The Market for Sharing Interest Rate Risk: Quantities behind Prices

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Abstract

We study the extent of interest rate risk sharing across the financial system. We use granular positions and transactions data in interest rate swaps, covering over 60% of overall swap activity in the world. 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 net demand that is supplied by dealers. However, two factors impede cross-sector netting and add to dealer imbalances across maturities: (i) PF&I, bank and corporate demand is segmented across maturities. (ii) Large volumes are traded by hedge funds, who behave like banks in the short-end and like PF&I in the long-end. This worsens segmentation, exposing dealers to a steepening or flattening of the yield curve in addition to residual duration risk. Consistent with this, we find that demand pressure, in particular hedge funds' trades, impact swap spreads across maturities. We also document that long-tenor pension fund trades are less likely to be centrally cleared, adding counterparty credit risk to demand imbalances.

Keywords: Interest rate risk, OTC derivatives, Hedge funds, Pension funds, Insurance companies, Banks, Non-financial corporations, Demand elasticities, Counterparty credit risk.

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 the 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 monetary policy 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. (1) What is the extent of risk transfers across sectors: do various end-users swap risks as their business models would suggest or trade in the same direction, amplifying demand imbalances? (2) How large are these imbalances, what causes them, and who is bearing them? (3) What are the consequences of demand imbalances for asset prices? (4) How do demand shocks from one part of the financial sector transmit across the system and do these shocks exacerbate risk mismatch? (5) Do demand imbalances give rise to counterparty credit risk? These questions have far reaching implications for the financial sector and the broader economy.

In this paper, we make progress on these questions by dissecting the quantities, i.e. the extent of risk transfers, that pin down asset prices using granular and high frequency data on a wide range of participants in this market. We uncover partial risk transfers and persistent demand imbalances and show that these imbalances have consequences for asset prices and ultimately risk mismatch across the financial system.

We exploit the most comprehensive trade-level interest rate derivatives data deployed in academic research to date. The over-the-counter (OTC) nature of derivatives markets typically limits visibility into the quantities traded by market participants. However, as part of the post-financial crisis effort to improve post-trade transparency, several regulatory authorities mandated the reporting of OTC derivatives to trade repositories. We source records of outstanding positions and new transactions from two large trade repositories where one of the entities to a trade is a UK entity. Given that London serves as the center of OTC derivative transactions, our data cover 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 entity's behavior taking account of a full history of trading information as captured by the stock of its outstanding positions. Second, our data span an unusually long time-period of five years from 2018 to 2022, which allows for important time-series analyses on the evolution of risk transfers. Third, 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. Fourth, we observe detailed characteristics for each position and trade, including notional amounts, trade direction, maturity, benchmark, and currencies. This allows us to accurately compute risk exposures. Moreover, granular characteristics permit us to assess segmentation in risk sharing along dimensions such as maturities and currencies. Finally, the variables available to us cover not only the economics of the trade itself, but also the settlement mechanism and the collateral relationship between the counterparties, which enable us to examine consequences of demand imbalances for counterparty credit risk.

We start by outlining the main facts on swap positions and trading across sectors. The main end-user segments are funds (including hedge funds and other asset managers), pension and insurance (PF&I), banks, corporations and public/sovereign institutions. Funds hold the largest stock of outstanding net positions, followed by PF&I and banks, and funds' trading volumes are orders of magnitude larger than all other sectors, particularly in shorter maturities where they are most dominant. However, they also trade the largest volumes in longer maturities where traditionally long-term investors like PF&I are presumed to dominate.

To quantify the extent of risk transfers, we examine the *net* exposures, i.e. receive minus pay fixed positions, at a sector level, and the duration risk of a one basis point movement in interest rates (DV01). There is significant heterogeneity in the direction of net outstanding positions across sectors. PF&I receive fixed: they add duration to their portfolios with swaps. In contrast, banks and corporations do the opposite: they pay fixed, i.e. sell duration with derivatives. Moreover, even in response to shifts in rates, PF&I and banks trade in the opposite direction. As rates fall, PF&I increase their net receive exposures, but banks increase their net pay exposures. In other words, PF&I buy (sell) duration, whereas banks and corporations sell (buy) duration in response to decline (rise) in rates. These factors 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 net short duration while banks are long duration.

On the other hand, funds have considerable heterogeneity in outstanding positions and trading across maturities: they pay the fixed rate in shorter maturities, just like banks, and consistently receive fixed in longer maturities, like PF&I. To better understand the economics that underpin funds' behavior, we split them into granular categories to capture various well known trading strategies, e.g., asset management, fixed income or bond, macro, quant & relative value, and liability-driven investment (LDI), and show that this heterogeneity is a result of different types of trading strategies. Macro funds have the largest exposures, primarily in the shorter maturities, where they hold a net paid position which increased tremendously in early part of the 2022 interest rate hiking cycle. Fixed income and LDI funds generally receive fixed, suggesting similar behavior to PF&I. In contrast, quant & relative value funds hold large but offsetting gross receive and pay positions, and undergo frequent changes in trading direction, consistent with their perceived role of exploiting relative value, e.g., across the term structure. Finally, we leverage the long time-series of our data and document that funds' reaction to changes in bond yields and slope of the yield curve varies over time. In the low-volatility period before the onset of COVID-19 pandemic, funds countercyclically sold duration when interest rates increased, similar to banks and corporations. After the onset of the pandemic, however, funds have procyclically bought duration following interest rate increases, behaving similar to PF&I. This time variation is in stark contrast to other sectors such as banks, PF&I and corporations that exhibit more consistent trading patterns.

We next 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 flip side of the net end-user demand. Thus, the dealer sector's balances are inverse of the aggregate net end-user demand. We observe that a large portion of PF&I positions are offset by the positions of banks and corporations. This results in significant cross-sector netting, reducing the total aggregate net demand that is 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. While much of PF&I activity is in the longer maturities (e.g., 70% of positions are over 5 years), a bulk of bank and corporations' positions are in the short and intermediate maturities. Second, funds, who trade large volumes, amplify dealer imbalances as they trade in the same direction as banks in shorter maturities and in the same direction as PF&I in longer maturities. Dealers have to receive fixed (long duration) in shorter maturities and pay fixed (short duration) in longer maturities, exposing them to non-parallel movements in rates in addition to the residual dollar duration.[1]

We next examine the consequences of demand pressure (and thus dealer imbalances) for asset prices. Using GBP swaps as a laboratory, for which we have the largest coverage both in terms of overall volume and end-user trading activity, we show that demand pressure, in particular that of funds, affects swap spreads. Specifically, as the demand to receive the fixed rate increases, swap spread, defined as the swap fixed rate minus the maturity matched bond yield, decreases. In other words, we observe that dealers are willing to offer a lower fixed rate, i.e. swaps become more expensive. Interestingly, while funds' trading volumes affect spreads across all maturities, different trading strategies affect prices of different parts of the term structure. Macro funds, who mainly pay fix at the short-end, affect short-to-intermediate maturity (e.g., 2 and 5 years) swap spreads. In contrast, the trading of fixed income funds, who largely behave like long-term investors, tend to affect long maturity swap spreads. Finally, we find that the intermediate period swap spreads are most predicted by the trading activity of quantitative funds who exploit relative value across the term structure. Our results suggest that supply for swaps is upward sloping and that dealers cannot hedge perfectly because of reasons including incomplete markets, transaction costs, or regulatory capital constraints. This implies that shocks in one sector can spillover to other parts of the economy via asset prices. We estimate investors' demand elasticities using plausibly exogenous variation in

[1]This is consistent with the evidence of dealer imbalances in other markets (e.g., S&P 500 index options (Gârleanu et al., 2008), inflation swaps (Bahaj et al., 2023)). The asset pricing implications of these imbalances are consistent with the literature on negative swap spreads (Boyarchenko et al., 2018, Klingler and Sundaresan, 2019, Hanson et al., 2022, Siriwardane et al., 2022).

dealers' constraints. Our results suggest that price shocks are in part absorbed through quantities, creating a potential for risk mismatch in various parts of the financial system.

We augment the analysis of interest rate risk transfer with another dimension that was pivotal during the financial crisis: counterparty credit risk (CCR). An important source of losses in OTC markets during the financial crisis was not the actual default of counterparties, but the decrease in their credit quality (Basel, 2009). The main reforms through which regulators addressed CCR post-2008 included a mandate to centrally clear trades and the introduction of both additional capital charges and bilateral margining requirements in the bilaterally (i.e. non-centrally) cleared segment. However, not all trades have to be centrally cleared, and not all non-centrally cleared trades incur all the capital charges. We evaluate if there are segments within the swaps market where imbalances in quantities demanded intersect with higher CCR. Given the regulatory focus on centralized clearing, we first document clearing behavior across sectors. We find that a majority of fund *trades* are not centrally cleared, but a majority of their *outstanding exposures* are cleared or collateralized, pointing to a distinction in the riskiness of trades that are turned over quickly and those that stay on the books. Second, we exploit a natural experiment, where investors with similar hedging behavior (pension funds and insurers) are subject to different regulatory provisions on centralized clearing. Bilaterally cleared pension fund trades are exempt from credit valuation adjustment (CVA) capital charge but the same does not apply to insurers. We find that pension funds preferentially allocate their riskier trades to the bilaterally cleared segment, where clearing declines as function of trade size and tenor. We argue that this type of market segmentation due to regulation may add uncapitalized counterparty credit risk to the system.

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 et al. (2015) show that interest rate derivatives amplify balance sheet fluctuations for U.S. banks. Hoffmann et al. (2019) find the opposite for Euro area banks. 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 et al. (2021) use a one-day snapshot of outstanding exposures to confirm that pension funds receive duration but with significant intra-sector heterogeneity. In a more recent work, McPhail et al. (2023) find that U.S. banks do not hedge the interest rate risk of their assets using interest rate swaps. 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 et al., 2021). However, few papers look at quantities behind prices, which is where we contribute. Relatedly, Bahaj et al. (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 counterparty credit risk, which has been the focus of regulations after the financial crisis. In this regard, Cenedese et al. (2020) show that some users incur additional X-Value Adjustment costs to trade derivatives bilaterally, while Du et al. (2019) show that the credit quality affects the choice of counterparties in the CDS market. Our findings suggest that regulatory provisions affect incentives to centrally clear trades, particularly those that worsen dealer imbalances. 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 et al. (2022) model swap spreads as a function of end-user demand and intermediary constraints, and J Jermann (2020) suggests that 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 main data source consists of census-level data on interest rate swap transactions where at least one of the counterparties is a UK entity.[2] We access the data from two Trade Repositories, DTCC and Unavista, which cover a large sample of transactions required to be reported by the UK European Markets Infrastructure Regulation (EMIR).[3] Our access to the data comes from a key post-GFC reform on derivatives trading. Reporting obligation 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. There are currently four authorised TRs, where DTCC and UnaVista together were reported to have 90% of the market share (Abad et al., 2016) in interest rate derivatives in 2016. We focus on the same two trade repositories, and we estimate

[2]Note that examples of UK entities include both UK branches and subsidiaries of any counterparty which may be headquartered in another jurisdiction. Also, prior to 2021 we were able to observe trades done by EU-domiciled banks with a non-UK counterparty, but as part of the post EU-exit arrangements of the UK those trades are no longer present in our observed data sample.

[3]More details on the 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.

that our sample covers 87% of GBP and 68% of USD swaps' world-wide turnover.

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.[4] 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 sample, but 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.[5] 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, remove any reporting trade duplication, and retain trades executed starting January 1, 2018. We apply a 5% window in number of days to classify trades into several maturity buckets such as 3, 6, 9 months, and then between 1 year to 50 years or more. We also account appropriately for forward starting trades, and conduct several cross-checks to correctly identify the type of clearing by combining information from several reported variables. 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 TR terminology, at a monthly frequency over the period of 2020 to 2022 (the accuracy of state files substantially improves starting 2020). 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 retain fewer variables from state files, but 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 the institutions in our sample.

[4] Changes in reporting obligations starting 2018 limit the usability of pre-2018 data.
[5] A recent report on (EU) EMIR data quality can be found here.

1.3. *Sector, price and other variables*

We augment the 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)[6], pension funds, insurance companies, corporations, public institutions (such as sovereign funds or supranationals) and central clearing houses (CCPs).[7] [8] 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 (the list of clearing members is retrieved directly from the website of London Clearing House (LCH)), GSIB banks, participating dealers as per the Federal Reserve Bank of New York[9], brokers, and non-bank liquidity providers. All banks not labelled as dealers are classified as Banks.

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.[10] 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.

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

[7]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.

[8]In the UK, some pension funds use Liability Driven Investment (LDI) funds to manage their funding risk, predominately via increased exposure to gilts. In our sample, LDI funds represent under 1.1% of fund trading volume and we do not re-categorize them to the PF&I segment.

[9]The list is available on NY Fed's website.

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

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. 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.[11] 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 1 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 2 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 January 2020 through December 2022 for a total of 36 snapshots of outstanding positions.

2. Risk Exposures Across the Financial System

2.1. Measurement of Risk Exposures

We construct the following measures to study the interest rate risk exposures of outstanding positions and traded volumes. We compute *net dollar exposures* (NDE), defined as the total notional in receive fixed swaps minus the total notional in pay fixed swaps at an end-user sector level.

$$NDE_t = \sum_p Signed\ Notional_{pt}, \tag{1}$$

where $Signed\ Notional_{pt}$ 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 NDE denote net receive fixed positions.

To account for the heterogeneity in the positions across maturities, we follow two strategies.

[11] BIS statistics are available here.

(a) We split swap maturities into five maturity segments: below 1 year, 1-5 years, 5-10 years, 10-20 years, and above 20 years. Within each maturity segment, we compute the net dollar exposures as described in Equation 1 and label these variables $NDE^{<1}$, NDE^{1-5}, NDE^{5-10}, NDE^{10-20}, $NDE^{>20}$.

(b) We compute the dollar durations, i.e. the dollar value of a one basis point parallel shift in interest rates, which we label as DV01.

$$DV01_t = \sum_p Notional_{pt} \times Duration_p, \tag{2}$$

where $Duration_p$ refers to the signed duration of the fixed rate leg of the swap. We calculate Macaulay Duration separately for USD, EUR and GBP swaps. Appendix A discusses the cash flows and the duration calculations for standard swaps.

2.2. *Key Facts on Interest Rate Swaps Positions and Trading*

We start by describing the main facts on the outstanding interest rate swaps positions and trading across end-user sectors.

2.2.1. *Size of net exposures and the main end-user sectors*

Figure 1 and Figure 2 show the net dollar exposures and DV01 of outstanding positions for the various end-user segments. The three main end-user segments by net exposures are hedge funds, PF&I, and banks. Hedge funds generally hold the largest stock of outstanding net positions, followed by banks and PF&I, respectively. For example, as of February 2022, hedge funds held \$457 billion, banks held \$261 billion and PF&I held \$189 billion of net dollar exposures (Figure 1). The other two end-user segments, public sector and corporations, hold relatively smaller net positions. Note that we postpone discussing aggregate net demand and the dealer segment until later in the section.

