Bank of England

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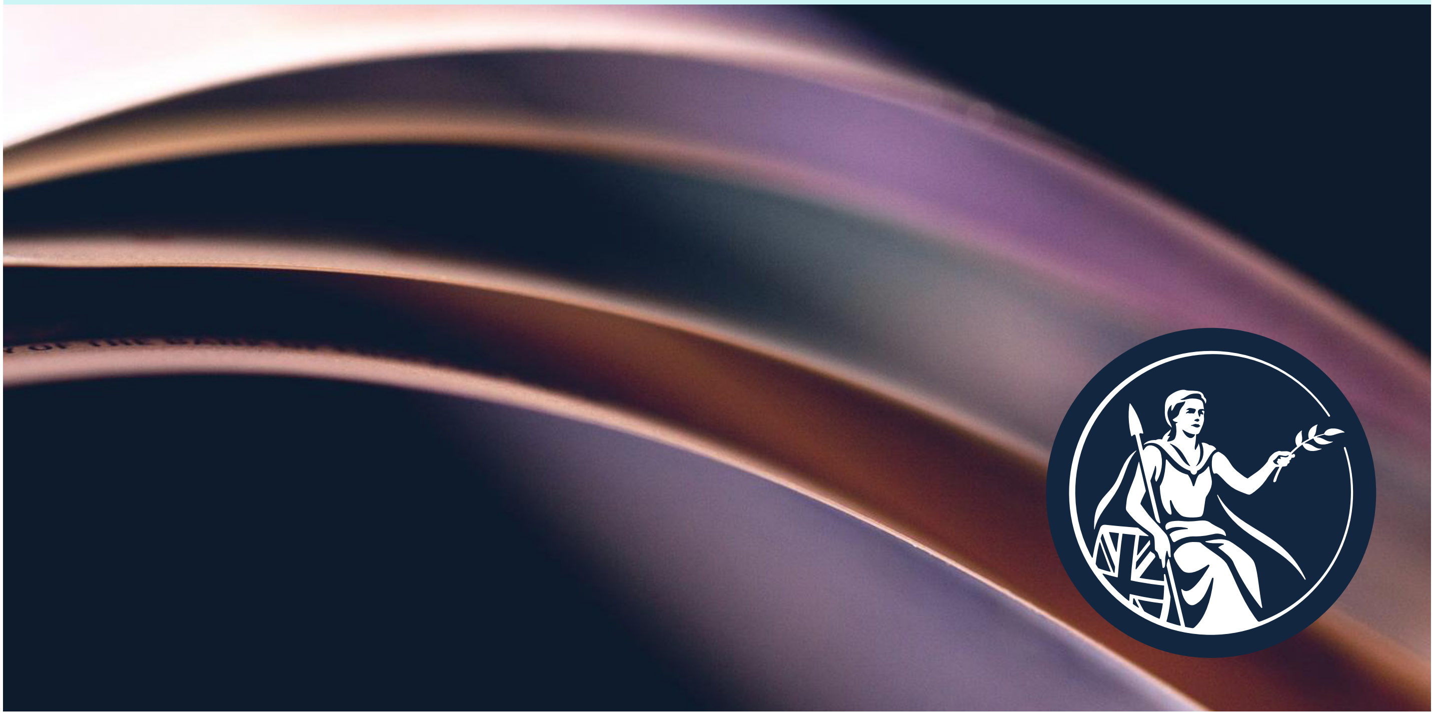

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The market for sharing interest rate risk: quantities and asset prices

Umang Khetan,(1) Jian Li,(2) Ioana Neamțu(3) and Ishita Sen(4)

Abstract

We study the extent of interest rate risk sharing across the financial system using granular positions and transactions data in interest rate swaps. We show that pension and insurance (PF&I) sector emerges as a natural counterparty to banks and corporations: overall, and in response to decline in rates, PF&I buy duration, whereas banks and corporations sell duration. This cross-sector netting reduces the aggregate demand that is supplied by dealers. However, two factors impede cross-sector netting and add to substantial dealer imbalances across maturities: (i) PF&I, bank and corporations' demand is segmented across maturities, and (ii) hedge funds trade large volumes with time-varying exposure. We test the implications of demand imbalances on asset prices by calibrating a preferred-habitat investors model with risk-averse arbitrageurs, who face both funding cost shocks and demand side fluctuations. We find that demand imbalances play a bigger role than arbitrageurs' funding cost in determining the equilibrium swap spreads at all maturities. In counterfactual analyses, we demonstrate how demand shocks, eg, regulation leading banks to hedge more, affect the hedging behaviour of PF&I. Our paper provides a quantity-based explanation for empirically observed asset prices in the interest rate derivatives market.

Key words: Interest rate risk, OTC derivatives, hedge funds, pension funds, insurance companies, banks, non-financial corporations, demand elasticities.

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

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Recent financial events, such as the failure of Silicon Valley Bank in 2023 and the UK LDI crisis in 2022, highlight the extent of maturity mismatch in many parts of the financial system. On one hand, long-term institutions such as pension funds and insurers have large asset-liability mismatches that make them particularly vulnerable to interest rate declines. On the other hand, banks typically engage in the opposite maturity transformation, lending long-term and borrowing short-term. Consistent with this business model, banks remain vulnerable when central banks across the world raise interest rates. In theory, interest rate derivative markets provide investors opportunities to transfer aggregate risks to other parts of the financial system and reduce any given sector's exposure to interest rate shocks. Indeed, the market for interest rate risk transfers (e.g., rate swaps) is enormous, with approximately $600 trillion in outstanding gross notional as of 2022.

Despite the large size of this market, several first-order questions remain unanswered, primarily due to lack of data on quantities. For example, (1) what is the extent of risk transfers across sectors: do various end-users swap risks as their business models would suggest, or amplify demand imbalances by trading in the same direction? (2) How large are demand imbalances and who is bearing them? (3) How do demand imbalances interact with other frictions to determine equilibrium prices? (4) How do demand shocks from one financial sector (e.g., regulation driving banks to hedge more) transmit across the system; do these demand shocks exacerbate risk mismatch in other sectors? These questions have far reaching implications for financial intermediaries and the broader economy.

In this paper, we make progress on these questions by exploiting the most comprehensive trade-level interest rate derivatives data deployed in academic research to date. We examine how different sectors (banks, pension funds, insurers, hedge funds, and non-financial corporations), each with unique hedging needs, engage in this market to share interest rate risks. We uncover partial risk transfers across sectors and persistent demand imbalances that are borne by dealers. Through the lens of a structural model, we quantify the effect of demand pressure on equilibrium prices (swap spreads) of different maturities, and in counterfactual analyses, we examine how demand shocks in one part of the financial system spill over to other parts through asset prices.

Our analysis leverages Bank of England confidential transaction and outstanding-position data that cover all sectors of the economy and over 60% of the global swaps trading volume. The following features of these data allow us to comprehensively examine the full extent of this market's dynamics. First, we observe both the outstanding positions of an entity and its new trade activity. Thus, we can characterize an investor's behavior taking account of his full history of trading information as captured by the stock of its outstanding positions. Second, we observe the exact counterparty for each trade. This facilitates the construction of granular sector classification to accurately characterize the extent of risk transfers at the sector level. Third, we observe detailed characteristics for each position and trade, including notional amounts, fixed rate, trade direction, maturity, floating rate benchmark, and currencies. These granular characteristics permit us to accurately compute risk exposures, capture the exact price contracted by each client at the time of the trade, and assess segmentation in risk sharing along dimensions such as maturities. Moreover, using the joint dynamics of swap prices and outstanding positions along the maturity curve, we can estimate user demand in different maturity segments in a fully flexible way, while also accommodating potentially correlated supply and demand side shocks. Finally, our data span a long time-period of five years from 2018 to 2022, which allows for important time-series analyses on the evolution of risk transfers.

Although existing literature has looked at how some sectors manage interest rate risk separately (e.g., Sen (2019) considers insurers, McPhail, Schnabl, and Tuckman (2023) and others study banks), to the best of our knowledge, our paper is the first to examine all sectors jointly in the interest rate swap market and document their relative sizes and interactions in different market segments. Putting different sectors in perspective allows us to compute demand imbalances along the maturity curve and draw asset pricing implications. Furthermore, the relative size and demand elasticities across sectors are also crucial for understanding the spillover effects of demand shocks in one sector to the others.

We start by outlining the main facts on swap positions and trading across sectors. First, there are four main end-user segments: (a) funds (including hedge funds and asset managers), (b) pension, liability-driven investment funds, and insurers (together referred to as PF&I), (c) banks (excluding the dealer subsidiaries), and (d) corporations.[1] In aggregate, funds usually hold the largest stock of outstanding net positions, followed by PF&I, banks and corporations. In addition, funds' trading volumes are orders of magnitude larger than all other sectors.

Second, to quantify the extent of risk transfers, we examine the direction of net outstanding positions. We construct two metrics: net swaps exposures (receive minus pay fixed) and the duration risk of a one basis point movement in interest rates (DV01). We find that there is significant heterogeneity in the direction of net outstanding positions across sectors. Looking at an aggregate level, we find that PF&I receive fixed, i.e. they add duration to their portfolios with swaps. In contrast, banks and corporations do the opposite; they pay fixed, i.e. sell duration with swaps. Looking within sectors at an entity level, we find that a large majority of entities within these sectors trade in one direction: PF&I receive fixed and

[1] We also observe the holdings of public and sovereign institutions. However, as they are relatively few, we omit discussing them in detail.

banks and corporations pay-fixed.

In contrast to PF&I, banks, and corporations, the funds sector exhibits substantial heterogeneity in the direction of positions. We find that to a large degree this heterogeneity is explained by different trading strategies. Specifically, we categorize the funds universe into the following types: macro, fixed income, quant and relative value, and asset managers. Macro funds have the largest net outstanding positions and primarily pay-fixed, similar to banks and corporations. Asset managers generally receive fixed. In contrast, quant & relative value and fixed income funds frequently flip trading direction. The holding patterns of funds suggest that some funds behave like end-users (e.g., macro), while others behave like arbitrageurs (e.g., quant & relative value).

Third, holdings are highly segmented across maturities. Specifically, we group swaps into four buckets: less than 3 months, 3 months to 5 years, 5 to 10 years, and above 10 years. PF&I largely hold long maturity swaps (above 10 years), and consistently do so throughout the sample. A bulk of banks' and corporations' positions are in the short to intermediate bucket (3 months to 5 years). Finally, hedge funds hold very short maturity swaps (under 3 months) and short to intermediate maturity swaps (3 months to 5 years). The segmentation along maturities is consistent with investors having preferred habitats (Vayanos and Vila, 2021).

Fourth, we evaluate how holdings evolve with changes in interest rates. We examine sensitivity of net exposures to lagged changes in the interest rate level factor, which we construct as the first principal component of yields at 3 month, 5 year, 10 year, and 30 year tenors. We find that PF&I and banks trade in the opposite direction in response to shifts in rates, consistent with what we observe about the levels of net exposures. As rates fall, PF&I increase their net receive positions, but banks and corporations increase their net pay positions. In other words, PF&I buy (sell) duration, whereas banks and corporations sell (buy) duration in response to decline (rise) in rates. These patterns suggest that PF&I are a natural counterparty to banks and corporations in the swaps market. This is consistent with the sectors' opposite underlying balance sheet maturity mismatch: PF&I are typically net short duration while banks are typically long duration.

Fifth, we turn to understanding the dynamics of aggregate end-user net demand and dealer balances. Since swaps are in zero net supply, the dealer sector takes the opposite side of the net end-user demand. Thus, the dealer sector's balances are equal to the negative net demand of the aggregated end-users. Two points are crucial to understand. (i) A large portion of PF&I positions is offset by the positions of banks and corporations, resulting in significant cross-sector netting. This reduces the aggregate net demand that needs to be met by the dealer sector. However, dealer imbalances still exist because even though PF&I trade in the opposite direction relative to banks and corporations, their respective demands are highly segmented across maturities, as discussed above.[2] Overall, for the majority of times during our sample, dealers receive fixed (are long duration) in short maturities and pay fixed (are short duration) in long maturities. (ii) Some end-user funds (e.g., macro) trade large volumes with varying directional exposure such that their trading makes dealer imbalances more volatile, particularly in the shortest maturity bucket. As a result, we observe that dealers (and some funds) participate in all maturities and flip direction from time to time in certain maturity buckets, suggesting that their economic behavior can be characterized as those of arbitrageurs.

Motivated by the empirical facts, we adapt a preferred-habitat investor model to study the asset pricing consequences of demand imbalances at different maturities and the spillover effects across different sectors. We model end-users such as banks, corporations and PF&I as preferred-habitat investors, who have downward-sloping demand for interest rate swaps of a specific maturity (Vayanos and Vila, 2021). Such demand arises because investors are exposed to interest rate shocks from other parts of their balance sheets and trading interest rate swap is a capital-efficient way to hedge that risk. Since in general investors can also use bonds for hedging, the relevant price for their demand for swaps should be the swap spread, which captures the price of swaps relative to bonds. Defining price this way also nets out the direct impact of bond yields on swap rates. We allow investors trading in different maturity segment to have different demand elasticities. In addition, there is a time-varying aggregate demand factor that shifts the demand curve in each maturity segment. Hence, all the sectors are subject to correlated demand shocks. Furthermore, we allow the exposure to the aggregate demand factor to be potentially heterogeneous across investors and of opposite signs, capturing the fact that macroeconomic conditions affect the hedging demand of investors differentially. Our empirical result on rate sensitivity suggests that at least part of this demand factor corresponds to the level of interest rates.

While preferred-habitat investors only trade in specific maturity segments, dealers, together with certain funds, act as arbitrageurs and trade across maturity groups to take advantage of the differences in prices. These arbitrageurs are risk-averse and face time-varying funding costs from holding swaps on their balance sheets (He, Nagel, and Song, 2022). Such funding costs could come from standard market risk requirements applicable to

[2] This is consistent with the evidence of dealer imbalances in other markets (e.g., S&P 500 index options (Gârleanu, Pedersen, and Poteshman, 2008) and inflation swaps (Bahaj, Czech, Ding, and Reis, 2023)). The asset pricing implications of these imbalances are consistent with the literature on negative swap spreads (Boyarchenko, Gupta, Steele, and Yen, 2018, Klingler and Sundaresan, 2019, Hanson, Malkhozov, and Venter, 2022, Siriwardane, Sunderam, and Wallen, 2022).

dealers holding financial instruments, or dealers leverage constraints if they choose to hedge the interest rate risk by holding government bonds (Bicu-Lieb, Chen, and Elliott, 2020, Du, Hébert, and Li, 2023). Arbitrageurs' funding cost may vary over time as the rest of the dealers' balance sheets changes. We model both the funding cost and the aggregate demand factor as AR(1) processes, where the shock components are potentially correlated.

Next, we calibrate the model to match the average level of swap spreads and net imbalances, as well as their dynamics in each maturity segment. We first discretize the maturity space into four groups: less than 3 months, 3 months to 5 years, 5 to 10 years and at least 10 years. This is supported by our empirical fact that holdings are highly segmented across these four maturity buckets. This also allows us to estimate the demand elasticity and exposure to the aggregate demand factor for each group in a non-parametric way. More specifically, we match the average swap spreads and end-users' net outstanding positions for all the maturity groups. These moments are informative about the average level of demand, demand elasticities and the average funding cost. We also target the variances and co-variances between spreads and equilibrium quantities for each of the four maturity groups, which are informative about the dynamics of the state variables (the funding cost and the aggregate demand factor), as well as each sector's exposure to the demand factor. Our model can match all the moments reasonably well.

We find that the demand pressure (defined as the average intercept of the demand function) is concentrated among investors trading in the short-to-intermediate maturity group (3 months to 5 years) and the long maturity group (above 10 years). The demand pressure in these two groups has the opposite sign — while investors in the short-to-intermediate group have preference to pay fixed, investors in the long maturity group demand receiving fixed. In addition, investors in these two groups have the opposite exposure to the aggregate demand shock. Even though we do not impose any sign restrictions on demand parameters for investors in different maturity groups, the estimated demand pressure and exposure to shocks are consistent with the types of institutions trading in each group and matches the reduced form facts. The demand parameters we uncover further confirm that investors in the short-to-intermediate group and long maturity group are natural hedgers with each other.

Furthermore, while preferred-habitat investors have inelastic demand in general, the relative comparison of elasticities across segments matches with the types of institutions trading in each maturity bucket. we find that investors in the shortest maturity group (below 3 months) have the most elastic demand, consistent with the fact that the dominant investor type in this group is hedge fund. Investors in the short-to-intermediate group are less elastic compared to those in the shortest maturity group, as a majority of investors are banks and corporations, who tend to be less price sensitive compared to hedge funds. Finally, investors in the longest maturity group, who are mostly PF&I, have the most inelastic demand.

We then use our model to quantify the contribution of different factors to the shape of the equilibrium swap spreads curve. During our sample period, the average swap spreads are large and the swap spread curve features a hump-shaped pattern: the average swap spread first increases with maturity, reaching 20 basis points (bps) around 5 years; it then decreases to negative 40 bps for swaps above 10 years. The literature has suggested both demand factors, such as pension funds hedging needs (Klingler and Sundaresan, 2019), and supply factors, such as dealer balance sheet costs (Jermann, 2020, Du, Hébert, and Li, 2023), affecting the equilibrium spreads. Using the calibrated model, we study the relative importance of supply and demand factors for equilibrium prices, taking into account dealers' net position along the entire swap curve. We find that while both matter quantitatively, investors' demand pressure plays a relatively more important role. To quantify this, we first set the funding cost to 0 for the arbitrageurs. This leads to a 7 bps change in swap spreads across all maturity groups. We then set the average demand pressure for all sectors to zero, which brings the swap spread to almost 0 for all maturities. The magnitude of change from shutting down the demand pressure is larger than that from removing funding costs.

Next, we leverage the model to study how demand shifts in one sector can spillover to other sectors through adjustments in swap spreads. Such demand shifts could come from regulatory changes that force one sector to hedge more interest rate risks. For example, recent banking crises motivated discussions on whether stress tests should focus more on interest rate risks.[3] Such measures could induce banks to increase their hedging demand in the swap market, particularly in the short-to-intermediate maturity group. Similarly, any regulatory pressure for pension funds to hedge more will also shifts their demand in the longest maturity group. Considering demand shifts in the banking sector could also be thought as a cross-country comparison: Hoffmann et al. (2019) document that banks in areas with different loan-rate fixation conventions in the mortgage market are exposed differentially to interest rate changes. This implies that banks residing in countries with fixed-rate mortgage convention tend to have higher hedging needs in the interest rate swap market than others, which could potentially impact how expensive it is for PF&I to hedge their positions as well. We use our model to quantify how demand shifts in one sector affects cost of hedging for investors in other maturity segments.

We interpret any change in banks' demand as shifting the demand of preferred-habitat investors in the short-to-intermediate group and any change in PF&I's demand as shifting demand in the longest maturity group. In the event of sector-specific demand shocks, we

[3] For example, see https://www.imf.org/en/Blogs/Articles/2023/10/16/new-look-at-global-banks-highlights-risks-from-higher-for-longer-interest-rates.

find that a one-unit increase (about 12%) in demand pressure from banks raises the swaps spread in the long-end by about 60 bps. Because demand elasticities are small, quantities (other than the shocked sector) barely change while prices adjust significantly. This implies that when banks increase their hedging demand, it becomes cheaper for PF&I to hedge their positions, because the two sectors have opposite demand. A back-of-the-envelope calculation suggests that the effect is significant: it will save PF&I in the long maturity group almost $2 billion in hedging cost each year.

Similarly, if PF&Is are required to hedge more of their positions, then it will also reduce the hedging cost for banks. Specifically, for the same magnitude of demand pressure increase in the long-end, it reduces the average swap spread in the short-to-intermediate group by 75 bps, which roughly translates into a $5.9 billion reducing in hedging costs for investors in that group. Interestingly, the same magnitude of change in the long-end has much larger impact on all swap spreads compared to the change in the short-end, because imbalances in the long-end are associated with higher risks for the dealer sector. Finally, the impact of demand shifts on swaps spreads would be much smaller if investors have more elastic demand, as part of the shock will be absorbed by quantity changes instead of price changes.

Related literature. Our paper contributes to the growing body of work that analyzes end-user participation in derivative markets. On the use of derivatives as a tool for hedging, Begenau, Piazzesi, and Schneider (2015) show that interest rate derivatives amplify balance sheet fluctuations for U.S. banks. Hoffmann, Langfield, Pierobon, and Vuillemey (2019) find the opposite for Euro area banks. In a more recent work, McPhail, Schnabl, and Tuckman (2023) find that U.S. banks do not hedge the interest rate risk of their assets using interest rate swaps. Sen (2019) documents the risk exposures embedded in derivative portfolios of insurers, while Kaniel and Wang (2020) show that mutual funds use index derivatives to amplify exposures. Baker, Haynes, Roberts, Sharma, and Tuckman (2021) use a one-day snapshot of outstanding exposures to confirm that pension funds receive duration but with significant intra-sector heterogeneity. Related, Jansen (2021) studies the hedging of pension funds with swaps, and Jansen, Klingler, Ranaldo, and Duijm (2023) examines the impact of Dutch pension funds under-fundedness on interest rate risk hedging and bond yields. We exploit our unique stock and flow data of interest rate swap transactions to document that banks, corporations and PF&I sectors in aggregate trade swaps in directions that appear consistent with hedging business risks, while funds appear to speculate. We distinguish banks from dealers, and analyze specific types of hedge funds to uncover heterogeneity in the use of derivatives by funds following different investment styles.

As the availability of data from OTC markets has improved, many studies document important pricing phenomena (Hau, Hoffmann, Langfield, and Timmer, 2021). However, few papers look at quantities behind prices, which is where we contribute. Relatedly, Bahaj, Czech, Ding, and Reis (2023) shed light on the players that trade UK inflation swaps. In a contemporaneous work, Pinter and Walker (2023) document that non-bank financial institutions amplify the duration of their bond holdings using interest rate derivatives. Our paper complements this strand of literature by unveiling significant maturity segmentation in end-user demand for swaps. This specific source of imbalance absorbed by dealers is harder to glean from aggregated data. We also link exposures to shifts in supply due to counterparty credit risk (CCR) and regulation. In this regard, Cenedese, Ranaldo, and Vasios (2020) show that some users incur additional X-Value Adjustment costs to trade derivatives bilaterally, implying, in our setting, higher costs to supply swaps in that segment. Du, Gadgil, Gordy, and Vega (2022) show that the credit quality affects the choice of counterparties in the CDS market, linking again with trading costs associated with CCR. Our findings suggest that regulatory provisions may lead to an additional dimension of heterogeneity and dealer imbalances, as they may shift supply curves for different end-users. Our paper highlights the importance of jointly assessing the transfer of interest rate and counterparty credit risk.

Finally, we link the imbalances in demand to asset pricing implications. Klingler and Sundaresan (2019) argue that the demand to receive fixed rates from underfunded pension funds explains why swap spreads turned negative after the financial crisis. We uncover the role of hedge funds as the marginal investor whose demand can influence swap spreads. We also show that this phenomenon links to the investment strategy followed by funds. Likewise, Hanson, Malkhozov, and Venter (2022) model swap spreads as a function of end-user demand and intermediary constraints. Jermann (2020) and Du et al. (2023) suggest that dealer frictions in holding bonds can explain negative swap spreads. We provide empirical support to the argument that, in addition to sectors that *hold* large exposures, shifts in demand from specific sectors that *trade* large volumes at high frequency can affect swap spreads.

1. Data

Our primary dataset comprises of interest rate swap transactions where at least one of the counterparties is a UK entity.[4] Our most restrictive sample covers three and a half years of data. It combines all new trades initiated from which we extract pricing information with

[4]Examples of UK entities include UK branches and subsidiaries of any counterparty which may be headquartered in another jurisdiction. Additionally, prior to 2021, we were able to observe trades between EU-domiciled banks and non-UK counterparties. However, as part of the post EU-exit arrangements of the UK, those trades are no longer present in our sample. We exclude such trades from the earlier part of our sample period for consistency.

monthly snapshots of outstanding positions which we use to derive quantities traded. Our access to these data is enabled via the Bank of England by a key post-financial crisis reform on derivatives trading, known as European Markets Infrastructure Regulation (EMIR). Reporting obligation in the EU and UK under EMIR started in February 2014, where all OTC and exchange-traded derivatives traded by EU counterparties since August 2012 (or open at that point) have to be reported to trade repositories (TRs).[5] There are four authorized TRs, two of which, DTCC and UnaVista, together had a 90% market share in interest rate derivatives in 2016 (Abad, Aldasoro, Aymanns, D'Errico, Rousová, Hoffmann, Langfield, Neychev, and Roukny, 2016). We source the data from these two TRs. Given that London serves as the center of OTC derivative transactions, we estimate that our data cover over 60% of the global swaps trading volume, with about 87% coverage for swaps denominated in GBP.

1.1. Trading volumes

We collect daily information on new single currency fixed-to-floating IRS trades initiated over a five year period, between from January 2018 until December 2022.[6] To the best of our knowledge, this is the largest ever analyzed sample of interest rate swaps, and among the few academic papers looking at trading activity at such a high frequency. We make use of the entire five year sample, and in some of our analyses we focus on swaps denominated in USD, EUR or GBP, where the floating rate benchmarks based off of LIBOR, EURIBOR, SONIA or SOFR are readily available. The key features which we construct and use from the database are: identity of the counterparties, who receives the fixed rate and who receives the floating rate, the underlying floating benchmark, the fixed rate at which the trade was initiated, maturity, trade size, currency, cleared status, and the type of collateralization at a portfolio level.

Data quality from these trade repositories is a known issue; accordingly, we dedicate an important amount of time to clean it.[7] We closely follow the cleaning procedures from Abad et al. (2016), Cenedese et al. (2020), and augment it as needed. We restrict our sample to OTC interest rate swap (IRS) and overnight indexed swaps (OIS) trades and remove any reporting trade duplication. As we cover a large number of currencies, we convert the notional

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

[6] Changes in reporting obligations starting 2018 and data quality limit the usability of pre-2018 data.

