tau))]dg_t}{|E[Q_t(\tau)]|} \tag{32}$$

Since all the variables are stationary, the above equation is a close approximation of the empirical counterpart in Equation 18. The variance of this object is

$$Var\left(\frac{dQ_t(\tau)}{|E[Q_t(\tau)]|}\right) = \frac{[\alpha(\tau)A(\tau)^\top - (0, \theta(\tau))]Var(dg_t)[\alpha(\tau)A(\tau)^\top - (0, \theta(\tau))]^\top}{|E[Q_t(\tau)]|^2} \tag{33}$$

We define $\tilde{M}$ to be a $T \times 2$ matrix, where the τth row is $[\alpha(\tau)A(\tau)^\top - (0, \theta(\tau))]/|E[Q_t(\tau)]|$.

Furthermore, define

$$\Lambda = \begin{pmatrix} \tilde{A} \\ \tilde{M} \end{pmatrix} \tag{34}$$

Hence, the variance-covariance matrix of spread changes and quantity changes is

$$Var\left(\begin{pmatrix} ds_t \\ \frac{dQ_t}{|E[Q_t]|} \end{pmatrix}\right) = \Lambda Var(dg_t) \Lambda^\top = \Lambda \left(\Gamma Var(g_t) \Gamma^\top + \Sigma\Sigma^\top\right) \Lambda^\top \tag{35}$$