2.2.2. *Direction of net outstanding exposures*

There is significant heterogeneity in the direction of net outstanding positions across sectors. PF&I and public institutions primarily receive fixed (positive net exposures), while banks and corporations pay fixed (negative net exposures). This suggests that PF&I and Public are natural counterparties to banks and corporations in the swaps market. Figure 1 shows that overall, hedge funds receive the fixed rate in the earlier part of the sample but pay fixed rate in the latter part, especially during the start of the 2022 rate hike cycle. However, in terms of the maturity adjusted net dollar risk measure (DV01 in Figure 2), hedge funds consistently receive fixed rates. This suggests considerable heterogeneity in their behavior across maturities, which we dissect with more granular data in the following subsection.[12]

We next document intra-sector heterogeneity in the direction of net outstanding exposures using LEI-level positions. 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 or position-weighted average of these values. Figure 3 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 rates on the right-hand side axis. Panel (a) uses a simple average of the LEI-level position scores while panel (b) weights them by the entity's average net absolute positions for the sample period.

Two findings emerge from Figure 3. (i) PF&I and Corporations are most homogeneous but in opposite directions, while Funds and Public sectors are most heterogeneous with nearly equal number of entities that are net receive or pay fixed rates at any point of time. (ii) Large funds drive the change in sector-level positions more significantly than large entities of other sectors. After weighting by size, we also note that while 80% of funds were net receive fixed rates at the start of our sample, this proportion dropped to 20% in mid-2022 and then went back up to about half by end-2022.

2.2.3. Distribution of positions across maturities

To understand how the positions are distributed across maturities, we next describe the net dollar exposures by various maturity segments. Figure 4 panels (a) through (e) show the dynamics of $NDE^{<1}$, NDE^{1-5}, NDE^{5-10}, NDE^{10-20}, $NDE^{>20}$ over time and Table 3 zooms into the exposures for February 2022 for ease of exposition. PF&I receive fixed, and banks and corporations pay fixed across all maturity segments. However, while much of PF&I activity is in the long-end (e.g., 70% of positions are over 5 years), a bulk of bank and corporations' positions are in the short end. Interestingly, hedge funds' trading direction varies across the maturity spectrum. Hedge funds pay the fixed rate in the below 1 and 1-5 years horizon, just like banks, particularly during the recent years of the sample. However, they consistently receive fixed in longer maturities, like PF&I. Moreover, their behavior appears more volatile relative to the other sectors, suggesting active engagement in making interest rate bets.

2.2.4. Interest rate swaps trading

We next describe the main facts on interest rate swaps trading across sectors. Table 4 shows the gross notionals and the net dollar exposures from new trading summed across all years in the sample. (Table C1 in Appendix C provides trade-level summary statistics by sector.) Consistent with outstanding positions, the three main end-user segments by traded volumes are hedge funds,

[12] 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). See Figure C1 in Appendix C.

banks, and PF&I. However, hedge funds' trading activities are orders of magnitude larger than the rest of the sectors, and the gap is larger than what the outstanding positions imply. For example, hedge funds traded over $469 trillion in gross notionals and $6.5 trillion in net dollar exposures combined over the five years in our sample. In comparison, PF&I traded $14 trillion in gross notionals and $292 billion in net dollar exposures. The gap between the size of outstanding positions and trading activity suggests that hedge funds have large turnover and they close open trades frequently. Interestingly, even in long maturity swaps, e.g., 20 years and above, hedge funds' trading is larger than the traditional long-term investors like PF&I.

Figure 5 shows the weekly net receive fixed trading volume of each of the five sectors with USD and GBP swap rates superimposed on them. We note that new trading volume of funds frequently moves between net receive and net paid positions, with a stronger correlation with interest rates than any other sector. Other sectors such as corporations and banks display more persistent activity in one direction. Furthermore, Figure 6 shows that the bulk of trades are contracted with standard maturities of 1 year, 5 years, 10 years, and 30 years for all sectors, but concentrated in shorter tenors for funds and longer tenors for PF&I.

Finally, we calculate the volatility in change of exposures as the standard deviation of weekly flow of net new exposure scaled by outstanding positions at a sub-sector level. Figure 7 plots this variable against the (log) size of each sub-sector: one for banks, six for funds, two for PF&I, three for corporations and three for public institutions. We note that three fund types display the highest volatility in the change of exposures: asset management, fixed income/bond, and quant/relative value. LDI funds behave similar to the PF&I sector and have lower volatility of exposure changes. Interestingly, financial corporations (for example, the financing arms of automobile manufacturers) exhibit greater volatility than non-financial corporations. In general across all sectors, larger sub-sectors exhibit lower volatility but within each size category, fund sub-sectors are most volatile.

2.2.5. Concentration

We assess the relative share of entities in each sector's overall positions and trading volumes. High level of concentration can point to the possibility of greater impact of idiosyncratic demand shifts on imbalances in market-level risk sharing. Using LEI-level activity and positions data, Figure 8 plots the cumulative share of volumes within each sector by activity in panel (a) and (net) outstanding notional in panel (b).

Perhaps unsurprisingly, public sector emerges as the most concentrated in both trading and outstanding positions due to a small number of sovereign and public institutions that trade swaps. However, we note an interesting contrast between the market concentration of trading activity and outstanding exposures for other sectors. The most striking difference in the two panels comes from funds where the top 10 entities hold 40% share in trading volume but over two-thirds share in outstanding notional as of February 1, 2022. 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.

2.2.6. *Co-movement of trading with macroeconomic conditions*

We next examine how swap positions vary with macroeconomic conditions, in particular the current level of interest rates and future expectations of rates as proxied by the term spread (Campbell and Shiller, 1991). Specifically, we run the following regression on trading data for each end-user sector at a weekly frequency:

$$EXPTRD_t = \alpha + \beta_1 \Delta Level_t + \beta_2 \Delta Slope_t + \epsilon_t \tag{3}$$

where the dependent variable $EXPTRD_t$ includes NDE_t and $DV01_t$. Note that we sum the total net exposures traded within a week for each end-user sector across all currencies to compute NDE_t and $DV01_t$. The independent variables $\Delta Level$ denotes the change in the first principal component of the government bond yields (2Y, 5Y, 10Y, 20Y, and 30Y) and $\Delta Slope$ denotes the change in 10Y year minus the 2Y yield.[13] To compute $\Delta Level$ and $\Delta Slope$, we subtract the average value for week $t-1$ from the average value for week t.

Table 5 shows the main results for the two dependent variables. (Table C2 in Appendix C reports results where the dependent variables are scaled by the respective sector's weekly total volume traded.) The overarching finding is that swap positions are sensitive to macro conditions across sectors, however, there are interesting cross-sector differences. First, note that β_1 (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.[14] In other words, as rates fall PF&I buy duration, and banks and corporations sell duration. Hedge funds do not show significant directional sensitivity to changes in yield and slope, but we attribute this to intra-fund heterogeneity, which we explore further. In a later section, we document that hedge funds indeed react to these macro variables in terms of volume traded.

The absolute size of coefficients in Table 5 denote the magnitude of response by each sector. PF&I add a DV01 of \$5.5 million when rates decline by 1 bps while banks and corporations reduce it by \$5.4 million and \$1.6 million, respectively. Even without considering funds and public institutions, there is an incomplete offset of DV01 across sectors and this imbalance is absorbed by dealers.

Funds display time-varying reaction to macroeconomic variables while other sectors have a more consistent behavior. We leverage the long time-series of our sample to split the data into low-volatility and high-volatility interest rate environments. We estimate Equation 3 for DV01 as the dependent variable using two time-periods: January 2018 through February 2020 (before the market turmoil caused by the COVID-19 pandemic), and March 2020 through to the end of our sample in December 2022. Table 6 reports the estimation results for all five sectors. Banks, PF&I

[13] While we regress the dependent variables on US Treasury yields, bond yields and slopes are strongly positively correlated across major currencies that constitute a bulk of trading in our sample.

[14] These results are robust to the exclusion of GBP LIBOR to SONIA transition period in 2021.

and Funds show generally consistent directional response to changes in yield and slope in both the sub-periods. However, funds behave similar to banks in the pre-COVID period and similar to PF&I in the post period. Public institutions also appear to change their trading behavior across these periods but trade much smaller magnitudes of DV01 compared to funds.

2.3. 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 et al., 2015, Domanski et al., 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.[15] This means that a bank wanting to close the mismatch between assets and liabilities with swaps would need to pay the fixed rate.[16] 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.

Another way to distinguish between hedging and taking active interest rate bets is to examine the extent to which a sector holds one-sided exposure or trades both ways. To examine this, Figure C2 and Figure C3 in Appendix C show the two measures of risk exposures scaled by the gross notionals. Consistent with hedging of balance sheet mismatch, PF&I, banks, corporations, and public sectors hold one-sided exposures. In contrast, hedge funds trade both ways and appear to be taking active interest rate bets.

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

[16] 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.

2.4. *Fund Heterogeneity*

To better understand the economics of hedge funds' trading, we split the hedge funds sector into more granular categories to capture various well known trading strategies. To do so, we scan the fund name strings to identify common patterns. We obtain the following main categories: (i) asset managers, (ii) fixed income, (iii) macro, (iv) quant & relative value, and (v) others. Table 7 shows the volumes and exposures for the different categories.

We find interesting differences in the trading and exposures across fund categories. Macro funds have 13% share in volume traded, 19% share in gross outstanding position, and 57% share in net (absolute) outstanding position, indicating more one-sided trading than other categories. In contrast, quant & relative value funds comprise of 22% share in volume traded, 27% of gross outstanding positions, but only 2% of net (absolute) outstanding positions, indicating that they hold large positions that net out, consistent with their perceived role of exploiting relative value, e.g., across the term structure. Asset managers have 16% share in volume traded but only 1% share in both gross and net (absolute) notional outstanding.

The hedge fund sector as a whole displayed insignificant directional sensitivity to weekly changes in bond yields and slope, as suggested by the results in Table 5. This does not preclude the possibility that the trading volume of funds, especially those following specific investment styles, gets affected by changes in these macroeconomic variables. We test this possibility by estimating a variant of Equation 3 where the dependent variable now is the gross notional volume.

$$NOT_t = \alpha + \beta_1|\Delta|Level_t + \beta_2|\Delta|Slope_t + \epsilon_t \tag{4}$$

where the dependent variable NOT_t is the gross notional traded (in logs) by the fund sector as a whole and by each of the five sub-types mentioned above. As in the case of estimating Equation 3, we sum the total volume traded within a week to compute NOT_t. The independent variables $|\Delta|Level$ denotes the absolute change in the first principal component of the government bond yields (2Y, 5Y, 10Y, 20Y, and 30Y) and $|\Delta|Slope$ denotes the absolute change in the 10Y minus the 2Y yield.

Table 8 reports the estimation results for the fund sector as a whole in column (1) and by the five sub-types in columns (2) through (6). Funds react strongly to changes in both the level of interest rates and the slope of the term structure. However, there is considerable heterogeneity in the magnitude of reaction by each fund type. Perhaps unsurprisingly, the fixed income/bond funds are most sensitive to both the variables. Macro, quant, and asset management funds show lower sensitivity. We note that the differences in investment strategies affect how different types of funds react to changes in the interest rate environment.

Next, Figure 9 highlights the heterogeneity in net dollar exposures across maturity buckets

(Figure C4 in Appendix C plots the time-series of overall net positions by fund type). Macro funds have the largest exposures, primarily in the shorter maturity buckets. Overall, macro funds held a net paid position during our sample and increased these positions in the early part of the 2022 interest rate hiking cycle. Quantitative funds do not show a consistent pattern across maturity buckets, indicating frequent changes in their trading direction over the business cycle. Fixed income and LDI funds are generally receive fixed, suggesting similar behavior as PF&I. Asset managers do not hold large outstanding positions and the other category dominates in the long-maturity bucket, predominantly receiving fixed.

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, the dealer sector's balances, who take the other side of the end-user net demand, are inverse of the aggregate net end-user demand.

$$\text{(5)} \qquad \textit{Dealer Balance}_t = -\sum_s NDE_t^s$$

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

Figure 1 and Figure 2, which we discussed above, also overlay the dealer sector balances (in brown). We observe that a large portion of PF&I positions are offset by the positions of banks and corporations, which trade in the opposite direction given that they have opposing underlying balance sheet mismatch. 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 that is supplied by the dealer sector.

However, two factors impede cross-sector netting and add to dealer imbalances across maturities. First, note that even though PF&I trade in the opposite direction relative to banks and corporations, their respective demands are highly segmented across maturities (Figure 4) with PF&I trading in longer maturities and banks and corporations trading in short and intermediate maturities.

Second, large volumes are traded by hedge funds. When we account for their activity, dealer imbalances worsen substantially. In particular, Figure 4 shows that hedge funds, by primarily paying fixed in short maturities, behave like banks in the short-end, and by primarily receiving fixed in longer maturities, behave like PF&I in the long-end. 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.

Figure 4 also plots the aggregate dealer balances by maturity segments, which show that dealers are receiving fixed in short maturities and paying fixed in the long maturities. These results are consistent with the literature on negative swap spreads (Boyarchenko et al., 2018, Klingler and Sundaresan, 2019, Hanson et al., 2022), and evidence of dealer imbalances in other markets (e.g., S&P 500 index options (Gârleanu et al., 2008), inflation swaps (Bahaj et al., 2023)).

2.6. Demand Pressure and Swap Spreads

What are the consequences of dealers carrying large net imbalances? If dealers could hedge the net imbalances perfectly then swap prices would be determined by the no-arbitrage condition and end-user demand pressure (and net imbalances) would have no pricing effects. However, if dealers cannot hedge perfectly, e.g., because of incomplete markets, transaction costs, or regulatory capital constraints, then end-user demand would affect swap spreads.

In this section, we test the extent to which demand pressure affects swap spreads. We focus on GBP swap spreads as we have the largest coverage of this market both in terms of overall volume and end-user trading activity (see Table 2), and five maturity points (2Y, 5Y, 10Y, 20Y, and 30Y).[17] Using weekly data, we estimate

$$SwapSpread_t^M = \alpha + \sum_s \gamma_1^s NDE_{s,t-1}^M + \gamma_2 Yield_{t-1}^M + \gamma_3 Slope_{t-1} + \epsilon_t, \tag{6}$$

where M denotes a specific maturity point and swap spreads are weekly averages. NDE^M denotes the total (maturity matched) net dollar exposures traded in the previous week (see Equation 1). We maturity match as follows: when testing the effects on the 2, 5, 10, 20, 30 year swap spread, NDE is the net dollar exposure in the <2, 2-5, 5-10, 10-20, and 20+ year buckets respectively. s denotes end-user sectors. Controls include the tenor matched average gilt yield and the average slope of the gilt curve. We repeat the regressions at monthly frequency for robustness.

Table 9 shows the results for weekly frequency and Table C3 in Appendix C for monthly frequency. A consistent pattern across weekly and monthly regressions is that demand pressure, in particular that of hedge funds, affects swap spreads. Specifically, we first find that γ_1^{Fund} is negative and statistically significant. The negative sign can be interpreted as follows. As NDE (demand to receive the fixed rate) increases, swap spread, which is the fixed rate minus the maturity matched gilt yield, decreases. In other words, we observe that dealers are willing to offer a lower fixed rate, i.e. swaps become more expensive. To highlight the economic magnitude, a one standard deviation increase in hedge funds' NDE^{10} in a given week is associated with a 1.2bps lower 10-year swap spread, which is about 3.8% of the unconditional average (-31 bps) 10-year swap spread during our sample period. (Figure C6 in Appendix C plots the 2Y, 10Y, 20Y and 30Y GBP swap spreads.) Second, hedge funds' trading volumes affect spreads across maturities, with stronger effects in short and intermediate horizons.