[7] A recent report on (EU) EMIR data quality can be found here.

values at the prevailing exchange rate against the USD in the reporting date, using the publicly available IMF FX Database. Trade duplicates can materialise from double reporting (both counterparties report the same trade) or from compression trades. We identify and remove duplicate trades, and keep the dealer reported ones, and we remove compressed trades. Compression entails netting out trades with similar economic characteristics at a counterparty level.[8]. Compressed trades are reported as new entries, and adding both the bilateral and compressed trades would double count the net notionals. We also appropriately account for forward starting trades by calculating maturity or tenor from the "effective date" of a swap rather than the "execution date". Similarly, to increase our data accuracy we cross-check other trade characteristics and duplicated trades by concatenating information as needed from several reporting fields.

1.2. Outstanding positions

Additionally, we collect and construct a dataset on outstanding positions, referred to as "state" files in EMIR TR terminology, at a monthly frequency over a period of July 2019 through December 2022 (the accuracy of state files substantially improves starting mid-2019). These positions capture all open outstanding trades in a given day, which not only include the new trades initiated that day, but also the existing trades which could have been initiated or modified in the past. We extract information such as the outstanding gross and net positions of each entity as on a given day, and the outstanding maturity of existing swaps. We clean them similarly to the daily activity files. The open monthly positions help us track outstanding exposures, while the daily new trades initiated permit a more granular analysis on the trading behavior of investors in our sample.

1.3. Sector, price and other variables

We augment the swap transaction dataset by identifying the names and jurisdictions of the counterparties using the GLEIF public database. Further, we classify the sectors of about twenty thousand unique entities by their Legal Entity Identifier (LEI) into dealers, banks, funds (including hedge funds and other asset managers),[9] pension funds, insurance companies, corporations, public institutions (such as sovereign funds or supranationals) and central clearing houses (CCPs).[10] [11]

[8] For more details, see e.g., LCH compression

[9] We use the terms funds and hedge funds interchangeably except where a distinction is necessary.

[10] Here again the caveat is that, even though trade repositories have a reporting field for the sector of the other counterparty, it is either sparsely or erroneously filled, so it cannot be confidently used.

[11] In the UK, some pension funds use Liability Driven Investment (LDI) funds to manage their funding risk, predominately via increased exposure to gilts. We consider LDIs as part of the PF&I segment.

We also make an economically meaningful distinction between "banks" that are more likely to trade on their own account and "dealers" that are more likely market-makers. Dealers include all clearing-house members, Global Systemically Important Banks (GSIBs), participating dealers as per the Federal Reserve Bank of New York, brokers, and non-bank liquidity providers.[12] All banks not labelled as dealers are classified as Banks. This distinction helps us capture the hedging of interest rate risk arising out of banking activities separately from intermediation services.

For the larger entities we are able to source their sectors via Capital IQ and Thomson Reuters, but a substantial number of LEIs were manually-classified. Manual classification was needed especially for funds, corporations and pension funds. For example, the challenge for funds is that a main fund family has scores of separate legal entities that each operate in the derivatives market, but they are too small to be reported in external data sources. We also manually classify a large number of small corporates and pension funds which cannot be found in standard financial data reporting of third-party sources.[13] Lastly, as we look over a five year period, some LEIs stopped being active, so we perform cross-checks to find their sectoral classification at the time of transaction. For the counterparty credit risk analysis, we analyze regulatory exemptions that affect only banks domiciled in the EU or the UK; therefore we add the jurisdictional information of both the LEI and the parent entities.

Further, in order to make use of the pricing information from the new trades initiated, we clean the floating rate indicators and add benchmark swap rates sourced from Bloomberg to construct the dealer spreads, measured as the difference between the fixed rate and the benchmark average rate corresponding to a trade based on the same floating rate and with a similar maturity. We source the underlying bond yields for these swaps from the respective regulators' websites and calculate the swap spreads as the difference between benchmark swap rates and similar maturity bond yields. We also use average bond yields in USD, EUR and GBP to calculate the currency-specific swap durations for all tenors.

1.4. Data coverage, flow and stock files

We use the flow of new trades initiated at a daily frequency, as it enables a more detailed trade-level analysis in terms of pricing and the characteristics associated with the demand for new trades, such as the maturity at which the trade was initiated. We focus on the dealer-client segment, and we ensure that we only capture client and self-cleared trades.

[12] We retrieve the list of clearing members directly from LCH Ltd. (formerly London Clearing House) website, the list of GSIBs from the Financial Stability Board website, and the list of participating dealers from the Federal Reserve Bank of New York website.

[13] Our classification has been fact-checked via random sampling to minimize human error.

After cleaning the data, we have in our sample over 20 million transactions totalling $3,500 trillion gross notional in turnover. Based on BIS turnover estimates, our data covers about 60% of the global IRS market.[14] BIS reports daily swap turnover of $2.1 trillion in the UK in 2022 and our data covers a substantial part of this universe, plus swaps executed outside the UK involving a UK entity. Table A1 reports the $ turnover by sector and year that our sample captures.

Our sample comprises of trades reported by two of the largest trade repositories in the OTC interest rate derivatives market. Put together, we estimate a coverage in excess of 87% for GBP swaps and 68% for USD swaps. (Table 1 provides the estimated coverage for major currencies.) The substantial turnover coverage allows us to analyze the interaction of prices and quantities demanded by different sectors.

We augment the flow data with monthly snapshots of the stock of all outstanding positions on the reporting date, which enables us to calculate the net exposures of these entities. Combining the two allows us to capture a meaningful distinction between the type of swaps that certain entities may want to trade, but not keep in the books by fast turnover. We use dates from beginning of each month from July 2019 through December 2022 for a total of 42 snapshots of outstanding positions.

2. Risk Exposures Across the Financial System

In this section, we document the main facts on outstanding interest rate swaps positions and trading across end-user sectors. We start by constructing measures of interest rate risk exposures of outstanding positions and traded volumes. We compute the net signed dollar exposures (Q_t), defined as the total notional in receive fixed swaps minus the total notional in pay fixed swaps at an end-user investor level at time t,

$$Q_t = \sum_p \text{Signed Notional}_{pt}, \tag{1}$$

where $\text{Signed Notional}_{pt}$ is the gross notional of position (or trade) p at time t, signed *positive* for receive fixed and *negative* for pay fixed swaps. Thus, positive values of Q_t denote net receive fixed positions. For sector-level analyses, we aggregate this measure across all the investors within that sector at time t.

To account for heterogeneity in exposures across maturities, we construct two measures. (i) We split positions into four maturity groups: below 3 months, 3 months to 5 years, 5 to

[14] BIS statistics are available here.

10 years, and above 10 years. For each segment, we compute the net dollar exposures as described in Equation 1 and label these variables $Q^{<3M}$, Q^{3M-5Y}, Q^{5Y-10Y}, and $Q^{>10Y}$. (ii) We compute dollar durations, i.e. the dollar value of one basis point parallel shift in interest rates, which we label as DV01.[15]

2.1. Main End-user Segments and Size of Net Exposures

Table 2 shows the total gross notional amounts and net exposures (Q_t) of outstanding positions for the various end-user segments as of February 1, 2022. There are five end-user segments: (a) funds (including hedge funds and asset managers), (b) pension, liability-driven investment funds, and insurers (together referred as PF&I), (c) banks, (d) corporations, and (e) public and sovereign institutions. In aggregate, funds hold the largest stock of outstanding gross positions, followed by PF&I, banks, public, and corporations respectively. For example, as of February 2022, hedge funds held \$1.6 trillion, PF&I held \$1.3 trillion, banks held \$472 billion, public held \$ 98 billion, and corporations held \$89 of outstanding positions. The net exposures also follow similar patterns. Columns (3) and (4) show the gross and net trading volumes. Similar to outstanding positions, funds' trading volumes are large, followed by PF&I and banks. However, the net-to-gross notional ratio is the smallest for funds, suggesting frequent two-way trading at a sector level.

Table 3 shows an LEI-level distribution of net exposures across sectors as of February 1, 2022. In our sample, 730 funds, 1,152 PF&I, 210 banks, 516 corporations, and 32 public institutions held outstanding GBP swap positions on this date. The average fund and bank is large, holding \$1.8 billion of net exposures, while the average PF&I and corporation holds \$0.6 and \$0.2 billion of net exposures, respectively. We only observe a few very large public and sovereign institutions. Because of their lower coverage and small size as a sector, we omit discussing them henceforth.

2.2. Trading Direction Across Sectors

We next examine the direction of net exposures of outstanding positions first at an aggregate level across sectors and then at an entity level within a sector.

First, there is significant heterogeneity in the direction of net exposures across sectors. Figure 1 shows the net exposures aggregated for all entities for a given sector at a monthly level. As a sector throughout the sample, PF&I receive fixed (they have *positive* net expo-

[15] Note that $DV01_t = \sum_p Notional_{pt} \times Duration_p$, where $Duration_p$ refers to the signed Macaulay duration of the fixed rate leg of the swap. Appendix A discusses the cash flows and the duration calculations for standard swaps.

sures), i.e. they add duration to their portfolios with swaps. In contrast, banks and corporations pay fixed (they have *negative* net exposures), i.e. they sell duration with swaps.[16] This suggests that PF&I are counterparties to banks and corporations in the swaps market. In contrast to banks, corporations, and PF&I, hedge funds flip trading direction: they typically receive fixed in the beginning of the sample, however, pay fixed in the later part of the sample, especially during the start of the 2022 rate hike cycle.

Second, we examine intra-sector heterogeneity in the direction of net exposures at an LEI level. We assign a value of +1 to LEIs that held a net receive fixed position and a value of -1 to LEIs that held a net paid fixed position as on a given date. Then, we calculate a sector-level "agreement score" as the simple average of these values. A high absolute score would imply significant homogeneity, while a score closer to zero would imply significant heterogeneity within a sector. Figure 2 plots the monthly time-series of the agreement score on the left-hand side axis and the proportion of entities in each sector that were net receive fixed on the right-hand side axis. Corporations, PF&I, and banks are most homogeneous, with a large majority trading in one direction. In particular, 83% of entities within corporations pay fixed, 80% of PF&I receive fixed, and 70% of banks pay fixed. Funds are most heterogeneous with an agreement score close to zero, and roughly half the entities receive fixed (while the other half pay fixed) at any point of time.[17]

Third, to better understand the economics of funds' trading, we split the funds sector into more granular categories. To do so, we scan the fund name strings to capture various well known trading strategies. We obtain the following main categories: (i) asset managers, (ii) fixed income/bond, (iii) macro, (iv) quantiative & relative value, and (v) others. Figure 3 plots the time-series of total net positions for these sub-categories and Table A2 shows the gross notionals and net exposures shares as of February 2022.

We find that, to a large degree, heterogeneity in funds' direction of exposure is explained by the different types of trading strategies they are expected to adopt. Macro funds are the largest, accounting for 45% of fund sectors' gross notional held. They primarily pay-fixed, similar to banks and corporations. Given that most of their holdings are in one direction, they account for a large fraction of the total net (absolute) exposures of the funds' sector (84%). Other funds, fixed income, and quant & relative value funds account for 23%, 18%, and 12% of gross notionals respectively. However, they frequently flip trading direction. For example, the ratio of (absolute) net to gross position for quant funds is only 0.04, implying that they

[16] Figure A1 shows that the net exposure of each end-user sector is directionally consistent when considering swaps denominated in all the currencies in our sample.

[17] Figure A2 shows that the patterns in disagreement scores and in the proportion of entities in each sector that were net receive fixed holds true for all currencies and not just GBP.

hold large positions that net out, consistent with their perceived role of exploiting relative value, e.g., across the term structure. Asset managers are small (2% of gross notionals), but trade in one direction (receive fixed). Overall, the holding patterns of funds suggest that some funds behave like end-users (e.g., macro and asset managers), while others behave like arbitrageurs (e.g., quant & relative value, fixed income).

2.3. Segmentation Across Maturity

We next show that holdings of the various end-users are highly segmented across maturities. Figure 4 panels (a) through (d) show the breakdown of net exposures in the four maturity groups - below 3 months, 3 months to 5 years, 5 to 10 years, and above 10 years, respectively. First, much of PF&I holdings are in the long-maturity group (e.g., above 10 years). Indeed, PF&I largely hold long maturity swaps consistently throughout the sample. In contrast, a bulk of bank and corporations' positions are in the short to intermediate maturity groups (3 months-5 years and 5-10 years), and remain so throughout the sample. Finally, hedge funds hold very short maturity swaps (under 3 months) and short to intermediate maturity swaps (3 months to 5 years). In fact, while their trading in the under 3 months segment is quite volatile, they largely pay the fixed rate in the 3 months to 5 years segment, just like banks, particularly during the recent years of the sample. Figure A3 confirms that all funds sub-types predominantly hold short maturity swaps.

The extent of segmentation looks even starker when we look at the maturity distribution of new trades. Panel A of Table 4 shows the fraction of LEIs within a given end-user sector that trades at least 50% of their total volume of swaps in a single maturity bucket. ∼90% of LEIs for any given end-user sector have a majority of their trading in a given maturity bucket, which we define to be an LEIs *dominant* maturity bucket. Panel B of Table 4 shows the distribution of the fraction of trades in the dominant maturity bucket for LEIs in each end-user sector. The average bank and fund has over 80% of its trades in its dominant bucket. The average PF&I has 73% and average corporation has 90% of trading in the dominant bucket.[18] Overall, the holdings and trading behavior of end users show strong segmentation on the dimension of maturity, consistent with investors having preferred habitats.

2.4. Sensitivity to Interest Rates

We examine the impact of changes in macroeconomic conditions on swap exposures held by each of the four main end-user sectors. Specifically, we consider movement in the level

[18] Figure A4 shows that the maturity distribution of new trades contracted by PF&I is more right-tailed than other sectors.

of interest rates that could affect fundamental hedging demand through the duration risk channel, or alter expectations of future swap returns. To test this relationship, we construct the month-on-month change in investor-level Q_t, defined in Equation 1, and regress it on the previous month's change in average bond yields. We estimate a model of the form

$$\Delta Q_{i,t} = \alpha_i + \beta \Delta Level_{t-1} + \epsilon_{i,t}, \tag{2}$$

where the dependent variable is the signed change in net outstanding position of an investor within the dominant maturity bucket of the sector to which it belongs. Based on the sector-specific maturity preferences documented earlier, we choose dominant maturity buckets as: below 3 months for funds, 3 months to 5 years for banks and corporations, and above 10 years for pension funds and insurance. The independent variable $\Delta Level_{t-1}$ denotes the change in bond yield over the previous month (we lag the regressor to avoid endogeneity arising from reverse causality). Our time-series runs from July 2019 through December 2022, and the specification accounts for investor fixed effects α_i.

For $\Delta Level_{t-1}$, we use the first principal component of the 3 month, 5 year, 10 year, and 30 year UK government bond (gilt) yields. We first extract the first principal component of daily yields of these tenors over the sample period, and then average it for each month. We also check for robustness to using individual yields such as the 10 year, 5 year and 3 month rates in separate estimations of Equation 2. Table 5 reports the estimation results.

Swap positions are sensitive to the interest rate level factor across sectors, but there is a striking cross-sector variation in the direction and magnitude of sensitivity. All four panels of Equation 2 show that β (loading on the level) is negative for PF&I and positive for banks and corporations. This implies that as rates fall, PF&I increase their net (receive) exposures. In contrast, banks and corporations increase their net (pay) exposures. In other words, as rates fall PF&I buy duration, and banks and corporations sell duration. Hedge funds also show some sensitivity to the 10-year yield in particular, again in a pro-cyclical manner similar to PF&I. Analogous to the overall positions documented in Figure 1, banks and corporations are natural counterparties to the PF&I sector.

The direction of loading on yield is consistent with these sectors' opposite underlying balance sheet maturity mismatch: PF&I are typically net short duration while banks are typically long duration. For example, as interest rates increase, the discounted liabilities of the PF&I sector fall, reducing the need to receive fixed rates as a hedge against those liabilities. The reverse holds true for banks that conduct the opposite maturity transformation. Corporations in our sample primarily hedge the interest rate risk arising out of floating rate liabilities, and this demand increases with overall increase in interest rates.

We also note that while sectors react contrarily to interest rate changes, the magnitude of reaction does not fully offset one another. Panel A of Table 5 shows that, for a one basis point decline in the first principal component of yields, banks and corporations add under $60 billion of new pay fixed rate exposure but funds and PF&I add $127 billion of new receive fixed rate exposure. Given the differences in size and sensitivities, dealers absorb the residual demand which we explore in detail below.

2.4.1. Are Net Positions Consistent with Hedging?

The net positions of PF&I, banks, and corporations appear consistent with hedging of their respective balance sheet interest rate mismatch. PF&I have long-dated liabilities and liabilities that embed fixed rate guarantees. The asset side of the balance sheet contains government and corporate bonds, which typically have shorter maturities than liabilities (Christophersen and Zschiesche, 2015, Domanski, Shin, and Sushko, 2017). As a result, the duration of their assets is shorter than the duration of liabilities, i.e. the sector has a negative duration gap and is therefore exposed to decline in interest rates. A pension fund or an insurer wanting to close the mismatch between assets and liabilities with swaps would need to receive the fixed rate. Moreover, as rates decline (increase), PF&Is should want to increase (decrease) duration, i.e. buy more receive (pay) fixed swaps.

In contrast to PF&I, banks engage in the opposite maturity transformation. They borrow short term and lend long term. As a result, banks typically run a positive duration gap because their assets, which include fixed rate mortgages and C&I loans, have longer duration that their liabilities, which are mainly short-term deposits.[19] This means that a bank wanting to close the mismatch between assets and liabilities with swaps would need to pay the fixed rate.[20] Moreover, as rates decline (increase), banks should want to decrease (increase) duration, i.e. buy more pay (receive) fixed swaps. Similarly, corporations issue debt at the floating rate and may wish to pay the fixed rate (and receive floating) to reduce their interest rate exposure. The observed net positions of these sectors and their responses to shifts in interest rates are opposite to the respective balance sheet interest rate mismatch, consistent with hedging.

[19] It is worth noting that deposits can be sticky, which provide banks a natural hedge against their longer-dated assets (Drechsler, Savov, and Schnabl, 2021).

[20] A bank hedging the prepayment option embedded in mortgages would need to receive the fixed rate (Hanson, 2014). This is less applicable to our sample, which primarily contains UK end-user banks where prepayment attracts a penalty.

2.5. *Aggregate Net Demand and Dealer (Im-)balances*

We next turn to understanding the dynamics of aggregate net end-user demand and dealer balances. Since swaps are in zero net supply, dealers take the other side of end-user demand, and their net position is the inverse of the aggregate net end-user demand. Dealer balance is defined as

$$Dealer\ Balance_t = -\sum_s Q_t^s, \tag{3}$$

where s denotes end-user sectors, including banks, funds, PF&I, corporations, and public.

Figure 1 and Figure A1, which we discussed above, also overlay the dealer sector balances (in brown). We observe that a large portion of PF&I positions is offset by the positions of banks and corporations, which trade in the opposite direction given that they have opposing underlying balance sheet mismatch.[21] Moreover, even in response to shifts in rates, PF&I and banks and corporations trade in the opposite direction: PF&I buy (sell) duration, whereas banks and corporations sell (buy) duration in response to decline (rise) in rates. In other words, PF&I sector are a natural counterparty to banks and corporations in swaps trading. This force results in significant cross-sector netting, reducing the total aggregate net demand supplied by the dealer sector.

However, two factors impede cross-sector netting and add to dealer imbalances across maturities. First, even though PF&I trade in the opposite direction relative to banks and corporations, their respective demands are highly segmented across maturities (Figure 4). The bulk of PF&I trading is concentrated in longer maturities (above 10 years) while that of banks and corporations is in short and intermediate maturities (up to 5 years). This results in dealers having to consistently receive fixed rate in the 3 month to 5 year tenor bucket and pay fixed rate in longer tenors. Another way to see this is through dealers' net DV01 (dollar value of one basis point parallel shift in the yield curve) position, depicted in Figure A7. Dealers consistently bear the risk of a downward parallel shift in the yield curve because long-tenor PF&I trades receive a higher weight in this risk measure. These results are consistent with the literature on negative swap spreads (Boyarchenko, Gupta, Steele, and Yen, 2018, Klingler and Sundaresan, 2019, Hanson, Malkhozov, and Venter, 2022), and evidence of dealer imbalances in other markets (e.g., S&P 500 index options (Gârleanu, Pedersen, and Poteshman, 2008), inflation swaps (Bahaj, Czech, Ding, and Reis, 2023)).

[21] A potential concern on selection bias can arise because, for non-UK entities, we observe only the trades booked with a UK counterparty. These entities may display a different exposure pattern when their global portfolio is considered. However, we find consistent results when considering the net exposures of UK entities only (for whom we observe all trades). Figure A6 shows that the exposures held by UK PF&I and UK banks are also in opposite direction and of comparable magnitude.

Second, large volumes are traded by hedge funds, particularly in the short tenor (Figure 4). In the shortest-tenor of under 3 months where other sectors are relatively small, we note that funds frequently change the direction of their net exposure, inducing volatility in the net demand that dealers need to absorb. In addition, some end-user funds (e.g., macro) trade large volumes in the 3 month to 5 year bucket. During our sample period, these funds substantially amplified the net position absorbed by dealers due to large pay fixed rate trades akin to banks, coinciding with the start of interest rate hike cycle of 2022. These two factors worsen dealer imbalances further in different parts of the term structure, exposing them to non-parallel movements in rates in addition to the residual dollar duration.

Overall, we note that dealers (and some funds) participate in all maturities of the swap curve, often with different directional exposure in different maturity buckets. In a large majority of times during our sample, dealers receive fixed (are long duration) in short maturities and pay fixed (are short duration) in long maturities. In the sections that follow, we term dealers and some funds as "arbitrageurs" when discussing their economic contribution to this market.

3. Model and Calibration

Since both quantities and prices are determined endogenously in equilibrium, we construct a model to match the price and quantity dynamics and to study the interaction of cross-sector hedging. Our reduced form empirical results suggest strong segmentation along the maturity dimension. Hence we construct and estimate a model with preferred-habit investors similar to Vayanos and Vila (2021). We then apply the model to study how different factors contribute to the equilibrium swap spreads and how demand shifts in one sector affect the hedging cost in other sectors.

3.1. Model

Time is continuous $t \in [0, \infty)$. The maturities of swaps lie in $(0, \infty)$. To fully control for the impact of interest rate movements, we focus on swap spreads instead of the fixed rate in the swap contract. 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.[22] This price captures the relative cost of hedging interest rate risk in the swap market versus

[22] 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 $P \equiv P_F/P_T$, $P = \exp(-\tau(y_F(\tau) - y_T(\tau))) = \exp(-\tau s(\tau)))$.

doing so in the cash market.

We assume in the very short-term market, the swap spread is always 0. That is,

$$\lim_{\tau \to 0} s_t(\tau) = 0 \quad \text{for} \quad t \geq 0. \tag{4}$$

Preferred-Habitat Investors: Preferred-habitat investors have demand for swaps in a specific maturity bucket and only trade in that maturity bucket. We verify empirically that this is true for most clients such as PF&Is, corporations and banks. In addition, funds that specialize in arbitraging between swaps and government bonds in a specific maturity bucket also act like preferred-habitat investors in our model. Following Vayanos and Vila (2021), investors with habitat τ have demand for swaps in maturity bucket τ

$$Q_t(\tau) = -\alpha(\tau) log(P_t(\tau)) - \theta_0(\tau) - \sum_{k=1}^{K} \theta_k(\tau)\beta_{k,t} \tag{5}$$

where $\alpha(\tau)$ is the demand elasticity; θ_0 captures the average demand and $\theta_k(\tau)$ captures the sensitivity of demand to the aggregate demand factor β_k. Investors in different maturity buckets may be exposed to similar demand shocks, such as the level of the risk-free rate, but the extent to which they are affected could be different. As Table 5 suggests, banks and PF&Is tend to be affected by the interest rate changes in opposite directions. Finally, if $Q_t(\tau) > 0$, investors are receiving fixed; otherwise, investors are paying fixed.

Investors' demand comes from interest rate hedging needs, which can be met either in the cash market or in the swap market. Investors often have a preference for hedging via the swap market because it is more capital efficient. But such demand would be weaker if the swaps are more expensive relative to bonds with similar maturity. Hence it is intuitive to specify the demand for swaps as a function of the relative price of swaps to bonds.

Arbitrageurs: Arbitrageurs are risk-averse agents who can trade *across* maturity buckets and do not have any preferences for specific maturities. Arbitrageurs include dealers as well as hedge funds who get funding from dealers in order to conduct arbitrage activities.

We assume that for each unit of swap held, the arbitrageur faces a cost c_t, which reflects funding costs and/or balance sheet constraints. This cost could come from multiple sources. First, if the dealer hedges the interest rate risk by holding government bonds, then the government bonds take up balance sheet space and may lead to tighter leverage constraints (Bicu-Lieb et al., 2020, He et al., 2022, Du et al., 2023). If the dealer chooses not to hedge his interest rate risks, then he faces higher capital charges because of standard market risk requirements applicable to financial instruments.[23] In either case, this imposes a cost for dealers trading swaps. Second, in addition to market risks, a sizable fraction of the swaps are not centrally cleared. In this case, the dealer is required to hold additional capital against counterparty risk, which is costly.[24] Finally, in some cases, hedge funds are performing the role of arbitrageurs in this market. Since hedge funds typically obtain funding from the dealer sector, dealers' balance sheet costs would get passed on to the hedge funds in the form of funding costs (Boyarchenko, Gupta, Steele, and Yen, 2018).

Arbitrageurs maximize a mean-variance objective over instantaneous changes in wealth dW_t. Denote the arbitrageur's position for swaps in maturity bucket τ as $X_t(\tau)$,

$$dW_t = \int_0^{\infty} X_t(\tau) \left(\frac{dP_t(\tau)}{P_t(\tau)} - c_t \right) d\tau \tag{6}$$

where $\frac{dP_t(\tau)}{P_t(\tau)}$ is the return of holding swaps of maturity τ and hedging it with government bonds with the same maturity.