Interestingly, γ_1^{Banks} are noisy and change sign across specifications. This is likely because

[17] We confirm that the exposures in GBP are similar to the overall sample, see Figure C5 in Appendix C.

traded volumes are significantly larger for hedge funds relative to the other sectors even though outstanding positions are similar. In fact, even for longer maturity swaps hedge fund volumes are larger than those of PF&I.

There is also interesting variation in demand pressure for the different hedge funds categories. Table 10 reports the estimation of Equation 6 by fund types and documents that (i) Macro funds, who mainly pay fix at the short-end affect short maturity (e.g., 2 and 5 years) swap spreads. (ii) In contrast, the trading of fixed income funds', who largely behave like long-term investors, tend to affect long maturity swap spreads. (iii) Finally, we find that the intermediate period swap spreads are most predicted by the trading activity of quant & relative value funds who trade across the term structure. A similar pattern is observed in Table C4 in Appendix C that reports results at a monthly frequency.

2.7. Demand Elasticities

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).[18]

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

[18] 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.

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

$$SwapSpread_t = \alpha + \beta Compression_{t-1} + Controls + \epsilon_t, \tag{7}$$

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 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

$$EXPTRD_t = \alpha + \theta^D \widehat{SwapSpread}_t + Controls + \epsilon_t, \tag{8}$$

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 11 reports the estimation results for pension funds. First, Panel B of Table 11 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.

3. Risk sharing and counterparty credit risk

In this section, 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.

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.[19] A primer on the institutional background of central clearing and CCR and CVA can be found in Appendix B.

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.

3.1. Fund and Pension fund trades display contrary clearing behavior

Table 12 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. The behavior for new trades contrasts with outstanding exposures, as described in Table C5 in Appendix C. Here we find that on average, over 70% of exposures of banks, funds and insurance companies are centrally cleared while under a quarter of pension funds' outstanding trades are centrally cleared. Pension funds predominantly trade in the long tenor, and the difference between their higher proportion of centrally cleared new trades and lower proportion of centrally cleared outstanding exposures can be explained by their legacy trades. By contrast, funds trade large volumes bilaterally at short maturities, while the total exposures on a given day are skewed towards central clearing. Unless well-capitalised, poorly collateralized bilaterally cleared trades can pose systemic risk concerns due to the high counterparty risk associated with them.

3.2. Pension funds preferentially allocate riskier trades to non-cleared 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.

[19]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.

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. At the time of writing, 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.[20]

We exploit this regulatory exemption and unpack the cash-constraints channel in the tightest comparison we can make between pension funds and insurance companies. They have similar business models and buy long-maturity swaps. The key difference is that when trading with pension funds, dealers are subject to CVA exemptions but not when trading 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.[21]

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 10.[22] This difference in behavior for entities with similar hedging behavior indicates that trades which hold the highest counterparty credit risk and are exempt from capital charges against it are, in fact, a source of uncapitalized counterparty credit risk to dealers.

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 linear probability model.

(9)

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

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

[20]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.)

[21]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 C6 in Appendix C.

[22]We also do not observe this pattern for other sectors. See Figure C7 in Appendix C.

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 13 reports the estimation results.

The most striking results come from pension funds, which are exempt from CVA capital charges: they 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.

This finding highlights a paradox whereby trades that are the most important contributors to counterparty credit risk are least likely to get centrally cleared. Arguably, the notional is not fully representative for trade riskiness, as a large notional can be broken down into smaller-sized trades. However, investors cannot split the tenor component, which we take to be the most informative measure of trade riskiness. 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 C8 in Appendix C and find that a larger tenor is always a strong negative predictor for centrally clearing pension fund trades but not for insurance trades.

Facilitated by the capital charge exemptions, we find that pension funds preferentially allocate riskier trades to bilaterally cleared segment. This in turn has negative implications for the risk-sharing in the IRS market, as it leads to potentially large uncapitalized counterparty credit risk.

4. Conclusion

This paper provides the first large scale empirical evidence on risk sharing in the interest rate swaps market. Using granular transaction-level data on both the stock and flow of swap trades, we trace the source of market fragmentation to differential maturity preferences of offsetting PF&I and bank flows, amplified by hedge fund activity. Furthermore, we show that the large, long-tenor imbalances dealers absorb from the pension fund sector are less likely to be centrally cleared, exacerbating counterparty credit risk. Consistent with these findings, we find that demand pressure, particularly driven by hedge funds' trades, has an impact on swap spreads across maturities. We document that while investors such as PF&I, banks and corporations trade in a manner suggestive of hedging underlying business risks, hedge funds show less consistent behavior and likely speculate. We trace the source of heterogeneity within the hedge funds sector to the differential investment strategies followed by them and the consequent impact of their demand on the specific segment of the swap spreads curve. These insights 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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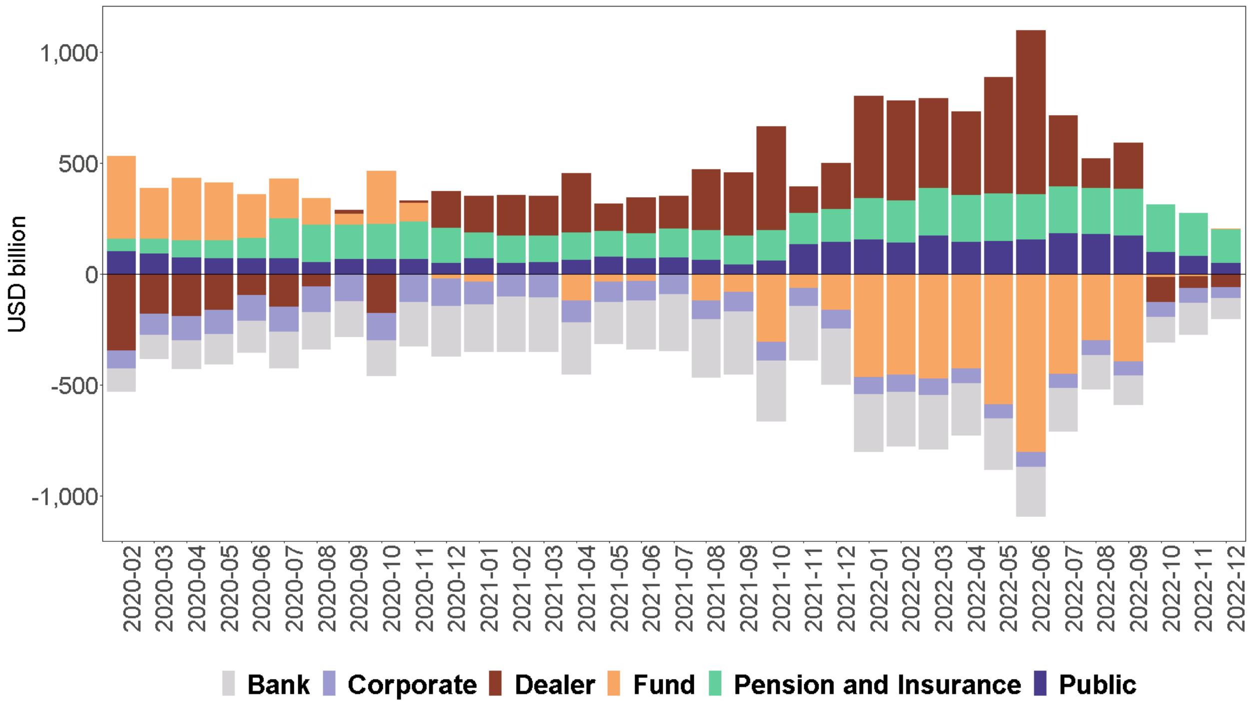


Figure 1: Sectoral distribution of outstanding net receive fixed swap notional. This figure shows the net received fixed notional outstanding in $ billion as on each date at a monthly frequency across five end-user segments and the inter-dealer segment. Inter-dealer position is calculated as the net of aggregate client-facing positions.

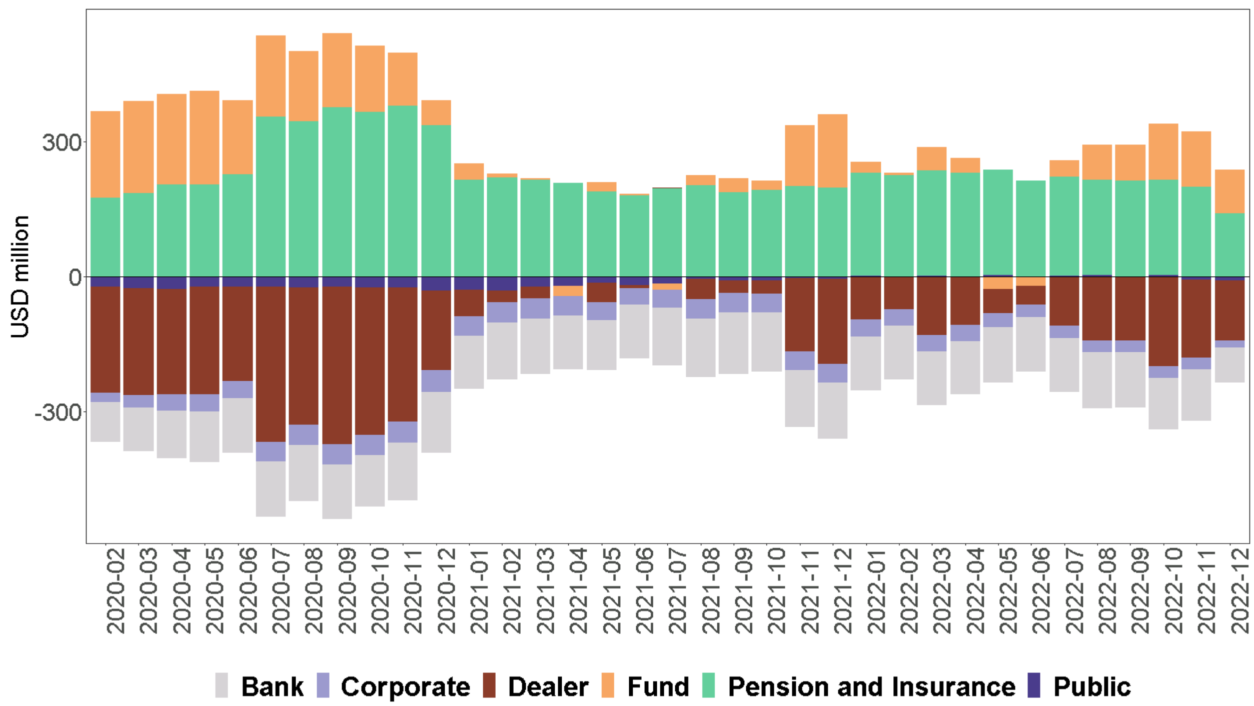
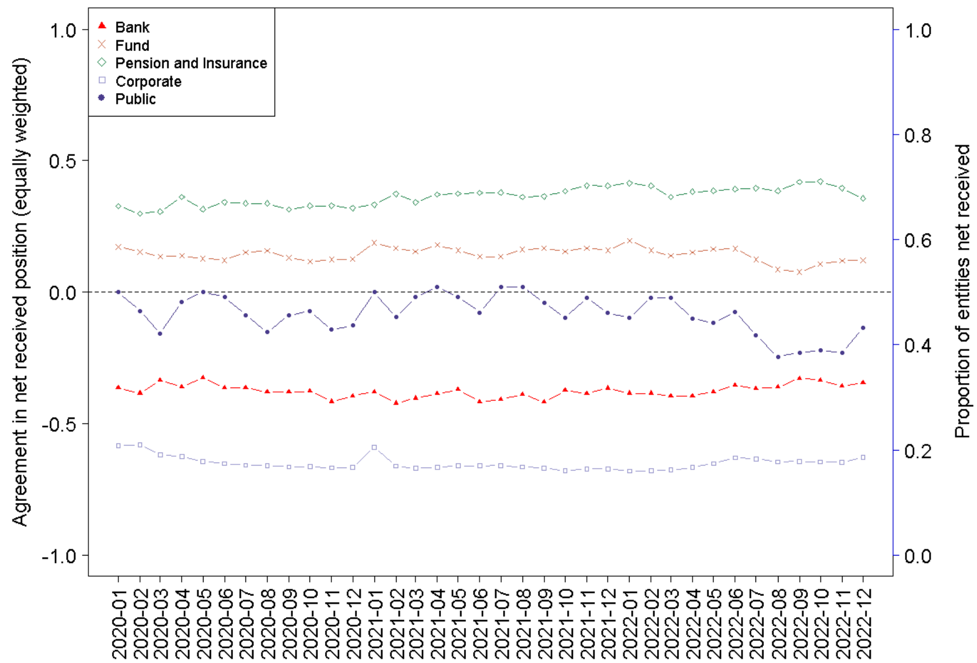
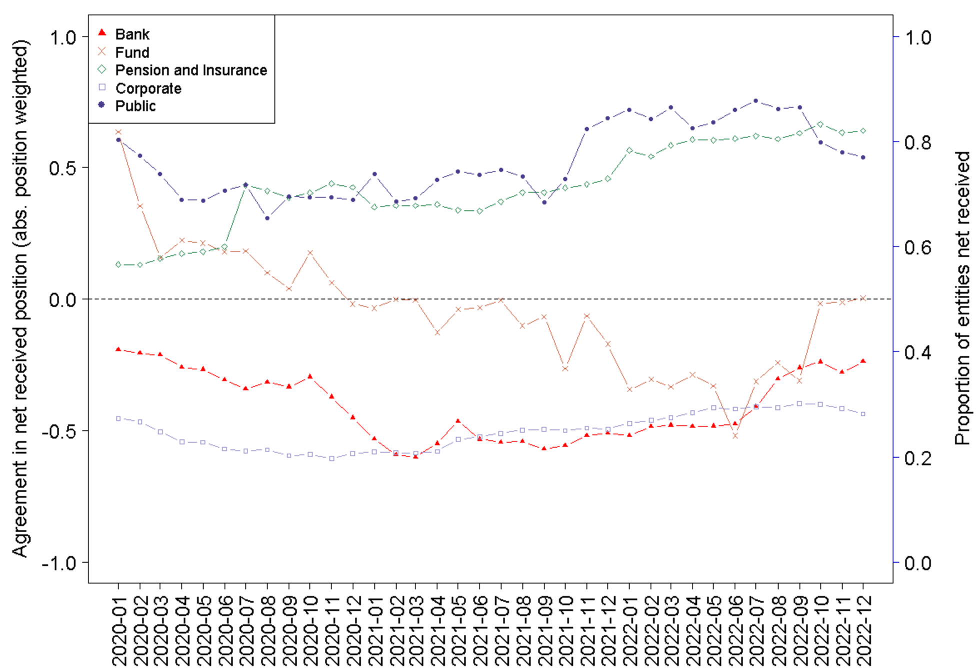


Figure 2: Sectoral distribution of outstanding swap DV01. This figure shows the DV01 of outstanding swaps in $ million as on each date at a monthly frequency across five end-user segments and the inter-dealer segment. Inter-dealer position is calculated as the net of aggregate client-facing positions.

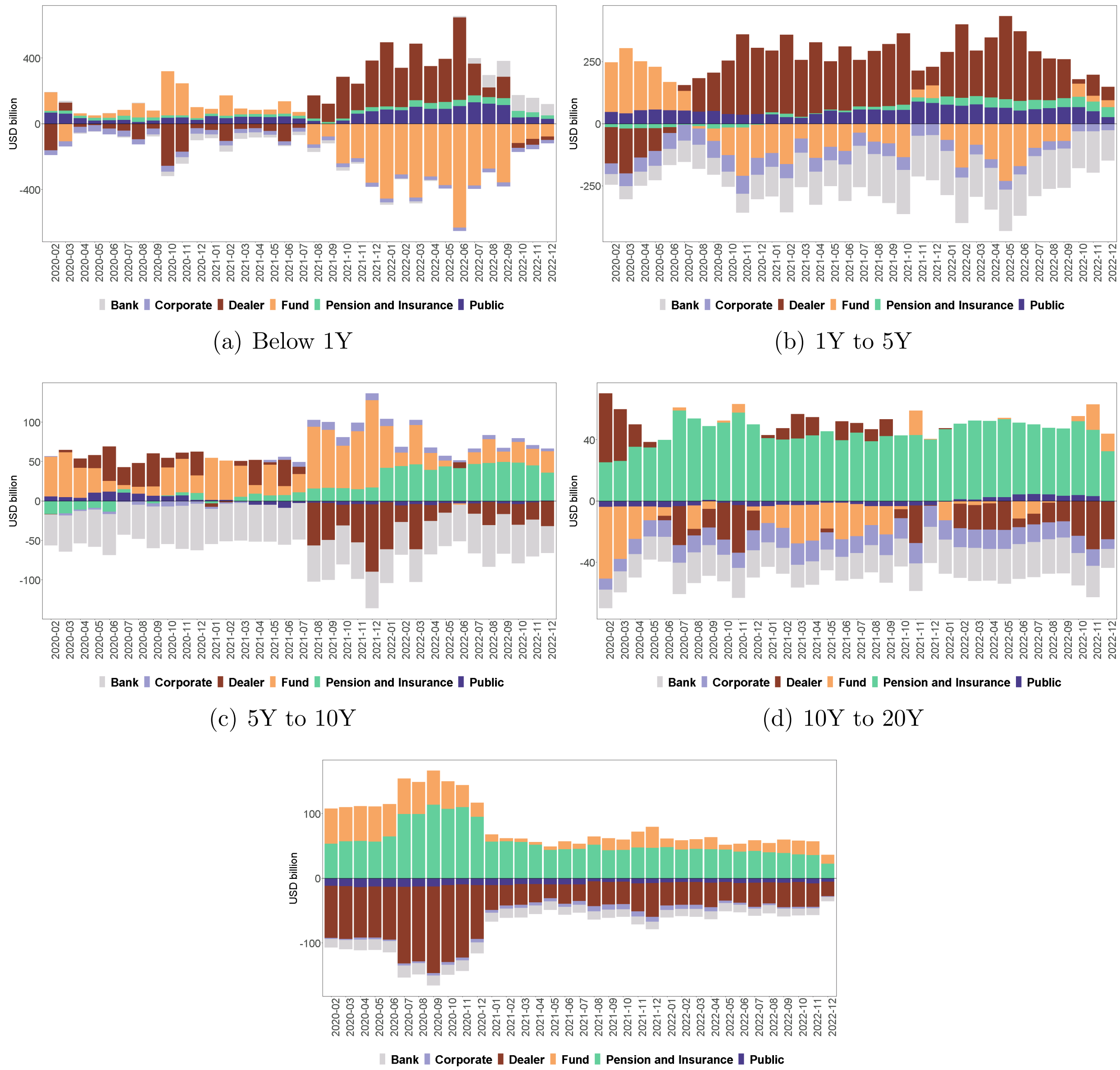


(a) Equally weighted



(b) Net exposure weighted

Figure 3: Intra-sector heterogeneity in net exposures. This figure plots the intra-sector heterogeneity in net exposures using monthly snapshots of LEI-level outstanding positions. The left-hand side axis reports the agreement score (sectoral average of +1 for net receive fixed and -1 for net pay fixed position of LEIs). The right-hand side axis shows the proportion of entities that were net receive fixed in each sector. Panel (a) weights all observations equally while panel (b) weights them by the LEI-level average (absolute) net outstanding position during the sample period.



(a) Below 1Y

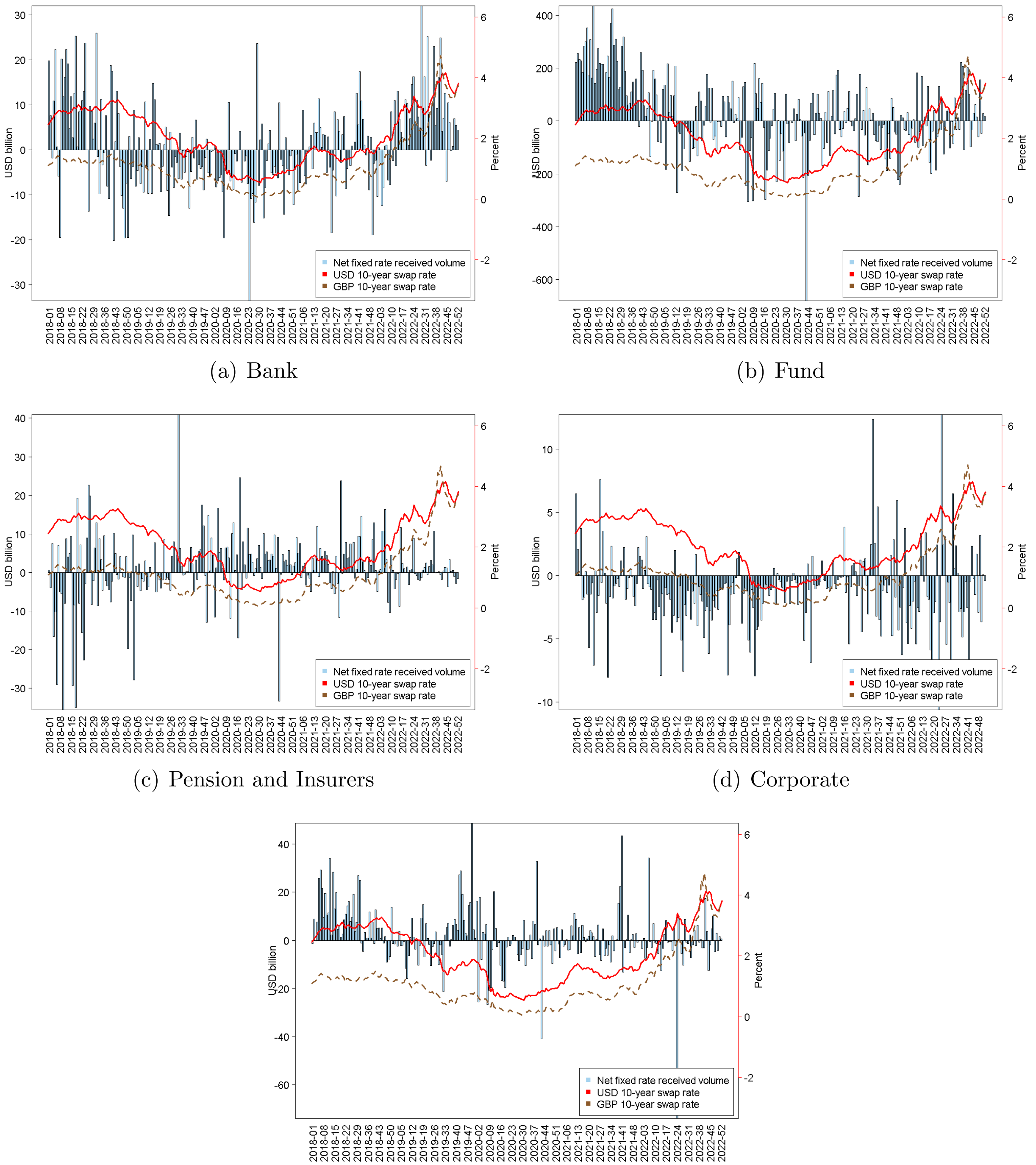
(b) 1Y to 5Y

(c) 5Y to 10Y

(d) 10Y to 20Y

(e) Above 20Y

Figure 4: Sectoral distribution of outstanding net receive fixed swap notional by maturity-buckets. This figure shows the net received fixed notional outstanding in five maturity buckets in $ billion as on each date 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.

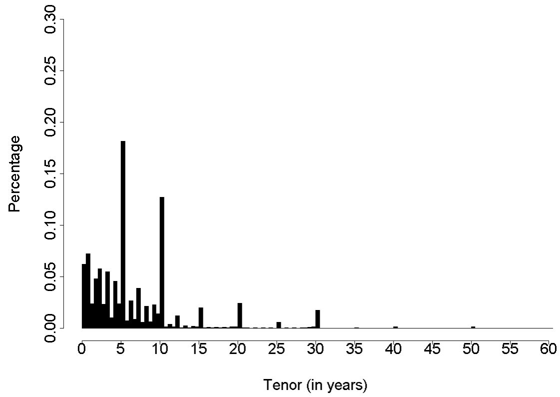


(a) Bank (b) Fund

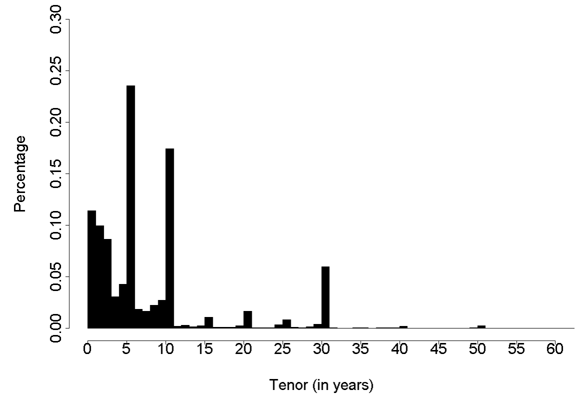
(c) Pension and Insurers (d) Corporate

(e) Public

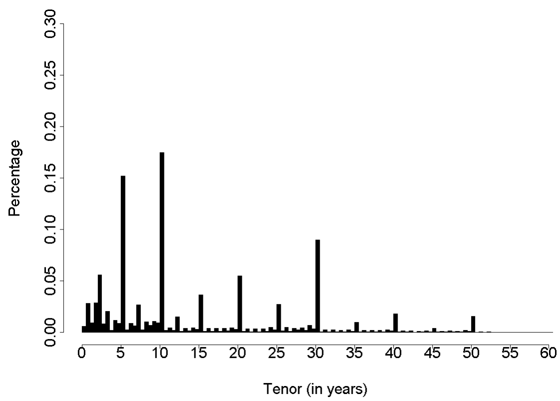
Figure 5: Weekly activity flow of net receive fixed swap notional. This figure shows the net received fixed swap notional initiated each week in $ billion and the corresponding USD and GBP ten-year swap rates across five end-user segments. Values above zero indicate net receive fixed rate and below zero indicate net pay fixed rate.



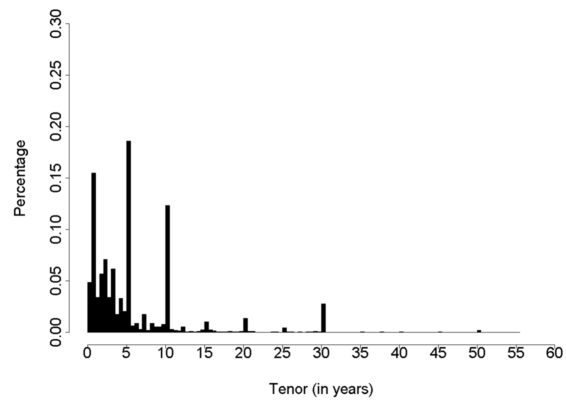
(a) Bank



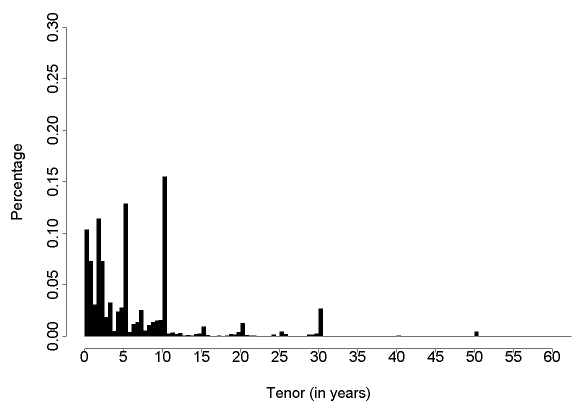
(b) Fund



(c) Pension and Insurance



(d) Corporate



(e) Public

Figure 6: Maturity distribution of new trades initiated. 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.