The arbitrageur's problem is

$$\max_{\{X_t(\tau)\}_{\tau=0}^{\infty}} \left[\mathbb{E}_t(dW_t) - \frac{a}{2} Var\left(dW_t\right) \right] \tag{7}$$

where $a \geq 0$ is the arbitrageur's risk aversion coefficient. Arbitrageurs benefit from the differences in swap spreads in different maturity buckets, however, they face risks from the time-varying funding cost c_t and demand shocks.

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

$$dg_t = -\Gamma(g_t - \bar{g})dt + \Sigma dB_t \tag{8}$$

$$\bar{g} \equiv \left(\bar{c}, 0, ..., 0 \right)^{\top} \tag{9}$$

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

[23]For details on market risk capital requirements see e.g., The Basel Framework.

[24]The Basel committee on Banking Supervision stipulates capital requirements for costs associated with the default of a counterparty, via Counterparty Credit Risk capitalization, or with changes in the credit quality of a counterparty, via the Credit Valuation Adjustment.

estimation that the net funding cost for the arbitrageurs are indeed positive.[25]

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

$$X_t(\tau) + Q_t(\tau) = 0 \qquad \forall \tau > 0 \tag{10}$$

Equilibrium Characterization: The model can be solved exactly following Vayanos and Vila (2021). We first guess that the relative price for swaps with maturity τ takes the form

$$P_t(\tau) = \exp[-(A(\tau)^\top g_t + C(\tau))] \tag{11}$$

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 of 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.

$$\Gamma^\top A(\tau) + A'(\tau) - \begin{pmatrix} 1 \\ 0 \end{pmatrix} - a \left[\int_0^\infty \left(\theta(\tilde{\tau}) \begin{pmatrix} 0 \\ 1 \end{pmatrix} A(\tilde{\tau})^\top - \alpha(\tilde{\tau}) A(\tilde{\tau}) A(\tilde{\tau})^\top \right) d\tilde{\tau} \right] \Sigma\Sigma^\top A(\tau) = 0 \tag{12}$$

$$A(\tau)^\top \Gamma \begin{pmatrix} -\bar{c} \\ 0 \end{pmatrix} + \frac{1}{2} A(\tau)^\top \Sigma\Sigma^\top A(\tau) + C'(\tau) - aA(\tau)^\top \Sigma\Sigma' \int_0^\infty \left(-\alpha C(\tilde{\tau}) + \theta_0(\tilde{\tau}) \right) A(\tilde{\tau}) d\tilde{\tau} = 0 \tag{13}$$

The boundary conditions are

$$A(0) = 0 \qquad C(0) = 0 \tag{14}$$

We leave the details of derivations to Appendix B.

3.2. Calibration

To bring the model to data, we discretize the maturity space into M maturity buckets, 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 bucket, $\tau \in$

[25] It is without loss of generality to assume that the demand factor $\beta_{k,t}$'s have mean 0.

$\{0, 1, ..., M-1\}$. A swap belongs to maturity bucket τ if its maturity is in $[m(\tau), m(\tau+1))$. Denote the average maturity of swaps in bucket τ by $\bar{m}(\tau)$.

We consider discretized term structure for two reasons. First, the preferred-habitat investor assumption is more likely to hold for a maturity bucket than for a specific maturity point. Second, it allows us to estimate investors' demand in each maturity bucket non-parametrically. We do not impose any parametric assumptions on demand side parameters $\theta_k(\tau)$, $\theta_0(\tau)$ and $\alpha(\tau)$. Hence we are able to learn from data what different preferred-habitat investors' demand looks like.

Denote $s_t(\tau)$ as the average swap spread in maturity bucket τ, and $X_t(\tau)$ as the total swap holdings by the arbitrageurs in maturity bucket τ. Furthermore, the relative price of the swap can be written as $P_t(\tau) = \exp(-\bar{m}(\tau)s_t(\tau))$. Finally, define $\delta(\tau) \equiv \frac{1}{\bar{m}(\tau)-\bar{m}(\tau-1)}$, which is the probability that a swap in maturity bucket τ transitions to maturity bucket $\tau-1$ in the next period. We can write the discrete versions of Equation 12 and Equation 13, respectively, as

$$\Gamma^\top A(\tau) + [A(\tau) - A(\tau-1)]\delta(\tau) - \begin{pmatrix} 1 \\ 0 \end{pmatrix} = a\left[\sum_{\tilde{\tau}} \left(\theta(\tilde{\tau})\begin{pmatrix} 0 \\ 1 \end{pmatrix} A(\tilde{\tau})^\top - \alpha(\tilde{\tau})A(\tilde{\tau})A(\tilde{\tau})^\top\right)\right]\Sigma\Sigma^\top A(\tau) \tag{15}$$

$$A(\tau)^\top\Gamma\begin{pmatrix} -\bar{c} \\ 0 \end{pmatrix} + \frac{1}{2}A(\tau)^\top\Sigma\Sigma^\top A(\tau) + [C(\tau) - C(\tau-1)]\delta(\tau) = aA(\tau)^\top\Sigma\Sigma'\sum_{\tilde{\tau}}\left(-\alpha C(\tilde{\tau}) + \theta_0(\tilde{\tau})\right)A(\tilde{\tau}) \tag{16}$$

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

In our baseline calibration, we set $M = 5$, with $m(1) = 0.05$, $m(2) = 0.25$, $m(3) = 5$ and $m(4) = 10$.[26] Under this definition of maturity bucket, we find that the preferred-habitat assumption is satisfied for most of the clients. As Table 4 shows, the majority of end-users concentrate their activities in a single maturity bucket. Under this partition, the main preferred-habitat investors in maturity group 1 (less than 3 months) are funds, while preferred-habitat investors in group 2 (maturity in 3 months and 5 years) include mainly banks, corporations and funds. Moreover, in the longest maturity group (maturity above 10 years), the dominant investors are PF&Is. For the first four maturity buckets, 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

[26]The swap spread at the ultra short-term should be 0. We take $m(1) = 0.05$ as an approximation for ultra short-term swap spreads.

group.[27] The parameters for the maturity buckets are summarized in Table 6.

We consider one aggregate demand factor, i.e., $K = 1$. Hence, we have two aggregate shocks in total, one for the supply side and one for the demand side. We refer to the shocks to arbitrageur funding cost c_t as the supply shocks, and shocks to the demand factor $\beta_{1,t}$ as the demand shocks. We do not take a stance on exactly what the demand factor is. The reduced form evidence in Table 5 suggests the demand factor is related to the level of the risk-free rate. We do not impose any assumptions on Σ, which means that the contemporaneous supply and demand shocks can be correlated.

We calibrate the model by matching a set of model-generated moments with the corresponding empirical moments. All the empirical moments are constructed using monthly observations from July 2019 to December 2022.[28] To calculate swap spreads for each month and each maturity group, we use the actual fixed rate observed in our data for new transactions between end-users and dealers in that month, subtract from it the maturity-matched bond yield as on the trade, and aggregate at month-maturity group level using notional-weighted averages.[29] We use Q_t in Equation 1 as our definition of quantities.[30]

For each maturity bucket τ ($\tau = \{1, 2, 3, 4\}$),[31] we first target the volume weighted average swap spreads and the average net notional held by end users across our sample period. These moments are informative about the level of the hedging needs $\theta_0(\tau)$, as well as the demand elasticities $\alpha(\tau)$. Empirically, the swap spread along the maturity curve features a hump-shaped pattern: it is positive in the short-end, ranging from 10 bps to 21.5 bps depending on the maturity group, and it is negative 37 bps in the long-end. Figure 5 shows that the hump-shaped pattern exists when we look at finer maturity groups as well. In terms of quantities, on average, clients in group 1 and 4 are receiving fixed, and clients in group 2 and 3 are paying fixed.

Furthermore, we target a set of second moments such as the variances and covariances

[27] Figure A4 plots the maturity distribution of new swaps by each sector in our sample.

[28] We acknowledge that the monetary policy regime changed significantly during our sample period and it would be interesting to estimate the model on the subsample of low interest rate period and high interest rate period separately. For now, we are limited by the number of observations.

[29] In order to reduce noise from mis-reporting in some trades, we subtract the fixed rate from corresponding market benchmark on that trade date, and retain swaps that fall within 2.5% to 97.5% of its distribution.

[30] We only include investors with more than half of their trading volume in their respective dominant maturity buckets. We include all the large pension funds, but we only include their positions in the maturity bucket above 10 years.

[31] Since the first maturity group $(0, 0.05)$ is chosen just to satisfy $s_t(0) = 0$ and there are few preferred-habitat investors in the very short-end, we only target the prices and quantities in maturity bucket 1-4.

of price and quantity changes. For scaling reasons, we consider the change in quantity as

$$\Delta q_t = \frac{Q_t - Q_{t-1}}{(|Q_t|+|Q_{t-1}|)/2}, \tag{17}$$

which enables comparison across sectors and is bounded between +2 and -2. We target the variances of swap spreads changes (Δs) and the variances of scaled quantity changes (Δq_t) for maturity bucket 1-4. We find that the volatility of quantity changes is lower for group 2 and 4, consistent with the fact that banks, corporations and PF&I have lower volatility in their exposures compared with funds (see Figure 6). To capture the correlation between prices and quantities, we also target the uni-variate regression coefficients of scaled quantity changes on swap spread changes for each maturity bucket respectively. The joint dynamics of spreads and quantities 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 7. The exact expressions for the model counterparts are presented in Appendix B.[32]

In terms of the parameter values, we have $3 \times (M-1) = 12$ demand side parameters (α, θ_0 and θ_1 for maturity group 1-4). Since the demand side parameters for group 0 do not affect prices and quantities in any other maturity buckets, we set them 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. Furthermore, we assume that Γ is a diagonal matrix, i.e., the predictable component of the change in the demand factor $d\beta_{1,t}$ only depends on the lagged demand and not the arbitrageur's lagged funding cost. Similarly, the predictable component of the change in funding cost only depends on lagged funding cost and not on factors on the demand side. Hence, there are 6 parameters that govern the law of motion of state variables. In total, we have 20 parameters.

4. Results and Counterfactuals

4.1. Calibration Results

Figure 7 presents the model simulated moments compared with the corresponding empirical moments. The model matches most of the moments reasonably well: The model can almost perfectly match the average swap spreads, the average quantities, and the regression coef-

[32]To obtain closed form results in the model, we construct the model counterpart of Equation 17 as the change in quantity scaled by the absolute value of the average quantity. Since all the variables are stationary, this approximation is close.

ficients of quantity changes on spread changes. Furthermore, the model does a decent job capturing the variances of price and quantity changes.

Table 8 shows the calibrated parameters of the model. First, the calibration confirms our prior that investors in the long-end market (above 10 years), who are mostly PF&Is, demand fixed payments, that is $\theta_0(4) < 0$. In contrast, investors in maturity group 2 (3 months to 5 years) pay fixed rates $\theta_0(2) > 0$. These include banks, corporations and funds. Second, $\theta_1(2)$ and $\theta_1(4)$ have opposite signs, which means that investors in the short-end and long-end have opposite exposure to demand shocks. The estimates are qualitatively consistent with the interpretation that the demand factor approximates interest rate movements. When the interest rate is high, the demand for fixed-rate from long-end investors decreases; the demand for floating-rate from the short-end investors also decreases. The opposite signs of demand intercept and exposure to the demand shock imply that the institutions trading at the short-end are natural hedging counterparties for the institutions trading at the long-end. However, market segmentation together with intermediary frictions prevent them from hedging with each other perfectly.

Furthermore, we find that preferred-habitat investors generally have very inelastic demand. Moreover, investors at the long-end have more inelastic demand compared to investors at the short-end. Investors in the first maturity group consist of funds that arbitrage between the swap and bond market, and they have the most elastic demand. As a result, their positions are more volatile compared to other sectors, consistent with panel (a) of Figure 4, and Figure 6.

In equilibrium, swap spreads load positively on the supply side factor c_t, i.e. the first element of $A(\tau)$ is positive. This means that, everything else equal, when dealers' balance sheet cost is high, swap spreads tend to be larger for all maturities. On the other hand, swap spreads load negatively on the demand side factor β_t, i.e., the second element of $A(\tau)$ is negative. This implies that when β_t is large, spreads are low. Furthermore, spreads for longer maturity swaps are more sensitive to both supply and demand shocks. Hence swap spreads are more volatile at the long-end. Finally, we find that the supply and the demand shocks are positively correlated in our calibration.

Next, we examine the contribution of different factors from the supply and demand side to the shape of the swap spread curve. In Figure 8 panel (a), we start with the baseline swap spreads, and we first remove the dealer sector balance sheet cost by setting $\bar{c} = 0$. During our sample period, on net, the dealer sector is holding positive amount of swaps. Dealers demand positive swap spreads to compensate for the balance sheet costs incurred. Hence setting the average funding cost $\bar{c}$ to 0 leads to an almost parallel downward shift in swap spreads for all maturities for about 7 bps. This change in swap spreads is relatively small given the fact that the average swap spreads ranges from negative 40 bps to 20 bps empirically.

We then remove the demand side pressure by setting the intercepts of all the preferred-habitat investors' demand to 0, i.e., $\theta_0(\tau) = 0$ for all τ. As shown in Figure 8 panel (a), removing demand pressure essentially brings swap spreads to 0 for all maturity groups, suggesting that demand pressure from different investors indeed plays a quantitatively significant role in driving the shape of the swap spread curve. Next, we set the demand shocks to 0, i.e., $\beta_{1,t} = 0$, this reduces the swap spread for all maturity because it reduces the risks born by the dealer sector. Finally, removing the supply side risks brings the swap spreads equal to 0 for all maturities, which is the frictionless case.

To further understand the relative importance of the demand pressure from different sectors, we set the demand intercept to 0 for maturity group 2 and the maturity group 4 one at a time. We ignore the other maturity groups because their demand intercepts are much smaller and are unlikely to play important quantitative roles. Figure 8 panel (b) shows the re-calculated swap spreads compared with the baseline case. As investors in the long-end and short-end are natural hedgers with each other, removing the demand intercept from either group results in more imbalance in net demand and the dealer sector needs to hold more inventories in equilibrium. This tilts the swap spread curve away from 0. In both cases, the impact is larger for the longer maturity swaps. Despite the fact that group 4 has smaller magnitude of demand ($|\theta_0(4)| < |\theta_0(2)|$) than group 2, their impacts on swap spreads is similar in magnitudes. This is because demand for longer maturity swaps exposes the dealer sector to more risks, hence each unit of long-term demand has larger impact on prices compared with the demand for short-term swaps.

Finally, using LEI-level activity and positions data, Figure A8 plots the cumulative share of net outstanding position within each sector for GBP swaps in panel (a) and all currencies in panel (b). We find that net positions are highly concentrated within sectors. For instance, the top 10 funds hold over 80% of all net outstanding GBP exposures of the fund sector in February 2022 and about 70% for all currencies.[33] In GBP swaps, banks also show higher concentration than both PF&I and corporations. A high level of concentration implies greater impact of idiosyncratic demand shifts on imbalances in market-level risk sharing. The large impact of demand on equilibrium swap spreads likely comes from a few large players.

[33]Given that our estimates are at an LEI level and many fund LEIs roll into a single fund family, these concentration measures are likely a lower bound.

4.2. Counterfactual Analysis

We conduct a series of counterfactual analysis in this section, motivated by regulatory discussions and differences in financial regimes across countries.

Demand Pressure: In light of recent banking turmoil, regulators are interested in taking measures that induce banks to hedge their interest rate risks more, for example, including more interest rate scenarios in the stress tests. Similarly, the UK pension fund crisis in 2022 also motivated various regulatory discussions on pension funds' interest rate hedging strategies. We examine how changes in investor demand affect the rest of the interest rate swap market, and the spillover effects to other participants in this market.

We start by considering regulations' impact on the level of demand. We treat regulations targeted towards the banking industry as affecting the demand of investors in group 2, which is the dominant maturity bucket for banks, and regulations targeted towards pension funds as affecting the demand of investors in group 4, which is where the majority of pension funds' trades are.

Conducting more stress tests targeted towards interest rate management would induce banks to hedge interest rate more. As banks demand more floating-rate payments in the second maturity bucket, $\theta_0(2)$ becomes more negative. On the other hand, if PF&I are required to hedge more, they will demand more fixed-rate payment in the longest-tenor maturity bucket. In other words, $\theta_0(4)$ becomes more positive. To make the two experiments comparable, we change the level of demand by one unit in both cases (but with opposite signs).

The results are shown in Figure 9. Because of the opposite hedging needs between banks and PF&Is, an increase in their hedging demand reduces the hedging cost for the other sector. When banks hedge more, this raises the swap spreads for all maturity groups, reducing the hedging cost for PF&Is. Specifically, a one-unit increase in banks' hedging demand raises the swaps spread for the longest maturity bucket by 60 bps. Since investors demands are inelastic, the net notional exposure barely changes. A back-of-envelope calculation suggests that this will save investors in the longest maturity group almost \$2 billion ($0.6\% \times 328 \approx 1.97$ billion) per year in terms of hedging cost. On the other hand, a one-unit increase in PF&I's hedging demand reduces the swap spread faced by the banking sector by about 75 bps, which leads to almost \$6 billion ($0.75\% \times 796 \approx 5.97$ billion) reduction in hedging costs.

In Figure 9 panel (c) and panel (d), we plot the change in swap spreads in the two experiments respectively. Comparing the two, we see that the effect on swap spreads is much larger when the pension fund sector's demand changes, even though the magnitudes of demand changes in the two experiments are the same. A one-unit change in banks' hedging demand leads to 33 bps change in swap spreads on average across the maturity bucket. The same magnitude of demand change in the pension fund sector leads to on average 83 bps change in swap spreads. This is because swaps with longer tenor carry more risks, hence any demand on the long-end have larger impacts on equilibrium prices. Furthermore, regardless of where the demand change originates, its impact on spreads is monotonically increasing in the swap's maturity. In both cases, the change in swap spreads in the longest maturity bucket is twice the size of that in the second maturity bucket.

Finally, we repeat the exercise when demand is more elastic. This could happen when market power of investors change or when it becomes easier to hedge interest rate risks using other instruments. Specifically, we increase the demand elasticities for all preferred-habitat investors by 10 fold. We then plot the change in swap spreads when banks' hedging demand increase by one unit (Figure 9 panel (e)) and when PF&I's hedging demand increase by one unit (Figure 9 panel (f)). We find that the same magnitude of demand changes lead to smaller effects on equilibrium prices, as larger fraction of the shock is absorbed by adjustments in quantities.

Demand Sensitivity: In addition to the level of demand, the proposed regulations also affect demand volatility. We consider what happens when the demand in different sectors becomes more sensitive to the aggregate factor. Similar to before, we focus on the two main preferred-habitat investors: the banking sector in maturity bucket 2, and the pension fund sector in maturity bucket 4.

In the first experiment, we increase the sensitivity of banks hedging demand to the aggregate factor by increasing the magnitude of $\theta_1(2)$ while maintaining the sign. In the second experiment, we increase the sensitivity of PF&I's demand by increasing the magnitude of $\theta_1(4)$ by the same amount. The equilibrium swap spreads are shown in Figure 10 panel (a) and (b). Changes in demand volatility leads to two counter-acting forces. First, when banks' demand is more sensitive to the aggregate demand factor, swap spreads become more exposed to demand shocks for all maturities. Since the "duration-weighted" average holding of dealers is negative, an increase in risks from demand shocks leads to higher prices and lower spreads. This is captured in the last term of Equation 13. On the other hand, because of the correlation between supply and demand shocks, higher sensitivity to demand shocks actually leads to overall less volatile prices, i.e., $A(\tau)^\top \Sigma\Sigma^\top A(\tau)$ becomes smaller in Equation 13. This increases average swap spreads because of the Jensen term in returns. We find that the latter force dominates when the change in sensitivity is small. When the change in $\theta_1(2)$ is large, we find that the first force becomes stronger for long-tenor swaps.

In Figure 10 panel (c) and (d) we plot the changes in swap spreads for each maturity group. Translating the spread changes into dollar amount saved, when the magnitude of $\theta(2)$ increases by 0.1, this saves the pension fund sector \$164 million ($0.05\% \times 328 \approx 0.164$ billion) in terms of hedging cost per year. In turn, if the magnitude of $\theta(4)$ is 0.1 larger, this reduces the banking sector's hedging cost by \$1.6 billion ($0.2\% \times 796 \approx 1.59$ billion) per year. As before, we find the same magnitude of changes in the long maturity group has much larger impact on all the swap spreads than that in the short maturity group. Finally, in Figure 10 panel (e) and (f), we repeat the counterfactual under more elastic demand. The spillover effect across different sectors is much smaller.

More Integrated Markets: A major friction in this market is that investors with opposite hedging needs trade in segmented markets. To understand the quantitative implication of market segmentation, we consider a hypothetical scenario where some PF&Is trade in the same maturity group as banks. Since it is not realistic to move all the long-term demand to short-term maturity bucket, we consider the case where $\gamma = 10\%$ of the demand in group 4 is moved to group 2 in Figure 11. We scale the demand parameters, θ_0 and θ_1, by $\bar{m}(4)/\bar{m}(2)$ so that PF&I's demand in duration term stays the same. Specifically, the new demand parameters $\theta_1'(\tau)$, $\theta_0'(\tau)$ and $\alpha'(\tau)$ equal to the baseline estimates for $\tau = 0, 1, 3$. For $\tau = 2$ and $\tau = 4$,

$$\theta_0'(2) = \theta_0(2) + \gamma \times \theta_0(4) \times \frac{\bar{m}(4)}{\bar{m}(2)} \tag{18}$$

$$\theta_1'(2) = \theta_1(2) + \gamma \times \theta_1(4) \times \frac{\bar{m}(4)}{\bar{m}(2)} \tag{19}$$

$$\theta_0'(4) = (1-\gamma) \times \theta_0(4) \qquad \theta_1'(4) = (1-\gamma) \times \theta_1(4) \tag{20}$$

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

We find that moving PF&Is to trade in the same maturity group as banks shifts down the swap spread curve, as shown in Figure 11 panel (a). This is mainly because merging sectors with opposite demand reduces the risks born by the dealer sector, leading to lower spreads. This leads to massive saving for banks in terms of hedging cost but it increases the hedging cost for PF&Is. On net, the hedging cost for the two sector combined is reduced by \$30 million.

In Figure 11 panel (b), we plot the net position in each maturity bucket. Moving part of the PF&I's demand to the same group as banks' demand facilitates netting and reduces outstanding for all maturity buckets. Specifically, it leads to 36% reduction in net position in maturity group 2 and 10% reduction in maturity group 4.

Arbitrageur's Risk Aversion: Lastly, certain dealer regulations may also induce dealers to behave as if they are more risk-averse. We find that an increase in arbitrageur's risk aversion coefficient lead to more positive swap spreads in the short-end and more negative swap spread in the long-end. In Figure 12, we double the magnitude of the risk-aversion coefficient, and we see that swap spreads are 40 bps higher in the short-term maturity groups, but 20 bps lower in the long-term maturity group. Equilibrium swap spreads reflect more the local preferred-habitat demand because dealers are more worried about demand shocks and hence conduct less carry trade.

4.3. Counterparty Credit Risk regulation and supply costs

Insofar we have assumed that trades with any clients incur the same balance sheet cost c_t. However, such cost is likely to be client or even trade specific due to counterparty credit risk (CCR) and the associated regulatory costs. Indeed, during our sample period, pension funds and insurers were subject to different central clearing and counterparty credit risk regulations both in the EU and the UK. This heterogeneity implies that different clients may be facing different supply curves, even when they are in the same maturity group.

Since the Global Financial Crisis, regulators around the world promoted ways of decreasing the counterparty credit risk (CCR) in derivative markets, via the introduction of mandatory central clearing and additional capitalisation against CCR in the bilaterally cleared segment. In the context of our framework, central clearing reduces the counterparty credit risk faced by the dealer smaller balance sheet cost c_t when intermediating swaps. As shown before, a reduction in such cost tends to lead to lower swap spreads. Another way to think about central clearing is that it leads to lower risk aversion coefficient (a) for the arbitrageurs. Our result above indicates that this may lead to flatter swap spread curve.

In our sample period, pension funds and insurers were subject to different central clearing and CCR. Specifically, when not obliged to centrally clear, dealers trading with pension funds did not have to hold capital against CCR, whereas they had to when trading with insurance companies.[34] We exploit this regulatory difference and we find that while insurance companies choose to centrally clear riskier trades, pension funds preferred to book riskier

[34]In 2022, regulation exempts dealers from the need to maintain additional capital buffers in the form of Credit Valuation Adjustment (CVA) capital for bilaterally cleared trades against pension funds. CVA capitalises against the risk of a deterioration in the credit quality of the counterparty. Cenedese, Ranaldo, and Vasios (2020) show that capital charges associated with counterparty credit risk are passed on to end-users in the IRS market.

trades in the bilaterally cleared segment. The full analysis and a discussion can be found in Appendix C. Several implications emerge. First, we find compelling evidence that dealers' funding cost affect which segment of the market that riskier trades are booked in. The fact that riskier trades with pension funds are bilaterally cleared indicates that the risk is not properly capitalised. Second, regulation creates differences in funding cost for dealers depending on who the counterparty is. This leads to additional heterogeneity on the supply side that would be interesting to explore further.

In further work we exploit this additional source of market segmentation and explore its implications on swap spreads, as well as hedging costs for different market participants.