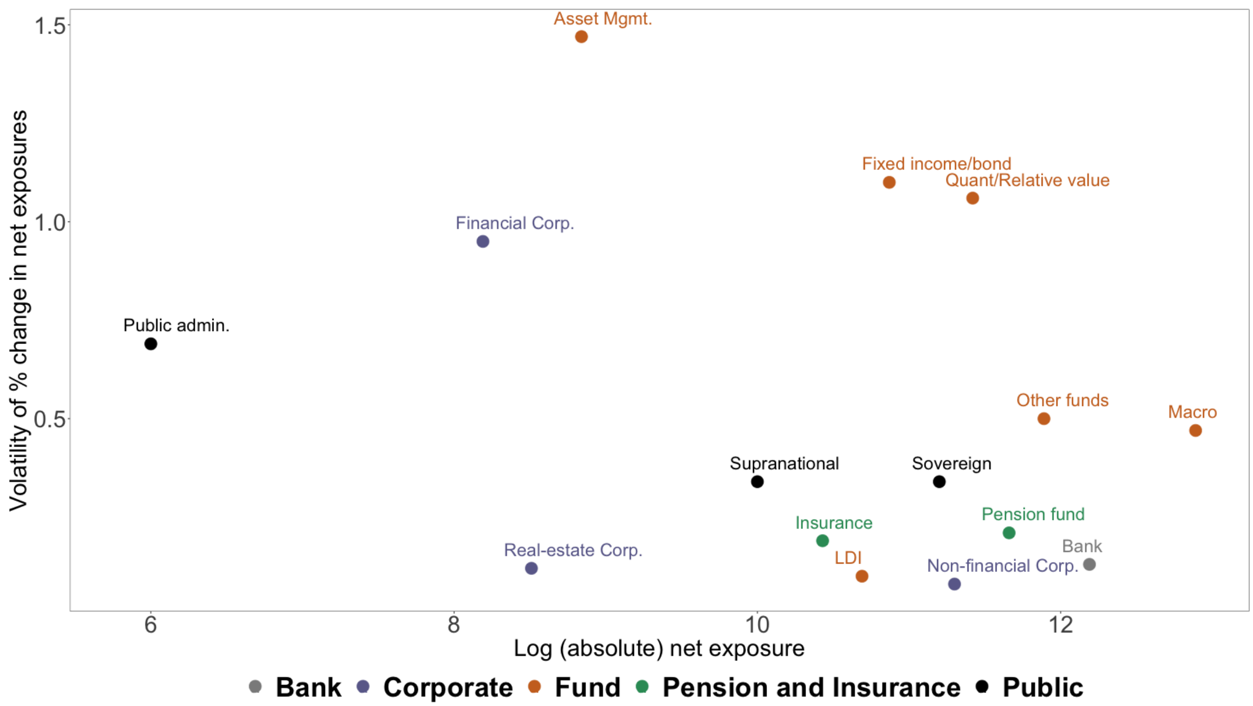
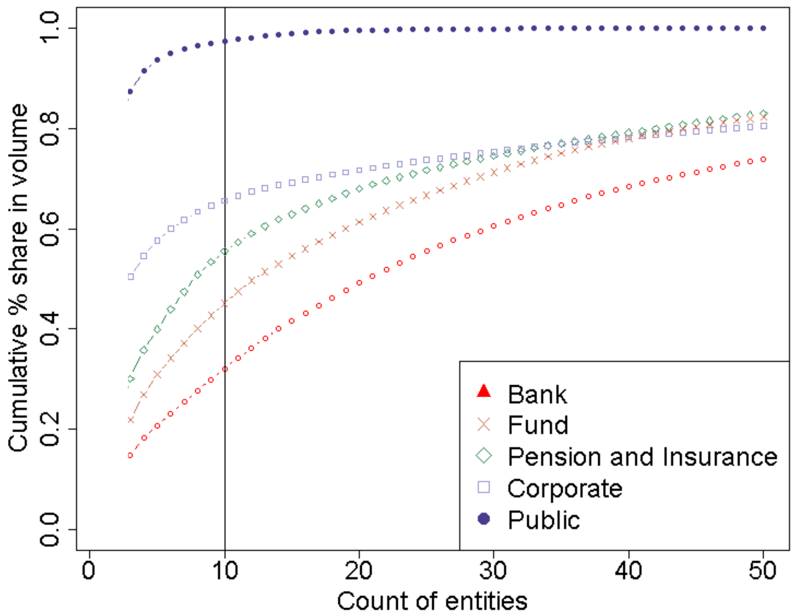
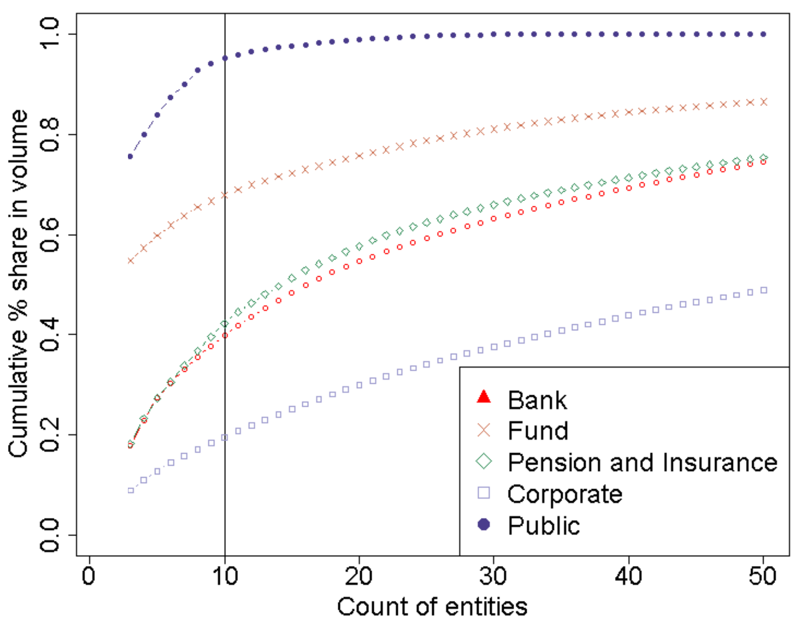


Figure 7: Sub-sectoral volatility of change in net exposures. This figure plots the standard deviation of the percentage monthly change in net exposures on the y-axis and the size of each sub-sector on the x-axis. Change in net exposure is calculated using monthly flow of signed new trading volume scaled by the outstanding positions. Size of sub-sector is calculated using the average log (absolute) net exposure throughout the sample period.

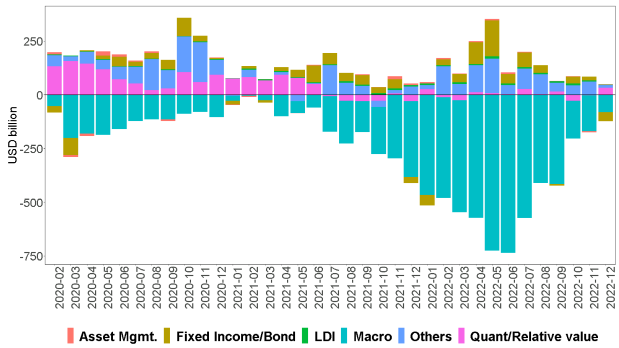


(a) Activity between 2018-22

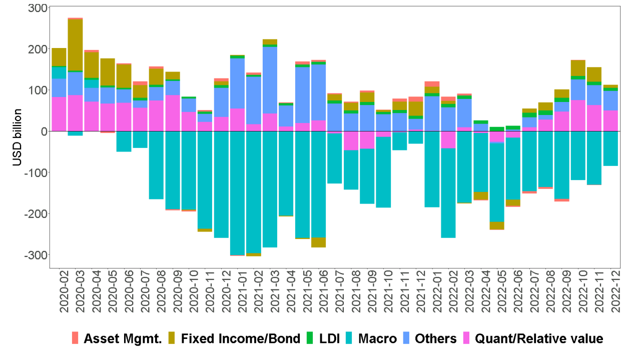


(b) Net outstanding on Feb 1, 2022

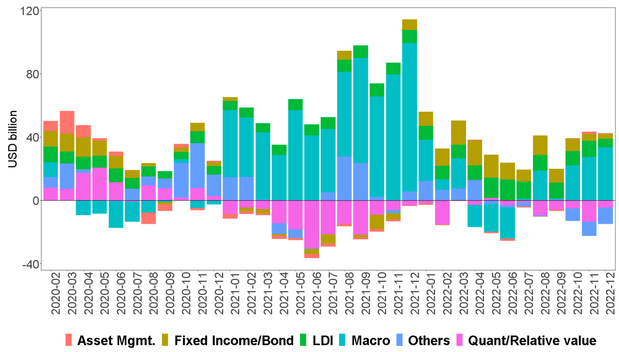
Figure 8: Concentration in volume by number of entities. This figure shows the cumulative share in trading volume over 2018-22 (panel (a)) and net (absolute) outstanding exposures as on February 1, 2022 (panel (b)) for each sector. The first point in both plots shows the share of top three entities put together in each sector.



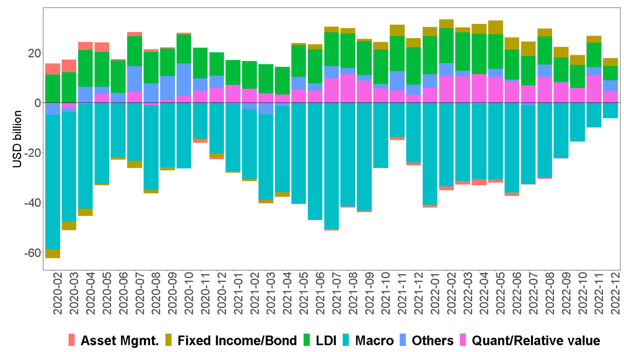
(a) Below 1Y



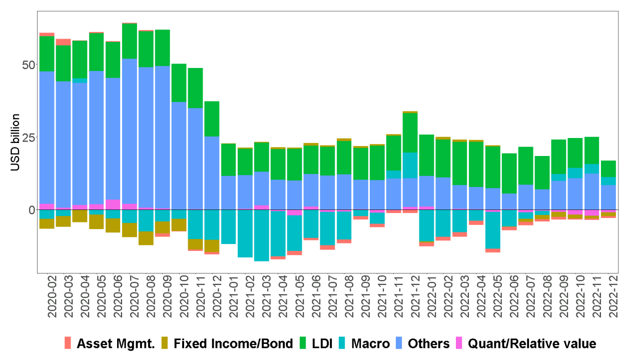
(b) 1Y to 5Y



(c) 5Y to 10Y

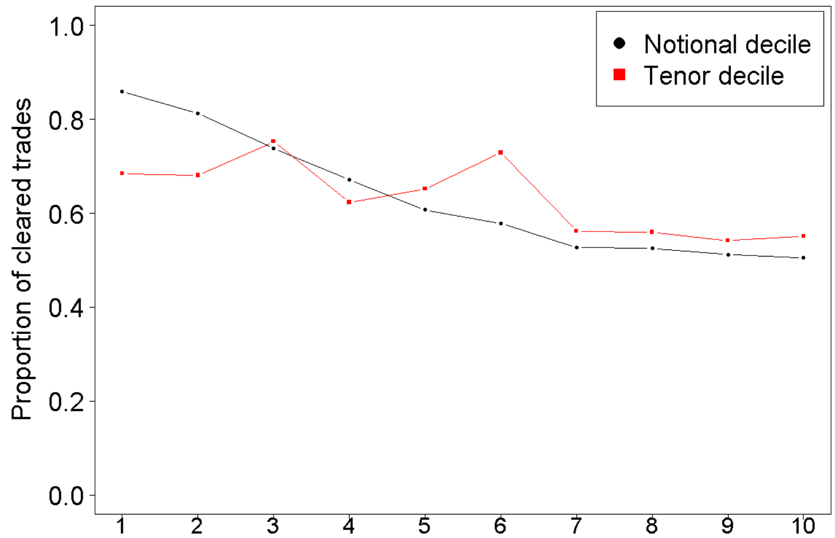


(d) 10Y to 20Y

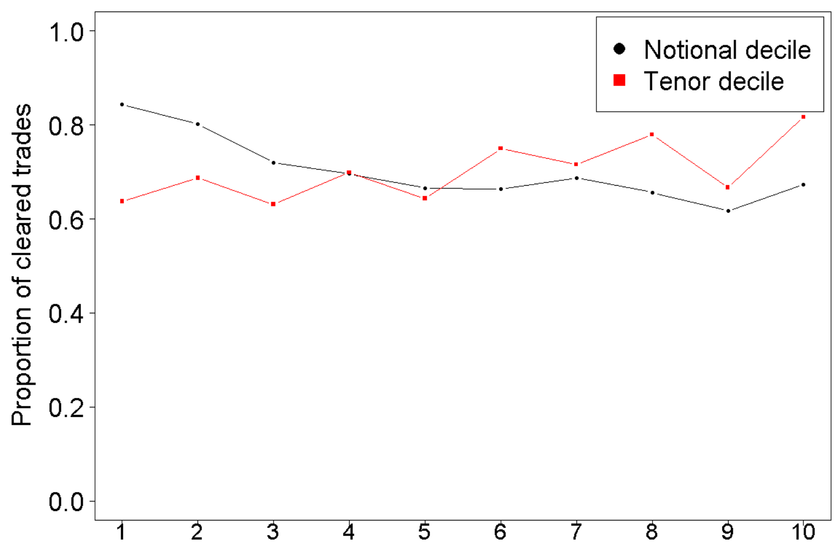


(e) Above 20Y

Figure 9: Fund-type distribution of outstanding net receive fixed swap notional by maturity-buckets. This figure shows the net received fixed notional outstanding in five maturity buckets in $ billion as on each date at a monthly frequency across six fund-types.



(a) Pension funds



(b) Insurance

Figure 10: Centralized clearing and riskiness of trades. This figure shows the proportion of trades that are centrally cleared by pension funds and insurers as a function of notional and tenor deciles.

Table 1: Annual traded volume of interest rate swaps by sector.

This table shows 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 (with common trade ID) and halving the volume of inter-dealer trades reported with clearing houses (with different trade IDs). Entities that cannot be classified into a sector due to missing LEIs are reported separately.

Gross notional ($ billion)	2018	2019	2020	2021	2022	Total
Bank	6,572	5,599	4,728	3,451	4,440	24,790
Fund	85,565	85,305	102,883	95,469	100,465	469,687
Pension and Insurance	3,679	2,855	2,746	3,081	1,726	14,088
Corporate	308	234	184	405	613	1,745
Public	1,409	1,831	1,972	1,544	1,362	8,118
Dealer (client facing + inter-dealer)	602,782	576,404	521,477	624,371	710,372	3,035,405
NA (missing LEI)	2,926	3,278	5,131	3,565	5,742	20,641

Table 2: Estimated coverage of volume by currency.

This table reports the estimated coverage of interest rate swaps observed in our data denominated in six major currencies. The coverage is benchmarked to the BIS April 2022 triennial survey on OTC interest rate derivatives turnover.

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%

Table 3: Gross notional and net receive fixed outstanding by maturity bucket.

This table reports the outstanding gross notional and net receive fixed positions by sectors and maturity buckets as on February 1, 2022. Outstanding maturity or tenor of a swap is calculated as the difference between the maturity date and date on which the positions are assessed (February 1, 2022 in this table). The dealer net receive fixed position is calculated as the balancing figure of all end-user positions combined.

Gross notional ($ billion)	Below 1Y	1Y to 5Y	5Y to 10Y	10Y to 20Y	Above 20Y	Total
Bank	697	983	332	73	23	2,108
Fund	5,176	3,240	1,147	314	226	10,103
Pension and Insurance	155	359	463	398	506	1,880
Corporate	45	125	45	24	11	250
Public	269	194	64	15	14	557
Net receive fixed ($ billion)	**Below 1Y**	**1Y to 5Y**	**5Y to 10Y**	**10Y to 20Y**	**Above 20Y**	**Total**
Bank	-5	-183	-42	-20	-11	-261
Fund	-309	-177	17	-2	14	-457
Pension and Insurance	19	32	44	49	44	189
Corporate	-24	-40	7	-13	-6	-75
Public	81	72	-6	1	-6	141
Dealer	239	296	-21	-16	-35	463

Table 4: Gross notional and net receive fixed new volume traded by maturity buckets.

This table reports the gross notional and net receive fixed volume traded between January 2018 and December 2022 by sectors and maturity buckets. Maturity or tenor of a swap is calculated as the difference between maturity date and effective date as reported in our data.

Gross notional ($ billion)	Below 1Y	1Y to 5Y	5Y to 10Y	10Y to 20Y	Above 20Y	Total
Bank	10,590	8,736	4,062	1,035	367	24,790
Fund	322,989	105,514	31,246	4,796	5,143	469,687
Pension and Insurance	3,123	4,069	2,872	1,720	2,303	14,088
Corporate	675	621	305	80	62	1,745
Public	4,955	2,405	595	84	79	8,118
Net receive fixed ($ billion)	**Below 1Y**	**1Y to 5Y**	**5Y to 10Y**	**10Y to 20Y**	**Above 20Y**	**Total**
Bank	631	-318	-92	-4	-13	203
Fund	3,982	1,604	574	141	184	6,485
Pension and Insurance	66	65	-31	109	84	292
Corporate	-164	-117	-5	-14	-1	-301
Public	375	33	45	-8	-15	431

Table 5: Quantities demanded with changes in macroeconomic variables.