5. Conclusion

This paper provides the first large scale empirical evidence on risk sharing in the interest rate swaps market, and quantifies how demand imbalances and frictions in the dealer sector affect swap spreads. Using granular transaction-level data on both the stock and flow of swap trades, we document trading patterns of four main end-user segments: funds, PF&I, banks and corporations. While PF&I mostly receive fixed, banks and corporations pay fixed. This implies that PF&I are natural counterparties to banks and corporations, and this cross-sector netting reduces the aggregate net demand held by dealers. While investors such as PF&I, banks and corporations trade in a manner suggestive of hedging underlying business risks, certain funds show less consistent behavior and act like arbitrageurs. Furthermore, the market is highly segmented across maturities: PF&I mostly hold long maturity swaps above 10 years, banks and corporations hold positions with maturity between 3 months to 5 years. This segmentation leaves large demand imbalances for dealers at different maturities. Finally, we find that as rates fall, PF&I increase their net receive positions, while banks and corporations increase their net pay positions.

Next, we apply a preferred-habitat investor model to the swap market, where dealers are modelled as arbitrageurs with funding costs. We calibrate the model using price and quantity moments across different maturity buckets. We impose very little assumptions thanks to our data richness. We use the calibrated model to quantify the contribution of supply and demand factors to the equilibrium swap spread curve. We find that demand pressure is concentrated in banks and PF&I, and it has a larger effect on explaining the shape of the swap spread curve than arbitrageurs' funding costs. We then explore how changes in regulation in a given sector or other shocks would have spillover effects on the interest rate risk hedging costs of others sectors. Lastly, we show how regulations on central clearing and counterparty credit risk can expose end-users in the same demand segment to different supply curves, suggesting further sources of imbalances and price dispersion. Our results highlight the complex interactions and consequences of demand imbalances in one of the largest and most liquid financial markets in the world.

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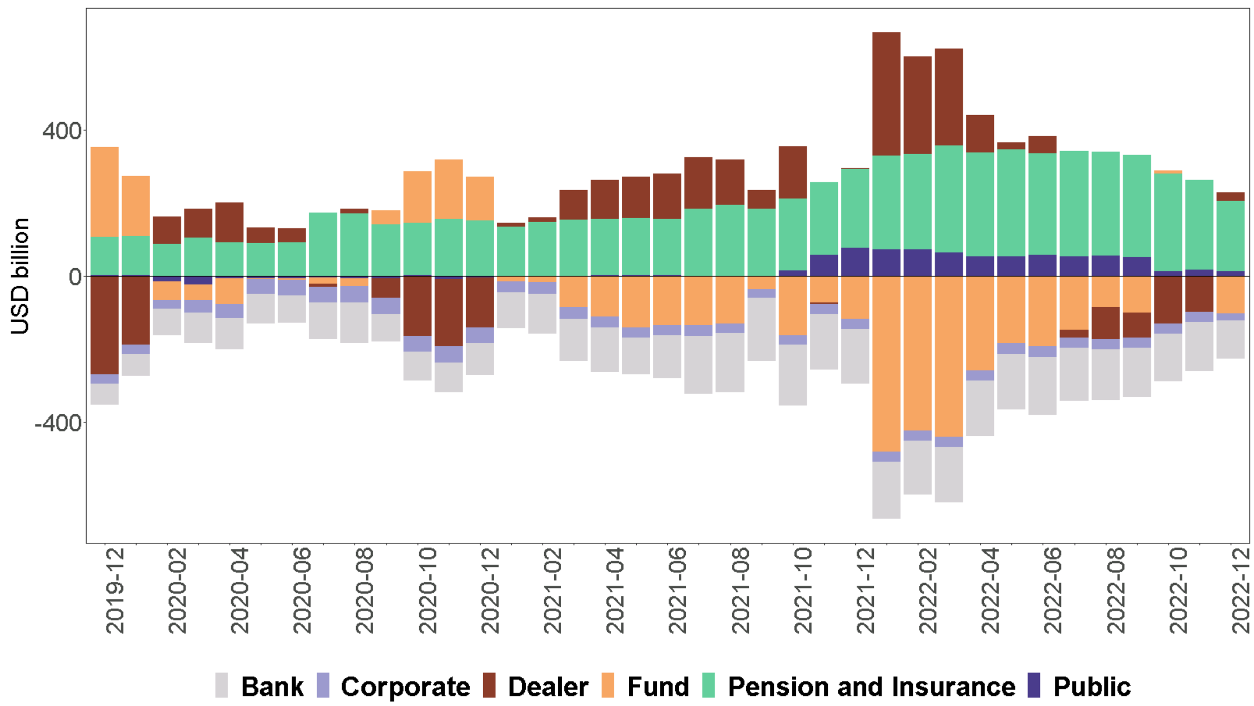
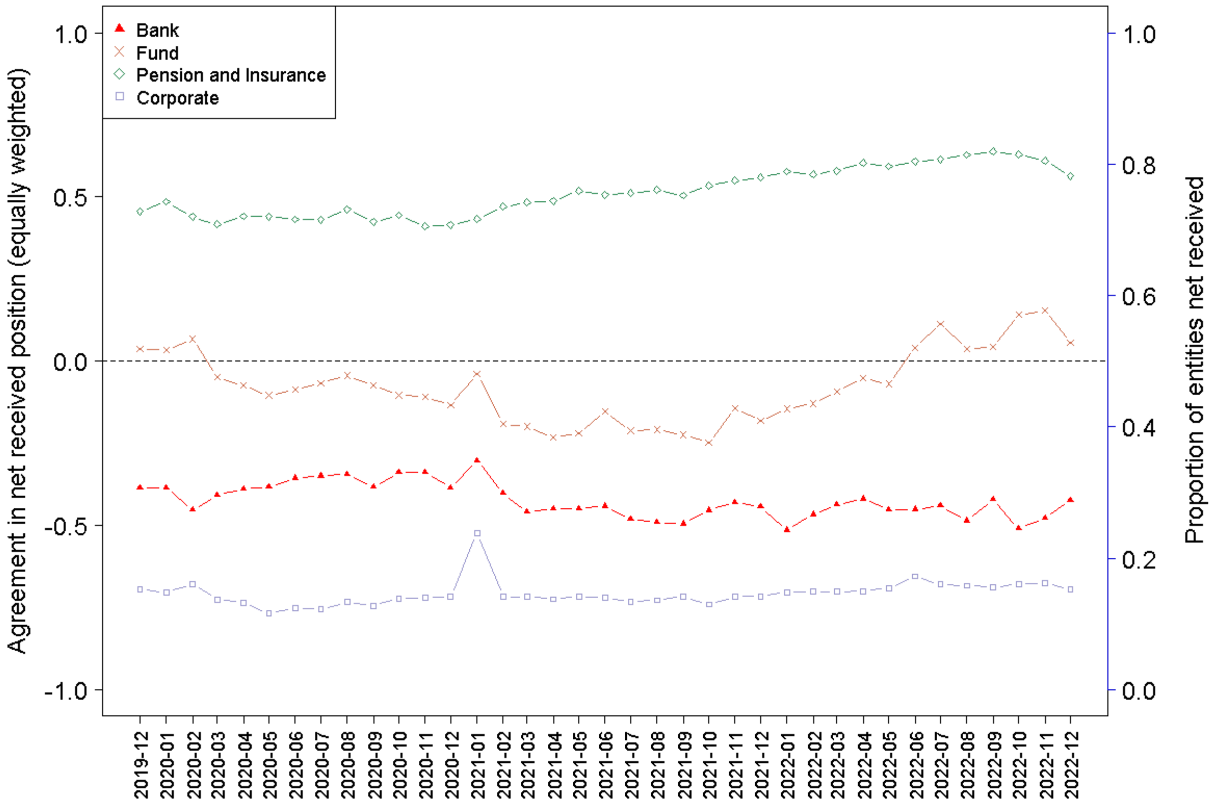
Figure 1: Net Outstanding Swap Notional



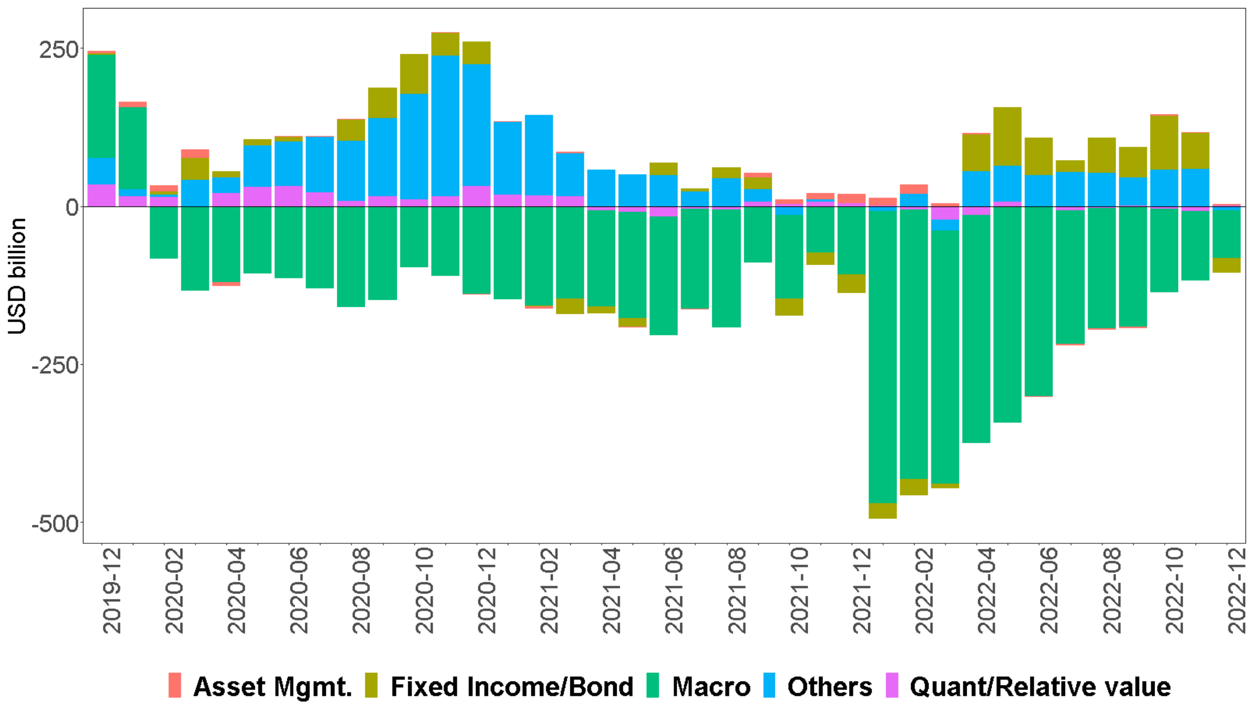
Notes: This figure shows the net received fixed notional outstanding in \$ billion at a monthly frequency across five end-user segments and the inter-dealer segment. Inter-dealer position is calculated as the net of aggregate client-facing positions. This figure considers swaps denominated in GBP, while Figure A1 considers all currencies in our sample.

Figure 2: Intra-Sector Heterogeneity in Exposures



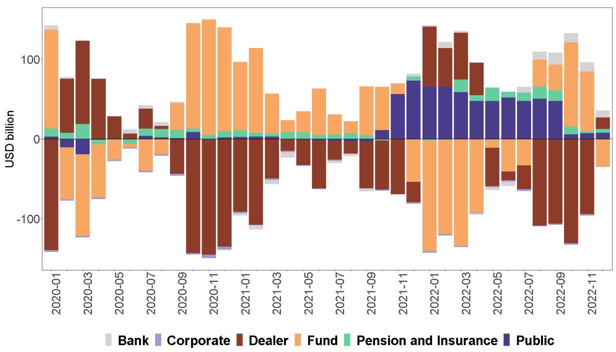
Notes: This figure shows the proportion of entities within a sector that hold net receive fixed swap position (right axis) and the agreement score (left axis) at a monthly frequency. We use equally-weighted net exposures at a legal entity identifier (LEI) level to calculate both measures. Agreement score is calculated by assigning +1 to entities with net receive fixed position, -1 for net paid, and averaged across all LEIs within a sector. This figure considers GBP swaps, while Figure A2 considers all currencies in our sample.

Figure 3: Net Outstanding Swap Notional by Fund Type

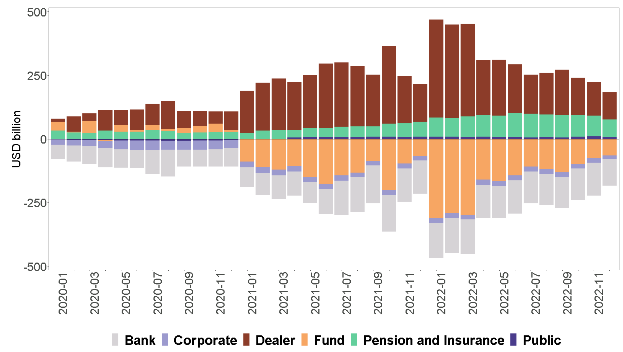


Notes: This figure shows the net received fixed notional outstanding in $ billion at a monthly frequency across five fund types for swaps denominated in GBP. We identify fund types using string matching of their names with common investment strategies at a legal entity identifier (LEI) level.

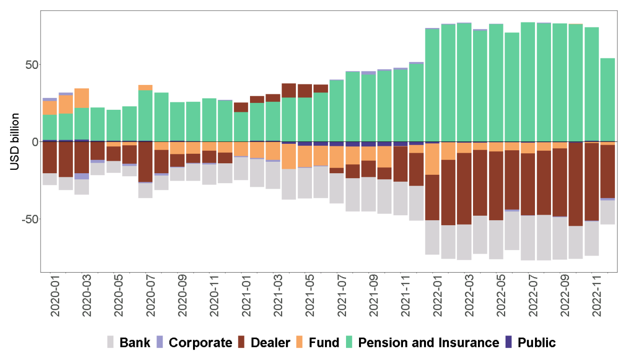
Figure 4: Net Outstanding Swap Notional by Maturity



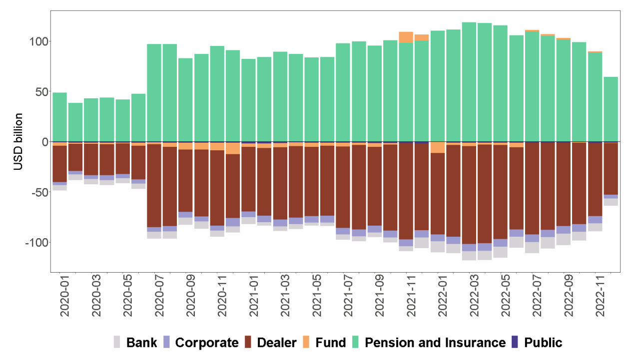
(a) Below 3 Month



(b) 3 Month to 5 Year



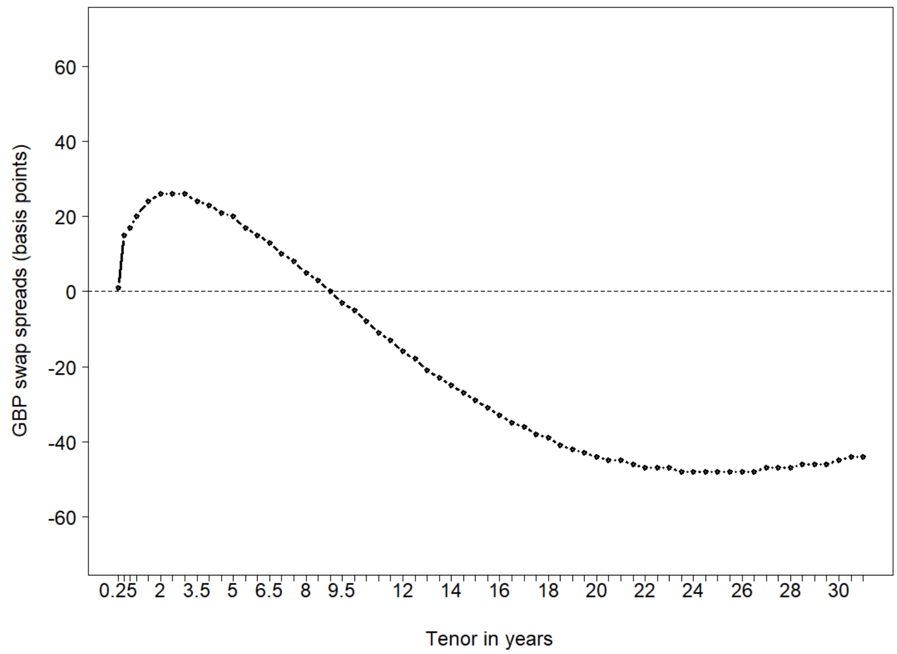
(c) 5 Year to 10 Year



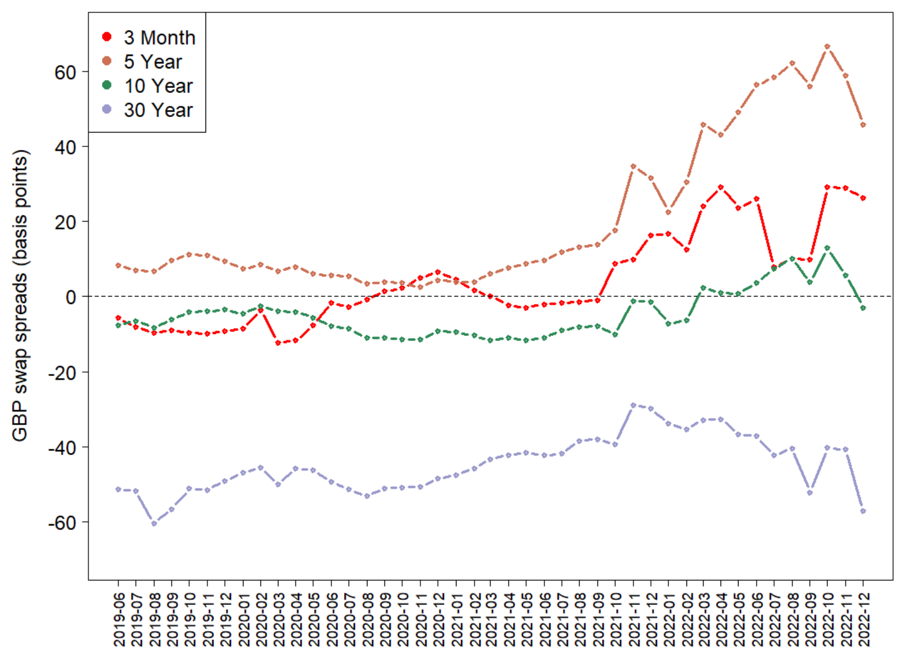
(d) Above 10 Year

Notes: This figure shows the net received fixed notional outstanding in $ billion across four maturity buckets for GBP swaps at a monthly frequency for five end-user segments and the inter-dealer segment. Inter-dealer position is calculated as the net of aggregate client-facing positions. To account for forward starting swaps, maturity is calculated from the "effective date" rather than execution date. Panel (a) considers swaps maturing within 3 months after the effective date, panel (b) considers swaps from 3 months up to five years, panel (c) includes swaps from 5 years up to 10 years, and panel (d) includes swaps with tenors exceeding 10 years.

Figure 5: Swap Spreads



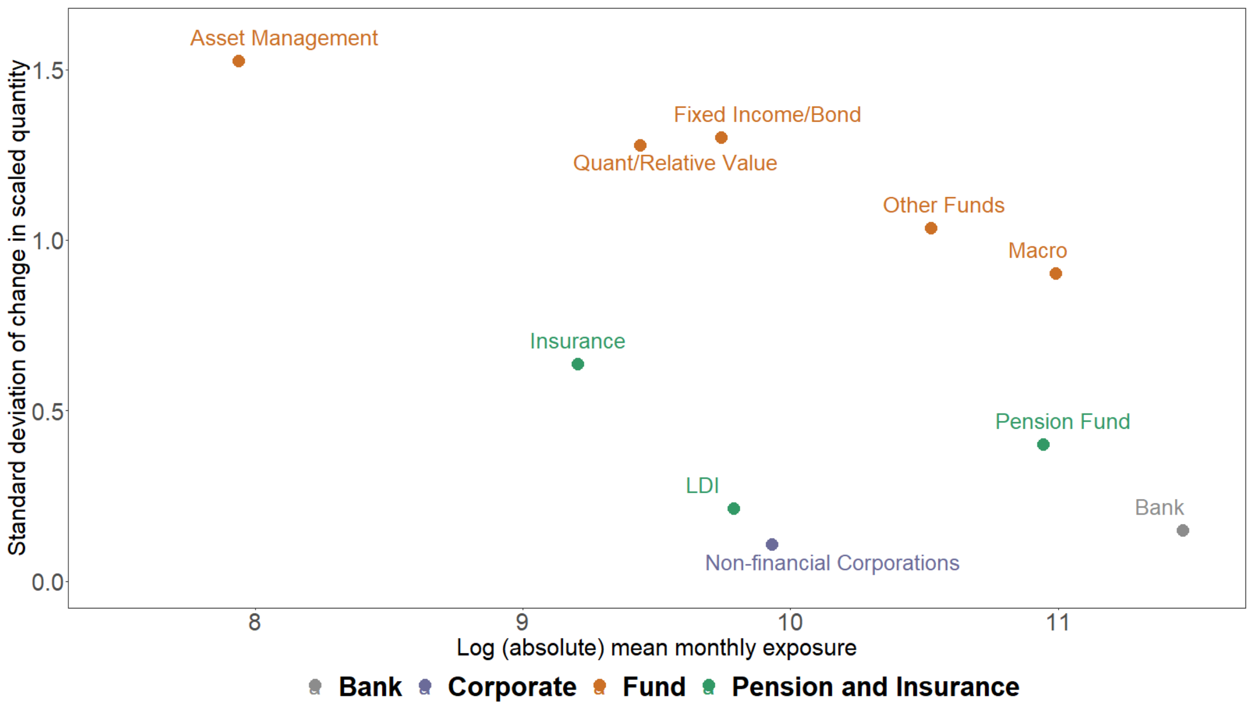
(a) Average Term Structure



(b) Time-series

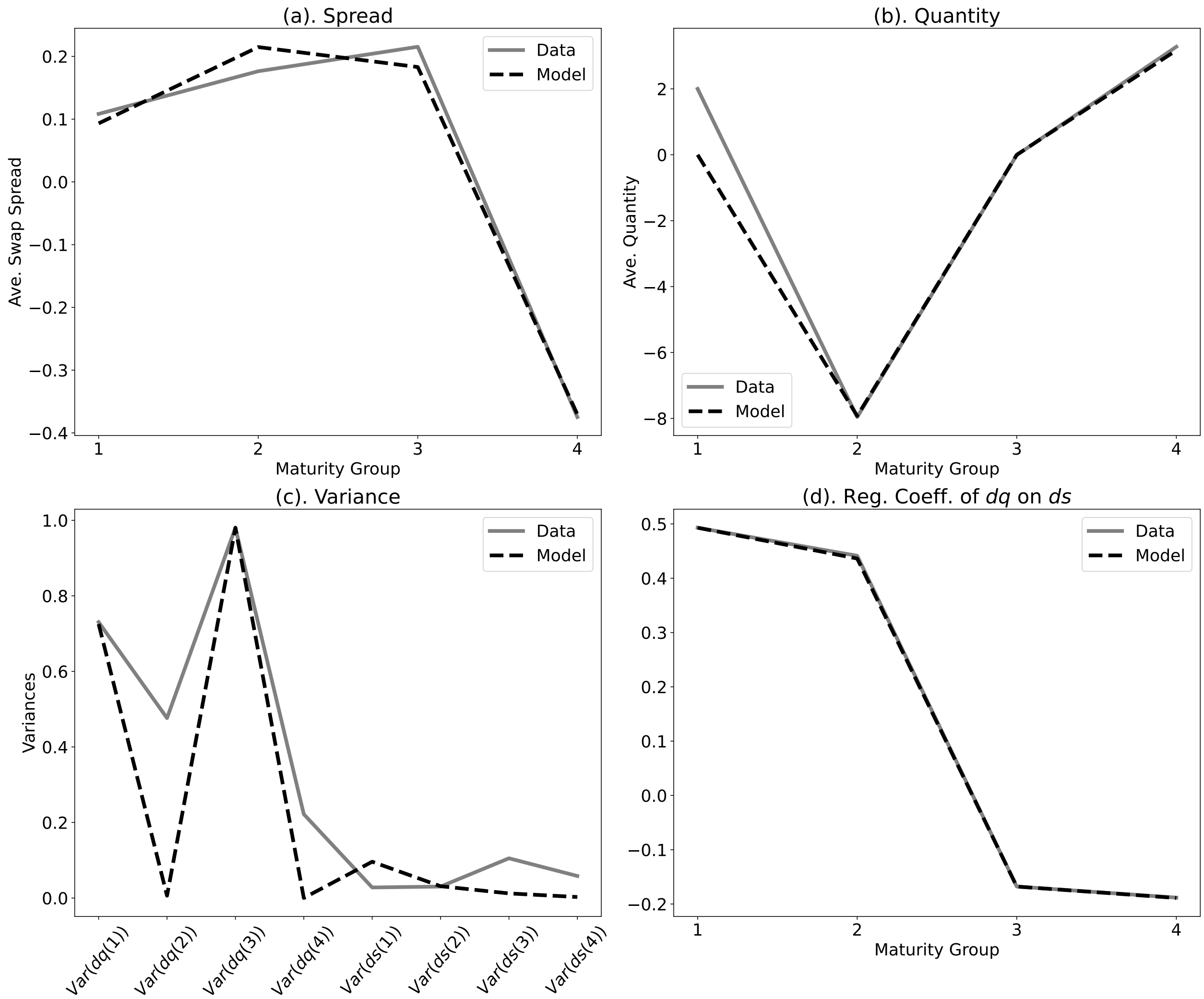
Notes: This figure plots GBP swap spreads, defined as the difference between swap fixed rate and the maturity matched bond (gilt) yield. Panel (a) shows the average term structure using 3-monthly intervals up to one year, and 6-monthly thereafter. Panel (b) shows the time-series for 3-month, 5-year, 10-year, and 30-year swaps.

Figure 6: Investor Size and Exposure Volatility



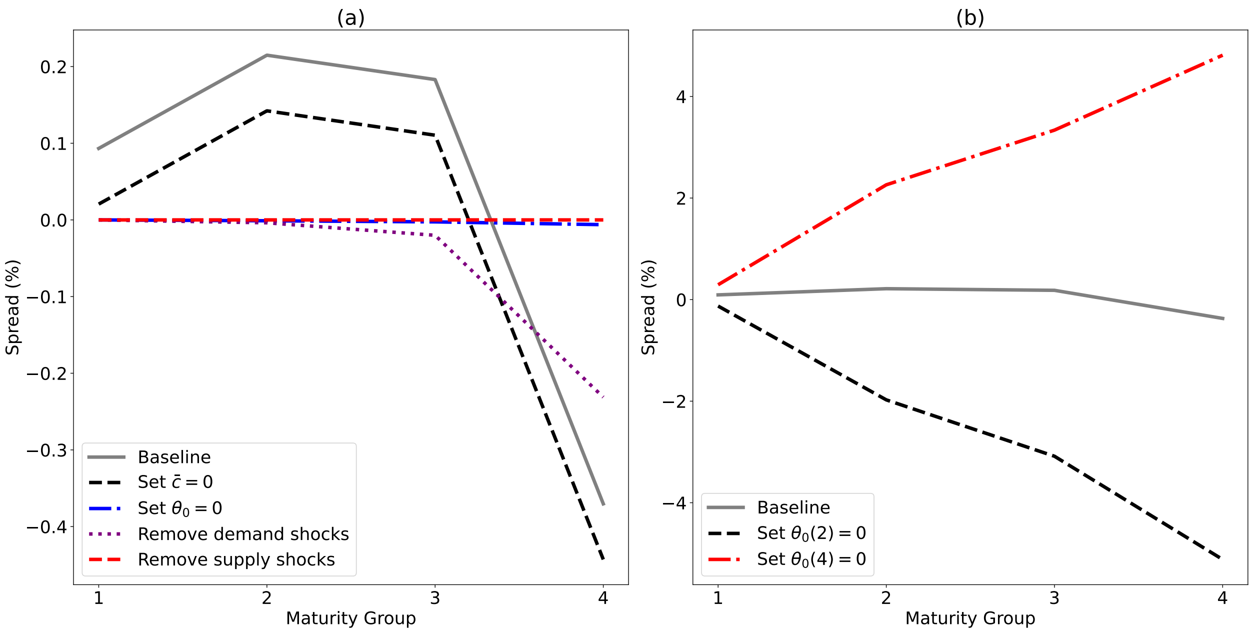
Notes: This figure plots the standard deviation of (scaled) monthly change in net exposures on the y-axis, and the size of each sub-sector on the x-axis. Change in net exposure is calculated using monthly outstanding GBP net receive fixed position, and is scaled by the average of the starting and ending position such that it is bounded between -2 and +2 (this variable is defined in Equation 17). Size of each sub-sector is calculated using the average log (absolute) net exposure throughout the sample period. All sub-sectors are represented using the color of the overall sector as reported in the legend.

Figure 7: Comparing Model Simulated Moments with Empirical Moments



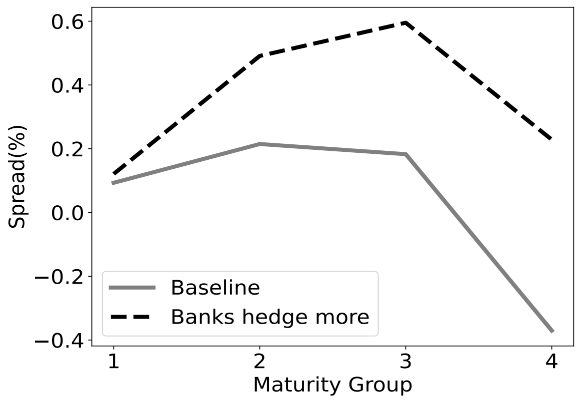
Notes: This figure compares the model simulated moments with the corresponding empirical moments from the data. All the spreads and yields are quoted in percentage terms. Quantities are in unit of $100 billion.

Figure 8: Decomposing Supply and Demand Factors

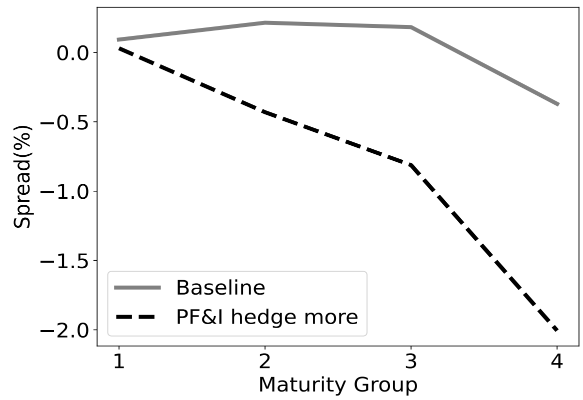


Notes: This figure plots the average swap spreads for different scenarios. In panel (a), we start with the baseline swap spreads, then we set $\bar{c} = 0$ and recalculate the swap spreads in equilibrium. Next, we set $\theta_0(\tau) = 0$ for all τ. We then remove demand side shocks, i.e. $d\beta_{1,t} = 0$ and finally remove all supply side shocks $dc_t = 0$. In panel (b), we set $\theta_0 = 0$ for one group at a time and recalculate the equilibrium swap spreads. Spreads are quoted in percentage terms.

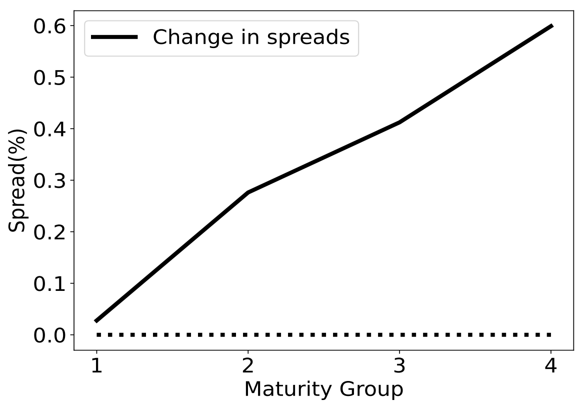
Figure 9: Counterfactual Analysis on Demand Pressure



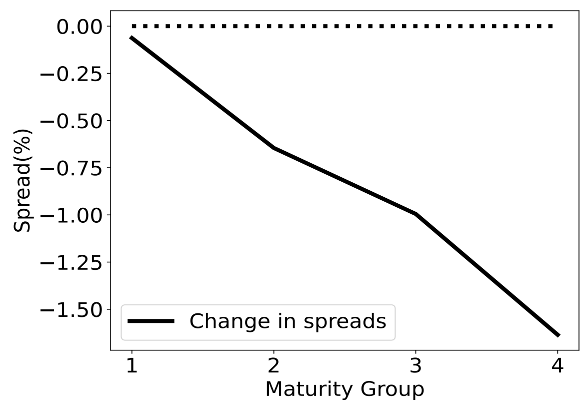
(a) Banks Hedge More



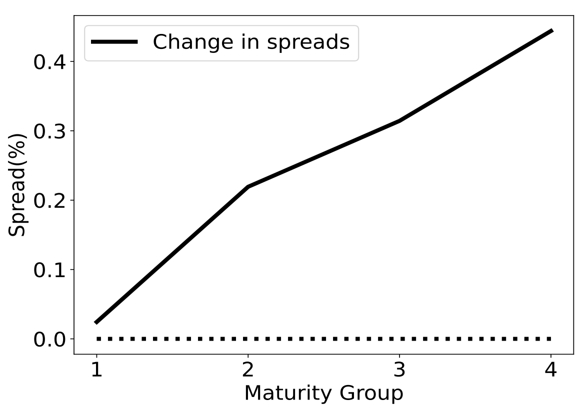
(b) PF&I Hedge More



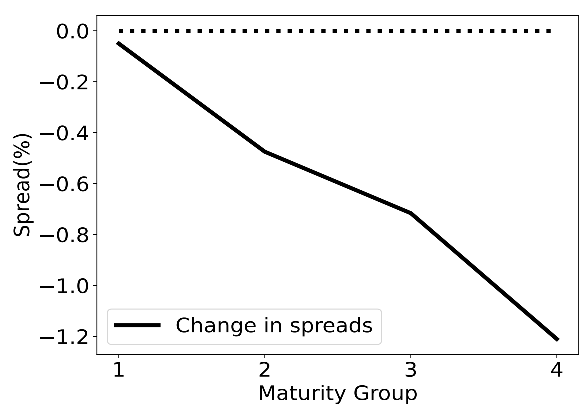
(c) Banks Hedge More



(d) PF&I Hedge More



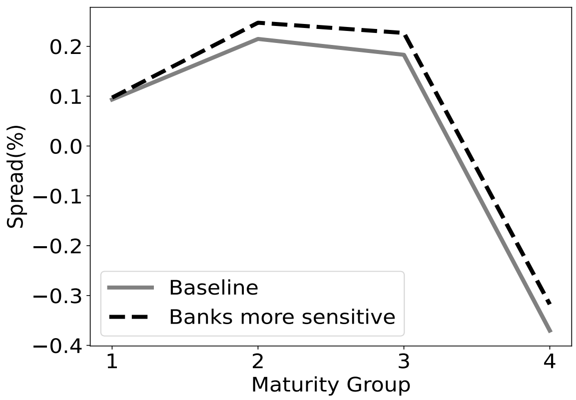
(e) Banks Hedge More (Elastic Demand)



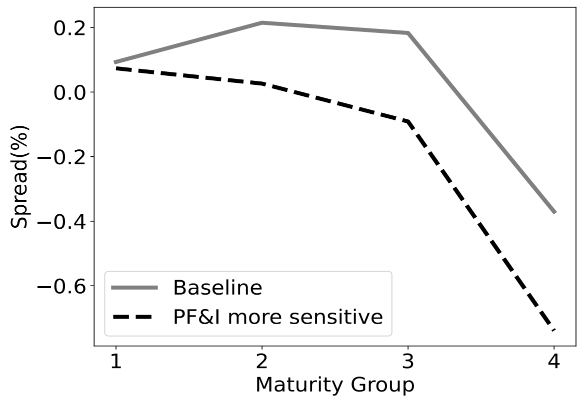
(f) PF&I Hedge More (Elastic Demand)

Notes: Panel (a) and (b) plot the counterfactual swap spreads when $\theta_0(2)$ is higher by one unit and $\theta_0(4)$ is lower by 1 unit respectively. Panel (c) and (d) plot the changes in spreads respectively. Panel (e) and (f) plot the changes in spreads for the two counterfactuals when demand for all sectors are 10 times more elastic.

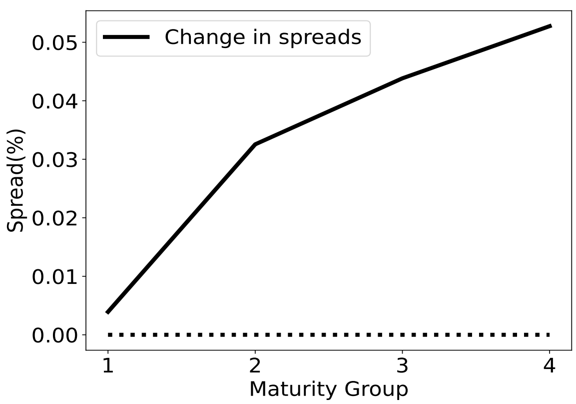
Figure 10: Counterfactual Analysis on Demand Sensitivity



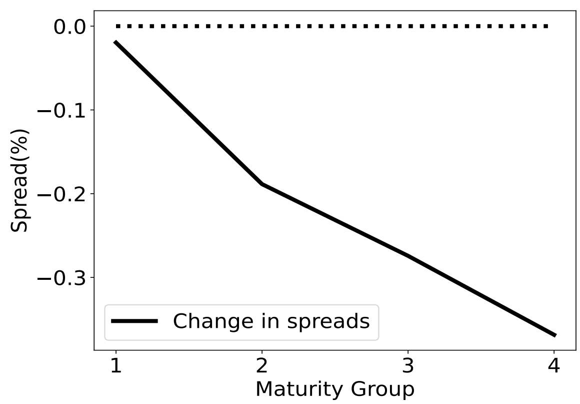
(a) Banks More Sensitive



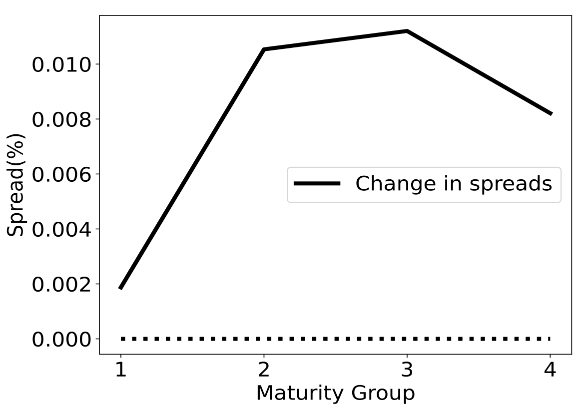
(b) PF&I More Sensitive



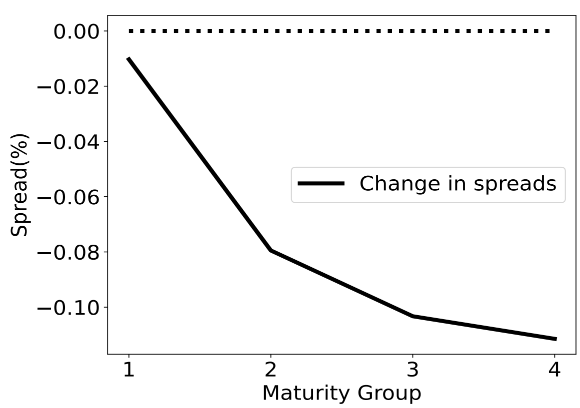
(c) Banks More Sensitive



(d) PF&I More Sensitive



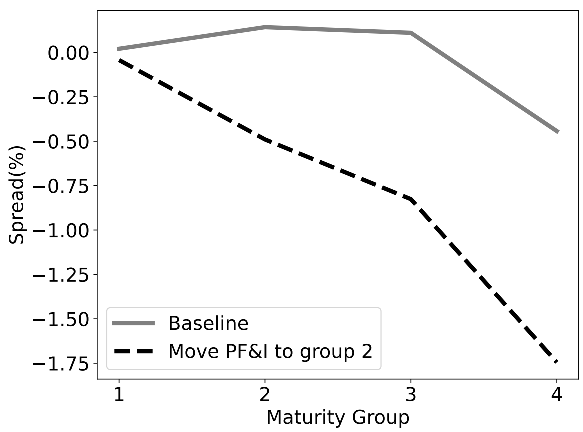
(e) Banks More Sensitive (Elastic Demand)



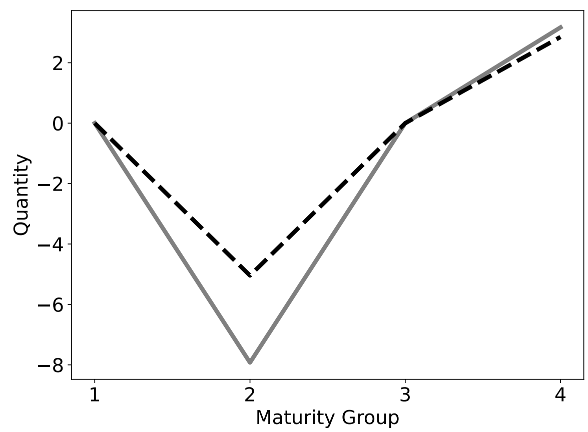
(f) PF&I More Sensitive (Elastic Demand)

Notes: Panel (a) and (b) plot the counterfactual swap spreads when $\theta(2)$ is lower by 0.1 and $\theta(4)$ is higher by 0.1 respectively. Panel (c) and (d) plot the changes in spreads respectively. Panel (e) and (f) plot the changes in spreads for the two counterfactuals when demand for all sectors are 10 times more elastic.

Figure 11: Counterfactual Experiment — Market Integration



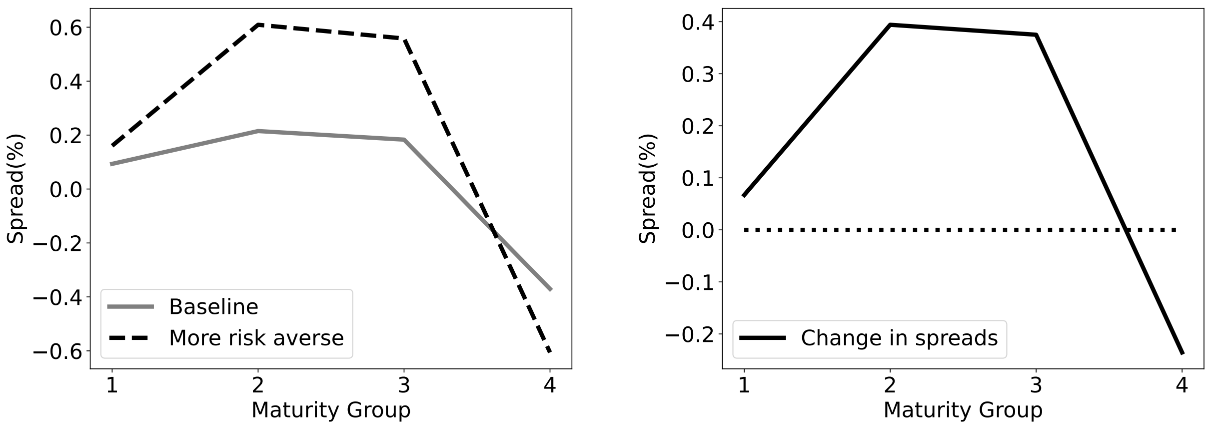
(a) Spread



(b) Quantity

Notes: This figure considers the counterfactual in which we move 10% of the demand in group 4 to group 2. For group 1 and 3 we do not change the demand parameter. For group 2 and 4, we adjust the demand parameters according to Equation 18 through Equation 21.

Figure 12: Counterfactual Analysis on the Risk Aversion Coefficient



(a) Spreads

(b) Change in Spreads

Notes: This figure considers the counterfactual in which the arbitrageurs become twice as risk averse as in the baseline case. We recalculate the equilibrium swap spreads. All spreads are quoted in percentage terms.

Table 1: Estimated Coverage of Trading by Currency

Currency	Daily average turnover			BIS benchmark	Estimated coverage
	Total ($ billion)	Inter-dealer	Client-facing	($ billion)	
GBP	303	75%	25%	350	87%
EUR	1402	82%	18%	1,753	80%
NZD	36	85%	15%	48	76%
USD	1541	89%	11%	2,276	68%
AUD	149	82%	18%	279	53%
JPY	39	58%	42%	117	33%

Notes: This table reports the estimated coverage of interest rate swap turnover observed in our data and denominated in six major currencies. The coverage is benchmarked to the BIS April 2022 triennial survey on OTC interest rate derivatives turnover that can be accessed here.

Table 2: Outstanding and Trading Swap Volume

	Outstanding Volume ($ billion, Feb 2022)		Trading Volume ($ billion, 2018-22)	
	Gross notional	Net notional	Gross notional	Net notional
	(1)	(2)	(3)	(4)
Bank	472	-161	3,285	-253
Fund	1,600	-425	94,757	2,482
Pension and Insurance	1,339	261	6,205	704
Corporate	89	-28	242	-107
Public	98	71	1,146	-63

Notes: This table reports the outstanding volume (columns (1) and (2)) and new trading volume (columns (3) and (4)) of GBP gross and net receive fixed notional across five end-user sectors. Positive net notional indicates net receive fixed rate and negative indicates net pay fixed rate. Outstanding notional amounts are as of February 1, 2022. New trading volume covers a period of January 2018 through December 2022. All numbers are reported in $ billion.

Table 3: Investor-level Descriptive Statistics for Outstanding Exposures

	Investor-level net exposure ($ million, absolute)					
	N	Mean	SD	p25	p50	p75
Bank	210	1,871	5,458	44	214	1,006
Fund	730	1,786	23,711	7	40	184
Pension and Insurance	1,152	577	2,078	27	80	287
Corporate	516	218	528	19	53	141
Public	32	4,659	17,079	37	212	552

Notes: This table reports the distribution of net (absolute) GBP swap exposures in $ million as on February 1, 2022 for investors within each sector. Investor is defined at a legal entity identifier (LEI) level. "N" refers to the count of unique number of LEIs that had any outstanding exposure in GBP swaps as on February 1, 2022 in our sample.

Table 4: Investor Maturity Preference

Panel A	Fraction of investors trading in one maturity bucket	
	(equally-weighted)	(notional-weighted)
Bank	0.94	0.91
Fund	0.93	0.97
Pension and Insurance	0.88	0.70
Corporate	0.96	0.95
Public	0.78	0.28

Panel B	Share of trades in dominant maturity bucket					
	N	Mean	SD	p25	p50	p75
Bank	160	0.81	0.18	0.69	0.85	1
Fund	1045	0.81	0.20	0.63	0.87	1
Pension and Insurance	747	0.73	0.19	0.57	0.70	0.90
Corporate	272	0.90	0.18	0.85	1	1
Public	18	0.77	0.25	0.60	0.84	1

Notes: This table shows that end-users in the interest rate swaps market exhibit preferred habitat behavior. Panel A reports the fraction of investors within each sector at a legal entity identifier (LEI) level that trade at least 50% of their total volume of swaps in a single maturity bucket. Maturity buckets are defined as: $[0, 3m)$, $[3m, 5y)$, $[5y, 10y)$ and $[10y, \infty)$. The first column equally weights all LEIs within the sector and the second column weights them by the total traded volume. Panel B reports the distribution of the proportion of trades that fall under each investor's own dominant maturity bucket. Investor-level shares are calculated at legal entity identifier (LEI) level and the distribution is constructed at the sector level. Trades are weighted by notional.

Table 5: Interest Rates and Quantity Changes

Panel A: PC1 (3M, 5Y, 10Y, 30Y)	Δ Quantity ($ billion)			
	Bank	Fund	PF&I	Corporate
Δ Bond Yield (PC1, t-1)	55.5**	-112.3*	-14.9***	4.15
	(25.4)	(58.2)	(5.21)	(2.65)
Observations	6,200	9,520	28,400	12,600
Adj. R^2	0.02	0.00	0.01	0.01
Panel B: 10Y yield	Δ Quantity ($ billion)			
	Bank	Fund	PF&I	Corporate
Δ Bond Yield (10Y, t-1)	96.2**	-221.8**	-23.7***	6.11
	(44.3)	(109.9)	(8.66)	(3.97)
Observations	6,200	9,520	28,400	12,600
Adj. R^2	0.02	0.00	0.01	0.01
Panel C: 2Y yield	Δ Quantity ($ billion)			
	Bank	Fund	PF&I	Corporate
Δ Bond Yield (2Y, t-1)	74.8**	-124.5*	-24.9***	5.83
	(36.7)	(74.0)	(8.85)	(4.88)
Observations	6,200	9,520	28,400	12,600
Adj. R^2	0.02	0.00	0.01	0.01
Panel D: 3M yield	Δ Quantity ($ billion)			
	Bank	Fund	PF&I	Corporate
Δ Bond Yield (3M, t-1)	97.8**	-101.0	-32.7***	12.1
	(46.6)	(121.2)	(10.6)	(8.24)
Observations	6,200	9,520	28,400	12,600
Adj. R^2	0.02	0.00	0.01	0.01
Dominant product	3M-5Y	Below 3M	Above 10Y	3M-5Y
Investor FE	Yes	Yes	Yes	Yes

Notes: This table reports estimates of a fixed-effects panel regression for the model of the form in Equation 2. The dependent variable is change in monthly outstanding exposure for each investor within the dominant product of their sector. The regressor in panel A is first principal component of 3-month, 5-year, 10-year, and 30-year GBP bond (gilt) yields. Panels B, C and D individually consider 10-year, 2-year, and 3-month yields, respectively. All columns include investor fixed effects at an LEI. Standard errors clustered by LEI are reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 6: Maturity Groups and Relevant Parameters

	Values
Maturity groups $\tau = 0, 1, ..., 4$	$\{(0, 0.05), [0.05, 0.25), [0.25, 5), [5, 10), [10, \infty)\}$
Ave. 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 summarizes the maturity groups, and the average maturity we use for each maturity group in the calibration.

Table 7: Targeted Moments

Moments	Data
Ave. swap spreads in group 1-4 (spread quoted in %)	[0.108, 0.176, 0.215, -0.375]
Ave. quantity in group 1-4 (100 Billion $)	[2 , -7.959 , -0.009, 3.278]
Variances of swap spread changes in group 1-4	[0.028, 0.03, 0.105 , 0.058]
Variances of scaled quantity changes in group 1-4	[0.73, 0.476, 0.980, 0.222]
Regression coefficients of scaled quantity changes on the corresponding swap spread changes for group 1-4	[0.493, 0.441, -0.168, -0.188]

Notes: This table summarizes the empirical moments that we target in our calibration. We use monthly data from July 2019 to November 2022. The swap spreads are the volume weighted average swap spreads for a given maturity group. The changes in quantities are calculated according to Equation 17.