This table reports estimates of the model of the form in Equation 3 at a weekly frequency. Bond yield (PC1, change) refers to the weekly change in the first principal component of 2Y, 5Y, 10Y, 20Y and 30Y US Treasury yields. Slope (change) refers to the weekly change in 10Y minus 2Y US Treasury yields. Standard errors are heteroskedasticity robust and reported in parantheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Net receive fixed ($ million)				
	Bank	Fund	PF&I	Corporate	Public
	(1)	(2)	(3)	(4)	(5)
Bond yield (PC1, change)	13,821.2***	39,777.9	-2,057.6	975.6	-1,489.5
	(2,948.6)	(49,013.9)	(3,286.7)	(1,324.8)	(8,305.5)
Slope (10Y-2Y, change)	-9,816.1	-175,201.1	-10,250.0	2,174.5	6,905.4
	(9,409.5)	(136,990.0)	(7,848.5)	(3,465.4)	(19,829.9)
Observations	259	259	259	259	259
Adj. R^2	0.06	0.00	0.00	0.00	0.01
	DV01 ($ million)				
	Bank	Fund	PF&I	Corporate	Public
	(1)	(2)	(3)	(4)	(5)
Bond yield (PC1, change)	5.36***	-7.04	-5.49**	1.64***	0.003
	(0.910)	(6.89)	(2.24)	(0.425)	(0.589)
Slope (10Y-2Y, change)	-0.657	-32.8	-5.06	0.680	-0.097
	(2.51)	(21.9)	(6.66)	(1.33)	(1.78)
Observations	259	259	259	259	259
Adj. R^2	0.07	0.01	0.01	0.03	0.01

Table 6: Quantities demanded with changes in macroeconomic variables: time-variation.

This table reports estimates of the model of the form in Equation 3 at a weekly frequency. Panel A reports the results for the sub-sample period of January 2018 through February 2020. Panel B reports the results for the sub-sample period of March 2020 through December 2022. Bond yield (PC1, change) refers to the weekly change in the first principal component of 2Y, 5Y, 10Y, 20Y and 30Y US Treasury yields. Slope (change) refers to the weekly change in 10Y minus 2Y US Treasury yields. Standard errors are heteroskedasticity robust and reported in parantheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	DV01 ($ million)				
Panel A: Jan-2018 to Feb-2020	Bank	Fund	PF&I	Corporate	Public
	(1)	(2)	(3)	(4)	(5)
Bond yield (PC1, change)	9.27***	31.4**	-12.3**	3.03***	2.65**
	(2.35)	(13.9)	(5.07)	(0.950)	(1.18)
Slope (10Y-2Y, change)	-3.61	-78.2	-20.2	0.604	11.6**
	(10.1)	(82.1)	(22.9)	(4.57)	(5.71)
Observations	111	111	111	111	111
Adj. R^2	0.09	0.02	0.04	0.03	0.10

	DV01 ($ million)				
Panel B: Mar-2020 to Dec-2022	Bank	Fund	PF&I	Corporate	Public
	(1)	(2)	(3)	(4)	(5)
Bond yield (PC1, change)	4.03***	-11.3*	-2.16	1.00**	-1.31**
	(0.899)	(6.78)	(2.42)	(0.472)	(0.594)
Slope (10Y-2Y, change)	-0.462	-33.7*	-1.88	0.658	-2.53
	(2.15)	(17.2)	(6.57)	(1.32)	(1.55)
Observations	148	148	148	148	148
Adj. R^2	0.08	0.05	0.01	0.02	0.06

Table 7: Turnover and outstanding positions by fund type.

This table shows the total turnover in $ billion and the share of each fund type in new trades initiated between 2018 and 2022. The table also reports the gross and net outstanding positions as of February 1, 2022. Funds are categorized into types based on string matching of their names with common investment strategies.

Fund type	Volume traded		Gross notional		Net receive fixed (absolute)		
	$ billion	Share	$ billion	Share	$ billion	Share	% of gross
Asset Management	80,263	16%	112	1%	12	1%	10%
Fixed Income/Bond	57,182	11%	2,257	24%	64	7%	3%
Macro	64,714	13%	1,854	19%	600	57%	32%
Quant/Relative value	111,466	22%	2,771	27%	22	2%	1%
Others	191,303	38%	2,532	25%	263	19%	10%

Table 8: Quantities demanded by funds with changes in macroeconomic variables.

This table reports estimates of the model of the form in Equation 4 at a weekly frequency for funds as a sector in column (1) and by five sub-types in columns (2) through (6). Bond yield (PC1, abs. change) refers to the weekly absolute change in the first principal component of 2Y, 5Y, 10Y, 20Y and 30Y US Treasury yields. Slope (abs. change) refers to the weekly absolute change in 10Y minus 2Y US Treasury yields. Standard errors are heteroskedasticity robust and reported in parantheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Gross notional (log)					
	All funds	Asset Mgmt.	Fixed Income	Macro	Quant	Others
	(1)	(2)	(3)	(4)	(5)	(6)
Bond yield (PC1, abs. change)	0.585**	0.584**	1.21***	0.467	0.527**	0.566*
	(0.256)	(0.289)	(0.274)	(0.342)	(0.259)	(0.288)
Slope (10Y-2Y, abs. change)	1.31**	1.14	2.10***	1.41	1.34*	1.35**
	(0.611)	(0.862)	(0.743)	(0.996)	(0.771)	(0.662)
Observations	259	259	259	259	259	259
Adj. R^2	0.06	0.03	0.13	0.02	0.04	0.04

Table 9: Price reaction to quantities demanded.

This table reports estimates of the model of the form in Equation 6 at a weekly frequency. The dependent variables are 2Y through 30Y GBP swap spreads in columns (1) through (5) in week t+1. The regressors include net receive fixed demand from each end-user sector in week t (in $ billion), the maturity-matched bond yield in week t, and the slope of the yield curve in time t. Standard errors are heteroskedasticity robust and reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Swap spreads (bps)				
Panel A: Split by sector	2Y (t+1)	5Y (t+1)	10Y (t+1)	20Y (t+1)	30Y (t+1)
	(1)	(2)	(3)	(4)	(5)
Bank net receive	0.524*	-0.299	-1.05***	1.57	1.50
	(0.280)	(0.313)	(0.372)	(1.10)	(3.64)
Fund net receive	-0.050***	-0.357***	-0.332***	-0.034	-1.24**
	(0.014)	(0.125)	(0.092)	(0.276)	(0.597)
PF&I net receive	0.234	2.04***	-0.017	0.505	0.085
	(0.179)	(0.555)	(0.247)	(0.314)	(0.384)
Corporate net receive	-1.36	0.494	-0.185	1.62*	-11.9*
	(1.47)	(0.781)	(0.884)	(0.936)	(6.64)
Public net receive	0.068	1.39***	-1.38	0.370	-3.52
	(0.093)	(0.489)	(1.08)	(1.39)	(5.66)
Bond yield	0.310***	0.179***	0.055***	0.005	0.049***
	(0.012)	(0.008)	(0.005)	(0.007)	(0.008)
Slope (10Y-2Y)	-0.043	-0.203***	-0.268***	-0.027	-0.031
	(0.028)	(0.024)	(0.017)	(0.021)	(0.019)
Observations	259	259	259	259	259
Adj. R^2	0.84	0.77	0.72	0.01	0.17

	Swap spreads (bps)				
Panel B: All sectors	2Y (t+1)	5Y (t+1)	10Y (t+1)	20Y (t+1)	30Y (t+1)
	(1)	(2)	(3)	(4)	(5)
Aggregate net receive	-0.045***	-0.256**	-0.342***	0.179	-0.131
	(0.014)	(0.126)	(0.084)	(0.216)	(0.324)
Bond yield	0.315***	0.180***	0.054***	0.005	0.046***
	(0.011)	(0.008)	(0.005)	(0.007)	(0.008)
Slope (10Y-2Y)	-0.050*	-0.208***	-0.273***	-0.031	-0.040**
	(0.027)	(0.024)	(0.016)	(0.019)	(0.019)
Observations	259	259	259	259	259
Adj. R^2	0.84	0.75	0.71	0.01	0.16

Table 10: Price reaction to quantities demanded by funds.

This table reports estimates of the model of the form in Equation 6 at a weekly frequency. The dependent variables are 2Y through 30Y GBP swap spreads in columns (1) through (5) in week t+1. The regressors include net receive fixed demand from each fund-type in week t (in $ billion), the maturity-matched bond yield in week t, and the slope of the yield curve in time t. Standard errors are heteroskedasticity robust and reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Swap spreads (bps)				
	2Y (t+1)	5Y (t+1)	10Y (t+1)	20Y (t+1)	30Y (t+1)
	(1)	(2)	(3)	(4)	(5)
Asset Mgmt. net receive	-0.058***	-0.078	0.173	-0.235	-1.70*
	(0.019)	(0.445)	(0.203)	(0.599)	(0.955)
Fixed income net receive	-0.061	0.063	-0.163	-2.66**	-12.6***
	(0.039)	(0.679)	(0.379)	(1.22)	(3.71)
Macro net receive	-0.092***	-0.536***	-0.308*	-0.208	-3.55
	(0.028)	(0.190)	(0.160)	(0.371)	(2.19)
Quant net receive	-0.030	-1.27**	-1.67***	-0.555	4.63
	(0.046)	(0.536)	(0.409)	(1.35)	(4.93)
Others net receive	-0.029	-0.260	-0.398***	0.568	1.10
	(0.022)	(0.220)	(0.122)	(0.415)	(0.948)
Bond yield	0.318***	0.181***	0.057***	0.005	0.055***
	(0.012)	(0.008)	(0.005)	(0.007)	(0.008)
Slope (10Y-2Y)	-0.045	-0.196***	-0.268***	-0.020	-0.024
	(0.028)	(0.024)	(0.016)	(0.019)	(0.019)
Observations	259	259	259	259	259
Adj. R^2	0.84	0.76	0.72	0.03	0.22

Table 11: Demand elasticity estimation for pension funds and insurance sector.

This table reports estimation results of Equation 7 in Panel B and Equation 8 in Panel A. The instrument variable 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. Standard errors are heteroskedasticity robust and reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Panel A: 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

Panel B: 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

Table 12: Descriptive statistics on centralized clearing and collateralization for new trades.

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.

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

Table 13: Centralized clearing as a function of trade features.

This table reports estimates from a linear probability model of the form in Equation 9 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. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	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

Appendix

A. A primer on Interest Rate Swaps

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:

$$V_{RFS} = V_{Fixed} - V_{Floating}, \tag{10}$$

$$V_{PFS} = V_{Floating} - V_{Fixed}. \tag{11}$$

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:

$$\Delta_{RFS} = \Delta_{Fixed} \tag{12}$$

$$\Delta_{PFS} = -\Delta_{Fixed} \tag{13}$$

where the dollar duration of the fixed rate bond is:

$$\Delta_{Fixed} = -\frac{MacDur \times V_{Fixed}}{1+y} \tag{14}$$

$$MacDur = \frac{1+y}{y} - \frac{1+y+N(c-y)}{c((1+y)^N - 1) + y} \tag{15}$$

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. 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.[23] This reform was accompanied by tighter regulation in the OTC market, and a mandate to report trades. Nonetheless, several exemptions were implemented in the EU and UK Capital Requirements Regulation (CRR). Further, we provide a brief description of the main concepts we use.[24]

B.1. 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 B1. 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 B1. 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).[25]In that case, the 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

[23]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.

[24]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).

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

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.

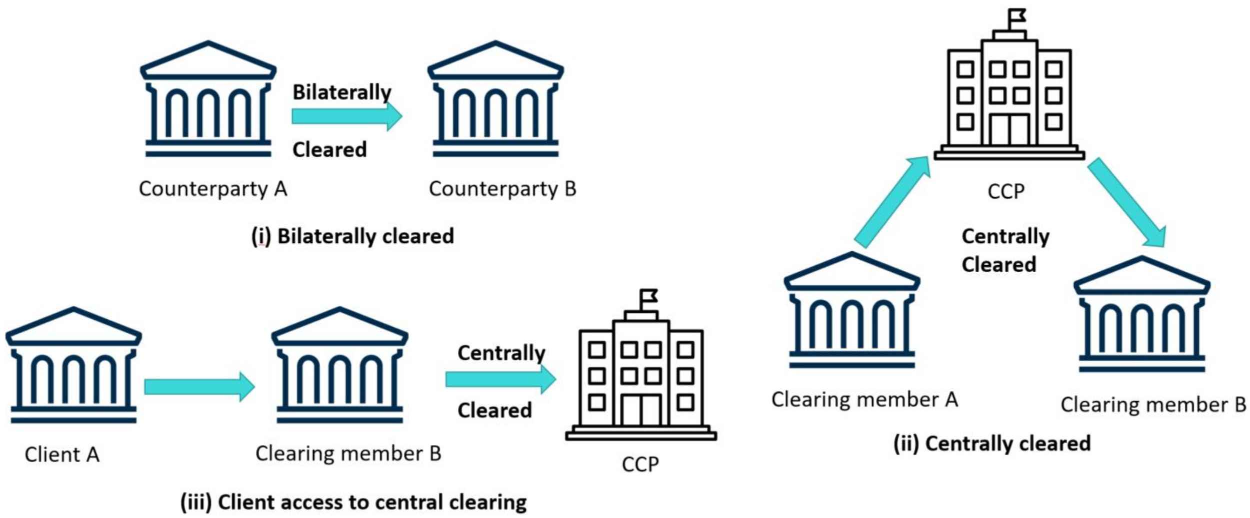


Figure B1: Clearing types

B.2. 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.[26] 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

[26]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).

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.[27] 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.[28]

The new perspective we bring on CVA is to test whether these exemptions lead to further market fragmentation in the IRS market and create new sources of uncapitalised risk.

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

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

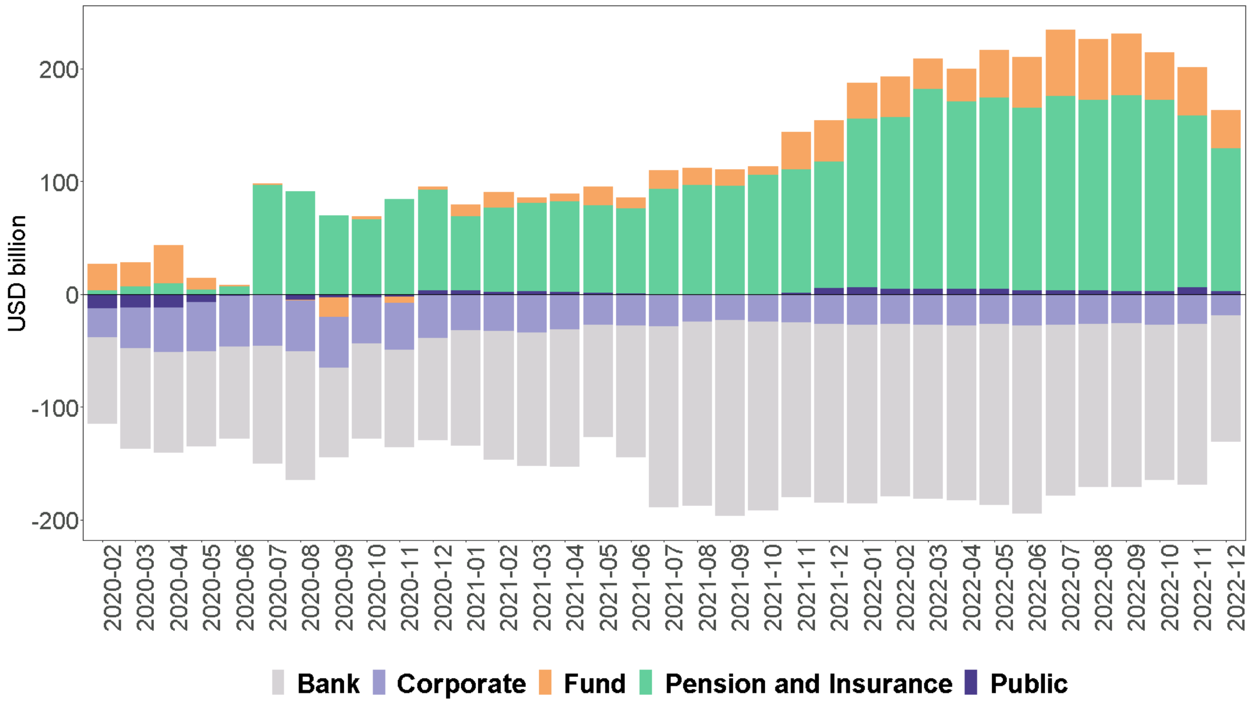


Figure C1: Sectoral distribution of outstanding net receive fixed swap notional for UK entities only. This figure shows the net received fixed notional outstanding in $ billion as on each date at a monthly frequency across five end-user segments where the jurisdiction of the LEI is in the UK.