Table 8: Calibrated Parameters

Parameters	**Values**
Arbitrageur risk aversion coeff. a	123.05
Arbitrageur avg. cost $\bar{c}$	7.26×10^{-4}
Demand elasticities α	$[1.51 \times 10^{-2}, 4.55 \times 10^{-5}, 1.14 \times 10^{-8}, 2.73 \times 10^{-7}]$
Demand intercepts θ_0	$[1.23 \times 10^{-6}, 7.925, 0, -3.17]$
Demand sensitivities to aggregate demand factor θ_1	$[1.93 \times 10^{-5}, -1.741, 0, 1.12 \times 10^{-1}]$
Speed of mean reversion Γ	$\begin{pmatrix} 7.16 \times 10^{-4} & 0 \\ 0 & 7.96 \times 10^{-3} \end{pmatrix}$
Variances of supply and demand shocks Σ	$\begin{pmatrix} 3.03 \times 10^{-3} & 1.19 \times 10^{-3} \\ 3.196 \times 10^{-1} & 1.585 \times 10^{-1} \end{pmatrix}$

Appendix for "The Market for Sharing Interest Rate Risk: Quantities behind Prices"

Umang Khetan Jian Li Ioana Neamțu Ishita Sen

January 2024

A. Interest Rate Swaps Primer

An interest rate swap is an agreement between two counterparties, A and B, to exchange a fixed interest rate for a floating interest rate, typically the 3-month LIBOR at quarterly frequency for the duration of the contract. The amount on which the payments are computed is the notional amount. The amount is not exchanged, but rather it is used to calculate the required payments which result from the fixed and floating swaps. A swap is a levered portfolio in bonds. For example, when the fixed leg is paid and the floating leg is received, the swap, Pay Fixed Swap (PFS), is a short position in the fixed rate bond and a long position in the floating rate bond of the same maturity and principal. Similarly, in the opposite case, Receive Fixed Swap (RFS), the investor is long a fixed rate bond and short a floating rate bond. The fair value of the swap and bond are therefore related as:

$$V_{RFS} = V_{Fixed} - V_{Floating}, \tag{22}$$
$$V_{PFS} = V_{Floating} - V_{Fixed}. \tag{23}$$

Interest Rate Exposures: The risk exposure of a swap is the difference between the dollar durations of the underlying fixed and floating bonds. However, as the sensitivity of the swap is largely due to the sensitivity of the fixed rate bond, we measure the risk exposure of swaps, Δ_j, by the dollar duration of the fixed rate bond. Thus:

$$\Delta_{RFS} = \Delta_{Fixed} \tag{24}$$
$$\Delta_{PFS} = -\Delta_{Fixed} \tag{25}$$

where the dollar duration of the fixed rate bond is:

$$\Delta_{Fixed} = -\frac{MacDur \times V_{Fixed}}{1+y} \tag{26}$$
$$MacDur = \frac{1+y}{y} - \frac{1+y+N(c-y)}{c((1+y)^N - 1) + y} \tag{27}$$

where $MacDur$ is the Macaulay duration, that is, the weighted average time to maturity and y is the prevailing yield to maturity of the fixed rate bond, N is the number of periods to expiry, c is the coupon, and y is the yield to maturity (Smith, 2014).

To compute the durations, we construct the zero curve by bootstrapping using Libor rates (3 and 6 months) and swap rates (1 to 10, 15, 20, 25, 30 years) from Datastream. For example, a 10-year receive-fixed swap which is at par has an exposure of 8.8% at the end of 2014. This implies that if rates decline by 100 basis points, a portfolio of \$1 in notional value would increase by 8.8%.

B. Equilibrium

To solve the equilibrium, apply Ito's lemma to the equilibrium price Equation 11 and plug in the expression of dg_t in Equation 17, 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

$$\mu_t(\tau) = A(\tau)^\top\Gamma(g_t-\bar{g}) + \frac{1}{2}A(\tau)^\top\Sigma\Sigma^\top A(\tau) + A'(\tau)g_t + C'(\tau) \tag{28}$$

Dealer's problem is

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

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

$$\mu_t(\tau) - c_t = aA(\tau)^\top\Sigma\Sigma'\left[\int_0^\infty X_t(\tau)A(\tau)d\tau\right] \tag{29}$$

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 28 into Equation 29. Matching the coefficients in front of g_t, we get Equation 12. Matching the coefficients in front of the constant terms, we get Equation 13.

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

$$E[s_t(\tau)] = \left[A(\tau)^\top \begin{pmatrix} \bar{c} \\ 0 \end{pmatrix} + C(\tau) \right] / \tau \tag{30}$$

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

$$E[Q_t(\tau)] = \alpha(\tau)[A(\tau)^\top \begin{pmatrix} \bar{c} \\ 0 \end{pmatrix} + C(\tau)] - \theta_0(\tau) \tag{31}$$

The change in spread is

$$ds_t(\tau) = \frac{A(\tau)}{\tau} dg_t \tag{32}$$

Hence the variance is

$$Var(ds_t(\tau)) = \frac{A(\tau)^\top}{\tau} Var(dg_t) \frac{A(\tau)}{\tau} \tag{33}$$

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

Plug in

$$dg_t = -\Gamma g_t + \Sigma dB_t \tag{34}$$

$$Var(dg_t) = \Gamma Var(g_t) \Gamma^\top + \Sigma \Sigma^\top \tag{35}$$

$$Var(g_t) = \rho \tag{36}$$

where ρ is the solution to

$$-\Gamma \rho - \rho^\top \Gamma^\top + \Sigma \Sigma^\top = 0 \tag{37}$$

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.,

$$\frac{dQ_t(\tau)}{|E[Q_t(\tau)]|} = \frac{\alpha(\tau)A(\tau)^\top dg_t - (0,\theta(\tau))dg_t}{|E[Q_t(\tau)]|} = \frac{[\alpha(\tau)A(\tau)^\top - (0,\theta(\tau))]dg_t}{|E[Q_t(\tau)]|} \tag{38}$$

The variance of this object is

$$Var\left(\frac{dQ_t(\tau)}{|E[Q_t(\tau)]|}\right) = \frac{[\alpha(\tau)A(\tau)^\top - (0,\theta(\tau))]Var(dg_t)[\alpha(\tau)A(\tau)^\top - (0,\theta(\tau))]^\top}{|E[Q_t(\tau)]|^2} \tag{39}$$

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

$$\Lambda = \begin{pmatrix} \tilde{A} \\ \tilde{M} \end{pmatrix} \tag{40}$$

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

$$Var\left(\begin{pmatrix} ds_t \\ \frac{dQ_t}{|E[Q_t]|} \end{pmatrix}\right) = \Lambda Var(dg_t)\Lambda^\top = \Lambda\left(\Gamma Var(g_t)\Gamma^\top + \Sigma\Sigma^\top\right)\Lambda^\top \tag{41}$$

C. Central clearing, Credit Valuation Adjustment and market segmentation

C.1. Background and hypotheses

We complement our analysis of risk sharing in the swaps market and evaluate another dimension of fragmentation via the counterparty credit risk (CCR) channel. We analyze the market effects of voluntary central clearing combined with regulatory exemptions on capital charges incurred by banks via the Credit Valuation Adjustment (CVA). We find that, when bilateral trading entails fewer regulatory costs, end-users choose to book their riskier trades in that segment.

We hypothesize that there are two main channels that drive the clearing decisions. First, a cost channel where bilaterally cleared trades entail a capital charge pass-through from dealers to end-users. Second, a cash-constraints channel, where the limited ability to post liquid collateral may disincentivize some investors from centrally clearing their OTC trades. For the cash-constraints channel, investors may optimally forgo the benefits of centralized clearing in the face of binding cash constraints.

To test these channels, we exploit a unique regulatory exemption that applies in the UK and the EU for interest rate derivatives traded with pension funds. In 2022, regulation exempts dealers from the need to maintain additional capital buffers in the form of CVA capital for bilaterally cleared trades for these entities, potentially reducing their cost of trading bilaterally (i.e., turning off the cost channel). Some of these entities are also perceived as cash-constrained, providing a further incentive for bilateral clearing with less than full collateralization.[35]

We exploit this regulatory exemption and unpack the cash-constraints channel by comparing pension funds and insurance companies. They have similar business models and buy long-maturity swaps, differing in regulatory treatment: dealers are subject to CVA exemptions when trading with pension funds, but not with insurance companies. Hence, if capital charges are passed-through (Cenedese et al., 2020), pension funds may face lower costs on bilaterally cleared trades, reflecting the risk not being captured.[36]

C.2. Fund and Pension fund trades display contrary clearing behavior

Table A3 provides sector-level descriptive statistics on clearing and collateralization for new trading activity. Over our sample period, we note that public institutions, insurance companies and pension funds centrally clear their trades the most on average, while funds and corporations sit at the other end of the distribution. Within the bilaterally cleared segment, at most 40% of the trades are fully collateralized with both initial and variation margin at a portfolio level. Unless well-capitalised, poorly collateralized bilaterally cleared trades can pose systemic risk concerns due to the high counterparty risk associated with them.

As a stylized fact, we split their trades in deciles based on tenor and notional size and observe a decline in central clearing of almost 40% points between the first decile (short maturity and/or low notional) and the last decile of pension fund trades. By contrast, insurance companies do not behave differently across different buckets - see Figure A9.[37]

C.3. Analysis

In a bilaterally cleared transaction, counterparty credit risk increases with trade size, the tenor or maturity of the trade, and the riskiness of the currency, while it decreases with better collateralization. To test for the intensive margin characteristics that determine the likelihood of clearing, we estimate the following

[35]The European Securities and Markets Authority (ESMA) reports that pension funds have argued against mandatory clearing due to their perceived inability to source collateral, especially during market stress episodes (see the technical report to European Commission here.)

[36]We note that pension funds and insurers are comparable in terms of the distribution of notional, maturity, direction, and overall likelihood of clearing their interest rate swaps. See Table A4.

[37]We also do not observe this pattern for other sectors. See Figure A10

linear probability model.

$$Pr(\text{cleared}_{i,j,t} = 1) = \beta_1 \cdot \text{Notional}_{i,j,t} + \beta_2 \cdot \text{Tenor}_{i,j,t} + \beta_3 \cdot \text{Currency}_{i,j,t} + \beta_4 \cdot \text{FullCollat}_{i,j,t} + \\ + \text{Dealer}_i FE + \text{Client}_j FE + \text{Day} FE, \tag{42}$$

where we estimate the probability of central clearing for a trade between dealer i with client j at time t. The loading on three trade-features indicates whether riskier trades are less likely to be cleared: $\text{Notional}_{i,j,t}$ in \$ billion, $\text{Tenor}_{i,j,t}$ in years, and $\text{Currency}_{i,j,t}$ is a dummy variable taking the value 1 if the underlying trade has USD, EUR or GBP as base currency and 0 otherwise. The $\text{FullCollat}_{i,j,t}$ value takes a value of 1 if the trade is marked as fully collateralized *i.e.* includes both initial and variation margin, and 0 otherwise. If the client-dealer portfolio is already fully collateralized, there is perhaps less incentive to centrally clear the trade despite potential netting benefits, as the risk is already factored in appropriately. To control for both demand and supply of trades, we include dealer, client and day fixed effects. Table A5 reports the estimation results.

We find that pension funds are less likely to centrally clear larger and longer maturity trades which bear the largest counterparty credit risk. Existing full colateralization at portfolio level is a negative predictor of central clearing across most sectors. Effects are stronger and most robust for pension funds and insurance companies, pointing to the cash-constraints channel. By contrast, even though funds do not clear almost 70% of their trades, their decisions do not seem to be influenced by trade riskiness.

We consider the tenor to be the most informative measure of trade riskiness, as it cannot be easily split. We show that these effects are robust to model specifications, by estimating the beta coefficient on tenor for pension funds and insurance companies. We plot the different estimates and their respective confidence intervals in Figure A11 and find that a larger tenor is always a strong negative predictor for centrally clearing pension fund trades but not for insurance trades.

This finding highlights a paradox whereby trades that are the most important contributors to counterparty credit risk are least likely to get centrally cleared, adding to potentially large uncapitalised CCR and market segmentation on yet another dimension.

C.4. Centralized Clearing Institutional Background

The post crisis regulatory framework changed the derivatives markets landscape, with a focus on incentivising clearing of Over-The-Counter (OTC) derivatives. The most important reform at European level was the European Market Infrastructure Regulation (EMIR) mandate to centrally clear a wide range of derivative contracts for a large number of counterparties.[38] This reform was accompanied by tighter regulation in the OTC market, and a mandate to report trades. Nonetheless, several exemptions were implemented

[38]The clearing mandate for IRS applies, among others, if the firm does interest rate derivative contracts worth more than EUR 3 bn. in gross notional value - for more details see the UK EMIR requirements.

in the EU and UK Capital Requirements Regulation (CRR). Further, we provide a brief description of the main concepts we use.[39]

The two main risk mitigants against CCR (higher capital charges and more collateralization in the bilateral segment, and mandatory central clearing) affect market participants in different ways.[40]

On the one hand, centralized clearing mitigates counterparty credit risk and improves transparency, but it can also be costly for cash-constrained counterparties due to margin requirements in the form of cash or highly liquid assets (Menkveld and Vuillemey, 2021, Braithwaite and Murphy, 2020). On the other hand, bilateral clearing allows for more bespoke trading conditions, but can entail additional costs due to fewer netting opportunities, and higher (pass-through of) capital charges due to higher risk or search frictions. These trade-offs affect the incentives to centrally clear derivatives and can exacerbate counterparty credit risk embedded in imbalanced demand.

C.5. Central and bilateral clearing

At a glance, a derivative trade between counterparty A and B can be executed in several ways, and that depends on both the preferences and market access of the said counterparties. First, the two counterparties can bilaterally agree the terms and conditions of the trade, including the collateralization requirements, as depicted in part (i) of Figure A12. Such a trade is referred to as bilaterally cleared, and bears counterparty credit risk(CCR) for both counterparties, as they can each have a worsening of their credit conditions or an inability to make payments or default. In this situation, there are no restrictions on the types of counterparties, even though they would typically happen between a dealer and an end-user.

A key way to mitigate CCR is via central clearing, where the trade is being intermediated by a Central Clearing Counterparty (CCP). Unlike the bilateral segment, trading with a CCP involves strict collateral posting rules and trade agreements. In this case, the CCP will be the one absorbing the counterparty credit risk, essentially guaranteeing to their clients that their trade conditions will be met. However, not everyone has direct access to a CCP. For instance, as described in the London Clearing House (LCH) membership conditions, clearing members are in general large financial groups, with large financial resources and capital, and also have to be of a high credit quality. If both counterparties are CCP members, they can directly centrally cleared the trade via a CCP, as depicted in part (ii) of Figure A12. For an end-user, the usual way to access central clearing is via a clearing member. In other words, Client A makes an OTC agreement with clearing member B, which in turn will take the position to the CCP - see part (iii).[41] In that case, the

[39] For a comprehensive analysis on the economics of central clearing please see Menkveld and Vuillemey (2021). For more institutional details on managing counterparty credit risk post 2008 see the Policy Context section of Cenedese et al. (2020).

[40] The two main additional costs associated with counterparty credit risk on additional capital buffers are CCR charges (linking to the probability that the counterparty may default) and Credit Valuation Adjustment (CVA). CVA charge capitalizes against a potential deterioration in the credit quality of the counterparty, and increases with the maturity, size, and risk weight of the trade.

[41] For more details see Braithwaite and Murphy (2020).

agreement between B and the CCP is the standardized CCP one, while the agreement between client A and B does not necessarily have to be an identical replica to the one between B and the CCP. For example, B may charge A higher rates while accepting worse quality collateral than the one B would need to post against the CCP.

To sum up, an OTC trade can either be bilaterally or centrally cleared. Counterparty credit risk is bared by both counterparties in the first case unless properly capitalised, while the CCP absorbs it in the later. Given our focus is only on the dealer-client segment, the two options for a client are (i) and (iii). We analyze the likelihood of central clearing, looking at intensive margin characteristics and collateral agreements, when clients have a choice.

C.6. Credit Valuation Adjustment

An important source of losses in OTC markets during the financial crisis was not the actual default of counterparties, but decrease in their credit quality (Basel, 2009). Based on that, the Credit Valuation Adjustment (CVA) capital charge was introduced to mitigate exposure of mark-to-market losses due to changes in the credit quality of the counterparty.[42] This capital charge applies only for bilaterally cleared transactions, and it is most material for derivative contracts with long maturities on poorly rated or unrated counterparties. However, the CRR introduced exemptions from CVA regulatory capital against transactions with (i) CCP and client-clearing transactions, (ii) non-financial counterparties (NFCs) below the EMIR clearing threshold, (iii) intragroup entities, (iv) pension funds, and (v) sovereigns. At the moment of writing, these apply to both UK and EU jurisdictions, but they do not exist in other countries.

Originally envisaged to be temporary by the EU, these exemptions have stayed in force since the beginning of the new regulatory regime, and reviewed in 2023 by several jurisdictions as part of the implementation of the most recent Basel package. Exempt entities have expressed concern about their operational readiness to centrally clear and post collateral on derivative trades, while some regulators argued that pension funds can in fact centrally clear.[43] On the other hand, industry has argued that clearing and/or CVA exemptions available in selected jurisdictions only has led to the creation of liquidity pools and market fragmentation, along with increased risk on balance sheet of dealers.[44]

[42] IFRS13 sets out how banks should calculate CVA on derivatives. Differently from the accounting rule, regulatory CVA is calculated without taking into account any offsetting debt value adjustment (i.e. a positive adjustment to derivatives value arising from the deterioration of own credit spreads).

[43] See, for example, the Jan 2022 European Securities and Markets Authority (ESMA) letter to the European Commission.

[44] See details in the May 2022 Risk.net article.

D. Portfolio Compression

Given that demand shocks affect swap spreads, shocks in one sector can therefore spillover to other parts of the economy via their effect on asset prices. To understand how demand shocks are absorbed, we would need to understand how elastic other investors are, which would in turn determine whether demand shocks are primarily absorbed through prices (if investors are largely inelastic) or through quantities (if investors are largely elastic). Disentangling these forces is important to understand the potential for risk mismatch in various parts of the financial system.

To this end, we estimate demand elasticities using plausibly exogenous variation in dealers' constraints (supply shifters). We measure changes in dealers' constraints using "portfolio compression", which releases capital and presumably lowers the price of swaps. Portfolio compression involves cancelling existing stock of offsetting derivatives and replacing them with a single netted out trade that retains the net exposures but reduces the gross notional outstanding. Regulatory requirements under the Basel III framework prescribe minimum leverage ratio based on gross notional of outstanding derivatives. Thus, portfolio compression can help reduce capital requirements (Duffie, 2018).[45]

We leverage our transaction-level data to identify trades that were compressed within a particular month and hypothesize that the consequent relaxation in capital constraints affects prices (swap spreads) in the subsequent month. Specifically, we construct a time-series of the volume of newly compressed trades each month and scale it by the stock of outstanding trades. We then use this variable to predict the following month's swap spreads. Since dealers are the main fixed rate payers in long-dated swaps, we expect compression exercise in one month to increase swap spreads (i.e. lower the price) in the following month. At the same time, compression activity in one period is unlikely to directly affect the quantities demanded by pension funds in the next period except through changes in price.

A vast majority of compression exercise in our data is carried out through the LCH Ltd that offers a platform named SwapClear for clearing and compression exercises. We restrict the analysis of demand estimation to GBP swaps because we do not observe compression carried out with other clearing houses outside of the UK and due to our larger coverage of activity in GBP swaps. Using the time-series of portfolio compression as an instrument, we estimate the demand elasticities using two-stage least squares. In the first stage we estimate

$$SwapSpread_t = \alpha + \beta Compression_{t-1} + Controls + \epsilon_t, \tag{43}$$

where $Compression_{t-1}$ refers to the flow of newly compressed trades in a particular month scaled by the stock of outstanding positions in that month. The dependent variable is the first principal component of

[45] Duffie (2018) suggests that regulatory capital and margin requirements have contributed to increased trade compression in OTC derivatives. Veraart (2022) argues that under a state of no defaults, portfolio compression also reduces systemic risk.

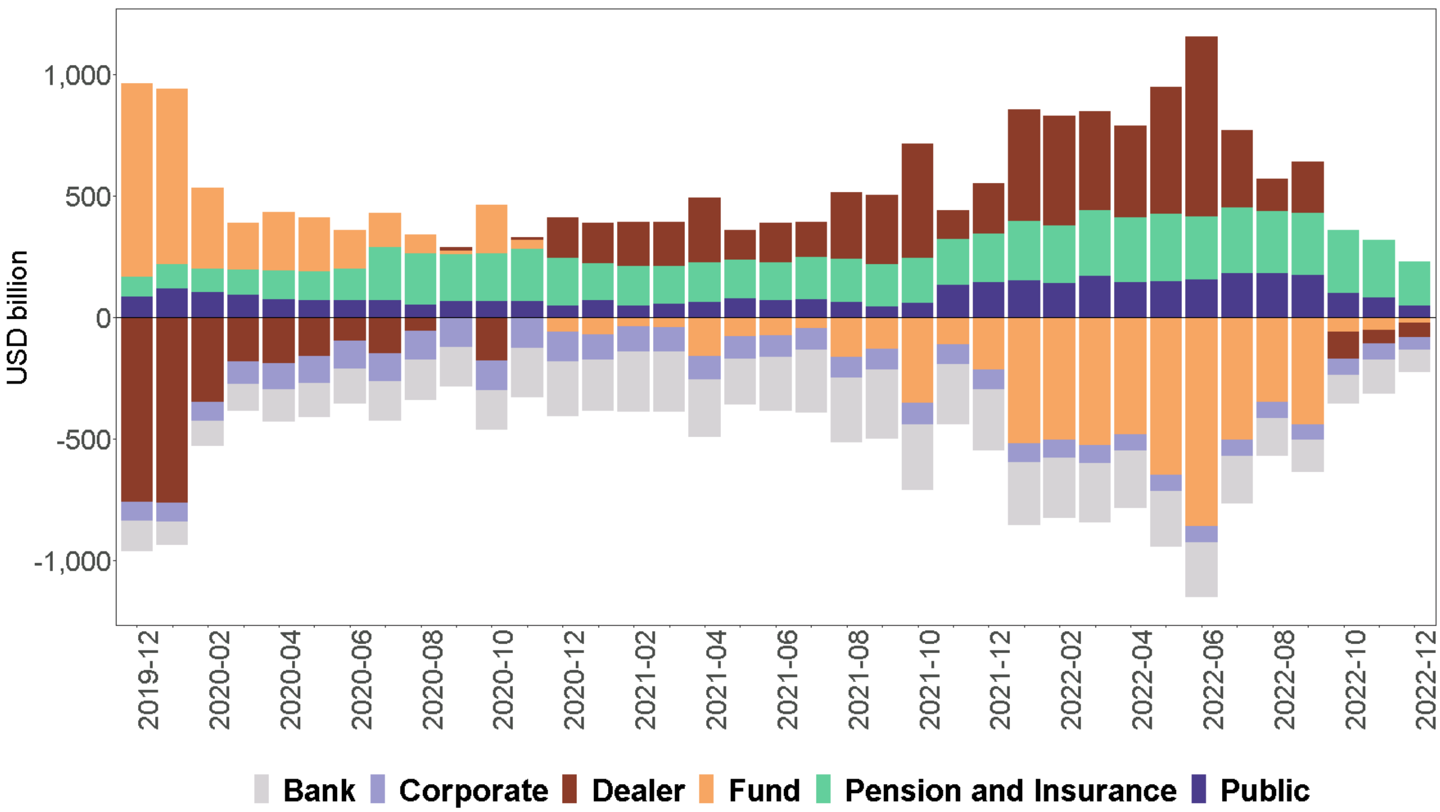
next month's swap spreads at five maturity points: 2Y, 5Y, 10Y, 20Y, and 30Y. We control for the level factor (first principal component of similar maturity gilt yields) and the slope at time t. We also control for aggregate net end-user demand at time $t-1$. In the second stage we estimate

$$EXPTRD_t = \alpha + \theta^D \widehat{SwapSpread}_t + Controls + \epsilon_t, \tag{44}$$

where $EXPTRD_t$ includes NDE_t scaled by the gross notional values and the parameter θ^D identifies the impact of instrumented swap spreads on swap demand.

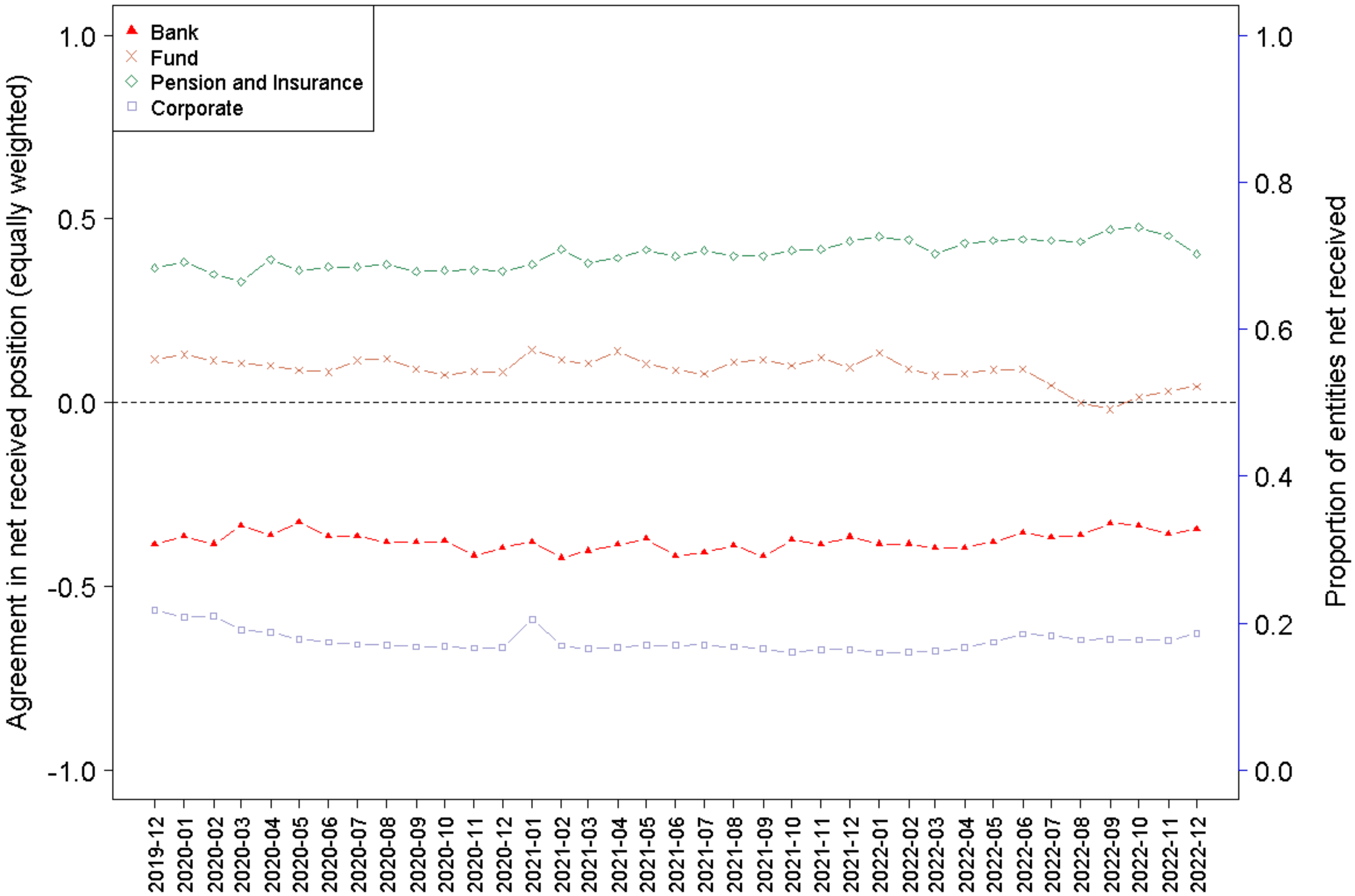
Table A6 reports the estimation results for pension funds. First, Panel B of Table A6 shows that the instrument strongly predicts the following month's swap spreads with a first stage F-stat of 10.2. A positive coefficient indicates that higher compression is associated with higher swap spreads, i.e. lower prices. A one standard deviation increase in Compression (=0.054) is associated with 11bps increase in swap spreads ($2.03 \times 0.054 = 0.11$). Next, Panel A reports the second stage. We observe that the impact of swap spreads on pension fund demand for swaps is positive and significant. For a one standard deviation increase in swaps spreads (=0.293), we find a \$12 million increase in new net received positions per billion dollar of existing positions (\$40.8 million $\times$ 0.293 = \$12 million), which represents a 1.2% increase in demand relative to existing stock of positions.

Figure A1: Net Outstanding Swap Notional (All Currencies)



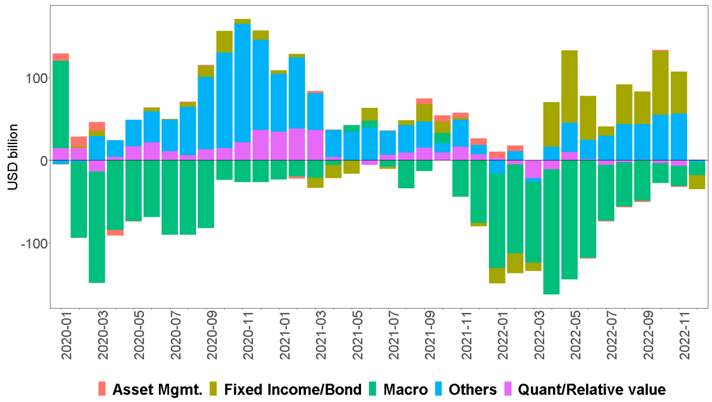
Notes: This figure shows the net received fixed notional outstanding in $ billion at a monthly frequency across five end-user segments and the inter-dealer segment. Inter-dealer position is calculated as the net of aggregate client-facing positions. This figure considers swaps denominated in all currencies in our sample, while Figure 1 considers GBP swaps.

Figure A2: Intra-Sector Heterogeneity in Exposures (All Currencies)

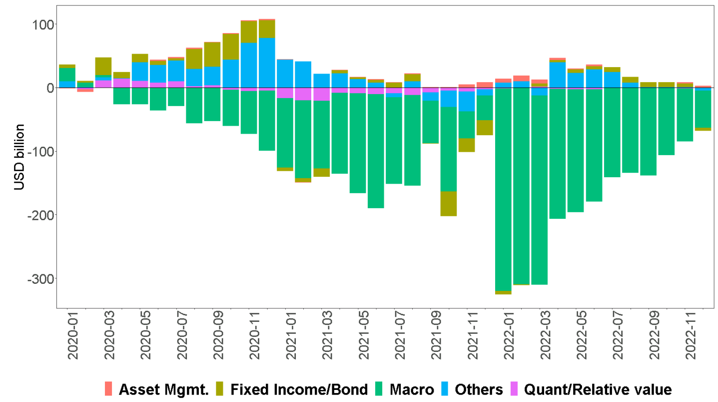


Notes: This figure shows the proportion of entities within a sector that hold net receive fixed swap position (right axis) and the agreement score (left axis) at a monthly frequency. We use equally-weighted net exposures at a legal entity identifier (LEI) level to calculate both measures. Agreement score is calculated by assigning +1 to entities with net receive fixed position, -1 for net paid, and averaged across all LEIs within a sector. This figure considers GBP swaps, while Figure 2 considers all currencies in our sample.

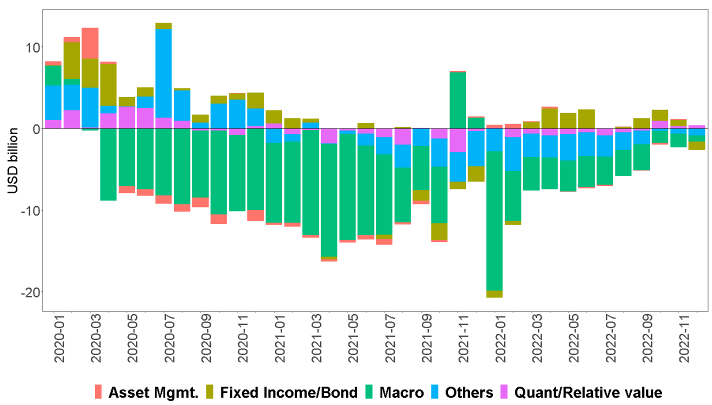
Figure A3: Net Outstanding Swap Notional by Maturity and Fund Type



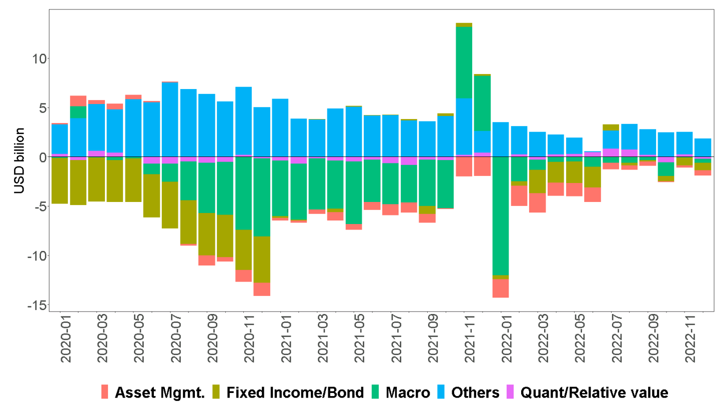
(a) Below 3 Month



(b) 3 Month to 5 Year



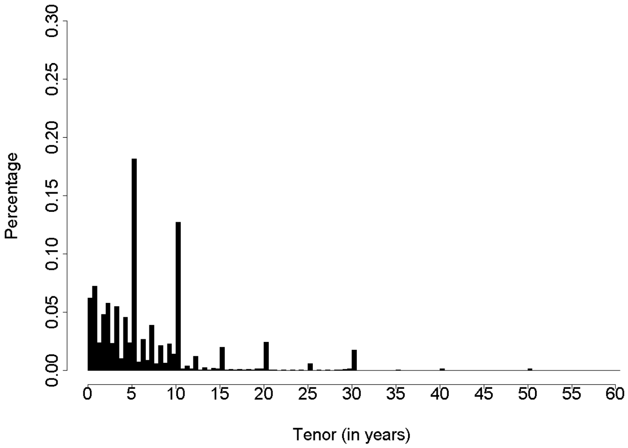
(c) 5 Year to 10 Year



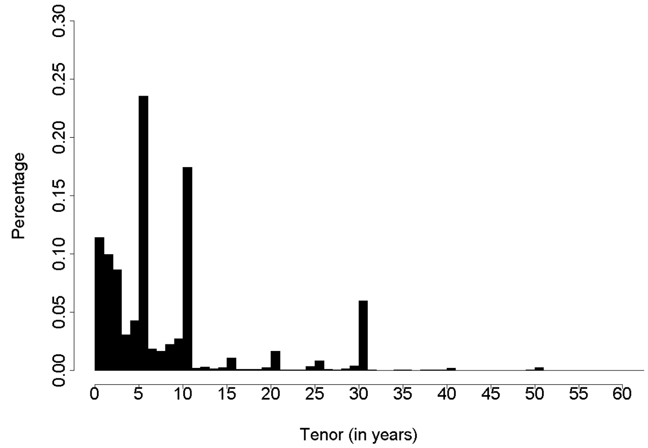
(d) Above 10 Year

Notes: This figure shows the net received fixed notional outstanding in \$ billion at a monthly frequency across five fund types and four maturity buckets for swaps denominated in GBP. We identify fund types using string matching of their names with common investment strategies at a legal entity identifier (LEI) level. o account for forward starting swaps, maturity is calculated from the "effective date" rather than execution date. Panel (a) considers swaps maturing within 3 months after the effective date, panel (b) considers swaps from 3 months up to five years, panel (c) includes swaps from 5 years up to 10 years, and panel (d) includes swaps with tenors exceeding 10 years.

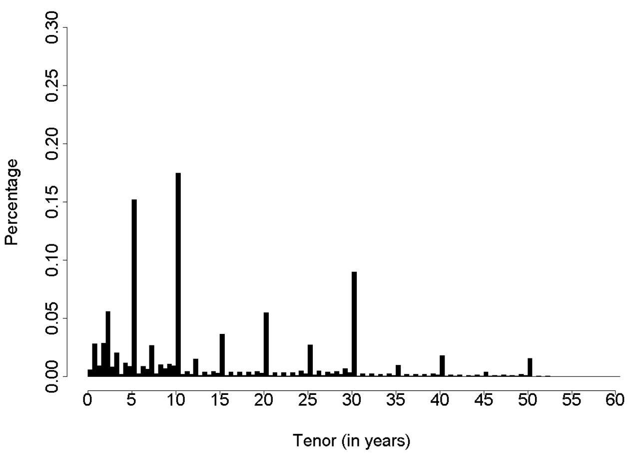
Figure A4: Maturity Distribution of New Swaps



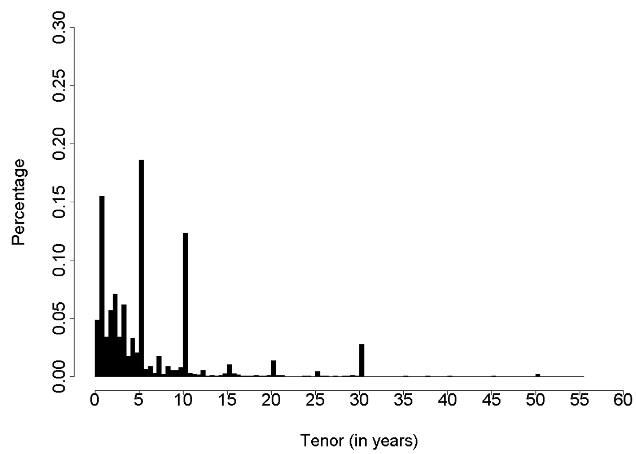
(a) Bank



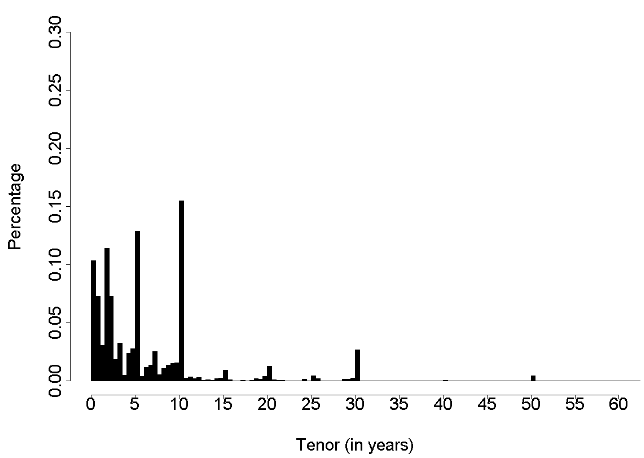
(b) Fund



(c) Pension and Insurance



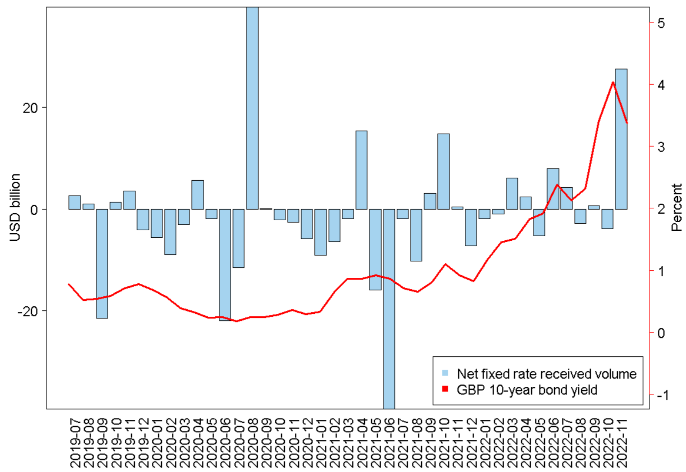
(d) Corporate



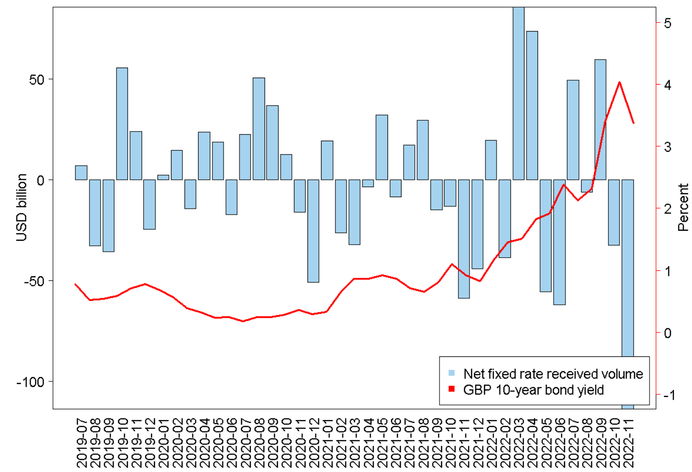
(e) Public

Notes: This figure shows the proportion of new trades initiated by each sector at yearly maturity points. Maturity is calculated as the difference between maturity date and effective date of the swap.

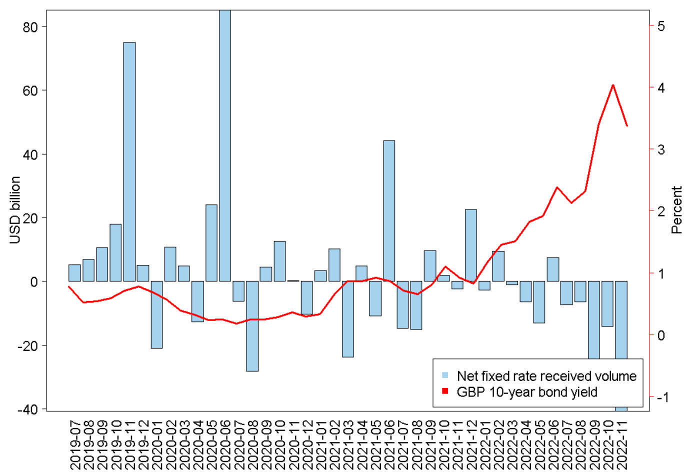
Figure A5: Interest Rates and Changes in Quantities



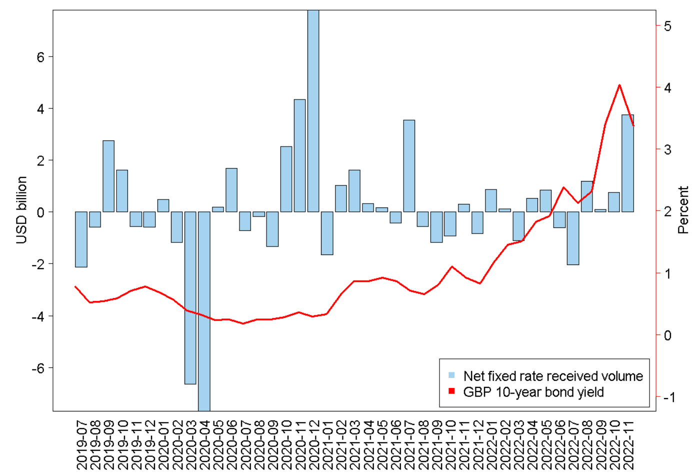
(a) Bank



(b) Fund



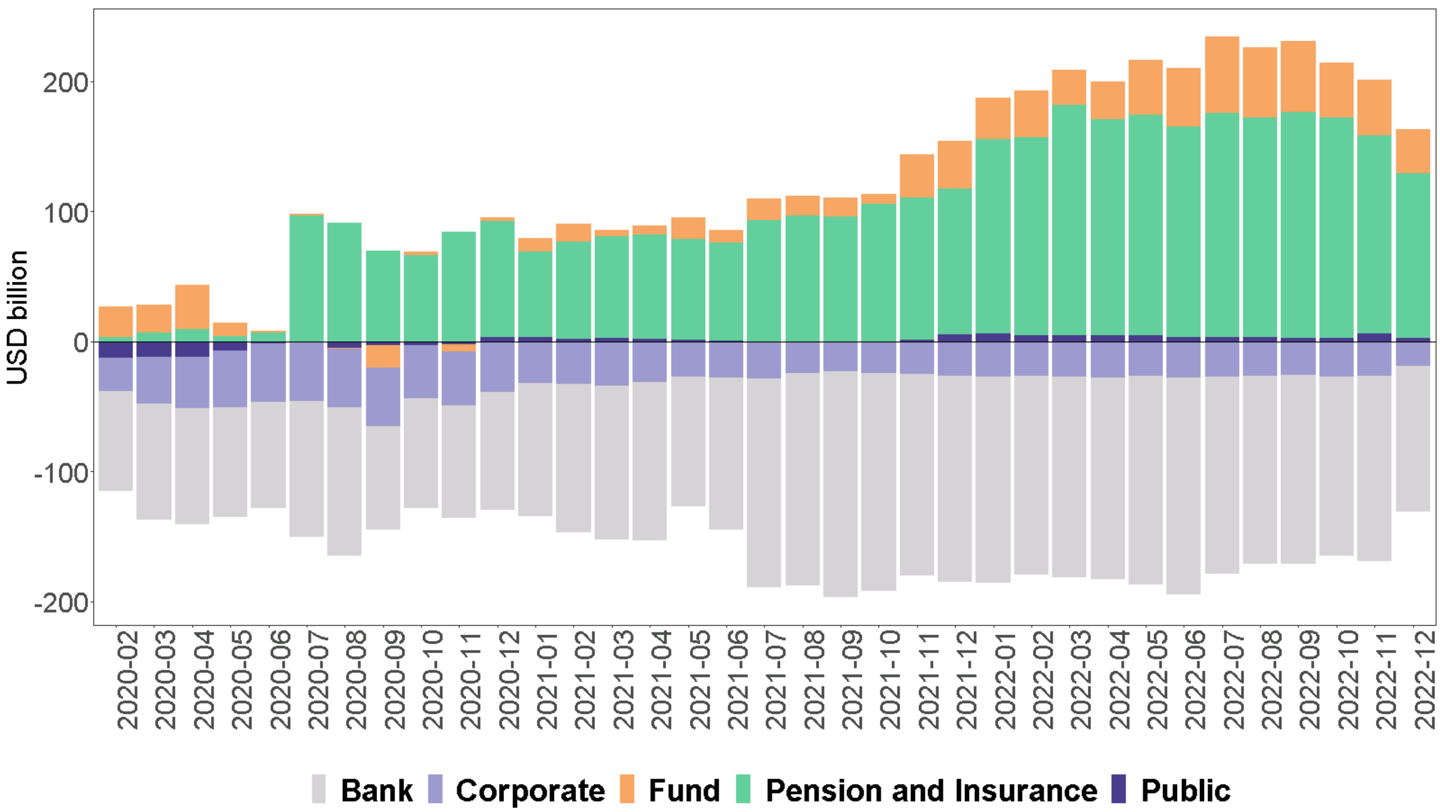
(c) Pension and Insurers



(d) Corporate

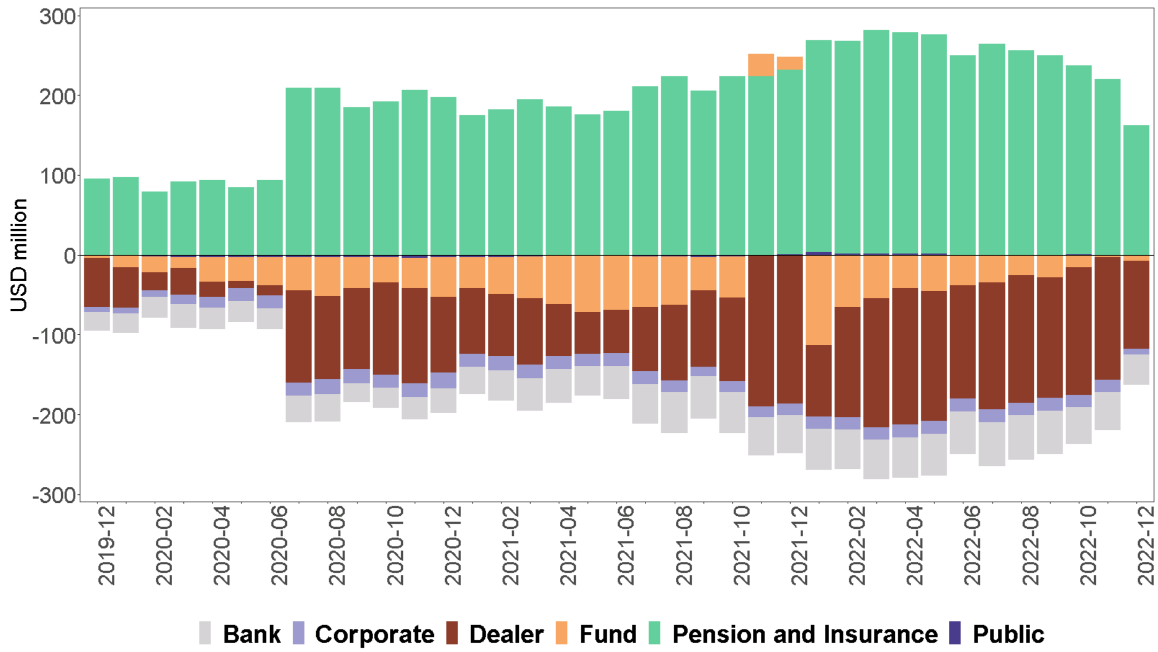
Notes: This figure shows the month-on-month change in net GBP swap position in $ billion (blue bars, left axis) and monthly average GBP 10-year bond yield (red line, right axis). Bars above zero indicate net receive fixed rate and below zero indicate net pay fixed rate. Panel (a) includes banks, panel (b) considers funds, panel (c) includes pension and insurers (including Liability Driven Investment funds), and panel (d) includes corporations.

Figure A6: Net Outstanding Swap Notional (UK entities)

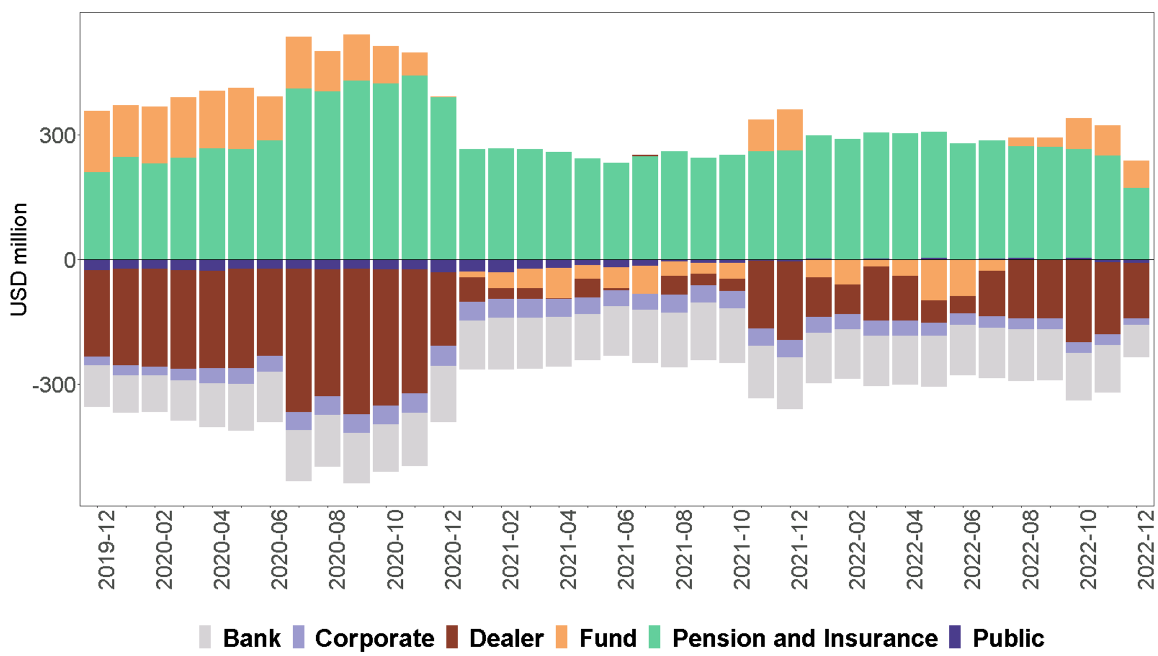


Notes: This figure shows the net received fixed notional outstanding in $ billion at a monthly frequency across five end-user segments, where the end-users are headquartered in the UK.