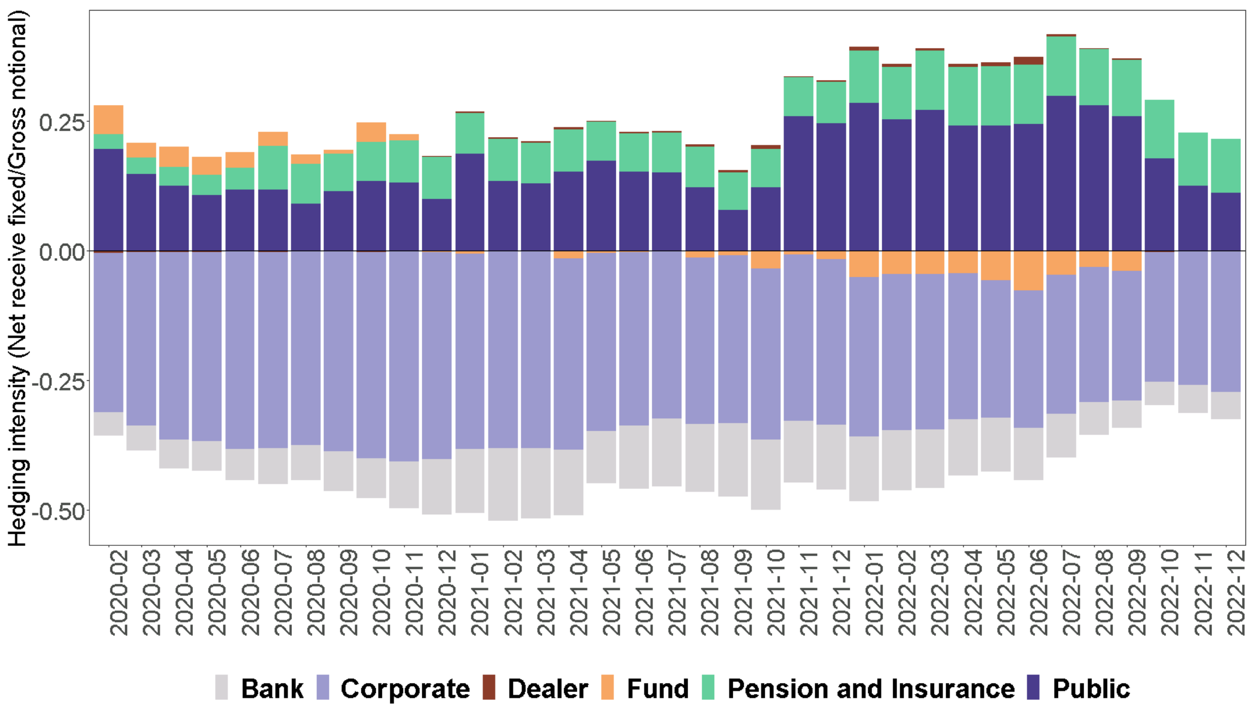


Figure C2: Sectoral distribution of hedging intensity (notional). This figure shows the net received fixed notional outstanding in $ billion scaled by the sector-level gross notional as on each date at a monthly frequency across five end-user segments and the inter-dealer segment. Inter-dealer position is calculated as the net of aggregate client-facing positions.

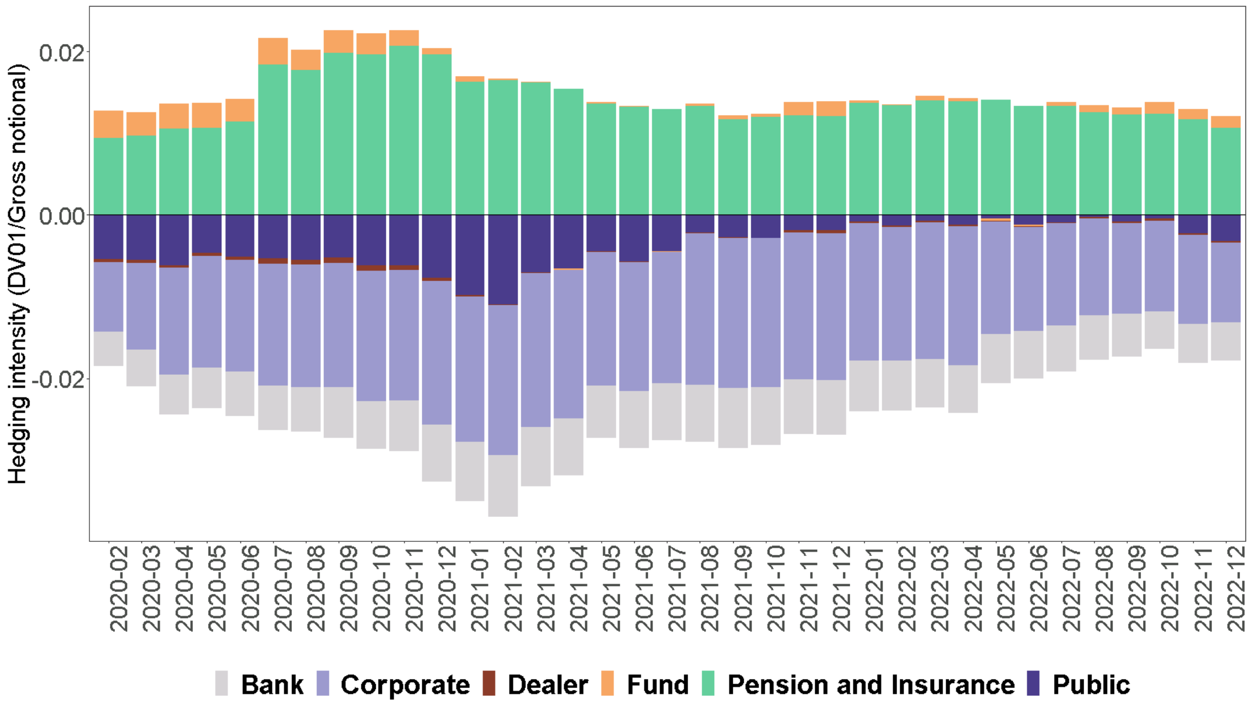


Figure C3: Sectoral distribution of hedging intensity (DV01). This figure shows the net DV01 position scaled by the sector-level gross notional as on each date at a monthly frequency across five end-user segments and the inter-dealer segment. The y-axis is multiplied by 1000 for ease of exposition. Inter-dealer position is calculated as the net of aggregate client-facing positions.

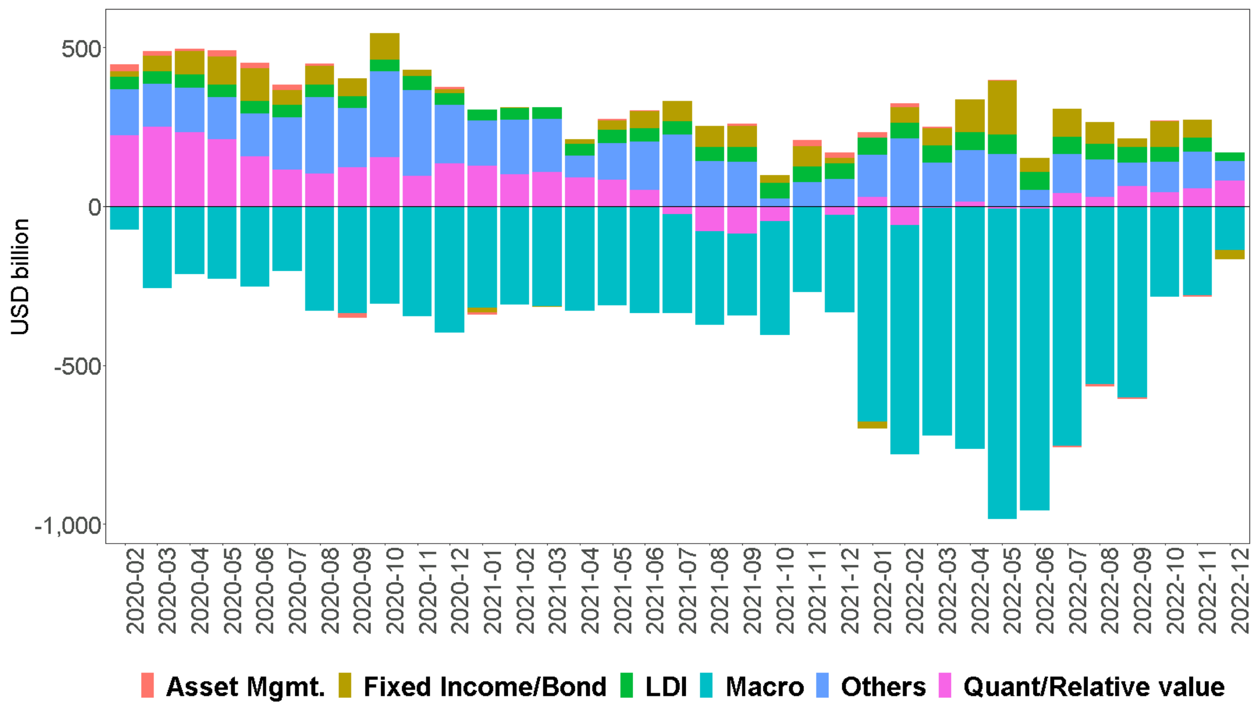


Figure C4: Fund-type distribution of outstanding net receive fixed swap notional. This figure shows the net received fixed notional outstanding in $ billion as on each date at a monthly frequency across the six fund types.

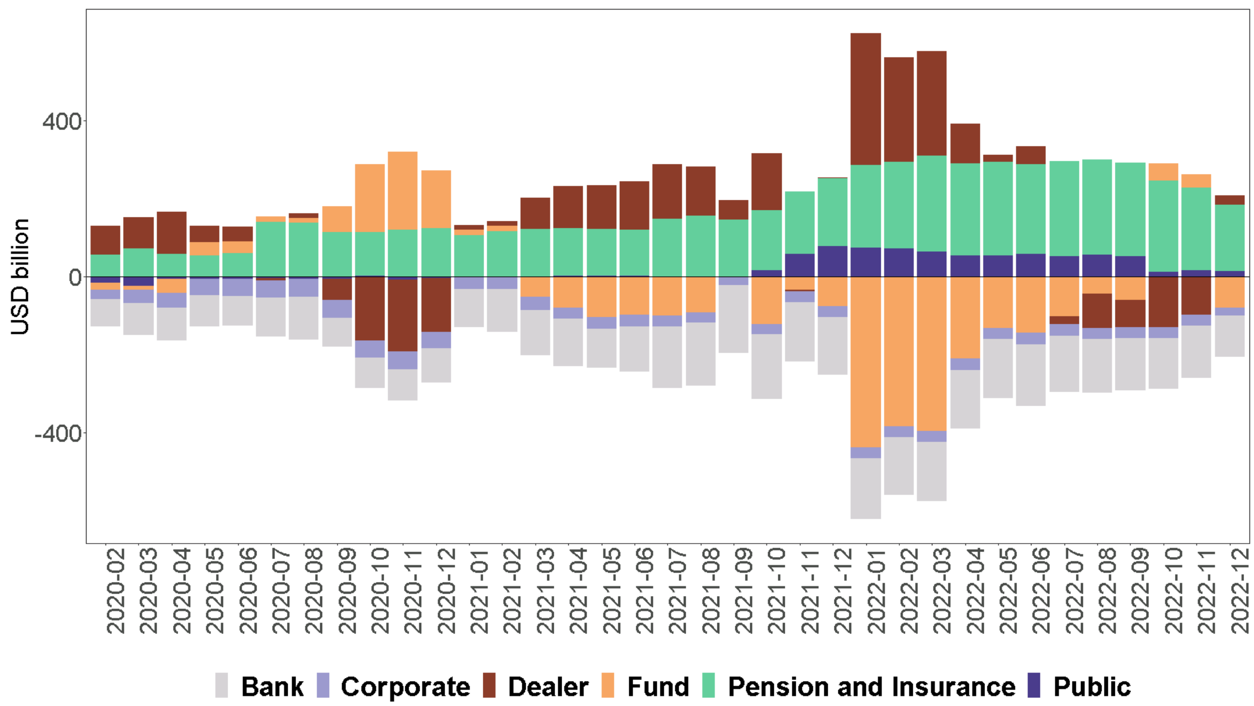


Figure C5: Sectoral distribution of outstanding net receive fixed GBP swap notional. This figure shows the net received fixed notional outstanding in $ billion as on each date at a monthly frequency across five end-user segments and the inter-dealer segment where the swap is denominated in GBP. Inter-dealer position is calculated as the net of aggregate client-facing positions.