Figure A7: Net Outstanding Swap DV01



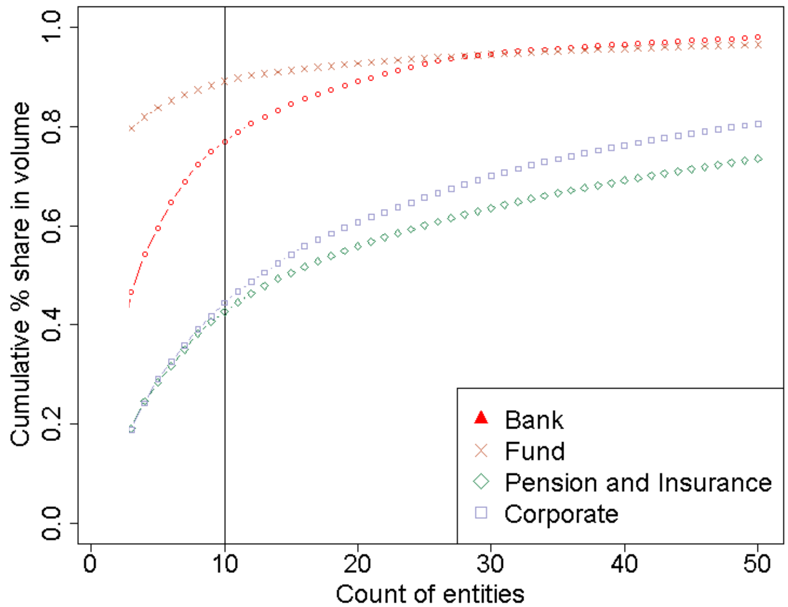
(a) GBP



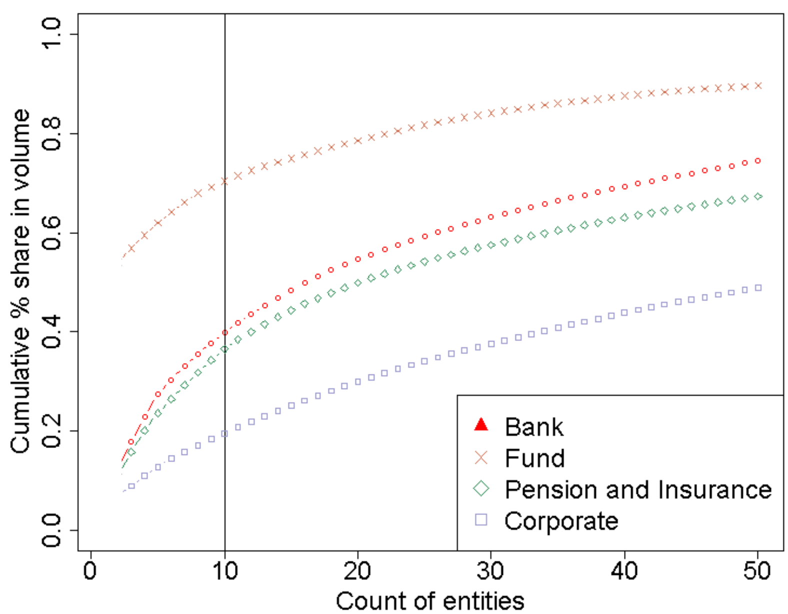
(b) All currencies

Notes: This figure shows the DV01 of outstanding swaps in $ million at a monthly frequency across five end-user segments and the inter-dealer segment. Inter-dealer position is calculated as the net of aggregate client-facing positions. Panel (a) represents the outstanding DV01 for GBP swaps only, while panel (b) considers all currencies in our sample.

Figure A8: Concentration in Net Exposures



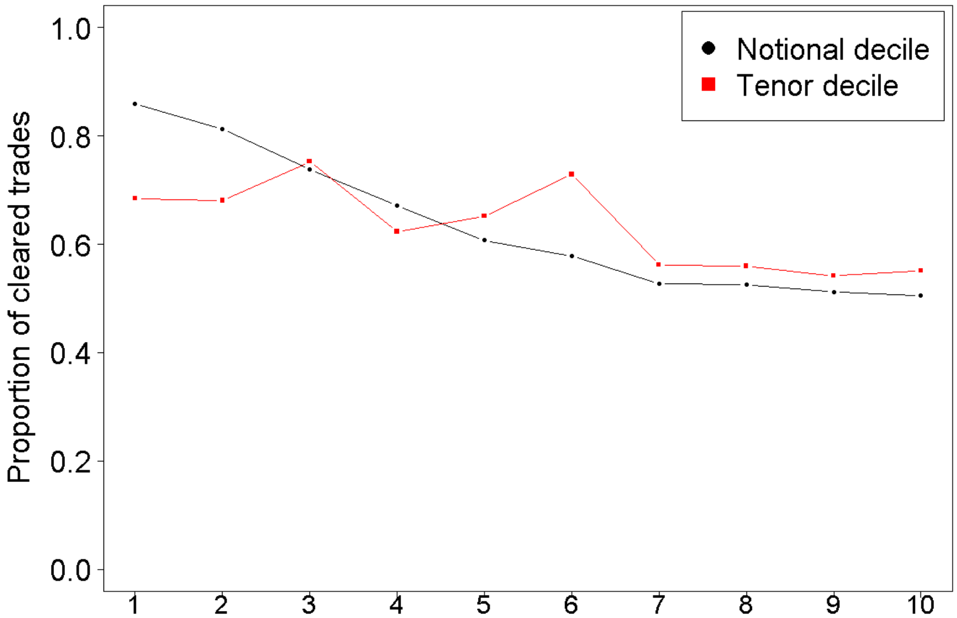
(a) GBP



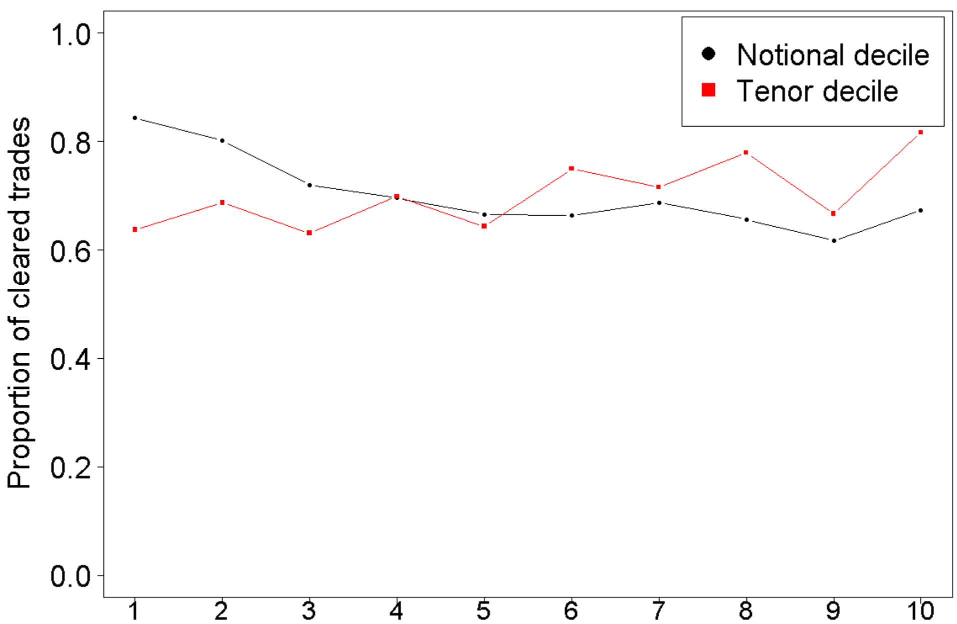
(b) All currencies

Notes: This figure shows the cumulative share of top 50 LEIs within each sector of the outstanding net (absolute) notional as on February 1, 2022. Panel (a) considers GBP swaps only, while panel (b) considers all currencies in our sample. The first point in both plots shows the share of top three entities put together in each sector.

Figure A9: Centralized Clearing and Trade Riskiness



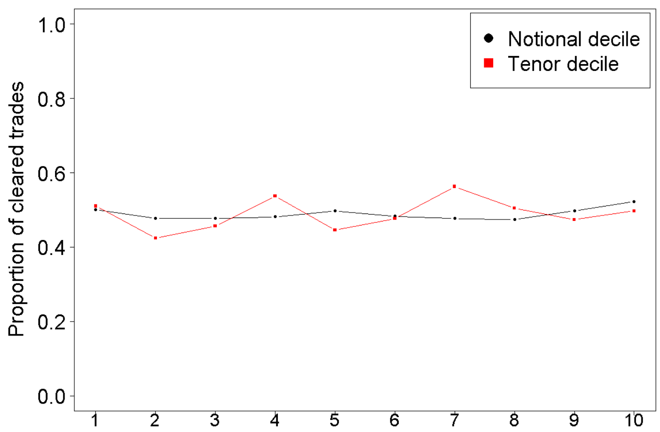
(a) Pension funds



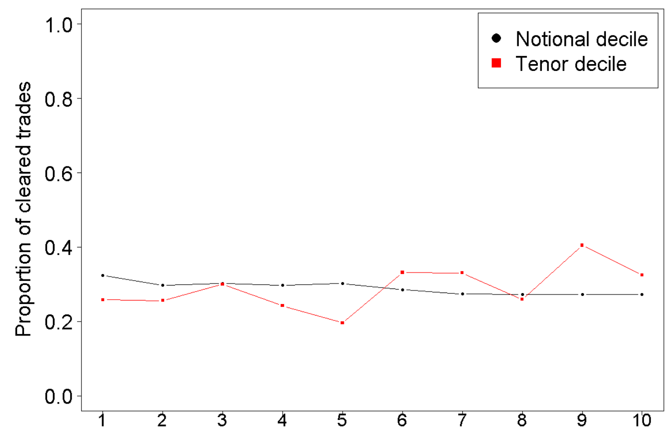
(b) Insurance

Notes: This figure shows the proportion of trades that are centrally cleared by pension funds and insurers as a function of notional and tenor deciles.

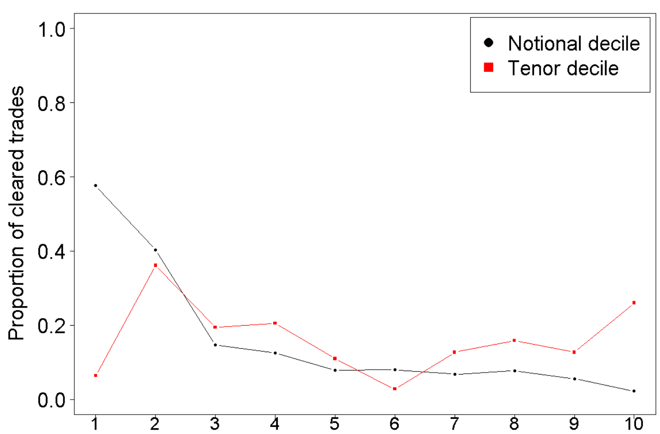
Figure A10: Centralized Clearing and Trade Riskiness



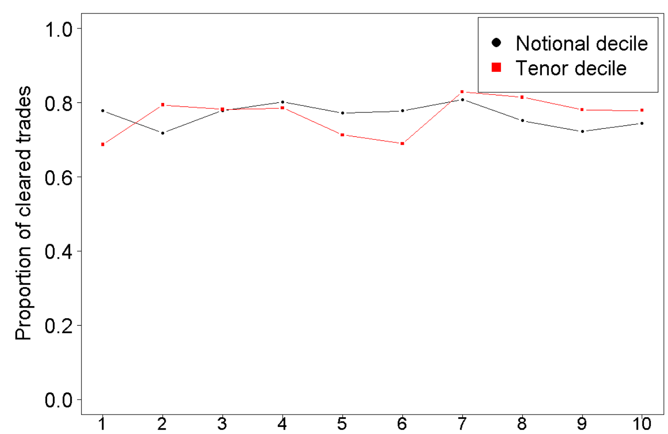
(a) Bank



(b) Fund



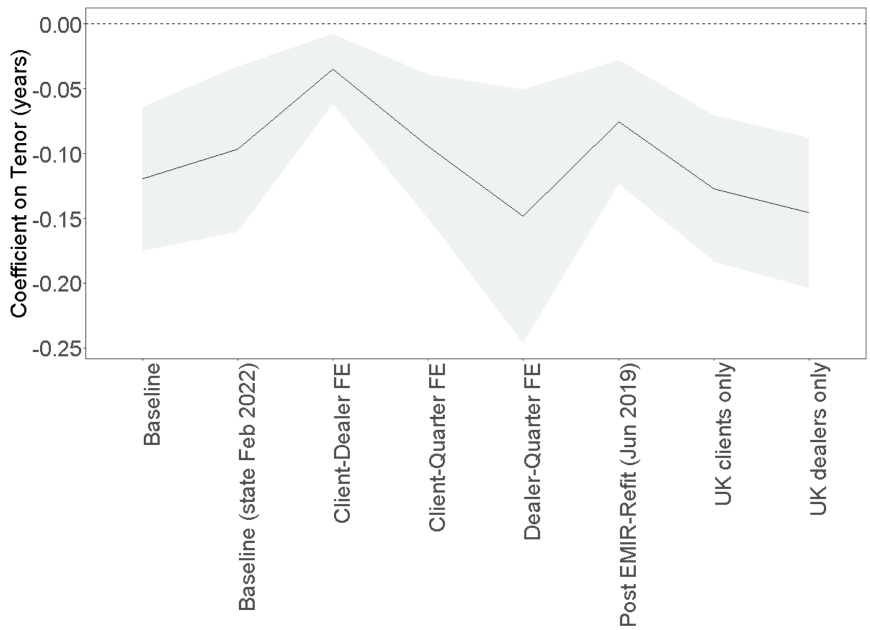
(c) Corporate



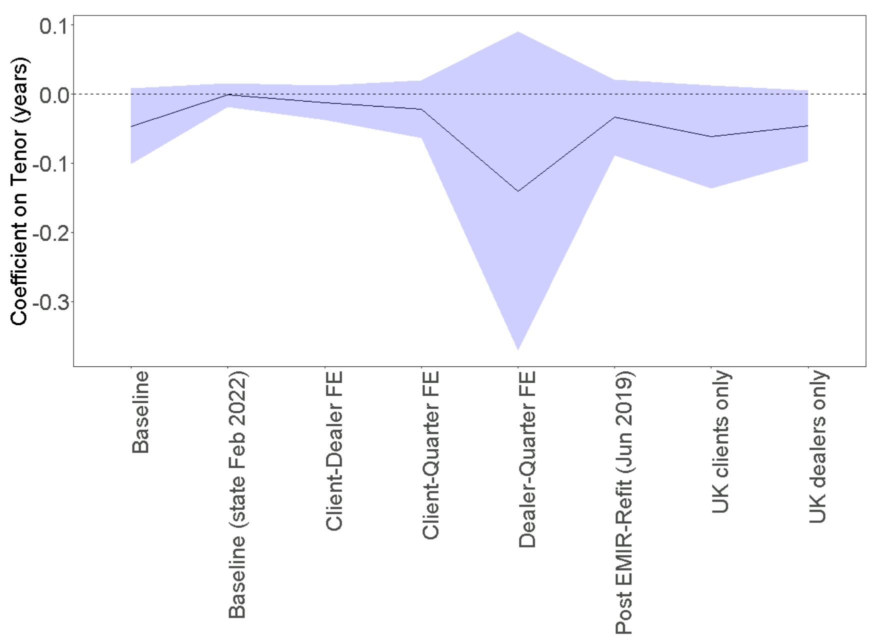
(d) Public

Notes: This figure shows the proportion of trades that are centrally cleared by four sectors, banks in panel (a), funds in panel (b), corporations in panel (c), and public in panel(d). The x-axis in each plot represents deciles of notional and tenor of the trade executed throughout our sample period.

Figure A11: Specification Curves for Centralized Clearing and Trade Riskiness



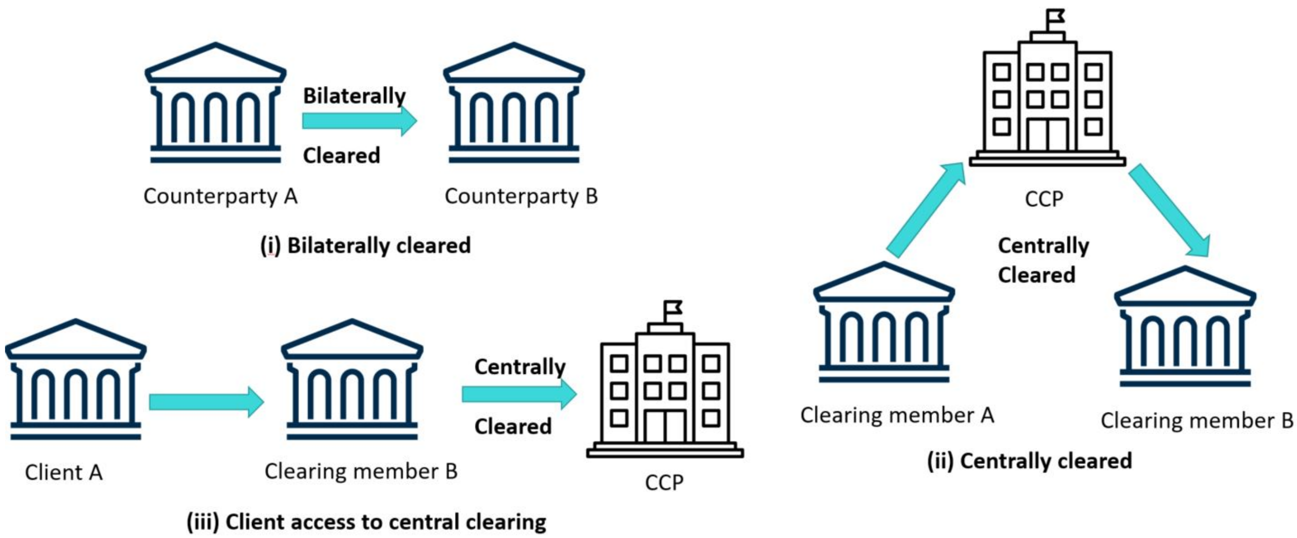
(a) Pension funds



(b) Insurance

Notes: This figure shows robustness of the estimation of Equation 42 to specification choices for pension funds in panel (a) and insurers in panel (b). Y-axis in both subplots corresponds to the coefficient on the tenor of swaps as a determinant of centralized clearing, and the bands around the central lines represent 95% confidence intervals.

Figure A12: Clearing Mechanism



Notes: This figure illustrates the mechanisms of clearing an OTC trade. Bilateral clearing does not involve a clearing house (CCP), unlike central clearing. However, most end-users do not have direct access to CCPs; they clear their trades through clearing members.

Table A1: Annual Swap Trading Volume

Panel A	All currencies					
Gross notional ($ billion)	2018	2019	2020	2021	2022	Total
Bank	6,543	5,598	4,725	3,450	4,437	24,753
Fund	85,355	85,165	102,719	95,187	100,222	468,648
Pension and Insurance	3,868	2,995	2,908	3,356	1,967	15,093
Corporate	308	233	183	403	612	1,739
Public	1,409	1,830	1,972	1,544	1,362	8,118
Panel B	GBP					
Gross notional ($ billion)	2018	2019	2020	2021	2022	Total
Bank	1,081	450	598	691	465	3,285
Fund	12,167	11,989	31,670	24,383	14,548	94,757
Pension and Insurance	1,151	1,048	949	1,958	1,099	6,205
Corporate	57	56	52	42	35	242
Public	117	209	393	236	192	1,146

Notes: This table reports the annual turnover (in $ billion) of new trades initiated in our sample at a sector level. We adjust for double counting of trades by retaining one copy of duplicate trades arising out of two-way reporting requirements under the EMIR regulations. Panel A includes swaps denominated in all currencies in our sample and panel B includes GBP swaps.

Table A2: Gross and Net Outstanding Swap Notional by Maturity and Fund Type

Panel A	Gross notional ($ billion)					
	Below 3M	3M to 5Y	5Y to 10Y	Above 10Y	Total	Share
Asset Mgmt.	8	15	3	6	31	0.02
Fixed Income/Bond	164	105	15	6	290	0.18
Macro	343	358	9	4	714	0.45
Quant/Relative Value	146	37	8	4	196	0.12
Other	192	132	20	25	369	0.23
Panel B	Net receive fixed ($ billion)					
	Below 3M	3M to 5Y	5Y to 10Y	Above 10Y	Net-to-gross	Share
Asset Mgmt.	7	9	1	-2	0.59	0.04
Fixed Income/Bond	-24	-1	0	0	0.09	0.05
Macro	-108	-310	-6	-3	0.60	0.84
Quant/Relative Value	-5	0	-1	0	0.04	0.01
Other	11	10	-4	3	0.07	0.05

Notes: This table reports the outstanding GBP gross notional (panel A) and net receive fixed positions (panel B) by five fund types and four maturity buckets as on February 1, 2022. Outstanding maturity or tenor of a swap is calculated as the difference between the maturity date and the later of the effective date or February 1, 2022. We identify fund types using string matching of their names with common investment strategies at a legal entity identifier (LEI) level. 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 type in the overall outstanding positions. The second-to-last column in panel B reports the ratio of net position to gross notional for each fund type using positions held across maturity buckets, and the last column reports the share of each fund type in the net (absolute) positions.

Table A3: Descriptive Statistics on Centralized Clearing and Collateralization

Proportion of cleared trades	N	Mean	SD	p25	p50	p75
Bank	440,857	0.49	0.50	0	0	1
Fund	2,952,302	0.29	0.45	0	0	1
Pension fund	187,628	0.61	0.49	0	1	1
Insurance	80,131	0.69	0.46	0	1	1
Corporate	19,251	0.16	0.37	0	0	0
Public	54,378	0.77	0.42	1	1	1
Proportion of fully collateralized bilateral trades	**N**	**Mean**	**SD**	**p25**	**p50**	**p75**
Bank	207,490	0.28	0.45	0	0	1
Fund	1,953,291	0.36	0.48	0	0	1
Pension fund	64,470	0.37	0.48	0	0	0
Insurance	22,318	0.25	0.43	0	0	0
Corporate	14,556	0.04	0.21	0	0	0
Public	11,522	0.21	0.41	0	0	0

Notes: This table reports descriptive statistics on the proportion of trades executed between 2018-2022 that were centrally cleared and the proportion of non-centrally cleared trades that were fully collateralised.

Table A4: Comparative Statistics for Pension Fund and Insurance Trades

Pension funds	N	Mean	SD	p25	p50	p75
Notional ($ million)	187,628	51	198	2	10	37
Tenor (years)	187,628	14	12	5	10	20
G3 currency (USD, EUR, GBP)	187,628	0.88	0.33	1	1	1
Cleared (1/0)	187,628	0.61	0.49	0	1	1
Insurance	**N**	**Mean**	**SD**	**p25**	**p50**	**p75**
Notional ($ million)	80,131	56	222	4	14	46
Tenor (years)	80,131	16	12	5	11	25
G3 currency (USD, EUR, GBP)	80,131	0.88	0.32	1	1	1
Cleared (1/0)	80,131	0.69	0.46	0	1	1

Notes: This table compares the distribution of the notional and tenor of new trades executed by pension funds and insurers between 2018-2022 across all currencies in our sample.

Table A5: Centralized Clearing and Trade Riskiness

	Cleared (100/0)					
	Bank	Fund	Pension fund	Insurance	Corporate	Public
	(1)	(2)	(3)	(4)	(5)	(6)
Notional (USD, log)	0.071	-0.128	-0.911***	-0.759**	0.002	0.005
	(0.179)	(0.144)	(0.249)	(0.310)	(0.090)	(0.173)
Tenor (years)	-0.003	-0.019	-0.119***	-0.046*	0.090	0.112*
	(0.022)	(0.024)	(0.027)	(0.026)	(0.058)	(0.055)
G3 currency (USD, EUR, GBP)	7.62***	1.05	3.85*	0.719	0.453	0.241
	(2.08)	(1.18)	(2.22)	(1.96)	(0.674)	(0.964)
Full collateralization	-13.9***	-11.5**	-23.4***	-35.7***	0.199	-33.5**
	(3.71)	(4.18)	(5.52)	(11.6)	(5.63)	(12.9)
Client, Dealer, Trade date FE	Y	Y	Y	Y	Y	Y
Observations	410,799	2,804,943	165,367	70,830	17,452	53,908
Adj. R^2	0.74	0.78	0.78	0.80	0.93	0.77
Within R^2	0.03	0.03	0.07	0.13	0.00	0.08

Notes: This table reports estimates from a linear probability model of the form in Equation 42 at a trade level. The dependent variable takes a value of 100 when the trade is centrally cleared and 0 otherwise. Regressors include the log $ notional of the trade, tenor (in years) and a binary indicator for whether the swap is denominated in one of USD, EUR or GBP, or not. Also included is an indicator of whether the end-user and the dealer had a fully collateralized portfolio agreement in place at the time of the trade. All columns include client, dealer, and trade date fixed effects. Standard errors are clustered by dealer and year-quarter, and reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A6: Portfolio Compression as Instrument for Swap Spreads

Panel A: First stage	Swap spread (PC 1)
Compression	2.03***
	(0.707)
Bond yield (PC 1)	0.179***
	(0.013)
Slope (10Y-2Y)	-0.526***
	(0.100)
Aggregate net receive ($ billion)	-0.020*
	(0.011)
Observations	59
Instrument F-statistic	10.2
Adj. R^2	0.84

Panel B: Second stage	Net fixed receive ($ billion per outstanding)
$\widehat{\text{Swap spread}}$ (PC 1)	0.041**
	(0.017)
Bond yield (PC 1)	-0.009***
	(0.003)
Slope (10Y-2Y)	0.004
	(0.009)
Aggregate net receive ($ billion)	0.0006
	(0.0008)
Observations	59
Adj. R^2	0.01

Notes: This table reports estimation results of Equation 43 in Panel A and Equation 44 in Panel B. The instrument is Compression, defined as the volume of newly compressed GBP swap trades in our sample in month t-1. The first stage regresses the first principal component of GBP swap spreads across 2Y, 5Y, 10Y, 20Y and 30Y tenors in month t on compression activity in month t-1. Controls include month t bond yield (first principal component of similar tenors), slope of the yield curve, and month t-1 aggregate net receive fixed activity by all end-user segments. The second stage regresses the month t net receive fixed rate activity of PF&I sector on the instrumented swap spreads and other controls. Heteroskedasticity robust standard errors are reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.