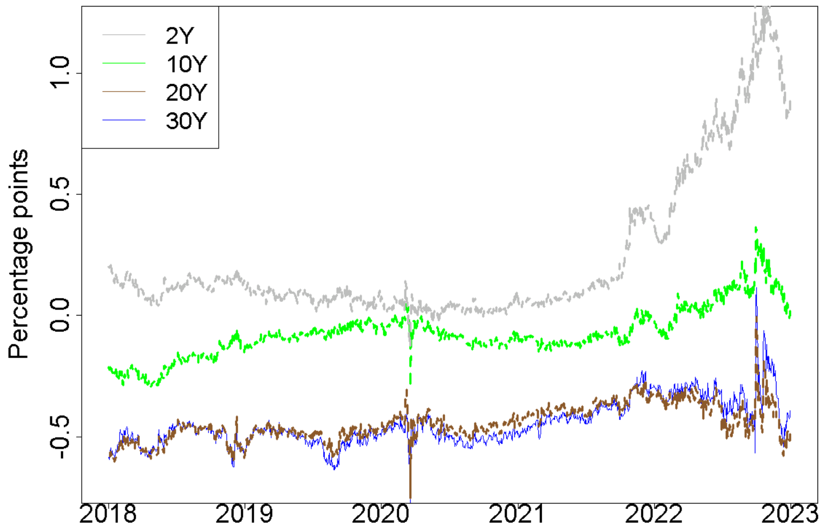
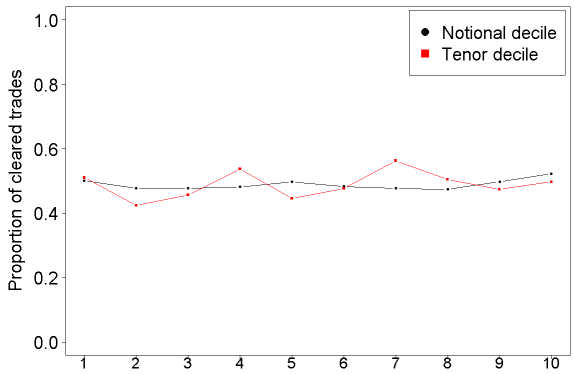
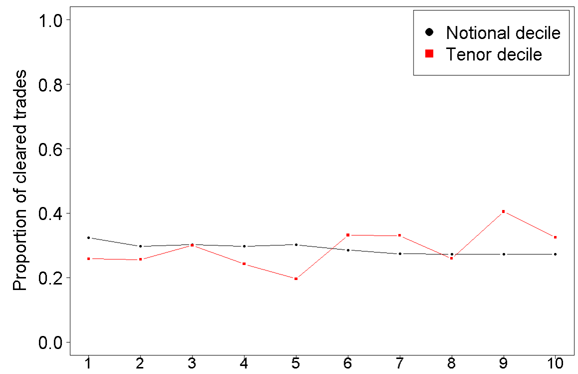


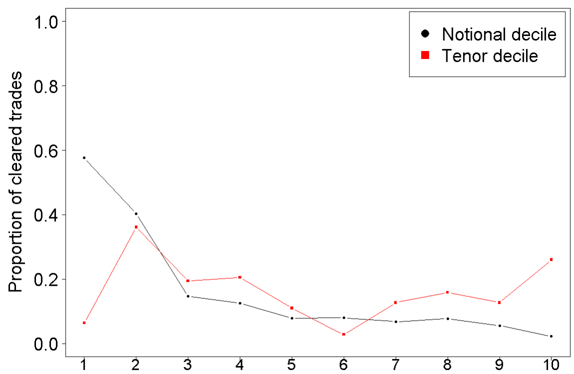
Figure C6: GBP swap spreads. This figure plots the time-series of GBP swap spreads, defined as the difference between maturity-matched swap rates and bond yields, for 2Y, 10Y, 20Y and 30Y tenors.



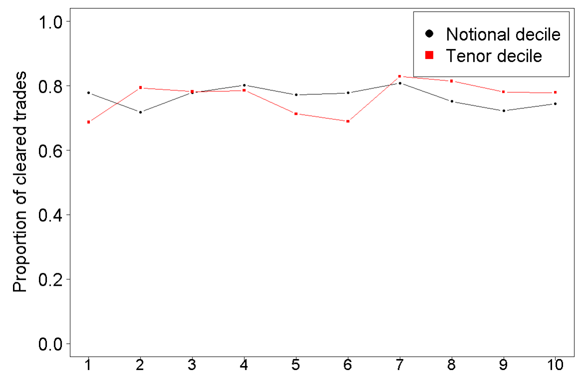
(a) Bank



(b) Fund

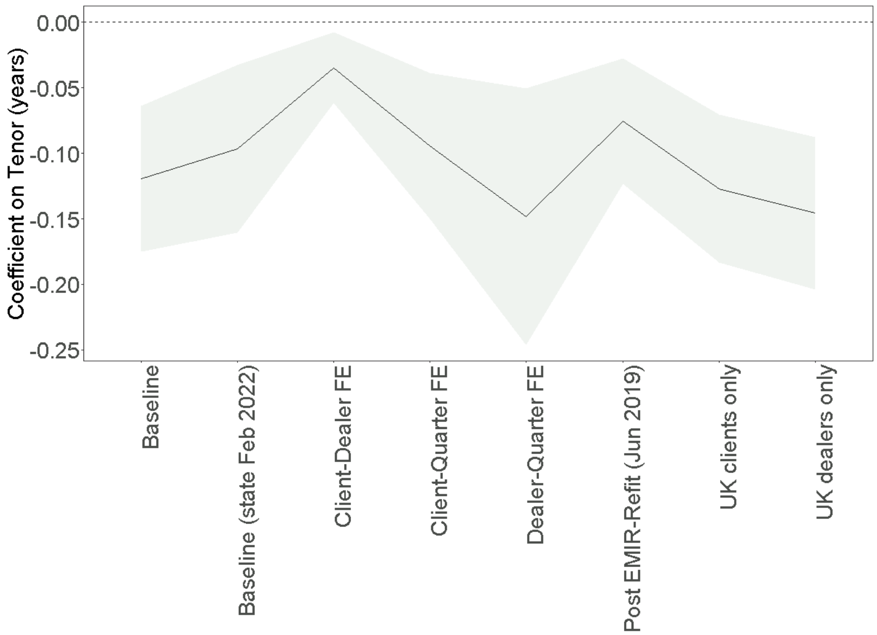


(c) Corporate

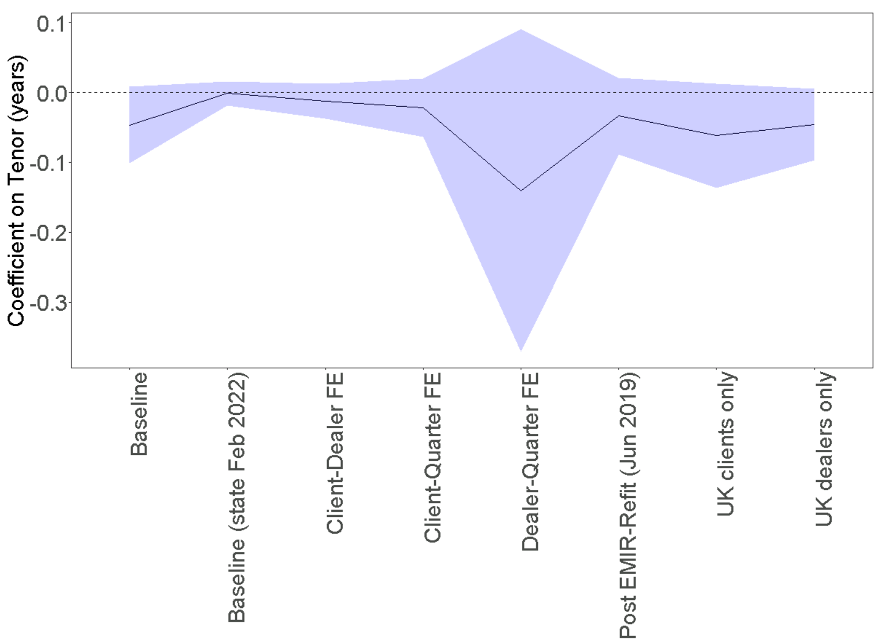


(d) Public

Figure C7: Centralized clearing and riskiness of trades. This figure shows the proportion of trades that are centrally cleared by four sectors (banks, funds, corporations and public) as a function of notional and tenor deciles.



(a) Pension funds



(b) Insurance

Figure C8: Specification curves. This figure shows robustness of the estimation of Equation 9 to specification choices for pension funds and insurers. 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.

Table C1: Descriptive statistics for all new trades executed between 2018-2022.

This table reports the distribution of notional (in $ million) and tenors (in years) by sector for new swap activity throughout our sample period.

Notional ($ million)	N	Mean	SD	p25	p50	p75
Bank	440,857	56	163	7	18	50
Fund	2,952,302	159	629	4	20	76
Pension and Insurance	267,759	53	205	3	11	40
Corporate	19,251	91	274	9	25	67
Public	54,378	149	471	12	35	110
Tenor (years)	**N**	**Mean**	**SD**	**p25**	**p50**	**p75**
Bank	440,857	7	6	2	5	10
Fund	2,952,302	8	8	2	5	10
Pension and Insurance	267,759	14	12	5	10	22
Corporate	19,251	6	7	2	4	7
Public	54,378	6	7	2	5	10

Table C2: Quantities demanded with changes in macroeconomic variables.

This table reports estimates of the model of the form in Equation 3 at a weekly frequency, with the dependent variables scaled by the gross volume traded in that week. Bond yield (PC1, change) refers to the weekly change in the first principal component of 2Y, 5Y, 10Y, 20Y and 30Y US Treasury yields. Slope (change) refers to the weekly change in 10Y minus 2Y US Treasury yields. Standard errors are heteroskedasticity robust and reported in parantheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Net receive fixed (scaled,per \$100)				
	Bank	Fund	PF&I	Corporate	Public
	(1)	(2)	(3)	(4)	(5)
Bond yield (PC1, change)	14.6***	1.23	-3.02	35.4***	-1.45
	(3.38)	(2.27)	(5.19)	(13.1)	(11.0)
Slope (10Y-2Y, change)	-8.75	-4.84	-33.5**	-88.3**	19.9
	(11.5)	(6.96)	(16.9)	(41.1)	(33.6)
Observations	259	259	259	259	259
Adj. R^2	0.05	0.01	0.01	0.03	0.01
	DV01 (scaled,per \$100)				
	Bank	Fund	PF&I	Corporate	Public
	(1)	(2)	(3)	(4)	(5)
Bond yield (PC1, change)	0.005***	-0.0003	-0.008*	0.023***	0.001
	(0.0009)	(0.0003)	(0.005)	(0.006)	(0.002)
Slope (10Y-2Y, change)	0.001	-0.002	-0.021	-0.025	-0.0006
	(0.003)	(0.001)	(0.014)	(0.024)	(0.007)
Observations	259	259	259	259	259
Adj. R^2	0.07	0.00	0.02	0.02	0.01

Table C3: Price reaction to quantities demanded.

This table reports estimates of the model of the form in Equation 6 at a monthly frequency. The dependent variables are 2Y through 30Y GBP swap spreads in columns (1) through (5) in month t+1. The regressors include net receive fixed demand from each end-user sector in month t (in \$ billion), the maturity-matched bond yield in month t, and the slope of the yield curve in time t. Standard errors are heteroskedasticity robust and reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Swap spreads (bps)				
Panel A: Split by sector	2Y (t+1)	5Y (t+1)	10Y (t+1)	20Y (t+1)	30Y (t+1)
	(1)	(2)	(3)	(4)	(5)
Bank net receive	0.296	0.346*	-0.460**	0.984	2.53
	(0.188)	(0.178)	(0.201)	(1.44)	(2.72)
Fund net receive	-0.021*	-0.285**	-0.212***	0.155	-1.48***
	(0.012)	(0.122)	(0.061)	(0.225)	(0.546)
PF&I net receive	0.201	1.53***	0.121	0.228	0.074
	(0.205)	(0.391)	(0.171)	(0.198)	(0.366)
Corporate net receive	-1.08	1.48	-0.128	2.03**	-12.3**
	(1.28)	(0.907)	(0.851)	(0.927)	(5.28)
Public net receive	0.084	0.445	-2.55**	0.602	-5.19
	(0.101)	(0.494)	(1.16)	(0.865)	(6.57)
Bond yield	0.322***	0.189***	0.065***	-0.004	0.058***
	(0.022)	(0.019)	(0.008)	(0.015)	(0.014)
Slope (10Y-2Y)	-0.069	-0.197***	-0.286***	-0.045	-0.007
	(0.070)	(0.056)	(0.037)	(0.046)	(0.043)
Observations	59	59	59	59	59
Adj. R^2	0.82	0.77	0.76	-0.06	0.22

	Swap spreads (bps)				
Panel B: All sectors	2Y (t+1)	5Y (t+1)	10Y (t+1)	20Y (t+1)	30Y (t+1)
	(1)	(2)	(3)	(4)	(5)
Aggregate net receive	-0.023**	-0.053	-0.195***	0.162	-0.309
	(0.010)	(0.170)	(0.057)	(0.155)	(0.335)
Bond yield	0.331***	0.188***	0.062***	0.0004	0.044***
	(0.021)	(0.020)	(0.007)	(0.012)	(0.015)
Slope (10Y-2Y)	-0.091	-0.232***	-0.280***	-0.034	-0.060
	(0.061)	(0.059)	(0.032)	(0.036)	(0.040)
Observations	59	59	59	59	59
Adj. R^2	0.81	0.71	0.74	-0.01	0.14

Table C4: Price reaction to quantities demanded by funds.

This table reports estimates of the model of the form in Equation 6 at a monthly frequency. The dependent variables are 2Y through 30Y GBP swap spreads in columns (1) through (5) in week t+1. The regressors include net receive fixed demand from each fund-type in month t (in $ billion), the maturity-matched bond yield in month t, and the slope of the yield curve in time t. Standard errors are heteroskedasticity robust and reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Swap spreads (bps)				
	2Y (t+1)	5Y (t+1)	10Y (t+1)	20Y (t+1)	30Y (t+1)
	(1)	(2)	(3)	(4)	(5)
Asset Mgmt. net receive	-0.040***	0.207	0.154	-0.080	-2.16
	(0.013)	(0.539)	(0.185)	(0.774)	(1.30)
Fixed income net receive	-0.008	1.21	-0.108	-3.20**	-7.27***
	(0.052)	(0.735)	(0.380)	(1.21)	(2.04)
Macro net receive	-0.046**	-0.359**	-0.166	-0.095	-2.96
	(0.017)	(0.141)	(0.151)	(0.403)	(2.15)
Quant net receive	-0.006	-1.08**	-1.20***	-0.264	2.44
	(0.041)	(0.465)	(0.393)	(1.04)	(4.43)
Others net receive	-0.018	-0.374	-0.185**	0.684***	0.275
	(0.022)	(0.237)	(0.085)	(0.238)	(0.793)
Bond yield	0.338***	0.196***	0.068***	0.003	0.073***
	(0.026)	(0.020)	(0.010)	(0.013)	(0.017)
Slope (10Y-2Y)	-0.090	-0.155***	-0.260***	0.016	-0.015
	(0.071)	(0.057)	(0.028)	(0.040)	(0.041)
Observations	59	59	59	59	59
Adj. R^2	0.81	0.74	0.77	0.14	0.27

Table C5: Descriptive statistics on centralized clearing and collateralization for outstanding positions.

This table reports descriptive statistics on the proportion of trades outstanding as of February 1, 2022 that were centrally cleared and the proportion of non-centrally cleared trades that were fully collateralized.

Proportion of cleared trades	N	Mean	SD	p25	p50	p75
Bank	71,174	0.77	0.42	1	1	1
Fund	63,621	0.78	0.41	1	1	1
Pension fund	24,168	0.22	0.41	0	0	0
Insurance	13,314	0.82	0.38	1	1	1
Corporate	4,235	0.06	0.24	0	0	0
Public	4,590	0.59	0.49	0	1	1
Proportion of fully collateralized bilateral trades	**N**	**Mean**	**SD**	**p25**	**p50**	**p75**
Bank	16414	0.22	0.41	0	0	0
Fund	13321	0.10	0.29	0	0	0
Pension fund	18,653	0.25	0.44	0	0	1
Insurance	1,930	0.20	0.40	0	0	0
Corporate	3419	0.01	0.10	0	0	0
Public	1384	0.01	0.08	0	0	0

Table C6: Comparative statistics for pension funds and insurers.

This table compares the distribution of the notional and tenor of new trades executed by pension funds and insurers between 2018-2022.

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